Online Appendix for: Health Recommendations and Selection in Health Behaviors

Emily Oster, Brown University

November 3, 2019

Appendix A: Figures and Tables

Table A1: **Information Events**

Behavior	***Event 1***	***Event 2***
Vitamin E Supplementation	**1993, Positive:** Two studies in NEJM report reduction in heart disease for both men and women with use of Vitamin E supplements	**2004, Negative:** Widely covered meta-analysis of Vitamin E shows high doses increase mortality. Large Google trends spike.
Vitamin D Supplementation	**2007, Positive:** Several studies, NEJM summary piece, NY Times coverage suggest Vitamin D good for health (cancer, fractures, etc). Corresponding growth in Google Trends.	**2011/2012, Negative:** IOM report suggests Vitamin D overblown, corresponding summary articles, coverage in NY Times. Additional studies in 2012 with similar findings. Google Trends stagnation.
Sugar in Diet	**2000, Negative:** First explicit mention in US Dietary guidelines of avoidance of added sugars.	**2011/2012, Negative:** Extensive media coverage of health costs of sugar; "toxic sugar" in NY Times and 60 Minutes Segment.
Saturated Fat	**1990, Negative:** First explicit restriction on saturated fat share in US dietary guidelines (<10%)	**2005, Negative:** Further restrict saturated fat to <7% for people with heart disease.
Mediterranean Diet	**2004, Positive:** Two JAMA articles show health benefits of Mediterranean diet. Google Trends spike.	**2009/2010, Positive:** Series of articles on role of Mediterranean diet in addressing cognitive decline. Google Trends spike.

Notes: This table shows the information events identified for each outcome. Events were identified by searching for well-cited publications, media coverage and Google search spikes.

Table A2: **Summary Statistics**

	Panel A: NHANES 1988-2013 N=55,548		Panel B: Nurses' Health Study 1984-2010 N=1,179,162		Panel C: HomeScan 2004-2016 N=795,077	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Vitamin E Supplement (0/1)	0.067	0.250	0.274	0.133		
Vitamin D Supplement (0/1)	0.073	0.260			0.074	0.261
Mediterranean Diet Score (0-9)	3.71	1.43				
Saturated Fat Share of Fat	0.327	0.068				
Sugar Share of Carbohydrates	0.443	0.142				
Smoking	0.23	0.42	0.13	0.60	0.122	0.327
Exercise	-0.141	0.940				
Diet Metric	0.59	0.42			-0.268	0.248
Education	3.16	1.32			4.47	1.01
Income	6.11	2.49			19.9	6.03
Heart Health Index	0.00	1.11				
BMI	28.4	6.54				
Mortality in Next 2 Years			0.019	0.012		

Notes: This table shows summary statistics for the variables used in the paper. Further details of data construction are in Section 2. NHANES and Nurse Health Study data are based on survey responses; HomeScan data is collected from scans of purchased items. Smoking is defined in the survey data based on reported current smoking; in HomeScan a household is coded as smoking if they purchase cigarettes during the year. Exercise in NHANES data is based on reported vigorous exercise and is standardized within each year. The NHANES diet metric is a indicator for consuming above the median in calories from vegetables. In HomeScan this is a diet score based on purchases, ranging from -1 to 1 (see Hut and Oster, 2019 for details). Education is measured in bins in the NHANES (1 to 5) and in HomeScan (1 to 6). Income is measured in bins in NHANES (1 to 9) and HomeScan (3 to 30). Heart health is the first principal component of blood pressure, total cholesterol and good cholesterol. BMI is weight in kilograms divided by height in meters-squared. Observations in all cases are person-years and represent the maximum number of observations in the dataset.

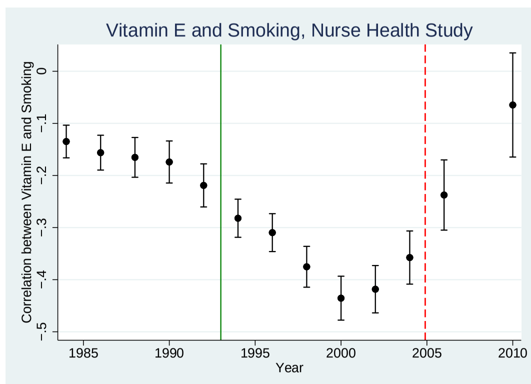
Table A3: **Correlation between Dietary Choices, Health Behaviors/Socioeconomic Status and Outcomes**

