Some remarks on interpreting dynamic panel models

…and how to get from data to causes

The general idea behind dynamic panel models

- Remember Baltes and Nesselroade’s (1979) Rational 5: Analysis of causes (determinants) of intraindividual change

- In the last part, I argued that—as compared to static models—dynamic models are particularly useful for studying (causal) psychological mechanisms. Ups, here it is: the c word…

- In this part, I would like to take a step back and reflect on this idea a little bit more.

- For reasons of simplicity (and to better connect to the existing literature), I will focus on discrete time models in this part but stress that all arguments generalize to continuous time models.

(When) do we need causality?

So, let's begin with the big questions:

(When) do we need causality in modern science anyway?

Would we be better off by getting rid of the entire concept and instead focus on studying "laws of (human) behavior"?

(When) do we need causality?

$$F = m \cdot a$$

$$a = \frac{F}{m}$$

$$m = \frac{F}{a}$$

$$\boxed{\frac{F}{m}} \xrightarrow{1} \boxed{a}$$

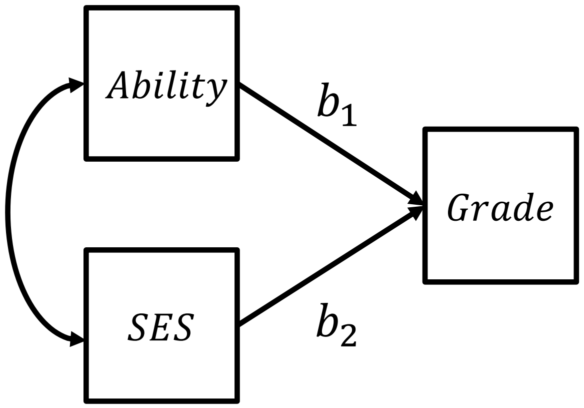
$$\boxed{\frac{F}{a}} \xrightarrow{1} \boxed{m} \quad ?$$

"[Physicists]…write equations in the office and talk cause-effect in the cafeteria" (Pearl, 2008, p. 338)

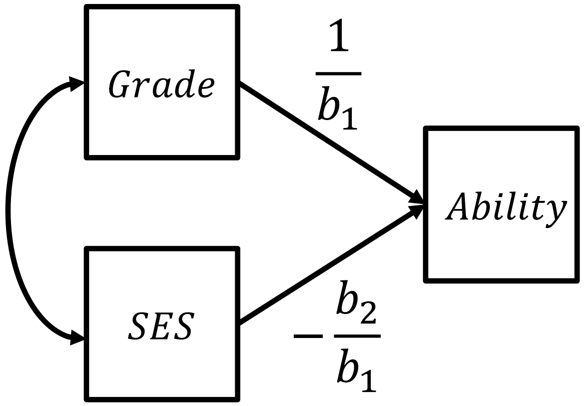
Pearl (2008)

(When) do we need causality?

$$Grade = b_1 \cdot Ability + b_2 \cdot SES$$



$$Ability = \frac{1}{b_1} \cdot Grade - \frac{b_2}{b_1} \cdot SES$$



?

- Causality is more than equations (using standard algebra)
- “No causation without [potential] manipulation” (Holland, 1986, p. 959)*

* But see Bollen & Pearl (2013)

What is causality and how can we infer it?

Rubin's causal model:

Potential outcomes $\begin{cases} Y_1(u) & \text{if } S(u) = 1 \\ Y_0(u) & \text{if } S(u) = 0 \end{cases}$

Causal effect: $Y_1(u) - Y_0(u)$

- *u* is the basic unit (e.g. a person) of study from population *U*. A variable *Y* is a real-valued function that is defined on every unit in *U*
- *S*(*u*) indicates [potential] exposure of *u* to a specific treatment

Holland (1986); Rubin (1986); West & Thoemmes (2010)

What is causality and how can we infer it?

The Fundamental Problem of Causal Inference

It is impossible to observe the value of $Y_1(u)$ and $Y_0(u)$ on the same unit u and, therefore, it is impossible to observe [but not infer] the effect on u (Holland, 1986, p. 947)

What is causality and how can we infer it?

Because the ideal design cannot be realized, we need to approximate it. Essentially there are two ways to do so, each associated with important assumptions:

1. WP Designs

   Assuming temporal stability and causal transience

2. Unit Homogeneity

   Assuming all units to be exchangeable so that the response of unit A and B to a treatment will be identical

3. Randomization (BP Design)

   Assuming that all units have the same chance of being in the treatment condition S(u).

Scientific solution

Statistical

Holland (1986); Rubin (1986); West & Thoemmes (2010)

What is causality and how can we infer it?

Problems with the statistical solution to causal inference
(randomized controlled trials)

- Often not possible (e.g., effect of lifestyle on well-being; effect of parenting on delinquency, medication on health, etc.)
- Based on asymptotic theory (but we often work with rather small samples)

Problems with the scientific solution to causal inference

- Strict assumptions that are hardly ever met in our field

1. Temporal stability vs. occasion effects (things happen)
2. Causal transience vs. the past matters
3. Temporal stability & causal transience vs. co-movement
4. Unit homogeneity vs. unit heterogeneity (people differ)

What is causality and how can we infer it?

- One solution to these problems is to work with **observational data** while **controlling for violations of core assumptions**
- If we observe an effect after controlling for all violations of assumptions, we may infer that this is a causal effect
- There are many different approaches how to achieve such a control. Longitudinal panel data models are a particularly useful one.

Building up a general dynamic cross-lagged panel model

What are examples of violations of assumptions and how can we control for them in longitudinal panel models?

Acknowledgement: All following animations are taken and adapted from a 3-day workshop by Michael Zyphur from the University of Melbourne and are based on the following two publications:

Zyphur, M. J., Allison, P. D., Tay, L., Voelkle, M. C., Preacher, K. J., Zhang, Z., . . . Diener, E. (2020). From Data to Causes I: Building A General Cross-Lagged Panel Model (GCLM). Organizational Research Methods. doi:10.1177/1094428119847278

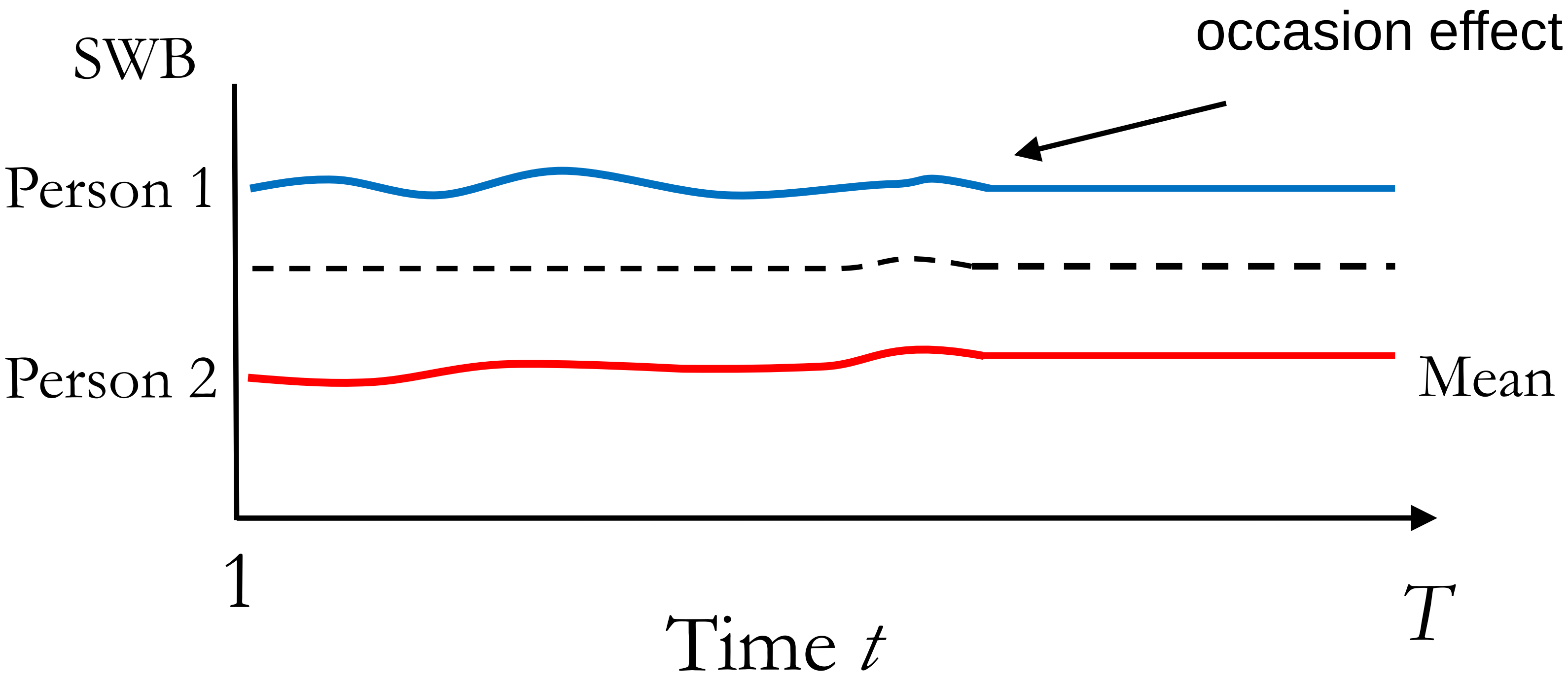
Zyphur, M. J., Voelkle, M. C., Tay, L., Allison, P. D., Preacher, K. J., Zhang, Z., . . . Diener, E. (2020) From Data to Causes II: Comparing Approaches to Panel Data Analysis. Organizational Research Methods. doi:10.1177/1094428119847280

Check out his presentation on youtube along with the additional material:
https://www.youtube.com/watch?v=tHnnaRNPbXs

