Joint Health Transitions of Spouses

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Abstract

Most studies of health status either focus on individual dynamics or on the correlation between spouses' static health status. This paper builds a bivariate probit (BP) model to analyze joint health dynamics of spouses. My BP model allows spouses to influence each other's health transitions and considers the effects of health insurance coverage on health. The data I use is the Health and Retirement Study (HRS). I use a detailed set of explanatory variables, including chronic diseases and health insurance coverage, to estimate the most detailed model to date for older Americans. The estimation results show that when the wife is originally in good health, then if her health stays in good next period, it raises the propensity of the husband to either change from bad to good health or stay in good health next period. But, this is not observed if the husband is originally in good health, and the impact of a wife's bad health is not statistically significant. Chronic diseases significantly increase the probability of bad health next period; and different types of health insurance affect household health transitions as well.

1 Introduction

The U.S. government has undertaken several reforms to expand health insurance eligibility and increase access to health care. These health related policies are meant to ensure people get health care that they need at an affordable cost. While many papers have analyzed the impact of either health care or health insurance on health, they often use static models because most available data is cross-sectional. Yet, health status is dynamic – it changes over time, and health in one period influences health in the next period, so estimating determinants of health transitions is critical to evaluating policy impacts. *People make just such implicit evaluations themselves when making decisions*, such as those involving saving and retirement, that affect their long-term health insurance coverage and health care access. Having access to longitudinal data can give researchers a better idea of how health insurance and health care reform affects health dynamically and how individuals make decisions that affect their long-term outcomes.

When researchers use panel data for such purposes, they have overlooked another important feature of living situations for many – marriage. Health dynamics of spouses may be interdependent for several reasons (Wilson 2002): 1) people tend to marry those with similar backgrounds, such as level of education and economic status, which are related to health status; 2) spouses tend to make similar choices that will affect their health, such as how much to smoke, drink, or eat; 3) spouses share emotional stresses, such as financial problems; 4) and importantly, one spouse might provide health care for the other one, and the burden of being a caregiver for a spouse in poor health may decrease the health of the caregiving spouse. This means that health-related policies should be evaluated for families, not just individuals.

I estimate a model of joint health transitions for older Americans. For an observed health status this period, the health of a spouse in the next period is assumed to depend on health and demographic characteristics, the other spouse's health, and the unobserved individual taste for being healthy. I also include the number of chronic diseases and different types of health insurance as explanatory variables, and I allow both spouses' health shocks to be correlated. While I discuss some possible sources of endogeneity later, I also note that it is difficult to analyze anything about spouses' influence on each other without raising some of these concerns.

I use data from the Health and Retirement Study (HRS), which collects information every two years about health and health insurance of individuals over age 50 and their spouses. I use self-reported information on health status and define excellent or good health as "good" and fair or poor health as "bad". My sample has 33,833 household health transitions, and I divide it into four subgroups based on the original household health status (both in good health, husband in good health and wife in bad health, etc.). Explanatory variables include the spouse's health, race and Hispanic ethnicity, age, education degree, number of chronic diseases, and two types of health insurance coverage. One includes Medicare below age 65 and Medicaid, and the other includes Medicare above age 65 and private insurance. I allow the transitions in individual health across time periods to be correlated for spouses and estimate this correlation coefficient.

I find the following. 1) When the wife is originally in good health, her health staying good next period raises the propensity that the husband's health either changes from bad to good or stays good next period. But, this is not observed if the husband is originally in good health, so him being in good health does not help the wife's health, and the impact of the wife originally being in bad health is not significant. This might be because wives in good health can provide better care to their husband, and wives usually take care of their husbands but not vice versa. This shows that spouses' health transitions should be considered jointly. 2) Receiving Medicare below age 65 or receiving Medicaid (signals of work-related disability and/or low income) significantly decrease the probability of being in good health next period. 3) Having more chronic diseases significantly decreases the probability of being in good health next period. Greater age reduces the likelihood of remaining in good health, even while controlling for chronic disease. However, age has no significant impact on the probability of remaining in bad health. 4) Being black or Hispanic significantly decreases the probability of being in good health next period even after controlling for health this period. 5) Having higher education significantly increases the probability of being in good health next period, and the magnitude of the effect on staying in good health is around twice as big as the effect on switching from bad to good.

In future work, I can use these estimates to simulate the effects of several policies on health, such as the effect of prescription drug plan coverage that helps to cure chronic disease, and the effect of the Patient Protection and Affordable Care Act that increases health insurance access. Besides, since spouses usually make decisions (such as saving and retirement) together, and many of these decisions are affected by their health status and demand for health care, one application of my analysis is to the estimation of dynamic structural models of household joint behaviors.

2 contribution to the Literature

A growing number of papers use dynamic structural models to study the joint retirement behavior of married couples. These papers (Blau 1998; Blau & Gilleskie 2006; French & Jones 2004; Casanova 2009) calculate husband's and wife's health transitions separately. For each spouse, they assume the health transition probability is a function of current health status and some demographics, such as age and race. They consider the husband's and wife's health transitions as two independent processes. While these papers study household joint decisions about retirement, none consider possible correlation between husband and wife's health transitions due to marriage sorting, similar living style, or shared family income and health insurance coverage.

I follow these papers by assuming that each spouse's health transition probability is a function of his current health status, demographic variables, and some unobserved individual health shock. I further allow both spouses' health transitions to be correlated in two ways: 1) one spouse's health transition directly affects the other spouse's health transition; and 2) health shocks that the spouses experience to be correlated. Also, I include two more factors as dependent variables that might affect each spouse's health transition. One is the number of chronic diseases which gives more information about individual's current health status. It is common to use either self-reported health or a specific condition (heart attack, hospitalization, or death) when looking at health on the left-hand side (LHS), or to use self-reported health when looking at health on the right-hand side (RHS). The way I am handling it is more like estimating a health production function. The other factor I try to include is health insurance coverage, which might affect choices about health care treatment and thus health.

Another related literature examines the association between health insurance and health status. Some papers, based on observational data, compare health outcomes for insured people and uninsured people. They generally find small but significant positive correlations between health insurance and health (see Hadley 2003 for a review). Other papers use quasi-experimental approaches in which variation in health insurance coverage is due to some exogenous event. Most of these papers find positive effects of insurance on health only for certain groups of people, like infants, the elderly, and the poor (see Levy and Meltzer 2004 for a review). Most of these studies do not address the dynamic links between health insurance and health because they lack data sources that track individuals health insurance coverage and health over time. Two papers (Deb, Trivedi, & Zimmer, 2010; Zimmer 2012) study the dynamic effects of health insurance on health, but their analysis focus on individuals not households.

3 Data

I use the Health and Retirement Study (HRS), which is a detailed panel survey of individuals over age 50 and their spouses. It collects extensive information about general health status, chronic diseases, health insurance coverage, labor supply, and demographic characteristics such as age, gender, race, and education. The HRS began in 1992 and has re-interviewed the same households every two years thereafter.[1] There are currently nine available waves, covering from 1992 to 2008.

[1]New cohorts are added every three waves to make sure that every survey contains people representative of the population aged 51 and above.