Panel A: Levels of Behavior									
	Sugar Share of Carbohydrates			Saturated Fat (Share of Fat)			Med. Diet Score		
	Before 2000	2000-2012	After 2012	Before 1990	1990-2005	After 2005	Before 2005	2005-2010	After 2010
Average	0.456‡,‡‡	0.444‡	0.417	0.344‡,‡‡	0.328‡	0.322	3.67‡‡	3.68‡	3.78
	[N=15,682]	[N=26,954]	[N=8,683]	[N=7,771]	[N=21,003]	[N=26,774]	[N=13,444]	[N=15,701]	[N=14,865]
Panel B: Correlations between Dietary Choices & Health Behaviors/Socioeconomic Status									
	Sugar Share of Carbohydrates			Saturated Fat (Share of Fat)			Med. Diet Score		
	Before 2000	2000-2012	After 2012	Before 1990	1990-2005	After 2005	Before 2005	2005-2010	After 2010
Smoking	0.004‡,‡‡	0.011‡	0.0175	0.0026‡‡	0.0041	0.0050	-0.187	-0.171	-0.181
	[N=12,004]	[N=26,954]	[N=8,683]	[N=5,855]	[N=19,243]	[N=26,774]	[N=13,444]	[N=15,701]	[N=14,8645]
Exercise	0.0018‡,‡‡	-0.0049	-0.0040	-0.0017‡‡	-0.0007‡	-0.0043	0.087‡‡	0.108	0.137
	[N=15,682]	[N=26,951]	[N=8,683]	[N=7,771]	[N=20,997]	[N=26,774]	[N=13,438]	[N=15,700]	[N=14,864]
Education	0.010‡,‡‡	-0.0007	-0.004	-0.0011	-0.001	-0.0022	0.090‡,‡‡	0.128	0.152
	[N=15,582]	[N=26,925]	[N=8,679]	[N=7,718]	[N=20,931]	[N=26,752]	[N=13,418]	[N=15,682]	[N=14,857]
Income	0.0044‡,‡‡	-0.0064‡	-0.0108	-0.0016	-0.0025	-0.0035	0.123‡‡	0.121‡	0.175
	[N=14,234]	[N=24,807]	[N=7,872]	[N=6,932]	[N=18,920]	[N=24,486]	[N=11,931]	[N=14,413]	[N=13,441]
Panel C: Correlations between Dietary Choices and Health Outcomes									
	Sugar Share of Carbohydrates			Saturated Fat (Share of Fat)			Med. Diet Score		
	Before 2000	2000-2012	After 2012	Before 1990	1990-2005	After 2005	Before 2005	2005-2010	After 2010
BMI									
Raw	-0.098‡‡	-0.085‡	2.57	-1.32‡‡	-0.604‡	2.38	-0.202‡‡	-0.241‡	-0.524
	[N=15,651]	[N=26,423]	[N=8,606]	[N=7,746]	[N=20,632]	[N=26,476]	[N=13,075]	[N=15,508]	[N=14,720]
Adjusted	0.853‡‡	0.029‡	2.44	-0.498‡‡	0.431‡	2.16	-0.268‡‡	-0.284‡	-0.483
	[N=10,800]	[N=24,308]	[N=7,800]	[N=5,166]	[N=16,910]	[N=26,216]	[N=11,582]	[N=14,223]	[N=13,310]
Heart Health									
Raw	-0.206‡,‡‡	-0.554	-0.444	-0.395‡‡	-0.334‡	-1.14	0.027‡,‡‡	0.055	0.045
	[N=14,766]	[N=24,854]	[N=8,205]	[N=7,199]	[N=19,551]	[N=24,948]	[N=12,001]	[N=12,773]	[N=12,176]
Adjusted	-0.364	-0.510	-0.386	-0.463‡‡	-0.286‡	-0.907	0.017‡	0.038	0.031
	[N=10,196]	[N=22,912]	[N=7,457]	[N=4,804]	[N=16,052]	[N=22,876]	[N=10,675]	[N=11,797]	[N=11,080]