…any mistakes in the adaptations are mine…

Building up a general dynamic cross-lagged panel model

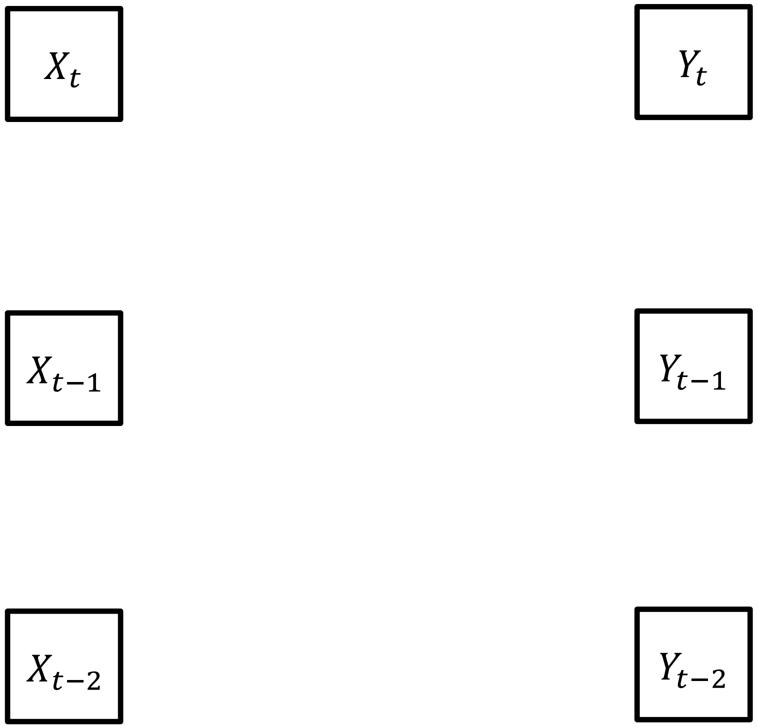
1. Temporal stability vs. occasion effects (things happen)



→ Controlling for occasion effects by “taking out” occasion specific means (e.g., freely estimating means in dt models)

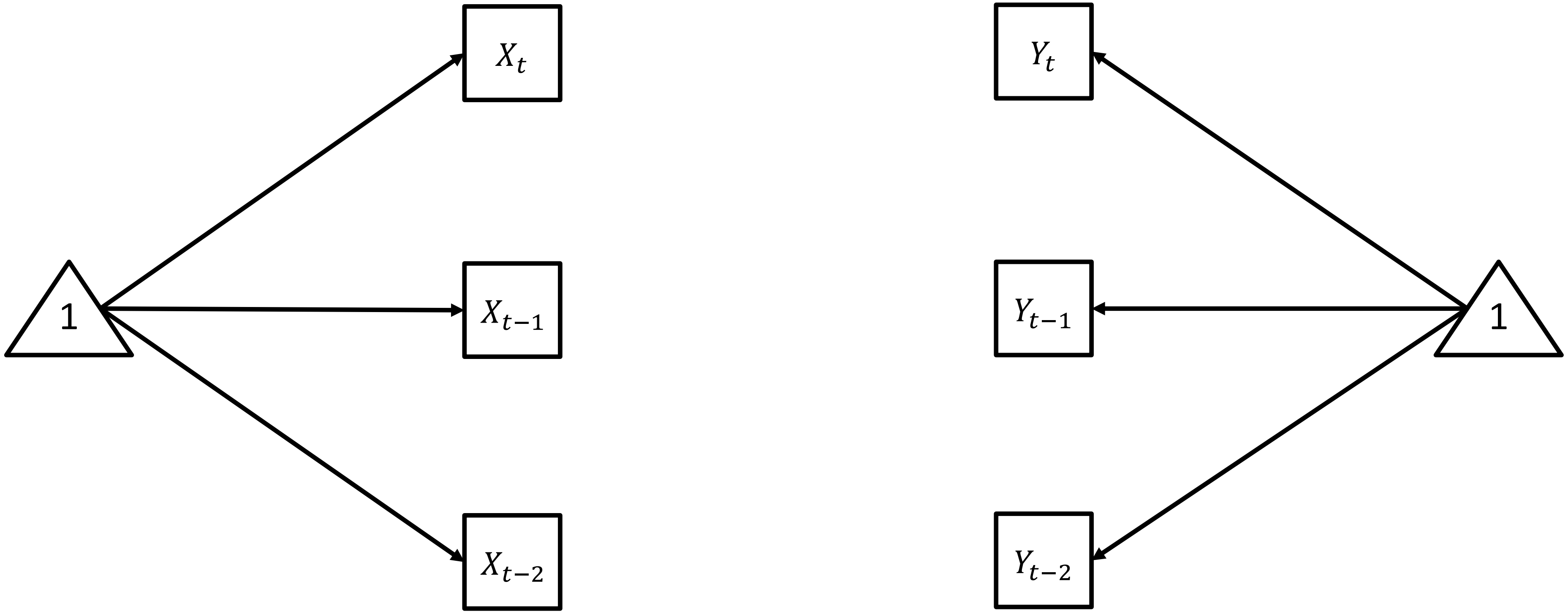
Building up a general dynamic cross-lagged panel model

Illustration of a bivariate panel model (without measurement model):



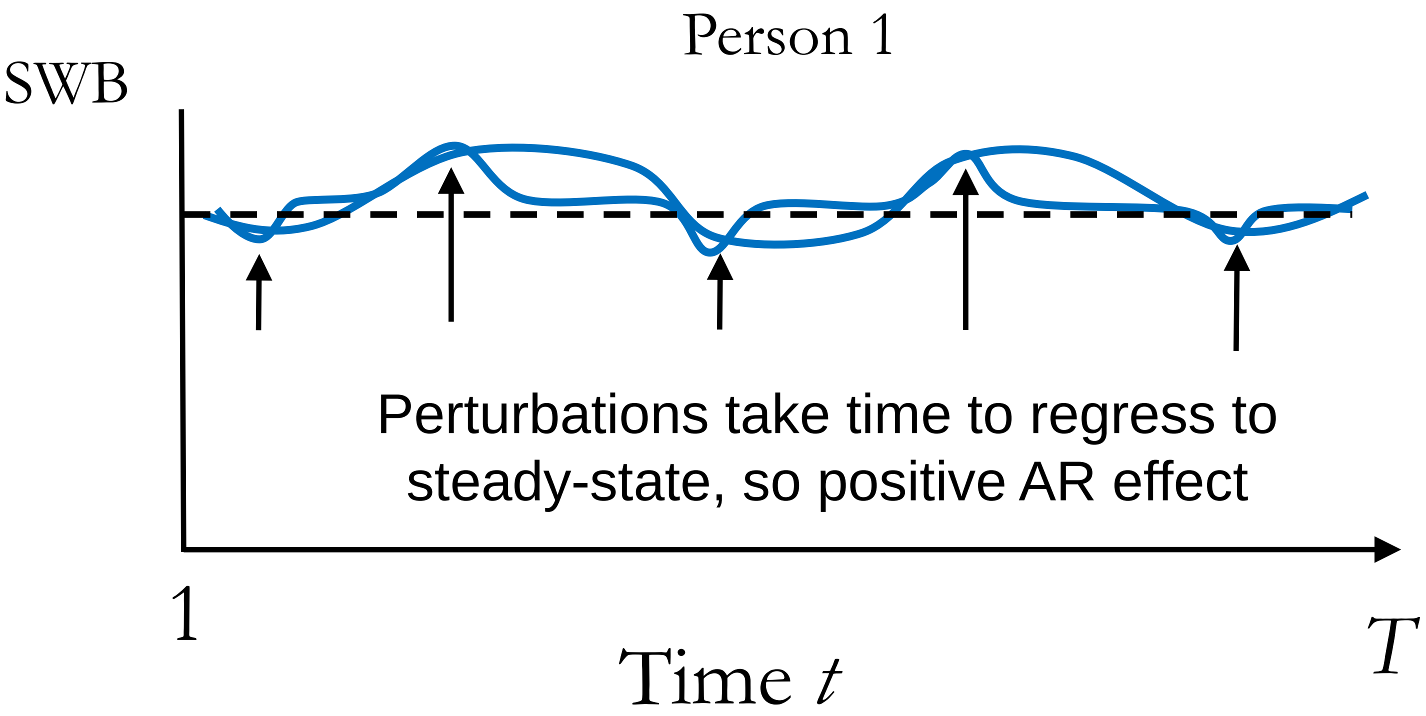
Building up a general dynamic cross-lagged panel model

1. Controlling for occasion effects



Building up a general dynamic cross-lagged panel model

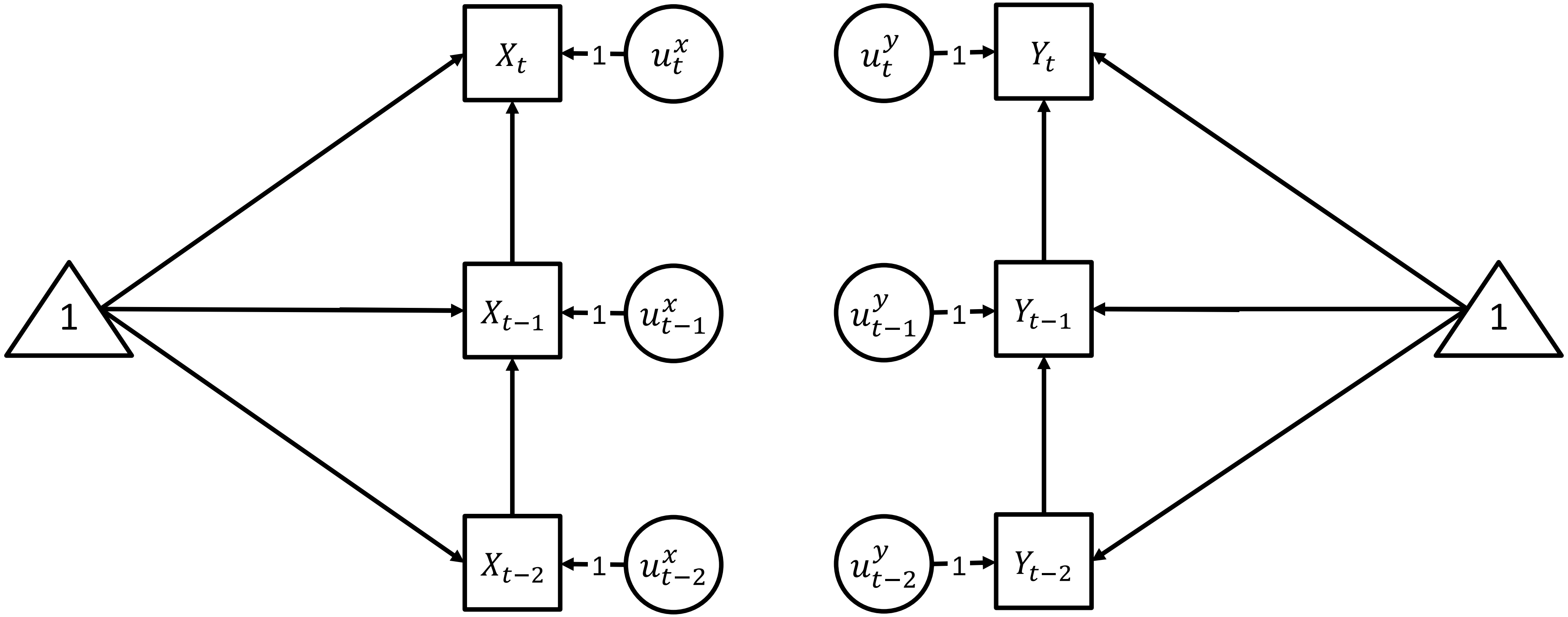
2. Causal transience vs. the past matters