I use the Rand HRS data file (from the RAND Center for the Study of Aging), which is a user-friendly file derived from all waves of the HRS. For most individual-level variables, Rand cleans variables, and imputes values for those missing information using consistent and model-based imputations. [2]

3.1 Main Variables

General Health Status

To study health transitions, I start by measuring health status by the response to the question *"Would you say your health is excellent, very good, good, fair or, poor?"* I define general health status as good if their answer is excellent, very good, or good, and bad otherwise. Although several researchers raise concerns about the reliability of self-reported health status, I do not worry about this here. First, respondents should report their true health status because the HRS data has very high level of confidentiality. Second, when people make choices that are affected by their health status, their choices rely on individual perceptions of health more than they depend on an objective measure of health status.[3]

Chronic Diseases

Besides general health status, the (Rand) HRS records which of the following eight chronic diseases he/she has been diagnosed for that wave.[4] 1) high blood pressure or hypertension; 2) diabetes or high blood sugar; 3) cancer or a malignant tumor of any kind except skin cancer; 4) chronic lung disease except asthma such as chronic bronchitis or emphysema; 5) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; 6) stroke or transient ischemic attack (TIA); 7) emotional, nervous, or psychiatric problems; and 8)arthritis or rheumatism. I am interested in this variable because chronic disease is an obvious predictor of bad health; interestingly, I find later that not all people with chronic conditions report being in bad health, but that having a chronic condition in one wave has a significant effect on transitioning to bad health in a later wave. In order to treat this information in a parsimonious fashion, I count up the number of chronic conditions that an individual reports in the variable *chronic_disease*s, which takes values from 0 to 8.

[2] See *RAND HRS Data Documentation, Version J* for more information about imputation and data cleaning.

[3] In future research it might be preferable to treat health as multinomial rather than binomial.

[4] The HRS chooses these eight chronic health conditions as ones to report.

Health Insurance Coverage

Health insurance coverage might affect a person's health transition through choices about health treatment. The Rand HRS includes information on coverage by Medicare, Medicaid, and employer-provided health insurance. For the latter, the HRS then

both public and private health insurance coverage for each respondent. It has variables that indicate whether the respondent is covered by Medicare and Medicaid. It records whether the respondent is covered by any employer-provided health insurance. If the respondent says yes, then the data asks the source of the health insurance: from his current or previous employer or from the spouse's current or previous employer.

Health insurance coverage and type may reflect how sick someone is, and may be correlated with unobserved individual taste for health insurance. These might cause an endogeneity problem. For example, people covered by private health insurance usually have better health and higher income, while people covered by Medicaid are usually poor or disabled. Including a health insurance dummy as an explanatory variable might cause biased estimates due to two endogeneity problems of insurance coverage: individuals can choose employer-provided health insurance coverage and health can affect their choices. I solve the first problem by studying elder households who are far away from the age making decision about employer-provided health insurance, and solve the second problem by controlling differences in original health–including chronic diseases and dividing sample into four subsamples by originally household health status.[5] [6]

I divide health insurance into two types. Type I health insurance includes Medicare below age 64 and Medicaid, and type II health insurance includes Medicare above age 64 and employer-provided health insurance (no matter from which spouse's employer). Type I health insurance is available to people with worse health, either because of disability or because of a lack of health care due to low income. Type II health insurance coverage depends on age or job characteristics, but is less related to current health status or access to health care. Distinguishing these two types of health insurance enable us to have a better understanding about the effects of health insurance coverage on health transitions.

Other Demographics

I use information on the highest educational degree attained to measure the respondent's education level, and I use three categories for educational attainment: no degree; less than BA; and BA or more.[7]

[5] More detailed discussion about endogeneity problem of health insurance coverage is in section 6.

[6] In Section 5, I compare alternative models to the BP model, and the results show that including health insurance coverage can explain the observed health transitions of spouses better.

[7] The second category includes having a degree of HS, GED, AA or Lt BA, and the third category includes having a degree of BA, MA, MBA, Law, MD, or PhD.

The data include other demographic variables such as age, Hispanic ethnicity, and race, for each respondent. Since people tend to marry someone of the same race/ethnicity, I generate variables to represent Hispanic status and race at the household level. I use two categories for household Hispanic: both spouses are Hispanic and otherwise, and use three categories for household race: both are white, both are black, and otherwise.

3.2 Sample

I restrict my sample to married couples because I study household health transitions. From each wave, I choose couples where both spouses can be observed in two adjacent waves. I choose couples initially in wave 1 to wave 8 because I cannot observe health transitions for those in the last wave. Because the HRS is panel data, I sometimes observe several health transitions for the same household. In this paper, I treat these health transitions of one household as different independent data points in my sample. [8] In other words, each observation in my sample is one household two-year health transition. Table 1 lists the sample selection criteria, which involve eliminating observations who are missing any of the data I use in my model. Most missing data is due to non-response to chronic disease questions.[9] After selecting for various reasons, there are 33,833 household health transitions left in my sample.

Table 1: Sample Selection Criteria

[8] This means I do not consider some unobserved time-invariant household heterogeneity, so the estimator is not efficient. I do not consider a random effects estimator for two reasons: 1) In this paper, I divide the data into subsamples by current health status to allow health transition processes to differ by initial health status, households switch subsamples as their health changes. 2) Households in the sample stay in the data set for varying periods. Therefore, I treat the data set as pooled cross sectional data instead of unbalanced panel data.

[9] Data is missing on chronic diseases due to two mains reseasons: 1) In wave 2, if it is a reinterview and the condition is reported in wave 1, the question about whether or not a doctor has told the respondent he/she had these conditions is skipped, except for the heart condition question which asks about the time since last interview. This cause a lot of missing data on chronic diseases for the waves 1-2 and 2-3 health transitions. For example, 4265 individuals have missing data on whether they have high blood pressure in wave 2. 2) I include the number of chronic diseases that have been diagnosed as an explanatory variable. Thus, non-response to any of the 8 chronic diseases will create a missing data for this variable.

Cause	# Obs Lost	Proportion of Total	# Remaining
			42173
Missing data on hispanic or race	35	0.0008	42138
Missing data on husband's chronic disease	4777	0.1133	37361
Missing data on wife's chronic disease	2817	0.0668	34544
Missing data on husband's eligiblity for type I HI	73	0.0017	34471
Missing data on husband's eligiblity for type II HI	204	0.0048	34267
Missing data on wife's eligiblity for type I HI	63	0.0015	34204
Missing data on wife's eligiblity for type II HI	268	0.0064	33936
Missing data on husband's education	79	0.0019	33857
Missing data on wife's education	24	0.0006	33833
Number Remaining in Sample	33833	0.8022	

The effects of household and individual characteristics on household health transitions might depend on initial health status. For example, the effect of health insurance coverage on the transition from bad health to good health might differ from that on staying healthy. In order to distinguish the effects of characteristics on health transitions for households with different initial health status, I divide the sample into four subsamples based on the original household health status in a particular HRS wave: both in good health (GG), husband in bad health and wife in good health (BG), husband in good health and wife in bad health (GB), and both in bad health (BB). Table 2 shows how many households are in each subsample by wave. The last column shows that each wave contributes evenly to the whole sample. The only exception is wave 2, which contributes about half of other waves. This is because in wave 2, many observations are excluded from the sample due to missing data on chronic diseases.[10] The last row shows that both spouses are in good health in more than 60% of the whole sample, while both spouses are in bad health in less than 10%.

Table 2: Sample Size By Waves And Original Household Health Status

[10]The reason of missing data on chronic diseases is explained in footnote 6.

