# A Longitudinal Test of the Potential Reciprocal Effects between Self-rated Global Physical Health and Depression

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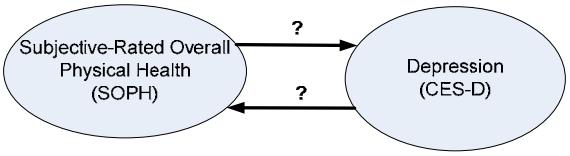
## My Background

- I'm a methodologist with a focus on measurement and causal modeling
  - Especially via structural equation modeling (SEM)
- I have substantive training in social psychology and sociology of aging
- I'm currently interested in measurement models of physical health and psychological well-being and the causal linkages between these constructs
- Among other projects, I'm working with Neal Dawson and Eleanor Stoller on their Hepatitis C grant

## Outline of Presentation

1. Obtain your prediction regarding the causal order between self-rated physical health and depression
2. Provide an overview of longitudinal analysis via growth curves vs. auto-regressive models vs. new "hybrid" models
3. Use an auto-regressive model to test for the potential reciprocal effects between self-rated health & depression

## "Tease"
## Predict Causal Link between SOPH and Depression




1. Does SOPH (e.g., self-rating based on "excellent," "good," "fair," "poor") cause depression?
2. Does depression cause SOPH?
3. Or is there a **reciprocal** association between them?

- Show of hands for 1 vs. 2 vs. 3?

## Research Based on **Cross-Sectional** Survey Data

- A multitude of studies treat Physical Health (e.g., SOPH) as the predictor of Depression
- A multitude of studies treat Depression as the predictor of Physical Health
- Both of the above positions can't be right

## Problems with Cross-Sectional Survey Data

- If the **causal order** researchers declare by "fiat" is **wrong**, their estimates of **effect size** will be **distorted**
- This bias occurs whether the hypothesized causal order is completely wrong, or the causal order is reciprocal

## Benefits of Longitudinal (Panel) Survey Data

- Provides **empirical test** of causal order
- I'm assuming here that it is not feasible for one to use a true experimental design to test the causal order among variables whose causal order is in question

## Problems with Longitudinal Analysis

- It is an order of magnitude more difficult than cross-sectional analysis
  - I'm assuming here that one is conducting longitudinal analysis with the more sophisticated (i.e., more appropriate) procedures
- Requirements
  - Extensive methods training
  - Extensive ("hands-on") experience with the procedures
  - Much more time to produce a final product
  - Enough "journal space" to adequately describe what one has done (especially given that it requires more "education" of the typical reader)

## Overview of Longitudinal Analysis via Panel Designs

- Non-experimental research design
- Collects data on multiple individuals for at least two time points
- My focus here is on analytic tools for continuously-distributed outcome variables
  - Not survival (event history) analysis
- I would argue that SEM generally provides the best technique for analyzing these "repeated measure" designs based on interval-level outcome variables
  - Allows one to adjust for random and non-random measurement error
  - Is enormously flexible in the types of models it can test

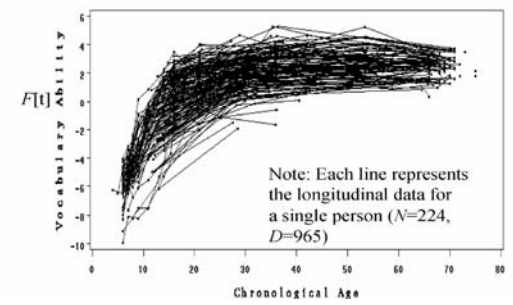
## Two Major Types of Longitudinal Designs for Interval-Level Outcomes

- Auto-Regressive Models
  - Model "dynamic," "time-specific" causal processes
  - Used in current study to test potential reciprocal effects
  - "Standard" procedure until recently
- Growth Curve Models
  - Model "developmental" processes with "time-invariant" predictor variables (i.e., predictors that don't change over time)
  - Does not model reciprocal effects easily
  - Currently very "hot" technique that continues to grow in popularity

## Brief Overview of Growth Curves

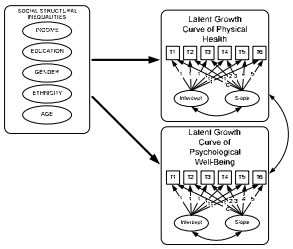
- Focus is on linking a person's score on a variable across all waves of data collection to create an individual "slope" (which can be linear or nonlinear)
- "Growth curve" is a bit of a misnomer, given that an individual's slope can be **negative** instead of **positive**

*Fig. [7]: New longitudinal scores from the estimated IRT-scaled vocabulary (N=224)*




**Social Status Characteristics as Time Invariant Predictors of the Latent Growth Curves of Physical Health and Psychological Well-being***