→ Controlling for the past by modeling its effects (e.g., by including autoregressive effects)

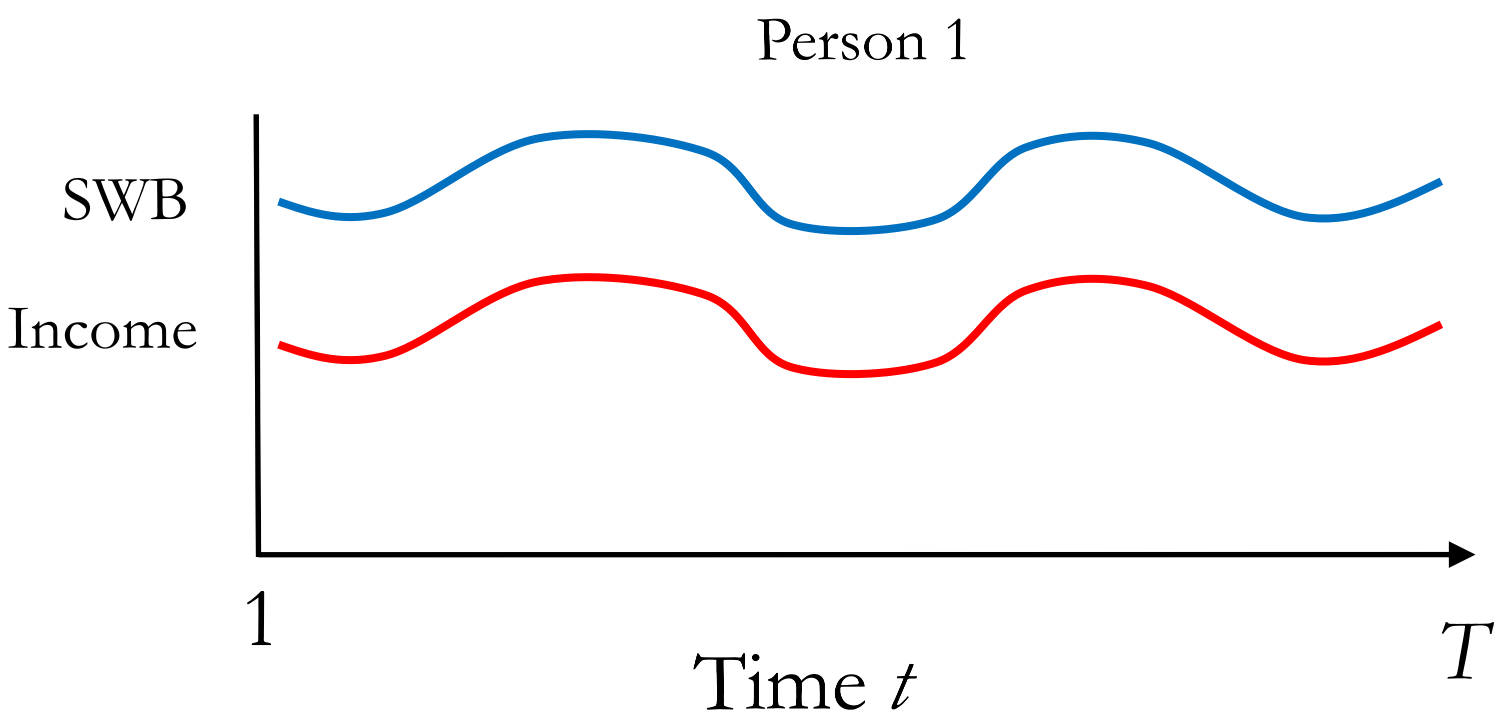
Building up a general dynamic cross-lagged panel model

2. Controlling for the past



Building up a general dynamic cross-lagged panel model

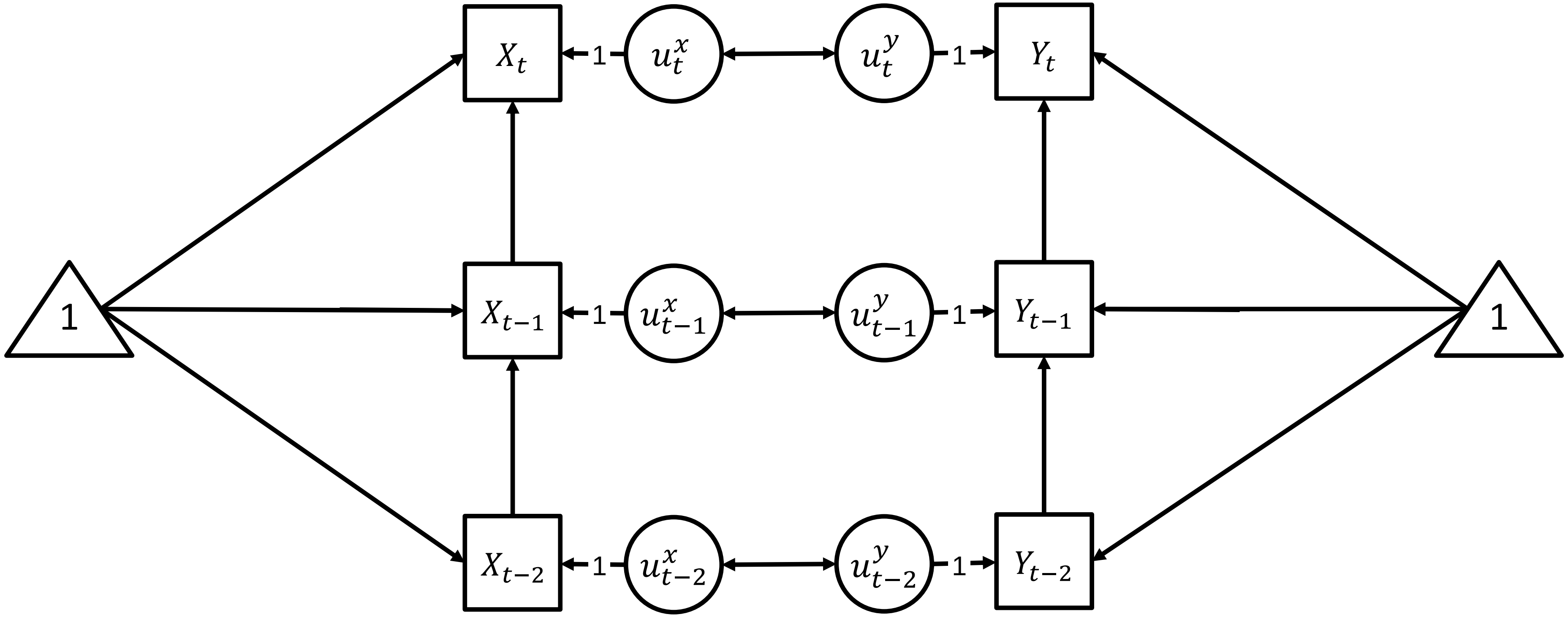
3. Temporal stability & causal transience vs. co-movement



→ Controlling for co-movement by allowing for contemporaneous correlations

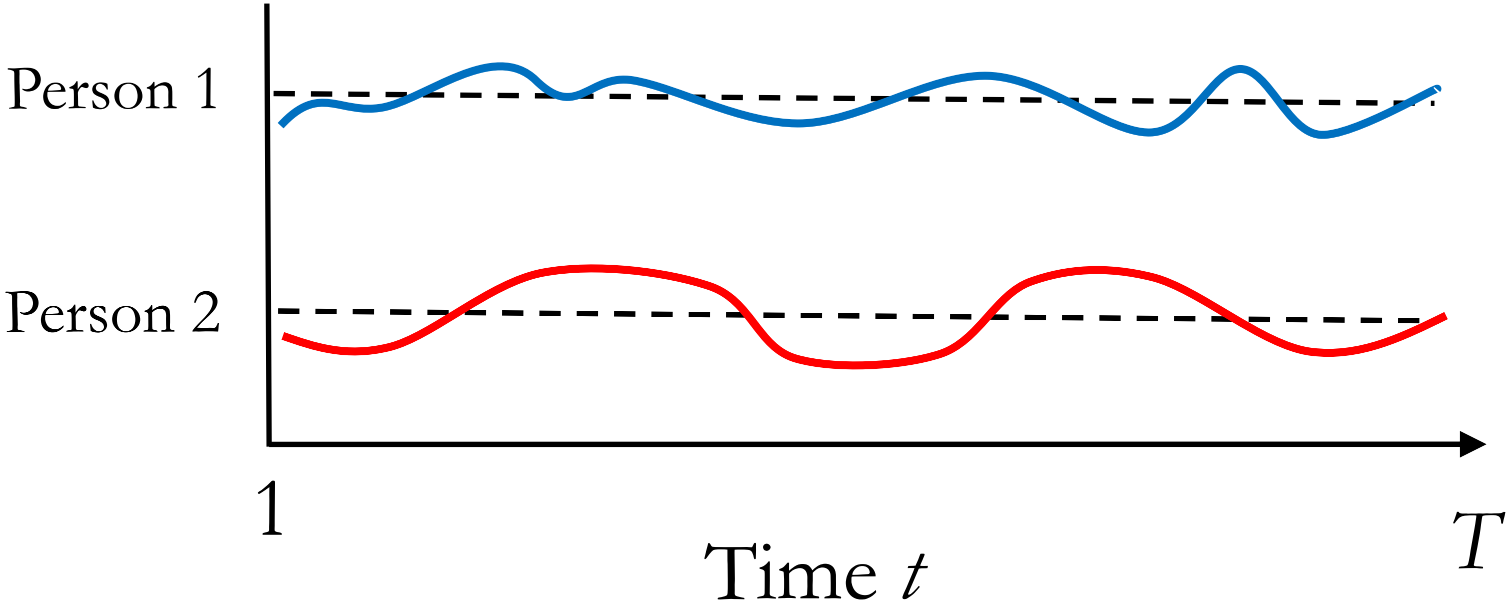
Building up a general dynamic cross-lagged panel model