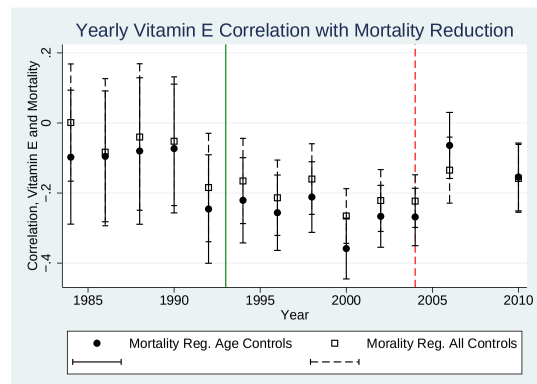
Notes: This table shows the results on diet. All data come from the NHANES for 1998 through 2015. The periods are divided based on the events detailed in Appendix Table A1. Panel A shows the mean levels of diet behavior over time. The Mediterranean diet score is created based on Trichopoulou et al (2003) and ranges from 0 to 9. Panel B shows results of estimating regressions of the form in Equation (3), with dietary patterns rather than Vitamin E as the outcome. Panel C shows the results of estimating Equation (4) with BMI or the index of heart health as the outcome. The first row for each outcome control for only age, age squared and gender; the second set include controls for education, income, marital status, race, smoking behavior and exercise. Number of observations in square brackets.‡ significantly different from next period at 5% level; ‡‡significantly different from two periods later at 5% level.

Figure A1: **Yearly Coefficients from Nurse Health Study**

Panel A



Panel B



Notes: These graphs show the correlations between Vitamin E and smoking and Vitamin E and mortality by year in the Nurse Health Study data. In Panel A events are marked with vertical lines; details of the events appear in Appendix Table A1. Error bars show 95% confidence intervals.

Appendix B: Theory

This appendix outlines one model of behavior which would produce the implications which I test for in the empirical section of the paper.

Model of Behavior

Setup

I consider a set of individuals who have the option to undertake health behaviors from a vector $\Lambda = (\Lambda_1, ..., \Lambda_n)$. Assume each behavior Λ_j is binary, i.e. $\Lambda_j \in \{0,1\}^n$, with a value of 1 indicating undertaking the behavior. The assumption that behaviors are binary is taken for simplicity of exposition. All results would hold if $\Lambda \in [0,1]^n$ instead. Without loss of generality, I define all health behaviors as "positive", so they increase health outcomes. Although of course some behaviors may be bad, we can define the Λ_j corresponding to that behavior as *not* doing the behavior.

Health behavior j has a perceived health value $\kappa_j \geq 0$. Individual i has a health benefit function $U_i = \alpha_i \sum_{j=1}^{n} \kappa_j \Lambda_j$. This utility varies across individuals in α_i. We will define individual i as having a higher health value than individual j if $\alpha_i > \alpha_j$. These health values are drawn *iid* from some arbitrary non-degenerate distribution on $\mathbb{R}_+$ with positive density everywhere, so $E[\alpha_i] > 0$.

The assumption of a linear form in the health value (i.e. using $\sum_{j=1}^{n} \kappa_j \Lambda_j$) introduces weak substitutability of different behaviors; the main results developed here would strengthen if the health behaviors were complements. The assumption on α_i rules out some distributions but allows, for example, various Gaussian distributions.

Each behavior also has a cost, which is specific to individual i and denoted $c_{i,j}$ for behavior j. These costs are drawn *iid* from a normal distribution with mean $\overline{c_j} > 0$ and variance σ_j^2. This allows for heterogeneity in costs across individuals and average differences across behaviors, but assumes these costs are independent of other characteristics of individuals. Notably, the distribution of $c_{i,j}$ is drawn independently of the α_i values.

Each individual chooses their optimal set of behaviors, trading off their utility value of health against the cost. We can write the problem for individual i as:

$$max_{\Lambda} \alpha_i \sum_{j=1}^{n} \kappa_j \Lambda_j - \sum_{j=1}^{n} c_{i,j} \Lambda_j$$

Note that $c_{i,j}$ may be zero or negative so individuals may engage in some of these behaviors even if they do not confer health benefits. The individual adopts j if the health benefit of this behavior exceeds its cost: $\alpha_i \kappa_j \geq c_{i,j}$.

Under this model, individuals with a higher health value will undertake more health behaviors on average than those with a lower health value. They will also be more likely to engage in any particular health behavior with a positive health value.