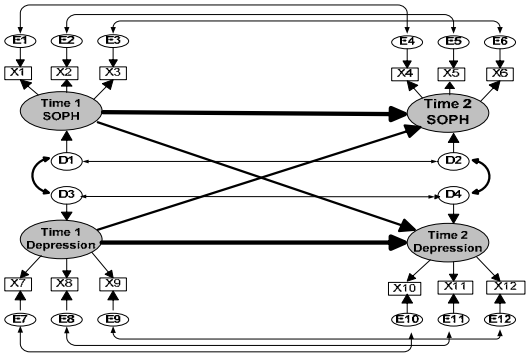
*Modified Diagram from Dissertation Perspectus of Chris Burant




## Pros and Cons of Growth Curve Models

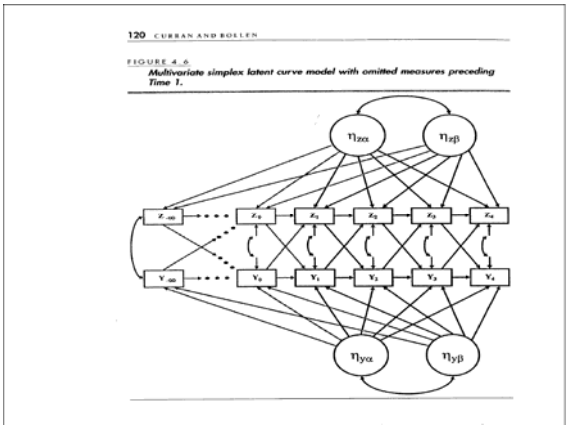
- Is ideal tool for modeling processes that may have an underlying "biological" component
  - Cognitive development
  - Anti-social behavior
  - Problem drinking, etc.
- But many (most?) variables do not have an underlying "developmental" trajectory
- Time-varying predictors generally cannot affect the growth process
- Does not easily incorporate reciprocal effects among variables

## Auto-Regressive Model of SOPH and Depression



## Pros and Cons of Auto-Regressive Models

- Readily incorporates time-varying predictors (time-specific, “dynamic” processes)
- Better design than growth curves for modeling reciprocal causal effects
- Cannot handle developmental processes




## Pros and Cons of “Combo” Models

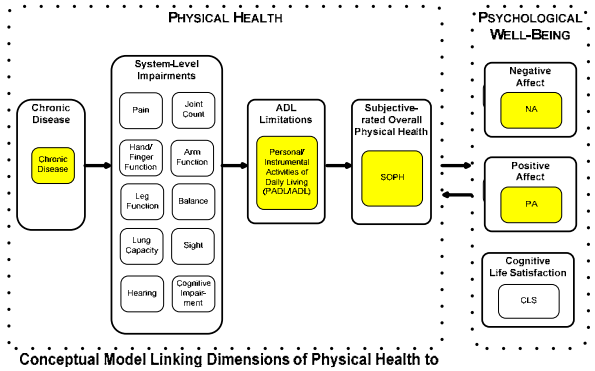
- Incorporates both dynamic and developmental processes
  - Controls for bias that can occur when modeling one process in the presence of the other process
  - Would appear to represent the current “state-of-the-art” for analyzing panel designs with interval-level outcome variables
- More complex than either auto-regressive or growth curve models
- Few researchers have any experience in using the procedure

## References on Longitudinal Analysis

- Email me at kxk@case.edu
- I’ll send you a list with my recommendations on what order to read the material
- If your email system will handle large PDF files, I’ll send you the recommended articles via attached email

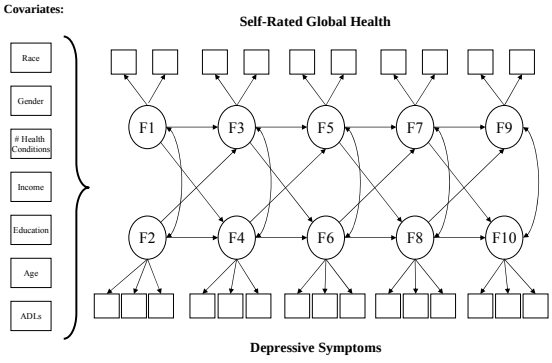
# Theoretical Background for Proposed Reciprocal Effects between SOPH and Depression

- As noted earlier, my colleagues and I have found no research that tests for reciprocal effects between SOPH (or other dimensions of physical health) and depression
- However, there are various conceptual models researchers have proposed
- The next figure represents a summary of that conceptual background




Conceptual Model Linking Dimensions of Physical Health to dimensions of Psychological Well-Being

Figure 1
Auto-Regressive Cross-Lagged Model of Global Health and Depression [a]