3. Controlling for co-movement



Building up a general dynamic cross-lagged panel model

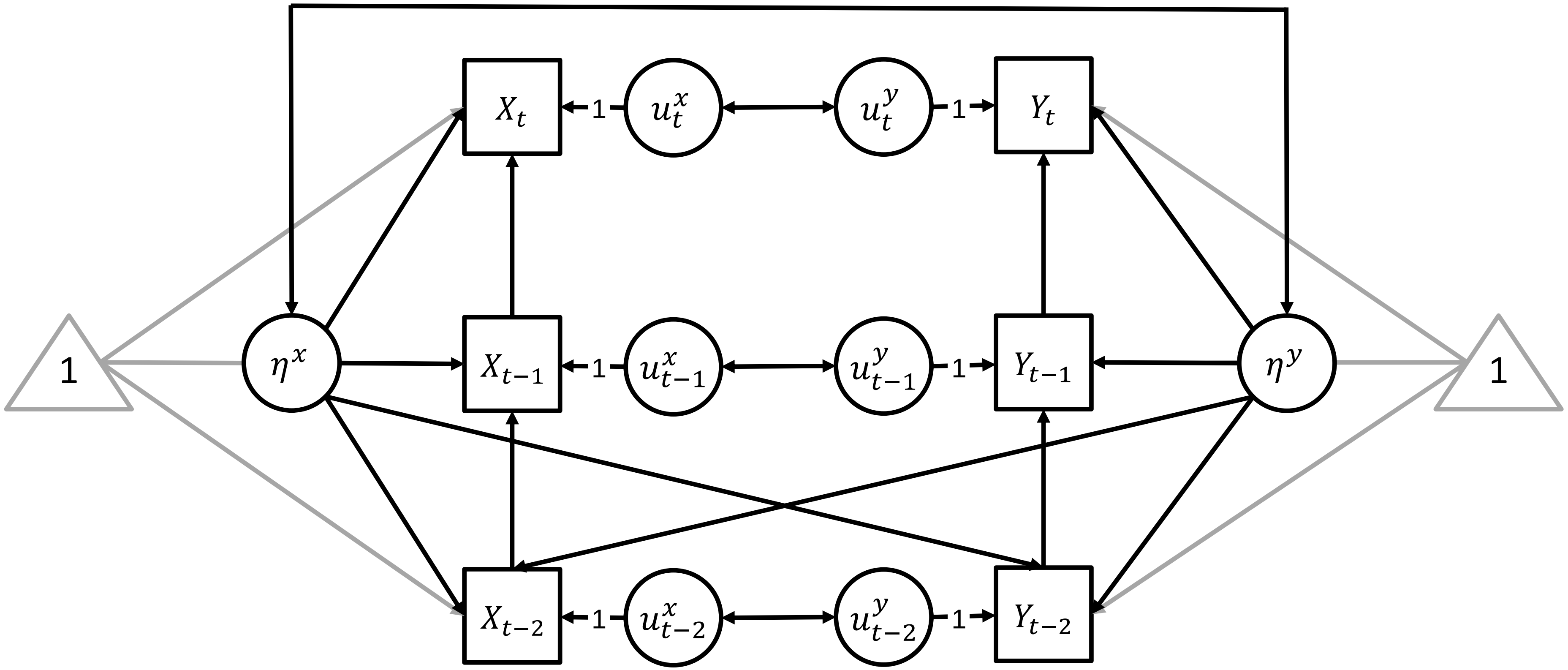
4. Unit homogeneity vs. unit heterogeneity (people differ)



→ Controlling for unit heterogeneity by estimating the mean/intercept for each unit $i = 1, \ldots, N$ (e.g., by including random intercepts).

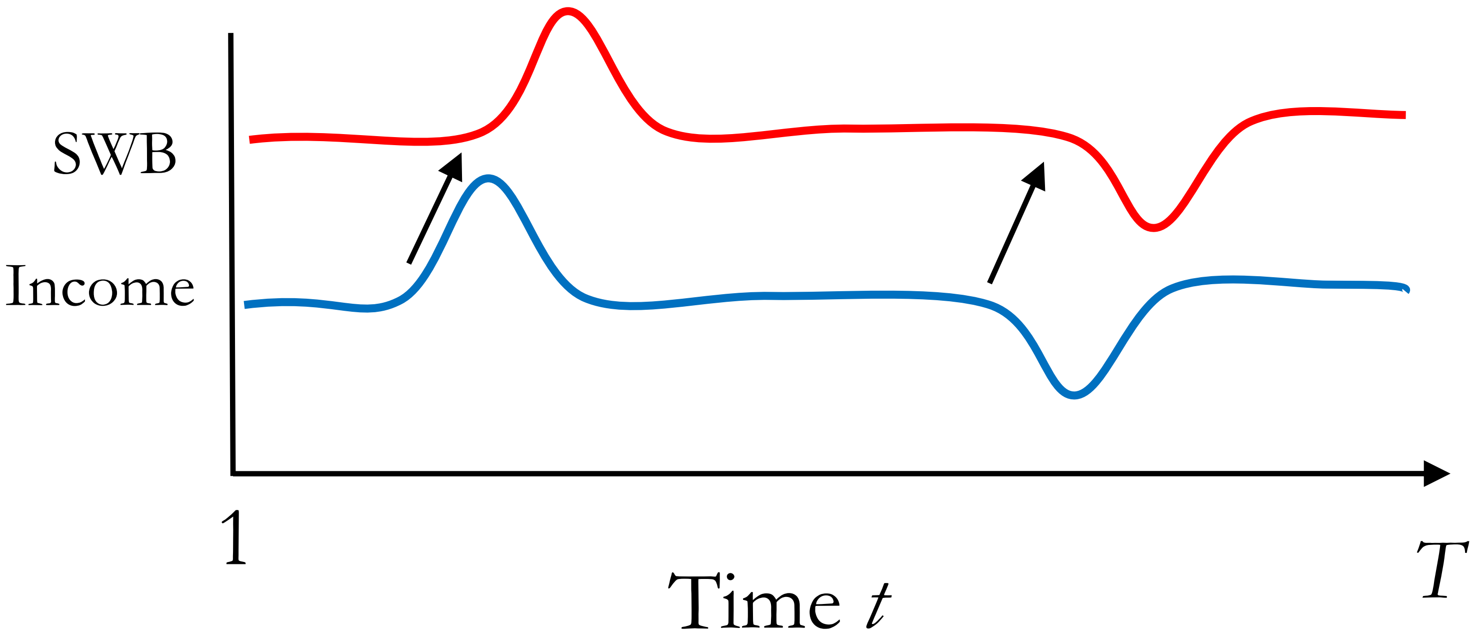
Building up a general dynamic cross-lagged panel model

4. Controlling for unobserved heterogeneity



Building up a general dynamic cross-lagged panel model

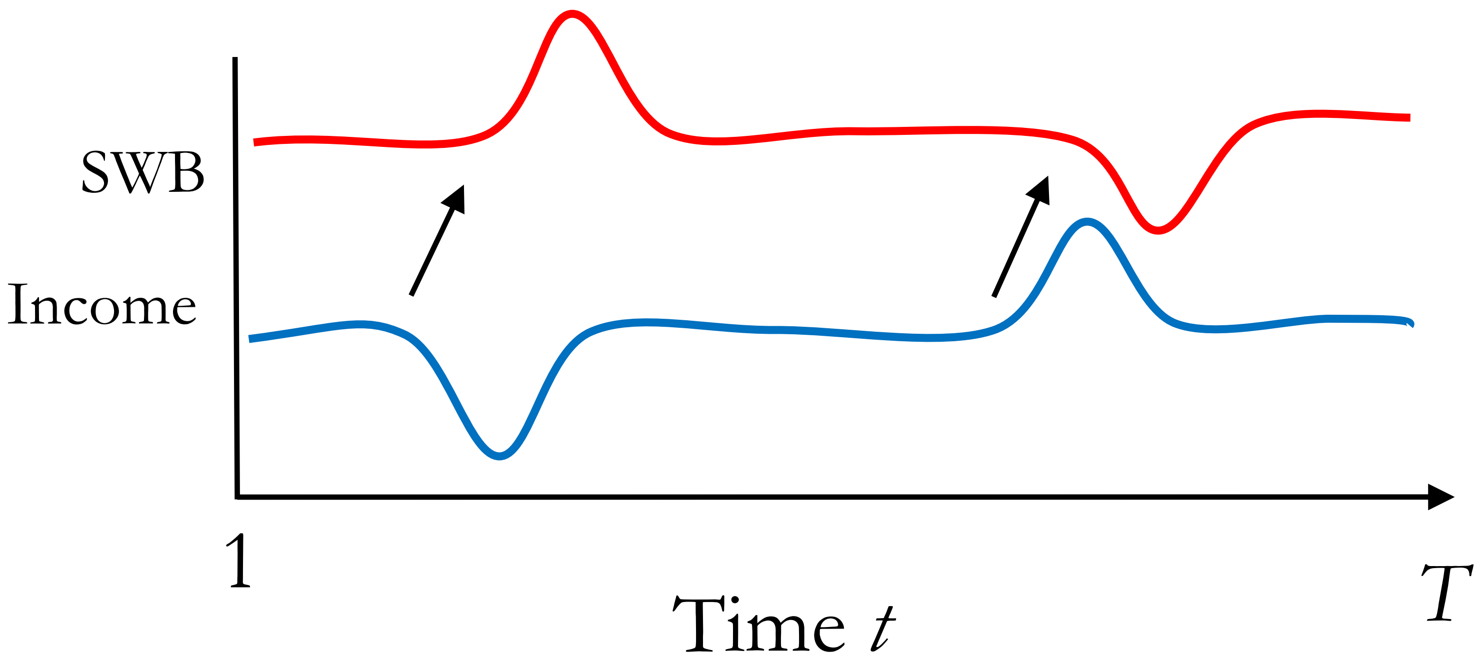
Causal effects should remain [positive effect of income on SWB]