	Subsample BB	Subsample BG	Subsample GB	Subsample GG	Total	Percentage
wave 1	269	576	484	3030	4359	*0.13*
wave 2	196	319	263	1256	2034	*0.06*
wave 3	287	551	481	2505	3824	*0.11*
wave 4	489	778	648	3059	4974	*0.15*
wave 5	368	668	590	3104	4730	*0.14*
wave 6	395	663	554	2885	4497	*0.13*
wave 7	438	721	597	3173	4929	*0.15*
wave 8	375	672	566	2873	4486	*0.13*
Total	2817	4948	4183	21885	33833	
Percentage	0.08	0.15	0.12	0.65		

3.3 Sample Descriptive

Table 3-1 shows means of the explanatory variables for each subsample. Households originally in bad health are older, are more likely to be Hispanic, have more chronic diseases, have less education, are more likely to be covered by Type I health insurance (Medicaid or Medicare below age 64) but less likely to be covered by Type II health insurance (Private or Medicare above age 64), and are less likely to be uninsured. Table 3-2 lists raw transition rates across states. Good health is a more stable status than bad health. The probability of staying in the initial health status is 0.82 for subsample GG where both are initially in good health, and is a little less than 0.6 for other three subsamples. For subsample GG and subsample BB, it is the least likely to change to BB and GG health status, respectively; while for subsample GB and subsample BG, it is more likely to change to GG than to BB health status.

Table 3-1: Sample Statistics

Variables	subsample BB Mean	subsample BB Std. Dev.	subsample BG Mean	subsample BG Std. Dev.	subsample GB Mean	subsample GB Std. Dev.	subsample GG Mean	subsample GG Std. Dev.
Health next period_h	0.25	0.43	0.32	0.47	0.79	0.41	0.89	0.32
Health next period_w	0.24	0.43	0.83	0.37	0.32	0.47	0.91	0.28
Hispanic	0.21	0.41	0.08	0.26	0.12	0.32	0.04	0.20
Race								
white (base)								
black	0.17	0.37	0.14	0.35	0.13	0.34	0.07	0.25
others	0.11	0.31	0.06	0.24	0.08	0.27	0.05	0.22
Age_h	68.34	10.12	67.13	9.78	66.39	10.11	64.37	9.07
Chronic_disease_h	2.61	1.47	2.53	1.38	1.45	1.21	1.34	1.15
Type I insurance_h	0.23	0.42	0.13	0.34	0.06	0.23	0.02	0.15
Type II insurance_h	0.78	0.42	0.86	0.35	0.87	0.33	0.91	0.28
Education_h								
Less HS (base)								
HS	0.38	0.49	0.52	0.50	0.52	0.50	0.53	0.50
College & above	0.07	0.25	0.14	0.34	0.15	0.35	0.31	0.46
Age_w	64.66	10.40	63.29	10.37	63.29	10.31	60.83	9.58
Chronic_disease_w	2.78	1.44	1.47	1.18	2.55	1.42	1.26	1.12
Type I insurance_w	0.22	0.42	0.05	0.21	0.14	0.34	0.02	0.14
Type II insurance_w	0.71	0.45	0.84	0.36	0.80	0.40	0.88	0.33
Education_w								
Less HS (base)								
HS	0.45	0.50	0.65	0.48	0.58	0.49	0.66	0.48
College & above	0.04	0.19	0.12	0.32	0.09	0.29	0.22	0.42

Table 3-2: Household Health Transition Rates

Health Status Next Period	subsample BB Transition Rate	subsample BG Transition Rate	subsample GB Transition Rate	subsample GG Transition Rate
Both in bad health	0.59	0.13	0.16	0.02
Only wife in good health	0.16	0.55	0.05	0.10
Only husband in good health	0.17	0.04	0.52	0.07
Both in good health	0.08	0.28	0.27	0.82

4 Empirical Approach

This section presents a bivariate probit model of spouses' health transitions, allowing for interdependence between them. Spouses' health transitions might be correlated because of sharing household resource and taking care of each other; one spouse may get health insurance coverage for the other spouse; and a spouse with better health can take care of the other. Thus, one spouse's health transition may not only be affected by household characteristics, individual characteristics (such as education, chronic diseases, and two types of health insurance coverage), and an individual health shock, but also by the other spouse's characteristics. The specification also accounts for the correlation between spouses' health shocks since they share emotional stresses and make similar choices (such as how much to smoke/drink/eat) that will affect their health .

4.1 Model

To capture the correlation between both spouses' health transitions, I build the following bivariate probit (BP) model:

$$\begin{cases} y^*_{nht} = \beta^h_0 + X'^H_{n,t-1}\beta^h_1 + X'^h_{n,t-1}\beta^h_2 + y^*_{nwt}\beta^h_3 + u_{nht} \\ y^*_{nwt} = \beta^w_0 + X'^H_{n,t-1}\beta^w_1 + X'^w_{n,t-1}\beta^w_2 + y^*_{nht}\beta^w_3 + u_{nwt} \end{cases} \qquad (*)$$

$$y_{nit} = \begin{cases} 1; & if\ y^*_{nit} > 0 \\ 0; & otherwise \end{cases} \qquad (i = h, w)$$

Here $y_{nt} = (y_{nht}, y_{nwt})$ denotes the health status next period of the husband, h, and wife, w, in household n. y_{nit} equals 1 if spouse i is observed in good health in the next period, and equals 0 if in bad health. Spouse i's latent health status in the next period, y^*_{nit}, is modeled as a function of household characteristics this period, $X^H_{n,t-1} = (HH\_Hisp_n, HH\_race_n)$; his/her individual characteristics this period, $X^i_{n,t-1} = (edu_{ni}, age_{ni,t-1}, chronic\_disease_{ni,t-1}, HI1_{ni,t-1}, HI2_{ni,t-1})$; his/her health shock for the next period, u_{nit}; and the latent variable of the other spouse's health status in the next period, $y^*_{n,-it}$.[11] This means that spouse i's characteristics this period can affect the other one's health transition only through i's latent health in the next period, so they serve as exclusion restrictions. Due to marriage sorting, people with high tastes for healthy life tend to marry other people with high tastes for healthy life. Thus, I allow both spouses' health shocks to be bivariate normally distributed,

$$(u_{nht}, u_{nwt}) \sim i.i.d\ N\left[0, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]$$

Thus, in this model, I allow for two types of interdependence between spouse's health transitions. I allow one spouse's health transition to directly affect the other spouse's health transition, and allow the health shocks that the spouses experience to be correlated.

[11] Since X^H_n, X^h_n, and X^w_n are vectors of variables, β^i_1 and β^i_2 are vectors of parameters.

4.2 Model Estimation

Let $\theta = (\beta^h, \beta^w, \rho)$ denote the vector of parameters in the BP model. I estimate θ using maximum-likelihood estimation (MLE), and using the optimization algorithm BHHH. Given data $\{(y_{nht}, y_{nwt}); X^H_{n,t-1}, X^h_{n,t-1}, X^w_{n,t-1}\}\,(n = 1, ..., N)$ on the observed states and health transitions of N households, one can estimate θ by finding the value $\hat{\theta}$ such that the predictions of the model fits the data best. In my case, $\hat{\theta}$ are the parameter values that maximizes the likelihood function $L(\theta)$ defined by

$$L(\theta) = \textstyle\sum_{n=1}^{N} log L_n(\theta)$$

where $L_n(\theta)$ is the likelihood contribution for household n. For any household, no matter it's original household health status, there are four possible health transition results: both in good health ($y_n = (1,1)$), only one spouse is in good health ($y_n = (0,1)\, or\, (1,0)$), and both in bad health ($y_n = (0,0)$) in the next period. $L_n(\theta)$ is a function of the possibilities for these four possible results:

$$L_n(\theta) = Pr[y_n = (1,1)]^{1(1,1)} \cdot Pr[y_n = (1,0)]^{1(1,0)} \cdot Pr[y_n = (0,1)]^{1(0,1)} \cdot Pr[y_n = (0,0)]^{1(0,0)}$$