[a] To simplify presentation, correlated measurement errors and auto-correlated disturbance terms are not presented

# Auto-Regressive Model (cont.)

- The previous causal model can incorporate equality constraints on factor loadings across waves
  - Important test of key assumption in longitudinal analysis
- Not depicted in previous diagram (to reduce clutter) are:
  - Auto-correlated disturbances
  - Auto-correlated measurement errors
- See prior – two-wave – model of SOPH & Depression for these additional auto-correlated paths

# Sample

- Data taken from Rand version of Health & Retirement Survey (HRS)
- Panels collected in 92, 94, 96, 98, 2000
- Ages 51 to 61 in 1992
- Current study uses persons who completed all 5 waves
- N = 8,836

# Measures

| | |
|---|---|
| **Depression (Short-version of CES-D)** | *Response options collapsed into dichotomy:*<br>1 = Present all or most of time<br>0 = Absent all or most of time |
| **V1** | **Negative Affect (3-item composite):**<br>• I felt depressed<br>• I felt lonely<br>• I felt sad |
| **V2** | **Positive Affect (2-item composite):**<br>• I was happy<br>• I enjoy life |
| **V3** | **Somatic Symptoms (3-item composite)**<br>• I felt everything I did was an effort<br>• My sleep was restless<br>• I could not get going |
| **SOPH** | |
| **V4** | **Graded Response**<br>*Would you say your health is*<br>1 Poor 2 Fair 3 Good 4 Very Good 5 Excellent |
| **V5** | **Work-Related Health**<br>*Now I want to ask how your health affects paid work activities. Do you have any impairment or health problem that limits the kind or amount of paid work activities?*<br>1 = No<br>0 = Yes |

# Measures (cont.)

| | |
|---|---|
| **Chronic Illness** **V6** | *Has a doctor ever told you had……..***(Seven-item composite with range 0 to 7)**<br>• High blood pressure<br>• Diabetes<br>• Cancer<br>• Lung disease<br>• Heart disease<br>• Stroke<br>• Arthritis |
| **Functional Disability** **V7** | **Activities of Daily Living (five-item composite)**:<br>*Response options collapsed into dichotomous indicators:*<br>1 = Any difficulty<br>0 = No difficulty<br>• Bathing<br>• Eating<br>• Dressing<br>• Walking across a room<br>• Getting in/out of bed<br><br>Cronbach's alpha = .70 |
| **Education** **V8** | *Five-point scale ranging from (1) high school dropout to (5) college graduate and above.* |
| **Income** **V9** | *Thirty-point scale ranging from no income to $145,000 and above in $5,000 increments.* |
| **Gender** **V10** | 1= Females<br>0 = Males |
| **Race** **V11** | 1= African-American<br>0 = Caucasian |

**Table 1**
**Means and Standard Deviations of Variables**
**(n=8836)**

| Variables | Wave 1 | Wave 2 | Wave3 | Wave 4 | Wave 5 |
|---|---|---|---|---|---|
| **Race** (0=White 1=Black) | .16 (.36) | - | - | - | - |
| **Gender** (0=male 1=female) | .59 (.49) | - | - | - | - |
| **# of Chronic Conditions** (0 to 7) | .95 (.99) | - | - | - | - |
| **Income** (0=no income to 30=$145,000 or more, $5,000 increments) | 10.7 (7.8) | - | - | - | - |
| **Education** (0= less than high school to 5=college grad or beyond) | 3.1 (1.4) | - | - | - | - |
| **Age** (actual age) | 54.9 (5.5) | - | - | - | - |
| **Functional Impairment** (0= none to 5=high impairment) | .06 (.35) | - | - | - | - |
| **Self-Assessed Health** (1=poor to 5=excellent) | 3.6 (1.1) | 3.5 (1.1) | 3.5 (1.1) | 3.2 (1.1) | 3.3 (1.1) |
| **Health Limits Work** (0=yes 1=no) | .82 (.39) | .78 (.41) | .76 (.43) | .75 (.43) | .73 (.44) |
| **Positive Affect** (0=high to 2=low) | .31 (.63) | .18 (.50) | .18 (.49) | .21 (.53) | .20 (.51) |
| **Somatic Complaints** (0=low to 3=high) | .30 (.65) | .66 (.94) | .63 (.91) | .79 (.95) | .75 (.94) |
| **Depressive Affect** (0=low to 3=high) | .12 (.47) | .41 (.87) | .43 (.85) | .51 (.91) | .52 (.92) |