→ Estimating (Granger-type-)causality via cross-lagged effects (after controlling for 1-4 and by using information on the temporal ordering)

Building up a general dynamic cross-lagged panel model

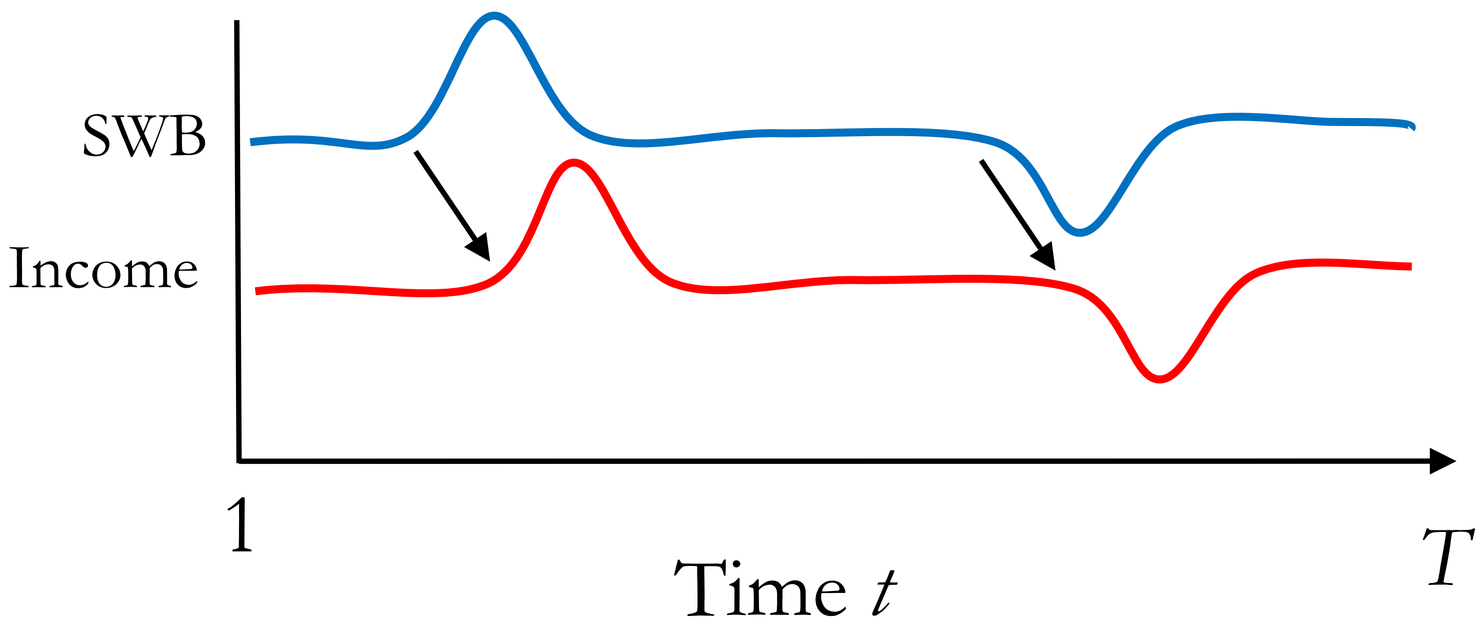
Causal effects should remain [negative effect of income on SWB]



→ Estimating (Granger-type-)causality via cross-lagged effects (after controlling for 1-4 and by using information on the temporal ordering)

Building up a general dynamic cross-lagged panel model

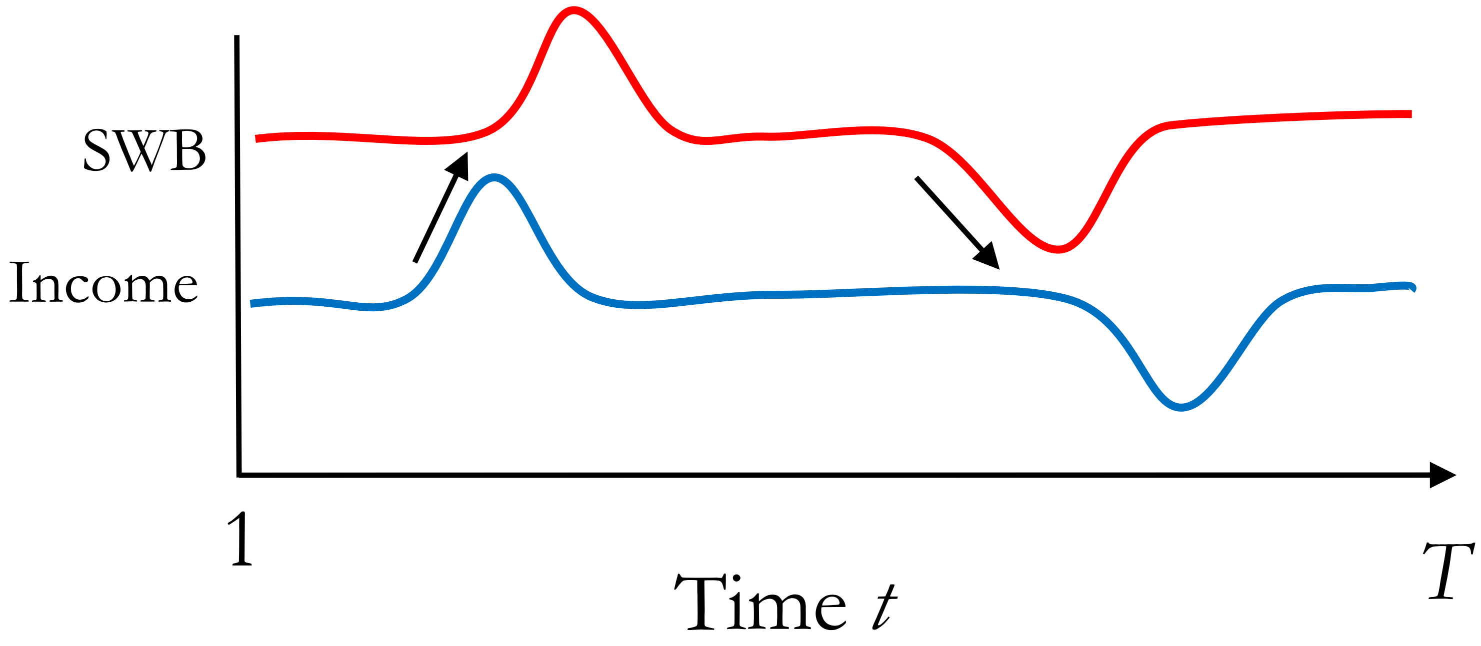
Causal effects should remain [positive effect of SWB on income]



→ Estimating (Granger-type-)causality via cross-lagged effects (after controlling for 1-4 and by using information on the temporal ordering)

Building up a general dynamic cross-lagged panel model

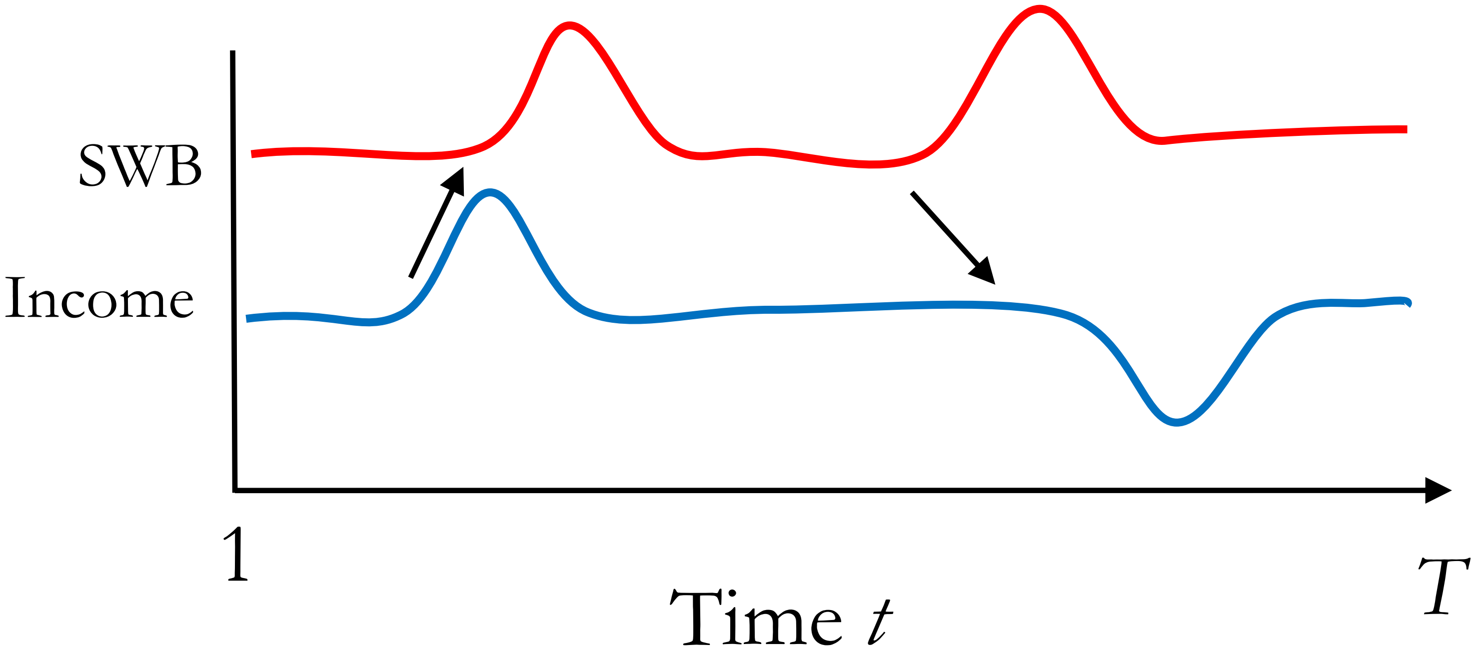
Causal effects should remain [positive effect of income on SWB and positive effect of SWB on income]