Individuals realize some positive health outcome (e.g. low cholesterol, healthy weight) which is a function of these health behaviors. I assume this outcome is a linear function of health behaviors and write

$$Y_i = \eta + \sum_{\Lambda_j \in \Lambda} (\vartheta_j \Lambda_{i,j}) + \epsilon_i$$

where the coefficients ϑ_j represent the true impact of each behavior Λ_j on the health outcome. Note that $\vartheta_j = 0$ would imply a behavior j does not matter for health outcome Y. Assume that $E[\epsilon_i | \{c_{i,j}\}, \alpha_i] = 0$.

This structure for outcomes assumes that there is no treatment effect heterogeneity, an assumption which will be important for the results later. In these contexts, where the effects I posit are biological, this assumption may be more appropriate than in some other settings.

Change in Value of Behavior

This paper is primarily concerned with the dynamics that occur when there is a change in the (perceived) value of a behavior. Here, I will develop the simplest case in which a behavior moves from having no perceived health value to having a positive value. In the case where the health value is initially positive these results may still hold (especially if the initial health value is small) but they are more sensitive and will not occur for all parameter values. In this sense, the result here is intended as a possibility result to develop intuition, which will be tested in the empirical portion of the paper. Note that all proofs for the results below appear in Appendix B.

Timing Consider a behavior Λ_j which is an element of Λ. In period $t = 0$ behavior Λ_j has a value $\kappa_j = 0$. Note that people may still engage in the behavior at baseline, for example if their cost of undertaking it is negative.

Between time $t = 0$ and $t = 1$ there is a (potentially misleading) signal about behavior Λ_j which leads people to update their beliefs, such that in period $t = 1$ the belief is $\kappa_j > 0$.

I will be concerned with the change, between $t = 0$ and $t = 1$, in the relationship between (i) behavior Λ_j and other behaviors; and (ii) behavior Λ_j and health outcomes.

Behavior Selection Dynamics Let $\Lambda_{j'}$ be a behavior with $\kappa_{j'}$ constant and positive in both $t = 0$ and $t = 1$. That is, this is a behavior which is understood to have health benefits. Recall from the setup above that the behavior $\Lambda_{j'}$ is more likely to be undertaken by individuals with a high value of α_i. The first result relates the behavior $\Lambda_{j'}$ to behavior Λ_j in period $t = 0$ and to $t = 1$.

Proposition 1 *Given behaviors Λ_j and $\Lambda_{j'}$ defined as above, $Cov_{t=1}(\Lambda_j, \Lambda_{j'}) > Cov_{t=0}(\Lambda_j, \Lambda_{j'}) = 0$.*

This proposition indicates that the relationship between the behavior of interest and the other positive health behaviors will become more positive after the change in recommendation. This result is immediate in this simple case where there is no perceived health value of Λ_j in the baseline period, since there is no positive covariance between the behaviors at $t = 0$.

This first proposition links behavior Λ_j to other health behaviors. In addition, we can consider links to other covariates. Specifically, assume that we are able to observe a variable Z, which is positively related to the health value α_i. This is intended to capture a variable like education or income. Similar logic leads to the following proposition.

Proposition 2 *For any random variable Z such that it is independent of $c_{i,j}$ and $\mathbb{E}[Z|\alpha_i]$ is increasing in α_i, $Cov_{t=1}(\Lambda_j, Z) > Cov_{t=0}(\Lambda_j, Z) = 0$.*

This indicates that we expect the relationship between behavior Λ_j and the covariate Z to strengthen after the change in recommendation.

Disease-Behavior Dynamics These above results relate directly to changes in selection. I turn now to the implications for the estimated relationship between behavior Λ_j and health outcomes.

Proposition 3 *Let Ω be a strict subset of Λ, which excludes behavior Λ_j and at least one other behavior Λ_p for which $\vartheta_p > 0$. Then, as long as κ_j and ϑ_j are not too large, we derive the following results. Precise conditions are given in Appendix B.*

(A) $Cov_{t=1}(\Lambda_j, Y) > Cov_{t=0}(\Lambda_j, Y)$

(B) $Cov_{t=1}(\Lambda_j, Y|\Omega) > Cov_{t=0}(\Lambda_j, Y|\Omega)$.

This says that as the behavior becomes more recommended, and thus the selection on the behavior changes, the estimated effect of the behavior on health outcomes will change. This will be true even if researchers observe and adjust for some of the confounding variables, as long as they do not observe all of them. Note if all elements of Λ were observed and controlled for then it would be possible to estimate the true effect of Λ_j on Y in all periods and these effects would not vary over time.