The BP model (*) is a simultaneous equations model, and its reduced form, after substituting out for the endogenous y^* term from the other spouse that appears in each spouse's health equation, is,

$$\begin{cases} y^*_{nht} = \dfrac{1}{1-\beta^h_3\beta^w_3}[(\beta^h_0 + \beta^w_0\beta^h_3) + X'^H_{n,t-1}(\beta^h_1 + \beta^w_1\beta^h_3) + X'^h_{n,t-1}\beta^h_2 + X'^w_{n,t-1}\beta^w_2\beta^h_3 + (u_{nht} + u_{nwt}\beta^h_3)] \\ y^*_{nwt} = \dfrac{1}{1-\beta^h_3\beta^w_3}[(\beta^w_0 + \beta^h_0\beta^w_3) + X'^H_{n,t-1}(\beta^w_1 + \beta^h_1\beta^w_3) + X'^w_{n,t-1}\beta^w_2 + X'^h_{n,t-1}\beta^h_2\beta^w_3 + (u_{nwt} + u_{nht}\beta^w_3)] \end{cases}$$

$$(u_{nht} + u_{nwt}\beta^h_3,\, u_{nwt} + u_{nht}\beta^w_3) \sim i.i.d\, N\left[0, \begin{pmatrix} (\sigma_1)^2 & \rho_{hw} \\ \rho_{hw} & (\sigma_2)^2 \end{pmatrix}\right]$$

where σ_1, σ_2 and ρ_{hw} are functions of $(\beta^h_3, \beta^w_3, \rho)$. As noted above, the other spouse's individual characteristics enter the reduced-form model in a restricted fashion, so that the reduced-form parameters uniquely identify the structural parameters from (*).

With the reduced-form model (**), I can write down the probability for each possible household health transition result, $Pr[y_n]$.

5 Results

In this section, I first discuss estimation results. Then, I test the goodness-of-fit of the BP model, and compare it to some alternative models.

5.1 Estimation Results

Table 4 - Table 7 report estimates of my structural model with spouse's health as an explanatory variable, explaining household joint health transitions for four subsamples, respectively. In each table reporting joint estimates, the left-hand side lists estimates for the husband's equation, and the right-hand side lists estimates for the wife's equation. In each case, a positive coefficient indicates that the right-hand side variable raises the propensity of the individual to be in good health next period. Table 8 - Table 11 report marginal effects of expanatory variables in the reduced form model, combining the effect of covariates on own health and on spouse's health through its effect on own health, for four subsamples, respectively. In each table, the first column shows the reduced-form marginal effects of each variable on a husband's probability of being in good health next period, and the second column shows the marginal effects on a wife's probability of being in good health next period.

i think you should start by showing, and discussing, GG, since that's where you get a significant effect of spousal health

Table 4: Structral Estimation Results for Subsample BB: Both are Originally in Bad Health

Husband Equation				**Wife Equation**			
Variable	Estimates		Std Err	Variable	Estimates		Std Err
Constant	-0.255		1.088	Constant	-0.575		0.843
HH_Hispanic	-0.061		0.081	HH_Hispanic	-0.171	*	0.081
HH_Race				HH_Race			
white (base)	omitted			white (base)	omitted		
black	0.058		0.074	black	0.033		0.075
others	-0.157		0.099	others	0.069		0.096
Chronic_disease	-0.165	**	0.02	Chronic_disease	-0.193	**	0.021
age	-0.004		0.032	age	0.015		0.026
age^2	0.000		0.000	age^2	0.000		0.000
Type I HI	-0.266	**	0.075	Type I HI	-0.176	*	0.077
Type II HI	0.076		0.08	Type II HI	0.164	*	0.074
Education				Education			
Less HS (base)	omitted			Less HS (base)	omitted		
HS	0.228	**	0.061	HS	0.216	**	0.059
College & above	0.276	*	0.107	College & above	0.087		0.142
Wife's latent health	0.083		0.081	Husband's latent health	0.063		0.098
Correlation Coefficient	0.035						

Note: 1) Subsample size: 2817; 2) Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 1% level.

Table 5: Structral Estimation Results for Subsample BG: Only Husband is Originally in Bad Health

Husband Equation				**Wife Equation**			
Variable	Estimates		Std Err	Variable	Estimates		Std Err
Constant	-0.491		0.74	Constant	-1.259		0.657
HH_Hispanic	-0.123		0.087	HH_Hispanic	-0.466	**	0.087
HH_Race				HH_Race			
white (base)	omitted			white (base)	omitted		
black	-0.138	*	0.061	black	-0.167	*	0.066
others	0.028		0.082	others	-0.078		0.097
Chronic_disease	-0.192	**	0.016	Chronic_disease	-0.253	**	0.02
age	0.016		0.022	age	0.083	**	0.021
age^2	0.000		0.000	age^2	-0.001	**	0.000
Type I HI	-0.303	**	0.064	Type I HI	-0.266	**	0.09
Type II HI	0.066		0.064	Type II HI	0.181	**	0.064
Education				Education			
Less HS (base)	omitted			Less HS (base)	omitted		
HS	0.124	**	0.044	HS	0.329	**	0.053
College & above	0.243	**	0.063	College & above	0.631	**	0.093
Wife's latent health	0.132	*	0.054	Husband's latent health	0.183	*	0.073
Correlation Coefficient	-0.238						

Note: 1) Subsample size: 4948; 2) Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 1% level.

Table 6: Structral Estimation Results for Subsample GB: Only Wife is Originally in Bad Health

Husband Equation				**Wife Equation**			
Variable	Estimates		Std Err	Variable	Estimates		Std Err
Constant	-0.172		0.837	Constant	-0.714		0.604
HH_Hispanic	-0.345	**	0.073	HH_Hispanic	-0.214	**	0.079
HH_Race				HH_Race			
white (base)	omitted			white (base)	omitted		
black	-0.149	*	0.069	black	-0.148	*	0.067
others	-0.024		0.09	others	0.063		0.082
Chronic_disease	-0.208	**	0.019	Chronic_disease	-0.161	**	0.016
age	0.043		0.025	age	0.026		0.019
age^2	0.000	*	0.000	age^2	0.000		0.000
Type I HI	-0.264	**	0.091	Type I HI	-0.43	**	0.071
Type II HI	0.279	**	0.074	Type II HI	0.111		0.061
Education				Education			
Less HS (base)	omitted			Less HS (base)	omitted		
HS	0.29	**	0.052	HS	0.094		0.049
College & above	0.564	**	0.08	College & above	0.177	*	0.081
Wife's latent health	0.077		0.076	Husband's latent health	-0.025		0.064
Correlation Coefficient	0.106						

Note: 1) Subsample size: 4183; 2) Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 1% level.

Table 7: Structral Estimation Results for Subsample GG: Both are Originally in Good Health

Husband Equation				Wife Equation			
Variable	Estimates		Std Err	Variable	Estimates		Std Err
Constant	-1.189	*	0.469	Constant	-0.475		0.391
HH_Hispanic	-0.304	**	0.057	HH_Hispanic	-0.395	**	0.058
HH_Race				HH_Race			
white (base)	omitted			white (base)	omitted		
black	-0.189	**	0.043	black	-0.156	**	0.048
others	-0.183	**	0.051	others	-0.141	*	0.056
Chronic_disease	-0.227	**	0.01	Chronic_disease	-0.246	**	0.011
age	0.082	**	0.014	age	0.063	**	0.012
age^2	-0.001	**	0.000	age^2	-0.001	**	0.000
Type I HI	-0.431	**	0.06	Type I HI	-0.426	**	0.068
Type II HI	0.136	**	0.042	Type II HI	0.123	**	0.04
Education				Education			
Less HS (base)	omitted			Less HS (base)	omitted		
HS	0.259	**	0.031	HS	0.326	**	0.035
College & above	0.554	**	0.037	College & above	0.573	**	0.047
Wife's latent health	0.073	*	0.035	Husband's latent health	0.129	**	0.038
Correlation Coefficient	-0.081						

Note: 1) Subsample size: 21885; 2) Double-starred items are statistically significant at the 5% level, and single-starred items are statistically significant at the 1% level.