→ Estimating (Granger-type-)causality via cross-lagged effects (after controlling for 1-4 and by using information on the temporal ordering)

Building up a general dynamic cross-lagged panel model

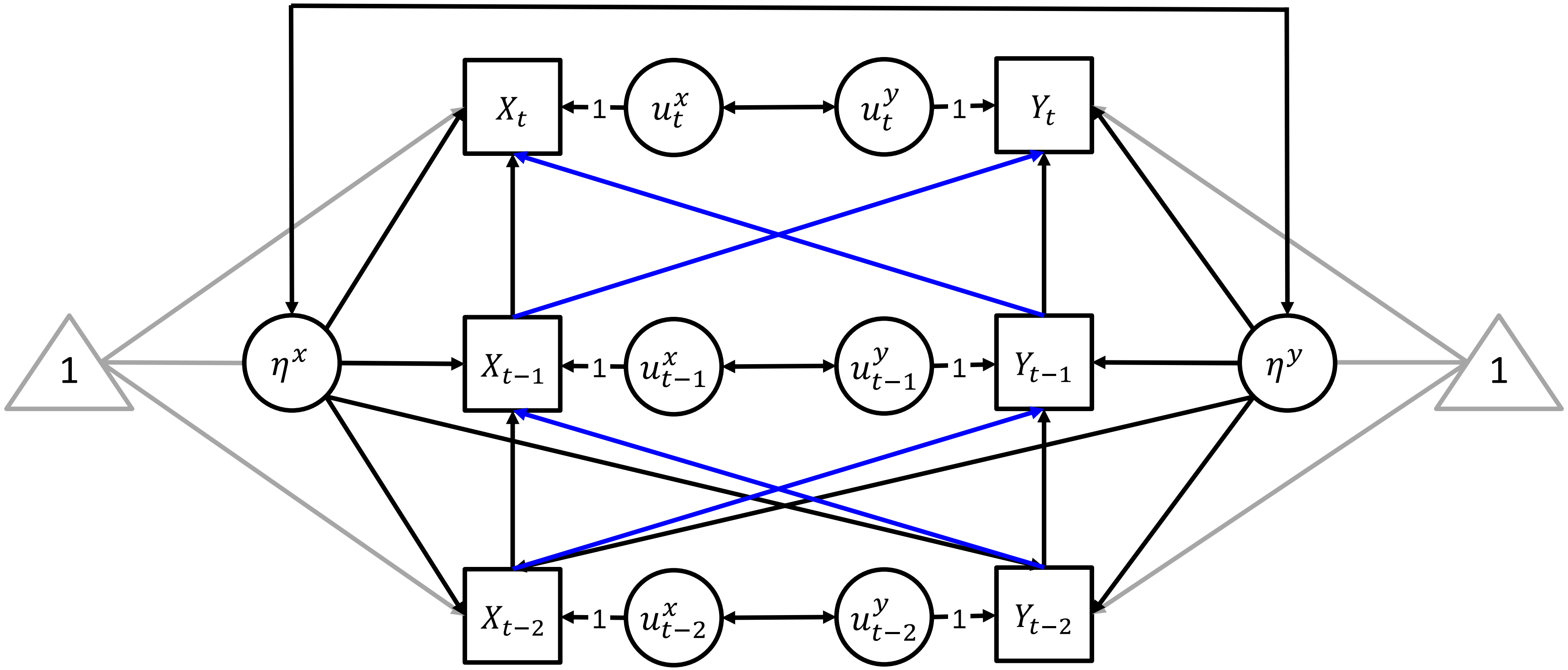
Causal effects should remain [positive effect of income on SWB and negative effect of SWB on income]



→ Estimating (Granger-type-)causality via cross-lagged effects (after controlling for 1-4 and by using information on the temporal ordering)

Building up a general dynamic cross-lagged panel model

→ Causal effects (should) remain



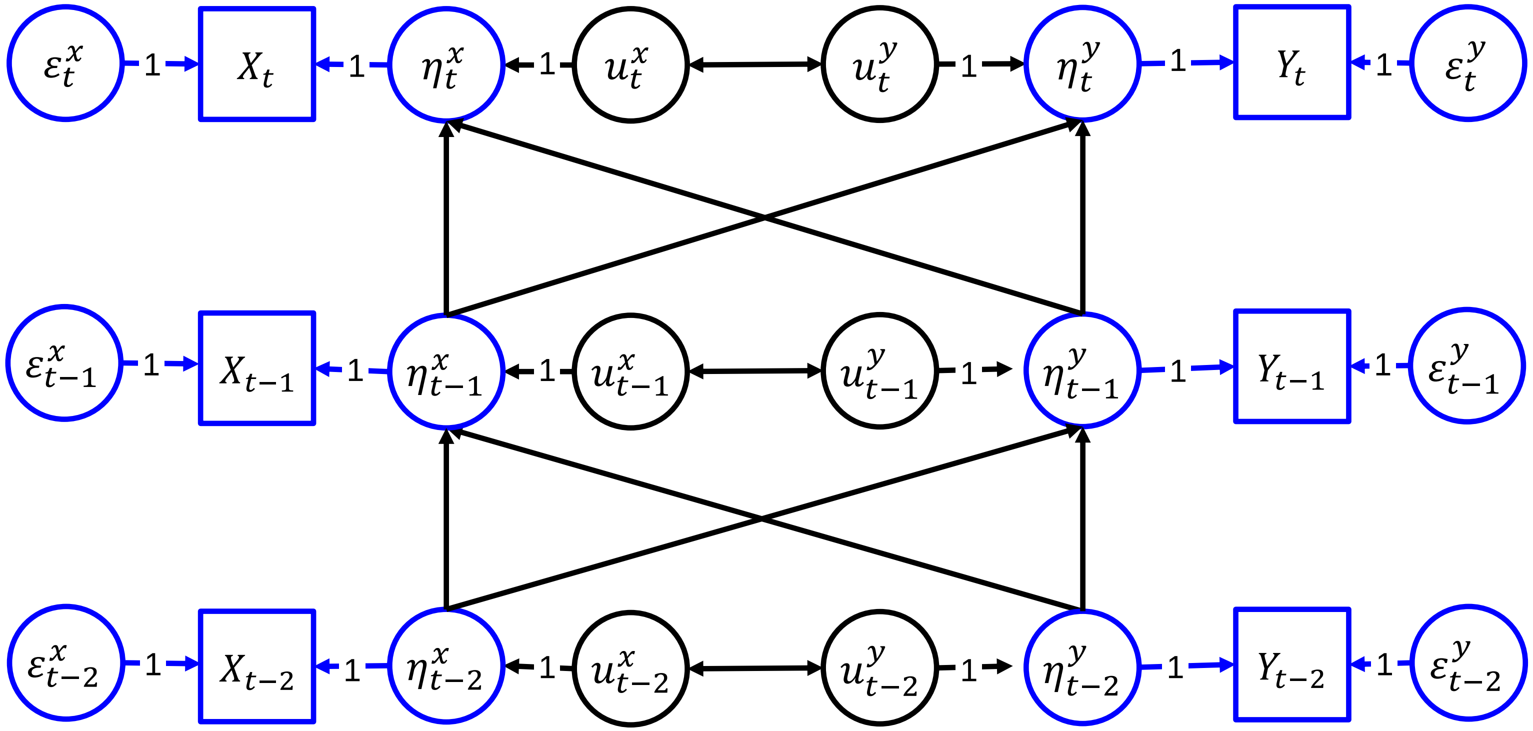
More complex dynamics

The basic model can be extended in various ways, for example by adding…

1. a measurement model
2. moving average effects (MA effects) to modify the persistence of an effect over time
3. cross-lagged moving average effects (CLMA effects) to modify the persistence of a cross-lagged effect over time
4. higher order lagged effects: AR(p) CL(c) MA(q) CLMA(l) effects