It is important to note that the results in this section are sensitive to the assumptions detailed above, including the distributions of c and α. As a result, it may be best to view these as possibility results. The purpose of this discussion is simply to make clear that we *could* see these types of dynamics; the empirical work will focus on whether we do.

Proofs

Proof of Proposition 1 (Baseline Case) At time $t = 0$, if $\kappa_j = 0$, then whether subject i undertakes Λ_j is solely determined by $c_{i,j}$, which is independent of $\Lambda_{j'}$. Thus, $Cov_{t=0}(\Lambda_j, \Lambda_{j'}) = 0$.

We then note

$$Cov_{t=1}(\Lambda_j, \Lambda_{j'}) = \mathbb{E}1[\alpha_i\kappa_j \geq c_{i,j}]1[\alpha_i\kappa_{j'} \geq c_{i,j'}] - \mathbb{E}1[\alpha_i\kappa_j \geq c_{i,j}]\mathbb{E}1[\alpha_i\kappa_{j'} \geq c_{i,j'}]$$

where $1[\cdot]$ is an indicator function.

Given that the costs are normally distributed and independent, denoting by Φ the cdf of the standard normal distribution, and using the law of iterated expectations, we obtain:

$$Cov_{t=1}(\Lambda_j, \Lambda_{j\prime}) = \mathbb{E}\Phi(\frac{\alpha_i \kappa_j - c_j}{\sigma_j})\Phi(\frac{\alpha_i \kappa_{j\prime} - c_{j\prime}}{\sigma_{j\prime}}) - \mathbb{E}\Phi(\frac{\alpha_i \kappa_j - c_j}{\sigma_j})\mathbb{E}\Phi(\frac{\alpha_i \kappa_{j\prime} - c_{j\prime}}{\sigma_{j\prime}})$$

where all expectations are taken with respect to health value α_i.

Note, that on this step we used the fact that both behaviors are independent conditionally on α_i, which is implied by the linear form.

The right hand side of the inequality has the form of $\mathbb{E}f(\alpha_i)g(\alpha_i) - \mathbb{E}f(\alpha_i)\mathbb{E}g(\alpha_i)$, where f, g are strictly increasing (given that $\kappa_j, \kappa_{j\prime} > 0$) bounded functions.

Given the assumption that α_i is not degenerate and has non-zero density everywhere, by the covariance inequality (Thorisson, 1995) this value is positive. Hence, $Cov_{t=1}(\Lambda_j, \Lambda_{j\prime}) > 0$.

Proof of Proposition 2 (Covariance with Other Variables) We assume that Z is independent of $c_{i,j}$. Since at time t we have $\kappa_j = 0$, then Λ_j only depends on $c_{i,j}$. Hence, $Cov_{t=0}(\Lambda_j, Z) = 0$. Now we will show that $Cov_{t=1}(\Lambda_j, Z) > 0$.

Similarly to the proof of Proposition 1, to establish the positive covariance between the variables at time $t = 1$ we use the law of iterated expectations and the fact that conditionally on α_i, Λ_j and Z are independent.

$$Cov_{t=1}(\Lambda_j, Z) = \mathbb{E}(\Phi(\frac{\alpha_i \kappa_j - c_j}{\sigma_j})\mathbb{E}[Z|\alpha_i]) - \mathbb{E}\Phi(\frac{\alpha_i \kappa_j - c_j}{\sigma_j})\mathbb{E}(\mathbb{E}[Z|\alpha_i]).$$

The assumption of increasing $\mathbb{E}[Z|\alpha_i]$ and the covariance inequality yield the result.

Proof of Proposition 3 (Disease-Behavior Dynamics)

(A) We can write the covariance thus:

$$Cov_{t=0}(\Lambda_j, Y) = Cov_{t=0}(\Lambda_j, \mu + \sum_{\Lambda_r \in \Lambda} \vartheta_r \Lambda_r + \epsilon_i) = \sum_{\Lambda_r \in \Lambda} \vartheta_r Cov_{t=0}(\Lambda_j, \Lambda_r).$$

Case 1 If $\vartheta_j = 0$, then from Proposition 1 it follows that $Cov_{t=0}(\Lambda_j, Y) = 0$. Analogously, from Proposition 1 it also follows that $Cov_{t=1}(\Lambda_j, Y) > 0$. Hence, in this case, **(A)** is established.