Table 8: Reduced-Form Marginal Effects for Subsample BB: Both are Originally in Bad Health

	Prob(health_h=1)		Prob(health_w=1)	
hispanic	-0.0222		-0.0496	**
	(0.0233)		(0.0229)	
Race				
Black (omitted)				
White	0.0187		0.0109	
	(0.0232)		(0.0222)	
Others	-0.0436		0.0174	
	(0.0279)		(0.0284)	
chronic_disease_h	-0.0469	****	-0.0030	
	(0.0067)		(0.0048)	
age_h	0.0006		0.0000	
	(0.0041)		(0.0003)	
Health Insurance				
No HI (omitted)				
HI1_h	-0.0766	****	-0.0049	
	(0.0219)		(0.0078)	
HI2_h	0.0226		0.0014	
	(0.0234)		(0.0027)	
< HS (omitted)				
HS_h	0.0693	****	0.0042	
	(0.0186)		(0.0067)	
college_h	0.0852	**	0.0051	
	(0.0353)		(0.0082)	
chronic_disease_w	-0.0048		-0.0529	****
	(0.0048)		(0.0085)	
age_w	-0.0002		-0.0019	
	(0.0006)		(0.0042)	
HI1_w	-0.0044		-0.0500	**
	(0.0047)		(0.0218)	
HI2_w	0.0041		0.0471	**
	(0.0045)		(0.0225)	
<HS_w(omitted)				
HS_w	0.0054		0.0639	****
	(0.0055)		(0.0179)	
College_w	0.0022		0.0247	
	(0.0041)		(0.0414)	

Table 9: Reduced-Form Marginal Effects for Subsample BG: Only Husband is Originally in Bad Health

	Prob(health_h=1)		Prob(health_w=1)	
hispanic	-0.0615	**	-0.1344	****
	(0.0257)		(0.0334)	
Race				
Black (omitted)				
White	-0.0541	***	-0.0471	***
	(0.0194)		(0.0173)	
Others	0.0062		-0.0169	
	(0.0282)		(0.0223)	
chronic_disease_h	-0.0633	****	-0.0082	***
	(0.0048)		(0.0031)	
age_h	-0.0026	*	-0.0003	**
	(0.0014)		(0.0002)	
Health Insurance				
No HI (omitted)				
HI1_h	-0.0996	****	-0.0131	**
	(0.0203)		(0.0057)	
HI2_h	0.0226		0.0028	
	(0.0217)		(0.0029)	
< HS (omitted)				
HS_h	0.0426	***	0.0053	*
	(0.0148)		(0.0027)	
college_h	0.0852	****	0.0102	**
	(0.0227)		(0.0046)	
chronic_disease_w	-0.0115	***	-0.0650	****
	(0.0044)		(0.0117)	
age_w	-0.0002		-0.0015	
	(0.0018)		(0.0011)	
HI1_w	-0.0121	**	-0.0683	**
	(0.0061)		(0.0283)	
HI2_w	0.0082	*	0.0441	***
	(0.0043)		(0.0170)	
<HS_w(omitted)				
HS_w	0.0150	**	0.0855	****
	(0.0062)		(0.0206)	
College_w	0.0289	**	0.1430	****
	(0.0117)		(0.0299)	

Table 10: Reduced-Form Marginal Effects for Subsample GB: Only Wife is Originally in Bad Health

	Prob(health_h=1)		Prob(health_w=1)	
hispanic	-0.1048	****	-0.0673	***
	(0.0285)		(0.0238)	
Race				
Black (omitted)				
White	-0.0441	**	-0.0477	**
	(0.0206)		(0.0214)	
Others	-0.0050		0.0221	
	(0.0234)		(0.0285)	
chronic_disease_h	-0.0586	****	0.0018	
	(0.0118)		(0.0046)	
age_h	-0.0037	**	0.0001	
	(0.0016)		(0.0010)	
Health Insurance				
No HI (omitted)				
HI1_h	-0.0756	**	0.0023	
	(0.0317)		(0.0058)	
HI2_h	0.0790	***	-0.0024	
	(0.0249)		(0.0061)	
< HS (omitted)				
HS_h	0.0821	****	-0.0025	
	(0.0215)		(0.0064)	
college_h	0.1440	****	-0.0048	
	(0.0316)		(0.0123)	
chronic_disease_w	-0.0033		-0.0525	****
	(0.0031)		(0.0051)	
age_w	-0.0002		-0.0024	
	(0.0003)		(0.0020)	
HI1_w	-0.0088		-0.1351	****
	(0.0086)		(0.0214)	
HI2_w	0.0023		0.0374	*
	(0.0025)		(0.0205)	
<HS_w(omitted)				
HS_w	0.0019		0.0319	*
	(0.0021)		(0.0165)	
College_w	0.0036		0.0607	**
	(0.0038)		(0.0287)	

Table 11: Reduced-Form Marginal Effects for Subsample GG: Both are Originally in Good Health

	Prob(health_h=1)		Prob(health_w=1)	
hispanic	-0.0690	****	-0.0787	****
	(0.0143)		(0.0150)	
Race				
Black (omitted)				
White	-0.0383	****	-0.0281	****
	(0.0092)		(0.0085)	
Others	-0.0369	****	-0.0255	***
	(0.0109)		(0.0096)	
chronic_disease_h	-0.0452	****	-0.0043	****
	(0.0049)		(0.0011)	
age_h	-0.0020	****	-0.0002	
	(0.0004)		(0.0002)	
Health Insurance				
No HI (omitted)				
HI1_h	-0.0943	****	-0.0083	****
	(0.0182)		(0.0024)	
HI2_h	0.0254	***	0.0025	**
	(0.0085)		(0.0010)	
< HS (omitted)				
HS_h	0.0551	****	0.0049	****
	(0.0092)		(0.0014)	
college_h	0.1010	****	0.0103	****
	(0.0126)		(0.0027)	
chronic_disease_w	-0.0032	**	-0.0408	****
	(0.0014)		(0.0051)	
age_w	-0.0001		-0.0012	***
	(0.0002)		(0.0004)	
HI1_w	-0.0056	**	-0.0778	****
	(0.0026)		(0.0182)	
HI2_w	0.0016	*	0.0187	***
	(0.0009)		(0.0065)	
<HS_w(omitted)				
HS_w	0.0042	**	0.0573	****
	(0.0019)		(0.0100)	
College_w	0.0074	**	0.0875	****
	(0.0033)		(0.0130)	

I discuss the estimation results below.

Spousal Effects on Health

The key coefficients in this paper are those on the latent variable of the other spouse's health status, (β_3^h, β_3^w), show the impacts of (continuous latent) health dynamics (y_{nmt}^*, y_{nft}^*) of one spouse on that of the other spouse. Table 5 and Table 7 show that, for subsamples in which wives are originally in good health, β_3^h and β_3^w are positive and statistically significant. These mean that when the wife is in good health, improvement in her (latent) health raises the husband's (latent) health next period. But, this is not observed if the husband is in good health. Also, for subsamples in which wives are originally in bad health (Table 4 and Table 6), one spouse's latent health still has positive impacts on the other one's, but the effects are not statistically different from zero. This might be because usually wives take care of their husbands: if a wife can keep in good health, then she can take good care of her husband, which makes the husband more likely to be in good health with her next period; while if a wife's health deteriorates, then the husband is less likely to receive care from his wife and thus more likely to be in bad health next period.