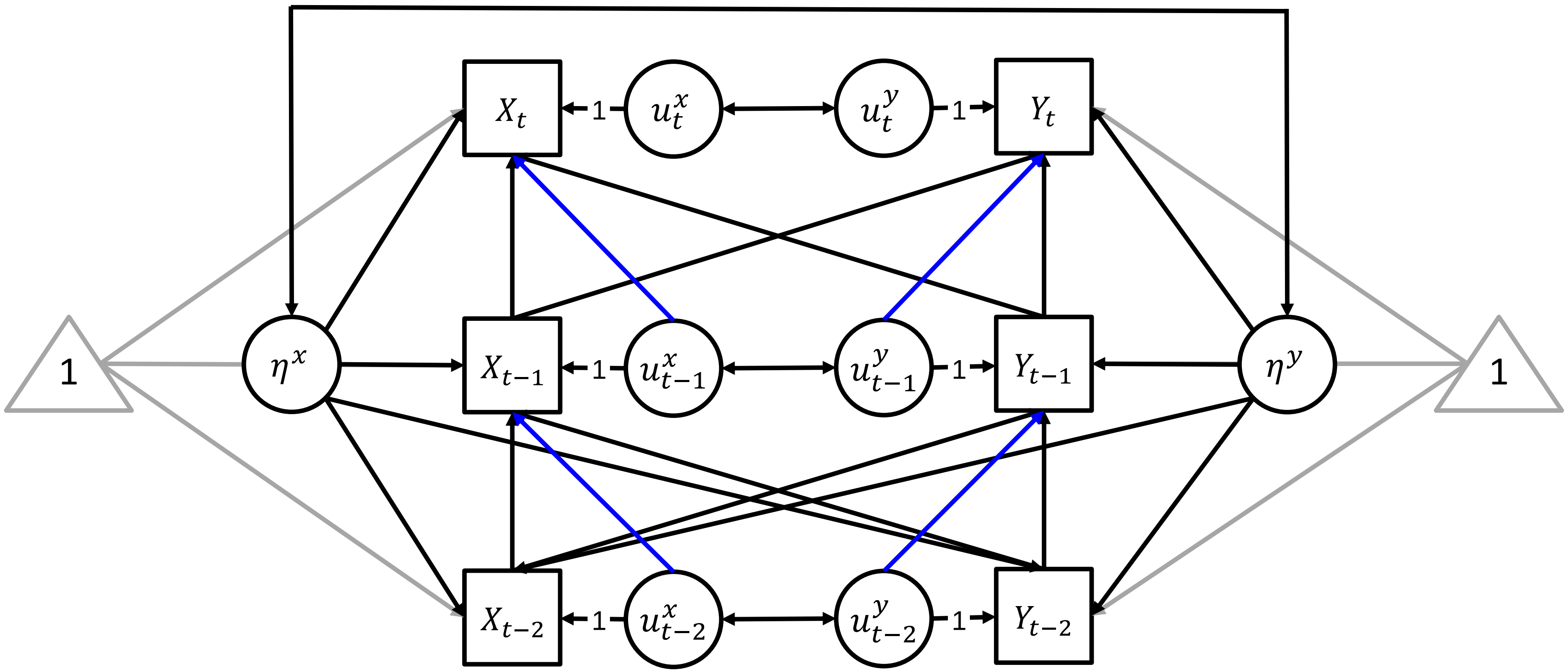
More complex dynamics

1. Adding a measurement model (illustration without occasion effects and unit effects)



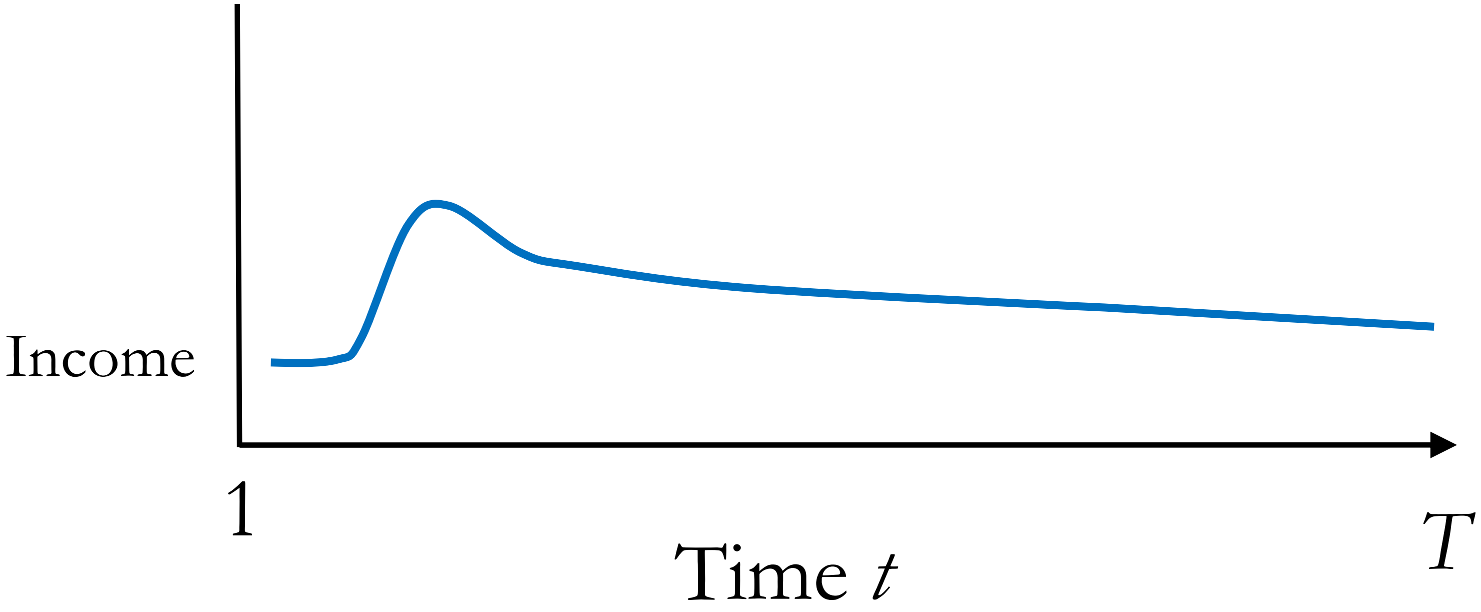
More complex dynamics

2. Adding moving average effects (MA effects)



More complex dynamics

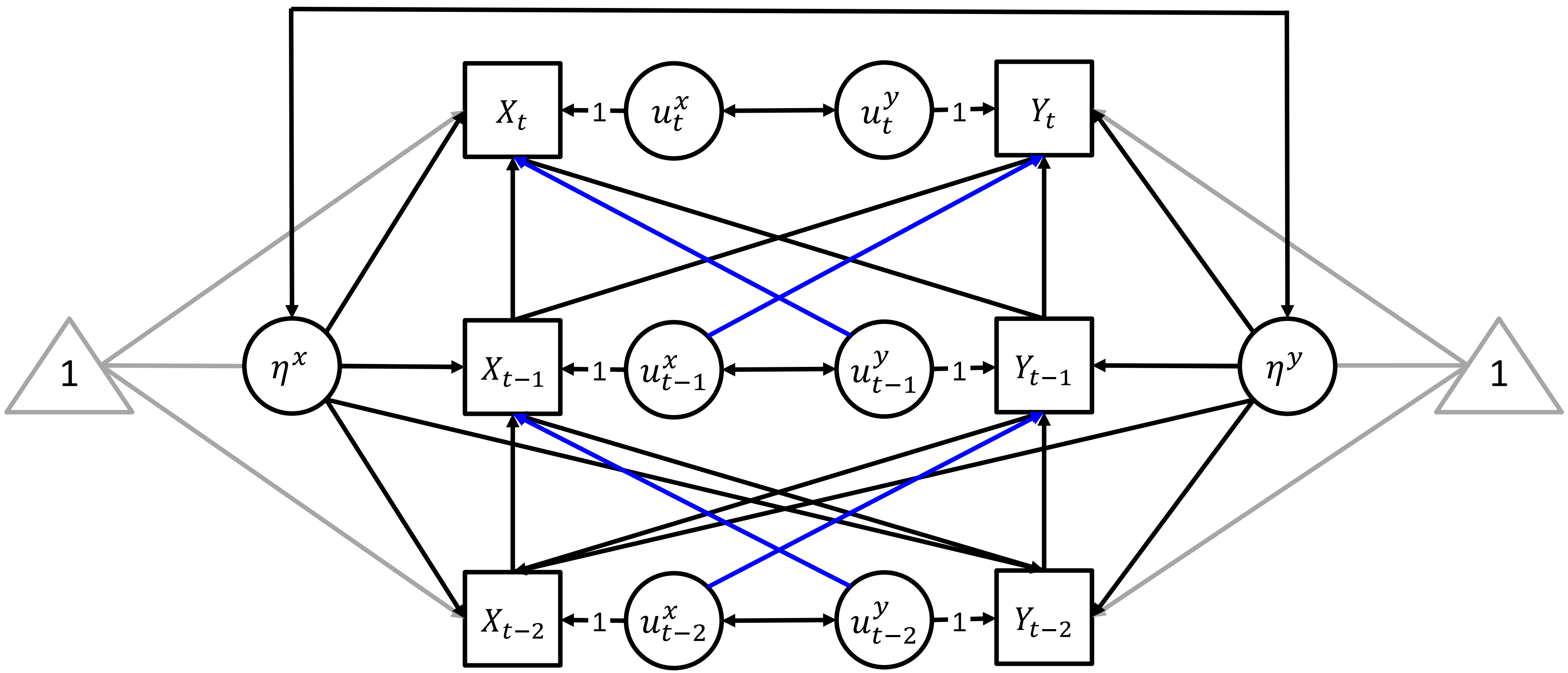
2. Adding moving average effects (MA effects)



→ MA terms may modify the persistence of an effect over time (e.g., by *initially* decreasing or increasing the effect of a past impulse)