Case 2 If $\vartheta_j \neq 0$ then

$$Cov_{t=0}(\Lambda_j, Y) = \vartheta_j Var_{t=0}(\Lambda_j)$$
$$Cov_{t=1}(\Lambda_j, Y) = \vartheta_j Var_{t=1}(\Lambda_j) + \sum_{\Lambda_r \in \Lambda / \Lambda_j} \vartheta_r Cov_{t=1}(\Lambda_j, \Lambda_r)$$

As a result, $Cov_{t=1}(\Lambda_j, Y) > Cov_{t=0}(\Lambda_j, Y)$ if and only if

$$\vartheta_j Var_{t=1}(\Lambda_j) + \sum_{\Lambda_r \in \Lambda/\Lambda_j} \vartheta_r Cov_{t=1}(\Lambda_j, \Lambda_r) > \vartheta_j Var_{t=0}(\Lambda_j)$$

Proposition 1 establishes that $\sum_{\Lambda_r \in \Lambda/\Lambda_j} \vartheta_r Cov_{t=1}(\Lambda_j, \Lambda_r) > 0$ but does not tell us how $Var_{t=1}(\Lambda_j)$ compares to $Var_{t=0}(\Lambda_j)$.

At time $t = 0$ we have $\kappa_j = 0$. Thus,

$$Var_{t=0}(\Lambda_j) = \mathbb{E}1[c_{i,j} \leq 0] - (\mathbb{E}1[c_{i,j} \leq 0])^2 = \Phi(\frac{-c_j}{\sigma_j}) - \Phi^2(\frac{-c_j}{\sigma_j})$$

.

At $t = 1$, $\kappa_j > 0$. Hence,

$$Var_{t=1}(\Lambda_j) = \mathbb{E}1[c_{i,j} \leq \alpha_i \kappa_j] - (\mathbb{E}1[c_{i,j} \leq \alpha_i \kappa_j])^2 = \mathbb{E}\Phi(\frac{\alpha_i \kappa_j - c_j}{\sigma_j}) - (\mathbb{E}\Phi(\frac{\alpha_i \kappa_j - c_j}{\sigma_j}))^2$$

.

It is possible that this variance is lower in $t = 1$ than in $t = 0$ if κ_j is very large at time $t = 1$. If almost everyone adopts behavior Λ_j, then $Var_{t=1}(\Lambda_j) \approx 0$. However, this will not happen as long as κ_j is relatively small.

(B)

Case 1 Assume $\vartheta_j = 0$. Recall Ω is defined as subset of Λ which excludes at least one behavior Λ_p for which $\vartheta_p \neq 0$. We will show the proof under the assumption that a single behavior is excluded from Ω; the result would strengthen with more behaviors excluded.

At time $t = 0$ we can write

$$Cov_{t=0}(\Lambda_j, Y|\Omega) = \sum_{\Lambda_r \in \Lambda} \vartheta_r Cov_{t=0}(\Lambda_j, \Lambda_r|\Omega).$$

Note that since $\kappa_j = 0$ at $t = 0$ we have Λ_j independent of Λ_r for any r, even conditioning on Ω. Hence, $Cov_{t=0}(\Lambda_j, Y|\Omega) = 0$.

At time $t = 1$, the proof of Proposition 1 shows that $Cov_{t=1}(\Lambda_j, \Lambda_r) > 0$. For $\Lambda_r \in \Omega$, we have $Cov_{t=1}(\Lambda_j, \Lambda_r|\Omega) = 0$. However, given that behavior Λ_p is not included in Ω we have $Cov_{t=1}(\Lambda_j, \Lambda_p|\Omega) > 0$ and, as a result, $Cov_{t=1}(\Lambda_j, Y|\Omega) > 0$.

Case 2 Assume $\vartheta_j > 0$. Combining the logic in **(A)** above with that in case 1 here, we can see the inequality holds if

$$\vartheta_j Var_{t=1}(\Lambda_j|\Omega) + \vartheta_p Cov_{t=1}(\Lambda_j, \Lambda_p) > \vartheta_j Var_{t=0}(\Lambda_j|\Omega)$$

As above, this will hold as long as κ_j is not very large at time $t = 1$.