It is also important to understand the magnitudes of these effects. Using the marginal effects I calculated, I can get the probablities of a husband being healthy next period conditional on his wife being healthy next period and conditional on his wife being unhealthy next period. The difference between these two conditional probabilities shows the impact of the wife's (discrete) health dynamics on the probability of the husband being healthy next period. Similarly, I can get the impact of the husband's (discrete) health dynamics on the probability of the wife being healthy next period.

If both spouses are currently unhealthy, a wife transitioning from bad to good health increases the probability that a husband transitions from bad to good health from 0.226 to 0.325, or by 43.7%. Similarly, a husband transitioning from bad to good health increases the probability that a wife transitions from bad to good health from 0.218 to 0.313, or by 43.6%.[12] If only the husband is currently unhealthy, a wife staying healthy in the next period increases the chance a husband transitions from bad to good health by 17.1%.[13] Yet, a husband transitioning from bad to good health increases the chance a wife staying in good health by only 3.4%.[14] If only the wife is currently unhealthy, a wife transitioning from bad to good health increases the chance a husband stays in good health by 8.9%.[15] Yet, a husband staying in good health increases the chance a wife transitions (from bad health) into good health by 38.3%.[16] If both spouses are currently healthy, a wife staying in good health increases the chance a husband stays

[12]The probability of husband transitions from bad to good health increases from 0.218 to 0.313.

[13]The probability of a husband transitions from bad to good health increases from 0.281 to 0.329

[14]The probability of a wife stays in good health increases from 0.823 to 0.851.

[15]The probability of a husband stays in good health increases from 0.766 to 0.834

[16]The probability of a wife stays in good health increases from 0.243 to 0.336.

in good health by 5.9%.[17] Similarly, a husband staying in good health increases the chance a wife stays in good health by 4.5%.[18]

Lastly, the correlation coefficient (rho) indicate the correlation between spouses' health shocks, independent of the direct effect of one spouse's health on the other. These correlation coefficients are statistically insignificant and generally small. The only one of a substantive magnitude is a negative correlation coefficient of -0.238 between shocks to spouses' health when the husband is originally in bad health and the wife in good health. It suggests that she may be more susceptible to health shocks when she is caring for him. Thus, the results show that modeling the causal effect of one spouse's health on the other is more important than allowing for health shocks to be correlated.

Health Insurance

Table 4 - Table 7 show that spouses covered by type I health insurance (Medicare below age 64 and Medicaid) are more likely to be in bad health in the next period, and the effects are significant. Medicare below age 64 and Medicaid are only available to people with worst health, either because of disability or because of lack of health treatment due to low income. Thus people covered by type I health insurance are less likely to be in good health next period. On the contrary, spouses covered by type II health insurance (Medicare above age 64 and private health insurance) are more likely to be in good health in the next period. The effects of type II health insurance coverage are only significant for people who are originally in good health. This shows type II health insurance coverage is more about help people to maintain good health rather than improve people's health.

Table 8 shows, when both spouses are currently unhealthy, type I health insurance decreases the wife's and the husband's probability of transitioning into good health by 5.0 percentage and 7.7 percentage points, respectively. Yet type II health insurance increases the wife's and the husband's probability of transitioning into good health by 4.7 percentage points and 2.3 percentage points, respectively.

Table 9 shows, when only the husband is currently unhealthy, type I health insurance decreases the wife's probability of staying in good health by 6.8 percentage points and decreases the husband's probability of transitioning into good health by 9.9 percentage points. Yet type II health insurance increases the wife's probability of staying in good health by 4.4 percentage points and increases the husband's probability of transitioning into good health by 2.3 percentage points.

Table 10 shows, when only the wife is currently unhealthy, type I health insurance decreases the wife's probability of transitioning into good health by 13.5 percentage points and decreases the husband's probability of staying in good health by 7.6 percentage points. Yet type II health insurance increases the wife's probability of

[17] The probability of a husband stays in good health increases from 0.84 to 0.89

[18] The probability of a wife stays in good health increases from 0.88 to 0.92.

transitioning into good health by 3.7 percentage points and increases the husband's probability of staying in good health by 7.9 percentage points.

Table 11 shows, when both spouses are currently healthy, type I health insurance decreases the wife's and the husband's probability of staying in good health by 7.8 percentage points and 9.4 percentage points, respectively. Yet type II health insurance increases the wife's and the husband's probability of staying in good health by 1.9 percentage points and 2.5 percentage points, respectively.

Education

Table 4 - Table 7 show that having higher education can significantly increase the probability of being healthy next period, and the magnitude of the effects of a college degree is around two times bigger than that of a high school degree. Also the magnitude of the effects on people originally in good health is around two to three times bigger than that of the effects on people originally in bad health.[19]

Table 8 shows that, when both spouses are currently unhealthy, compare to having no education degree, having high school degree increases the wife's and the husband's probability of transitioning into good health by 6.5 percentage points and 6.9 percentage points, respectively. And having college degree and above increases the wife's and the husband's probability transitioning into good health by 8.5 percentage points and 2.5 percentage points, respectively.

Table 9 shows that, when only the husband is currently unhealthy, having high school degree increases the wife's probability of staying in good health by 8.6 precentage points and increases the husband's probability of transitioning into good health by 4.3 percentage points. And having college degree and above increases the wife's probability of staying in good health by 14.3 percentage points and increases the husband's probability transitioning into good health by 8.5 percentage points.

Table 10 shows that, when only the wife is currently unhealthy, having high school degree increases the wife's probability of transitioning into good health by 3.2 precentage points and increases the husband's probability of staying in good health by 8.2 percentage points. And having college degree and above increases the wife's probability of transitioning into good health by 6.1 percentage points and increases the husband's probability staying in good health by 14.4 percentage points.

Table 11 shows that, when both spouses are currently healthy, having high school degree increases the wife's and the husband's probability of staying in good health by 5.7 percentage points and 5.5 percentage points, respectively. And having college degree and above increases the wife's and the husband's probability staying in good health by 8.8 percentage points and 10.1 percentage points, respectively.

These results indicate that educated people tend to be better at improving and

[19]The only exception is that in the subsample BB (both spouses are originally in bad health), college degree does not have any significant effect on wife's health improvement.

maintaining health.

Other Demographics

Table 4 - Table 7 show that regardless of original household health status, spouses with chronic diseases are more likely to be in bad health in the next period. Table 8 - Table 11 show that, in average, having one more chronic disease decreases the spouse's probability of being healthy next period by around 4 to 6 percentage points. For people in good health originally, aging can significantly decrease the probability of remaining in good health (after an age cutoff), even while controlling for chronic disease; while for people in bad health originally, aging has no significant effect. For example, in Table 7 (subsample where both spouses are originally in good health), after age 59, the older the husband, the more likely he will change to bad health the next period. For wife, the age after which aging increases the probability of being in bad health next period is 56.[20]

Besides age, household race and Hispanic ethnicity matters as well. Table 4 - Table 7 show that when both spouses are originally in bad health, household health transition of black households are not statistically significantly different from that of white households. But, when at least one spouse is originally in good health, black households are more likely than white households to be in bad health next period. Table 8 - Table 11 show that, compare to being black household, being white household decreases the husband's probability of being in good health next period by around 4 to 5 percentage points, and being white household decreases the wife's probability of being in good health next period by around 3 to 5 percentage points.

What's more, Table 4 - Table 7 show that, for households where husbands are originally in good health, Hispanic households are more likely to be in bad health next period. For households where husbands are originally in bad health, being Hispanic is negatively correlated with the wives being in good health next period, but not significantly correlated with the husband's health next period.

5.2 Specification Tests

In this part, first, I use two modified Chi-Square goodness-of-fit tests to measure how well my model predicts household health transitions. Then, I use score test to test the bivariate normality assumption in my model. And I use Likelihood Ratio (LR) tests to compare my BP model with some alternative models.