**Table 2**
**Correlations Among Exogenous Variables**
**(n=8836)**

| Variables | Gender | Chronic Conditions | Income | Education | Age | ADL Impairment |
|---|---|---|---|---|---|---|
| **Race** (0=White 1=Black) | .06* | .11* | -.14* | -.16* | -.01 | .07* |
| **Gender** (0=male 1=female) | | .01 | -.09* | -.06* | -.27* | .03* |
| **# of Chronic Conditions** (0 to 7) | | | -.16* | -.15* | .18* | .20* |
| **Income** (0=no income to 30=$145,000 or more) | | | | .38* | -.12* | -.13* |
| **Education** (0= less than high school to 5=college grad or beyond) | | | | | -.05* | -.11* |
| **Age** (actual age) | | | | | | .02 |
| **ADL Impairment** (0 = no impairment to 5=high impairment) | | | | | | — |

* p < .05

**Table 3**
**Effects of Covariates on Endogenous Variables [a]**
**(n=8836)**

| Variables | | Race | Gender | Chronic Conditions | Income | Education | Age | ADL |
|---|---|---|---|---|---|---|---|---|
| Self-Assessed Health | Time 1 | -.19* | -.02* | -.61* | .38* | .40* | -.11* | -.39* |
| | Time 2 | -.02 | -.01 | .02 | .01 | .03* | -.01 | .03* |
| | Time 3 | .01 | .01 | -.04* | -.01 | .02* | .01 | -.01 |
| | Time 4 | -.02 | .02 | -.03* | .01 | .02* | .01 | .01 |
| | Time 5 | -.01 | -.01 | -.01 | .01 | .02* | .01 | -.02 |
| Depression | Time 1 | .09* | .10* | .20* | -.21* | -.21* | -.06* | .31* |
| | Time 2 | .01 | .09* | -.06* | -.01 | -.08* | -.04* | .01 |
| | Time 3 | .01 | .02 | .01 | -.01 | -.05* | -.05* | .03* |
| | Time 4 | .02 | .06* | -.03* | -.01 | -.04* | .01 | -.01 |
| | Time 5 | -.01 | .08* | -.01 | .01 | -.01 | -.01 | .01 |

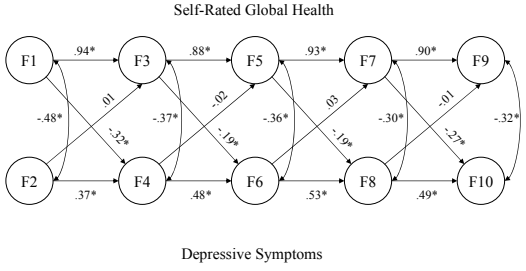
[a] Values at Time 1 are correlations; all other values are standardized regression coefficients
* p < .05

# Overall Model Fit

With unstandardized factor loadings constrained equal across waves:

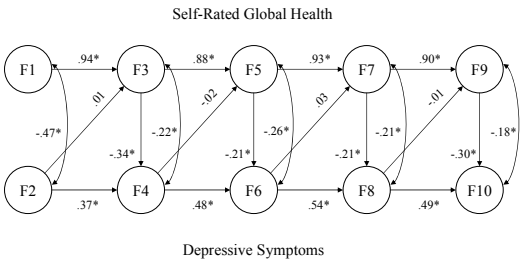
- CFI = .95
- Tucker-Lewis = .93
- RMSEA = .04
- SRMR = .06

Figure 2
Estimated Auto-Regressive Cross-Lag Model [a,b]
(n=8,836)




[a] To simplify presentation, correlated measurement errors and auto-correlated disturbance terms are not presented
[b] Standardized coefficients
* p≤.05

Figure 3
Auto-regressive Cross-Lag Model with Contemporaneous Effect of Health on Depression [a,b]
(n=8,836)




[a] To simplify presentation, correlated measurement errors and auto-correlated disturbance terms are not presented
[b] Standardized coefficients
* p≤.05

# Conclusions

- SOPH affects Depression
- Depression does not affect SOPH
- Accordingly, our study finds no evidence of reciprocal effects
- Cross-sectional studies should be cautious in their claims that depression affects physical health

# Future Research

- Replicate study using:
  - More complete measures of SOPH and Depression
    - Better second indicator for SOPH
    - Full CES-D with non-dichotomous response options
  - More complete set of measures for other physical health dimensions that we would treat as time-varying rather than time-invariant predictors (as in present study)
  - A sample of old-old persons for which SOPH will vary more (i.e., a sample that is not predominantly healthy)
  - More variation in SOPH would allow us to
    - Model ***shorter lag*** periods (e.g., 1-year rather than 2-year)
    - Model ***contemporaneous reciprocal*** effects more completely
  - "Hybrid" models that allow simultaneous assessment of developmental (growth curve) and dynamic (auto-regressive) processes