Goodness of Fit Tests

I use two different methods to do the goodness-of-fit tests for my BP model, with the null hypothesis is that my BP model (*) is a true model. These two methods are sim-

[20]The turning point equals $|coef.of\, age/(2 \cdot coef.of\, age^2)|$. For example, 59=|0.0815/(2*0.0007)|.

ilar to the standard Chi-Square goodness-of-fit test, and the only difference is how to generate cells and how to calculate degree of freedom. Method 1 is the Cg method developed by M. Fagerlan, D. Hosmer, and A. Bofin (2008). This method generates g cells based on the 'deciles' of the sum of estimated probabilities, $1-\hat{p}_{base}$. $\hat{p}_{base}$ is the predicted probability of staying in the same household health status next period. Let c be the number of possible outcomes of household health transitions, thus $c=4$ in this paper. The degree of freedom equals $DF=(c-1)\cdot(g-2)$. Method 2 is called G1*G2 method (also called adapted Hosmer-Lemeshow) which is introduced by R.Chiburis, J. Das and M. Lokshin (2011). This method first sorts the observations into $G1$ cells of roughly equal size based on the predicted probabilities, for wives, of being in good health next period. Within each of these groups, then sorts the observations into $G2$ subcells based on predicted probabilities, for husbands, of being in good health next period. In total, this method generates $G(=G1\cdot G2)$ cells. Again, c is the number of possible outcomes of household health transitions, and the degree of freedom is defined as $DF=(c-1)\cdot(G1\cdot G2-2)$.

Table 12 and Table 13 list results of goodness-of-fit tests for all subsamples by using these two methods, respectively.

Table 12: Goodness-of-Fit Tests using Cg Method

Subsample	χ2	DF	P-value
both spouses are originally in bad health	24.59	21	0.631
only husband is originally in bad health	20.34	21	0.185
only wife is originally in bad health	21.42	21	0.669
both spouses are originally in good health	22.32	21	0.178

g=9, c=4; df=(g-2)*(c-1)=21

Table 13: Goodness-of-Fit Tests using G1*G2 Method

Subsample	χ2	DF	P-value
both spouses are originally in bad health	24.59	21	0.266
only husband is originally in bad health	20.34	21	0.499
only wife is originally in bad health	21.42	21	0.434
both spouses are originally in good health	22.32	21	0.381

G1=3 G2=3, c=4; df=(G1*G2-2)*(c-1)=21

All P-values in both Tables are greater than 0.05. This means, no matter use which method, the null hypothesis that my BP model (*) is a true model cannot be rejected.

Normality Tests (Score Test for normality assumption)

I use the score test introduced by Murphy (2007) (corrected R. Chiburis (2010)) to test the normality assumption in the BP model (*). The results in Lee (1984) and Smith (1985) suggest that a truncated or type AA bivariate Gram Charlier series may be a suitable alternative to the standard bivariate normal density. The Gram Charlier expansion for a regular standardized bivariate density $f(u_1,u_2)$ with correlation coefficient ρ is the sum of the bivariate standard normal density and 9 terms of bivariate Hermite polynomials. Assuming a standard bivariate normal distribution means assume the 9 terms of bivariate Hermite polynomials equal zero, thus the score test statistics asymptotically approaches a χ^2 distribution with $DF = 9$. The null hypothesis is that unobserved error terms of husband and wife are (standard) bivariate normally distributed. Table 14 lists results of score tests of normality for all subsamples.

Table 14: Score Test for Normality Assumption

Subsample	$\chi 2$	DF	P-value
both spouses are originally in bad health	16.45	9	0.058
only husband is originally in bad health	11.3	9	0.256
only wife is originally in bad health	13.17	9	0.155
both spouses are originally in good health	29.44	9	0.0005

These P-values show that the null hypothesis cannot be rejected for the first three subsamples, but should be rejected for the last subsample. In other words, only for subsample in which both spouses are originally in good health, unobserved error terms of husband and wife should assumed to be type AA bivariate Gram Charlier series distributed, but not bivariate normally distributed. In type AA bivariate Gram Charlier series, non-normality is parametrized as non-zero third and fourth cumulants of the equation disturbances' joint distribution and is expressed functionally via Type AA curve, the bivariate Edgeworth expansion truncated at the fourth order. To find out how the joint distribution in subsample GG is different from the standard bivariate normal distribution, I check the parameters of those 9 terms of bivariate Hermite polynomials. The results show that the joint distribution with kurtosis at the axis of the husband is less than 3 (excess kurtosis is less than 0). This means, for subsample GG, the marginal distribution on the axis of the wife is close to the standard normal distribution. But the marginal distribution on the axis of the husband, compare to a normal distribution, has a lower and broader central peak, and has shorter and thinner tails.

Alternative Models Tests (LR Tests)

I compare the reduced-form BP model (**) to three alternative probit models that are restricted versions of the structural model that I estimated above. I use Likelihood Ratio (LR) tests to compare the BP model (**) and those probit models for all subsamples. The three probit models are defined as below:

Probit model 1: Regress one spouse's latent health status on both spouse's characteristics;

Probit model 2: Regress one spouse's latent health status on his/her own characteristics including chronic diseases and health insurance;

Probit model 3: Regress one spouse's latent health status on his/her own characteristics without chronic diseases and health insurance. (This is the model commonly used in the literature)

Compare to the BP model, Probit model 1 relax the assumption that spouses' health shocks are correlated. Then, Probit model 2 relax the interdependence between spouses' health transitions. Probit model 3 exclude chronic diseases and health insurance as explanatory variables.

Table 15 lists results of LR tests that compare the BP model and Probit model 1 for all subsamples. The null hypothesis is that Probit model 1 fits the data better than the BP model.

Table 15: LR Test Between Reduced-form BP Model and Probit Model 1

Subsample	χ2	DF	P-value
both spouses are originally in bad health	28.25	1	0
only husband is originally in bad health	3.07	1	0.004
only wife is originally in bad health	30.59	1	0
both spouses are originally in good health	58.84	1	0

The results show that the null hypothesis should be rejected for all subsamples. This means the BP model significantly fits the data better than Probit model 1. In other words, allowing husband and wife's health transition to be correlated can significantly improve the model.

Table 16 lists results of LR tests that compare the Probit model 1 and Probit model 2 for all subsamples. The null hypothesis is that Probit model 2 fits the data better than Probit model 1.

Table 16: LR Test Between Probit Model 1 and Probit Model 2

Subsample	χ2	DF	P-value
both spouses are originally in bad health	14.17	14	0.438
only husband is originally in bad health	31.34	14	0.005
only wife is originally in bad health	14.17	14	0.248
both spouses are originally in good health	97.23	14	0

The results show that for subsamples where wives are originally in good health, regardless of husband's original health, the null hypothesis should be rejected. It means when wives are originally in good health, including the other spouse's characteristics as independent variables can significantly improve the model. This is consistent with the estimation results of BP model (*).

Table 17 lists results of LR tests that compare the Probit model 2 and Probit model 3 for all subsamples. The null hypothesis is that Probit model 3 fits the data better than Probit model 2.

Table 17: LR Test Between Probit Model 2 and Probit Model 3

Subsample	χ2	DF	P-value
both spouses are originally in bad health	235.98	6	0
only husband is originally in bad health	485.13	6	0
only wife is originally in bad health	337.03	6	0
both spouses are originally in good health	1223.03	6	0

The results show that the null hypothesis should be rejected for all subsamples. In other words, adding chronic diseases and health insurance coverage as independent variables can significantly improve the model.

6 Discussion

I include health insurance coverage as explanatory variables in the regression model. Someone may argue that this might cause an endogeneity problem and then biased estimates: the error term that represents people's taste for health might be correlated with people's preference for health insurance coverage, and thus correlated with observed health insurance coverage.

In this paper, I categorize health insurance coverage into two types. Type I health insurance includes Medicaid and Medicare below age 64, and thus its coverage is determined by either household income (whether really poor) or disability degree, and thus is independent of individual taste for health.

Type II health insurance includes Medicare above age 64 and private health insurance (including both employer-provided health insurance and self-purchased health insurance). The coverage of Medicare above age 64 purely depends on age, and thus is exogenous. The coverage of employer-provided health insurance is a little bit complicated. I agree that individuals with higher taste for health would more likely to choose a job that offer health insurance. For most people, when they first choose the current job, they were young and single. However, my sample consists of households age older than 50. The individual taste in my model represents people's tastes at older ages, and might be interacted with the other spouse's taste within a marriage. Thus the individual taste included in the regression model should be different from people's tastes when they were young and single. Besides, most couples in my sample are covered by the same employer-provide health insurance coverage. If one spouse is covered by the other one's employer, the health insurance coverage has nothing to do with this one's taste for health. In summary, the correlation between individual taste for health and employer-provided health insurance coverage might be zero or very small, if there is any.

Many studies that convincingly address the endogeneity of health insurance suggest that health insurance may not always result in measurable improvements in health, especially for the populations most likely to be the targets of public coverage expansions: infants, the elderly and the poor. These results are similar to what I find in this paper.

Indeed, the endogeneity problem of health insurance coverage has not been solved in the literature. In most papers examining the relationship between health insurance, the endogeneity of insurance status is either ignored or at best addressed by controlling for observable differences between people with and without health insurance. In this paper, I try to address this problem by controlling for both observed differences and unobserved heterogeneity. Besides, to address the problem that health status might influence insurance coverage, I include chronic diseases as explanatory variables and divide households into different subsamples based on their original health status, and run estimations for the four subsamples separately.

Since health insurance coverage can affect health, I still want to include insurance coverage as explanatory variables in my model. I use a likelihood ratio test to compare my model and an alternative model which excluding insurance coverage. The test results show that the model including insurance coverage matches the data much better.

7 Conclusion

In this paper, I use a bivariate probit model to capture the health transitions of the husband and wife. I allow both spouses' health transitions to be correlated, and I consider chronic diseases and different types of health insurance coverage as factors that might affect household health transitions. The estimation results show that the husband and wife's health transitions are connected and should be considered jointly, not separately; chronic diseases and health insurance are critical to explain household health transitions; and different types of health insurance have different effects on household health transitions. Spouses covered by type I health insurance (Medicare below age 64 and Medicaid) are more likely to be in bad health in the next period, while spouses covered by type II health insurance (Medicare above age 64 and private health insurance) are more likely to be in good health in the next period.

I also test the goodness-of-fit of my BP model, and compare it to other alternative models. The tests results show that my BP model explains the data pretty well, and is better than any other alternative models.

With the estimates in this paper, in the future work, I can simulate the effects of several policies on health, such as the effect of a prescription drug plan coverage that helps to cure chronic disease, and the effect of the Patient Protection and Affordable Care Act that increases health insurance access.

References

[1] Amemiya, T. (1974) "Bivariate Probit Analysis: Minimum Chi-Square Methods" Journal of the American Statistical Association, Vol. 69, No. 348, pp. 940-944.

[2] Blau, D. M. (1998). Labor Force Dynamics of Older Married Couples. Journal of Labor Economics, Vol. 16, No. 3, 595-629.

[3] Blau, D. M., & Gilleskie, D. B. (2006). Health Insurance and Retirement of Married Couples. Journal of Applied Econometrics, Vol. 21, Iss. 7, 935-953.

[4] Card, D., Dobkin, C., & Maestas, N. (2004) "The Impact Of Nearly Universal Insurance Coverage On Health Care Utilization and Health: Evidence from Medicare" NBER Working Paper, No. 10365.

[5] Casanova, M. (2009). Happy Together: A Structural Model of Couples' Joint Retirement Choices. Working Paper, University of California at Los Angeles .

[6] Chiburis, C. R. (2010) "Score Tests of Normality in Bivariate Probit Models: Comment" Unpublished

[7] Chiburis, C. R., Das, J. & Lokshin, M. (2011) "A Practical Comparison of the Bivariate Probit and Linear IV Estimation" Policy Research Working Paper 5601, The World Bank.

[8] Contoyannis, P., Jones, A., & Rice, N. (2004) "The Dynamics Of Health In The British Household Panel Survey." Journal of Applied Econometrics, 19, 473-503.

[9] Currie, J., & Gruber, J. (1996a) "Health Insurance Eligibility, Utilization of Medical Care, and Child Health" The Quarterly Journal of Economics, Vol. 111, No. 2, pp. 431-466.

[10] Currie, J., & Gruber, J. (1996b) "Saving Babies: The Efficacy and Cost of Recent Changes in The Medicaid Eligibility of Pregnant Women." Journal of Political Economy 104(6):1263 - 1296.

[11] Currie, J., & Gruber, J. (1997) "The Technology of Birth: Health Insurance, Medical Interventions and Infant Health" National Bureau of Economic Research Working Paper 5985.

[12] Cutler, D., & Kadiyala, S. (1999) “The Economics of Better Health: The Case of Cardiovascular Disease” mimeo, Harvard University.

[13] Doyle, J. J. (2001) "Does Health Insurance Affect Treatment Decisions and Patient Outcomes? Using Automobile Accidents as Unexpected Health Shocks." Unpublished manuscript, University of Chicago.

[14] Fagerland, W. M., Hosmer, W. D., & Bofin, M. A. (2008) "Multinomial Goodness-of-Fit Tests for Logitstic Regression Models" Statistics in Medicine, 27, 4238-4253.

[15] French, E., & Jones, J. B. (2011). The Effects of Health Insurance and Self-Insurance on Retirement Behavior. Econometrica, Vol. 79, No. 3, 693-732.

[16] Hadley, J. (2003) "Sicker and poorer?the consequences of being uninsured: a review of the research on the relationship between health insurance, medical care use, health, work, and income." ?Medical Care Research and Review, 60, 3S-75S.

[17] Kiefer, M. N. (1982) "Testing for Dependence in Multivariate Probit Models" Biometrika, Vol. 69, No. 1, pp. 161-166.

[18] Levy, H., & Meltzer, D. (2004) "What Do We Really Know About Whether Health Insurance Affects Health?" In Health Policy and the Uninsured, Ed. CMcLaughlin, Urban Institute Press: Washington, D.C.

[19] Murphy, A. (2007) "Score Tests of Normality in Bivariate Probit Models" Economics Letters, 95, 374-379.

[20] Osius, G., & Rojek, D. (1992) "Normal Goodness-of-Fit Tests for Multinomial Models with Large Degrees of Freedom" Journal of the American Statistical Association, Vol. 87, No. 420, pp. 1145-1152.

[21] Perry, C., & Rosen, H. (2001) "The Self-employed Are Less Likely To Have Health Insurance Than Wage Earners. So What??" NBER Working Paper 8316.

[22] RAND HRS Data, Version J. Produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA March 2010

[23] Wilson, S. (2002) “The Health Capital of Families: An Investigation of the Inter-Spousal Correlation in Health Status.” Social Science and Medicine 55:1157-1172.

[24] Zimmwe, D. (2010) "State Dependence Among The Uninsured: Accounting For Feekback To Health And Employment" Forum for Health Economics & Policy, Vol. 13, Iss. 2 (Health Economics), Art. 4.

[25] Zimmwe, D. (2012) "The Dynamic Relationship between Health and Health Insurance" Working Paper