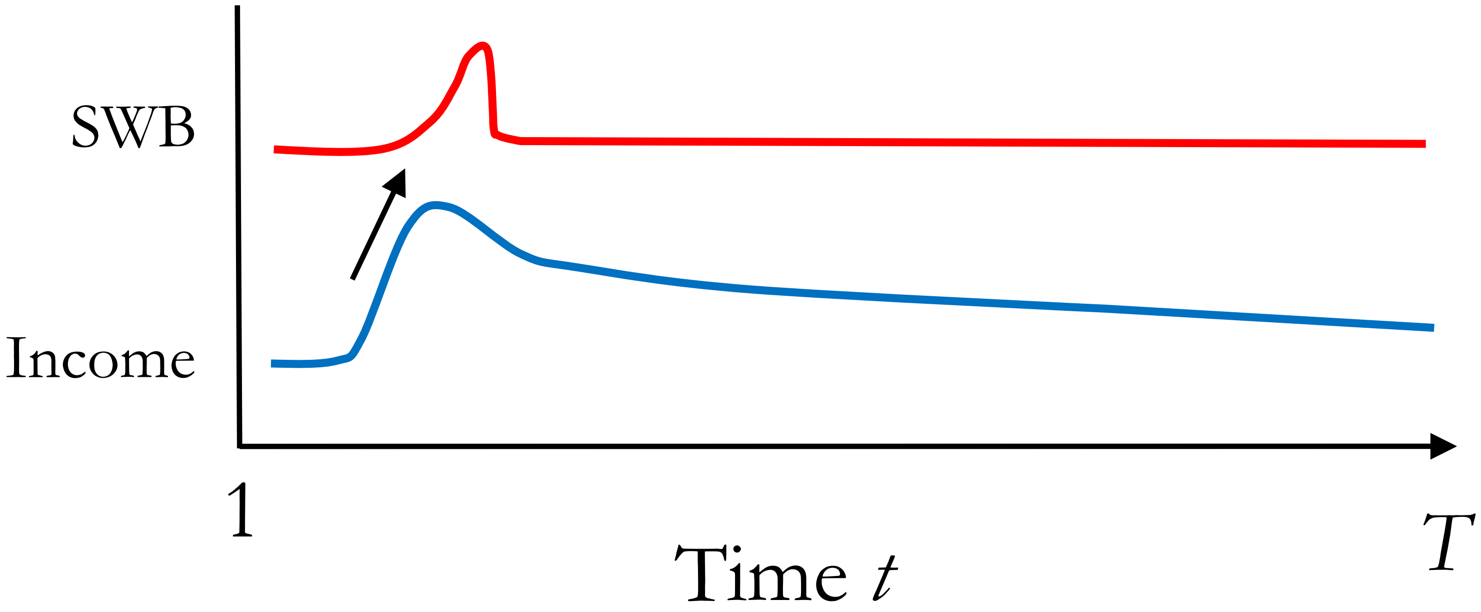
More complex dynamics

3. Adding cross-lagged moving average effects (CLMA effects)



More complex dynamics

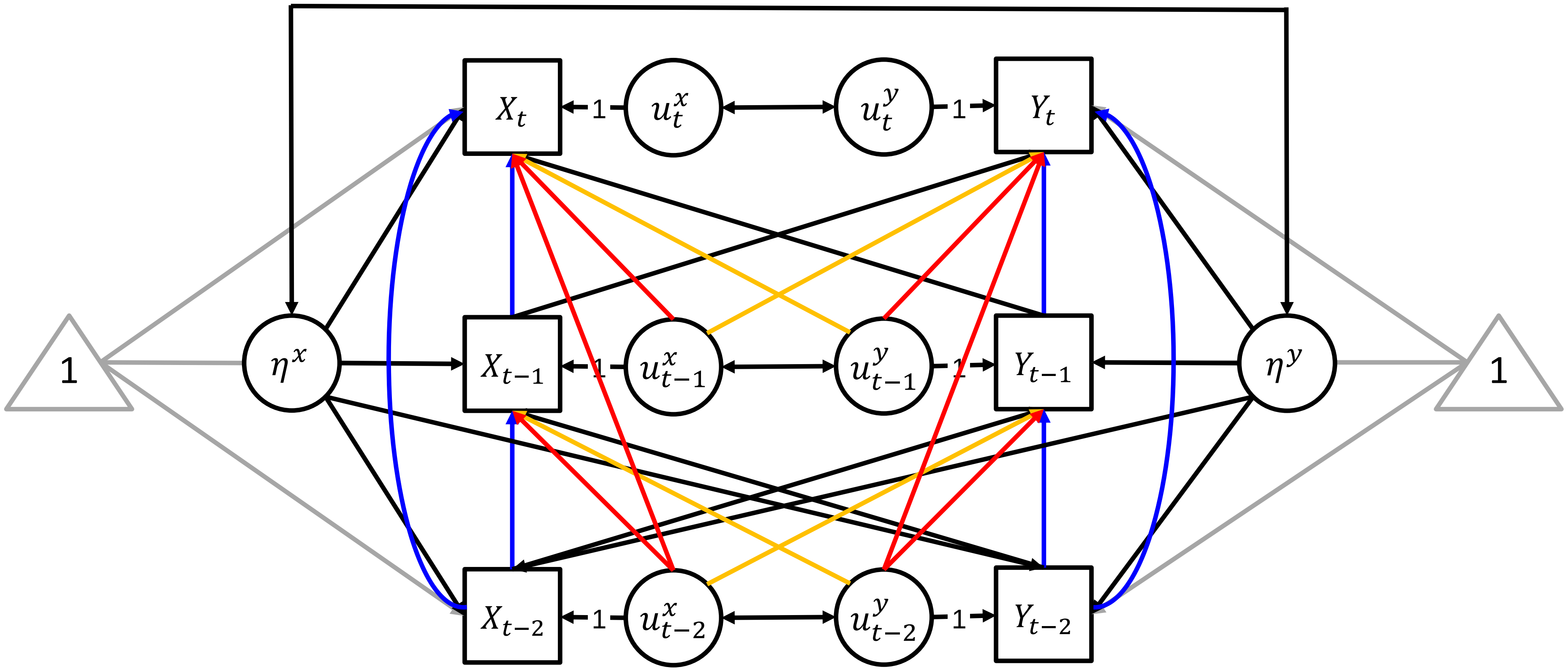
3. Adding cross-lagged moving average effects (CLMA effects)



→ CLMA terms may modify the persistence of a cross-lagged effect over time (e.g., by *initially* increasing or decreasing the effect of a past impulse on another variable)

More complex dynamics

4. Adding higher order lagged effects: AR(*p*) CL(*c*) MA(*q*) CLMA(*l*) effects (e.g., AR(2)CL(1)MA(2)CLMA(1))



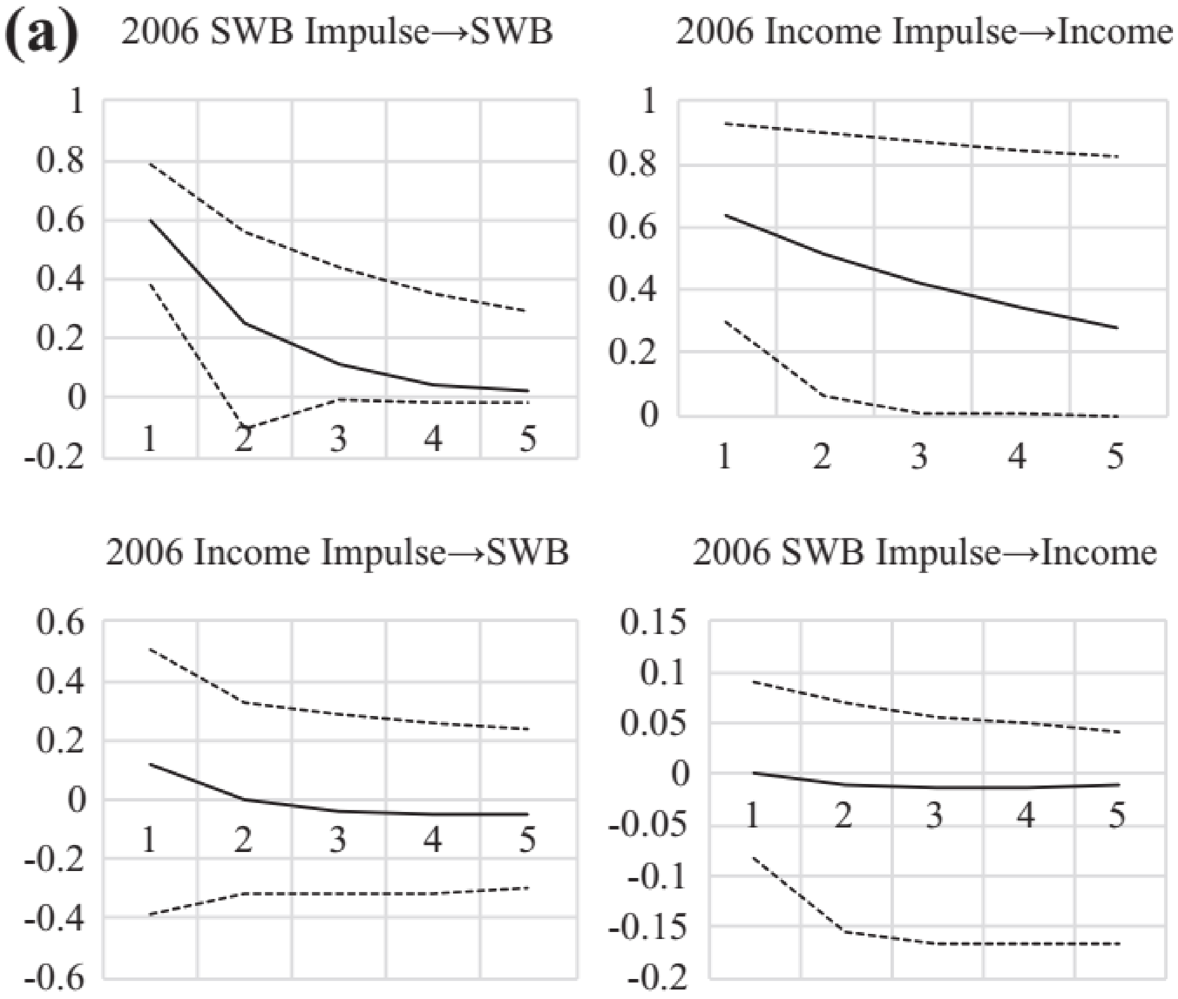
An empirical example

As an exercise, let's check out a basic AR(1)CL(1)MA(1)CLMA(1)) model

- As an example, let's use the Gallup World Poll data to study the causal relationship between income (equivalized, log-transformed and rescaled) and subjective well-being (0 to 10 scale)
- Data are available as part of the supplemental material of Zyphur et al. (2020)
- *N* = 135 countries (average scores per country, representative of about 95% of the world's adult population)
- *T* = 6 measurement occasions (2006 – 2011)
- Example lavaan script: AR1CL1MA1CLMA1.R
- For a comprehensive discussion including model checking and comparisons, see the two articles by Zyphur (2020). We just use this as a little example to demonstrate how a general discrete time cross-lagged panel model may be set up and how it can be extended.

An empirical example

Interpreting effects by means of impulse response functions



Zyphur (2020; p. 16)

Summary

- Causality goes beyond equations and “laws”. We need causality to understand and manipulate the world.
- We cannot directly measure causality (-> fundamental problem), be we can <u>infer</u> causality using different research designs.
- Longitudinal panel designs are a particularly useful approach to causal inference (practical yet powerful, because they allow to control for occasion effects, the past, co-movement and unit-heterogeneity)
- Structural Equation Modeling and standard SEM software allows the flexible specification of general cross-lagged panel models (ARCLMACLMA…)
- But: The discrete time models are limited with respect to how they treat time. This problem is resolved in continuous time dynamic modeling.

Some selected further readings

- Allison, P. D., Williams, R., & Moral-Benito, E. (2017). Maximum likelihood for cross-lagged panel models with fixed effects. Socius: Sociological Research for a Dynamic World, 3, 1-17. doi:10.1177/2378023117710578
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- Zyphur, M. J., Allison, P. D., Tay, L., Voelkle, M. C., Preacher, K. J., Zhang, Z., . . . Diener, E. (2020). From Data to Causes I: Building A General Cross-Lagged Panel Model (GCLM). Organizational Research Methods. doi:10.1177/1094428119847278

Study Questions

Question 1:

Explain in your own words: What is the fundamental problem of causal inference? How can we deal with it?

Question 2:

List and describe four major problems with the “scientific solution” to causal inference discussed in class.

Question 3:

Describe at least two extensions to standard discrete time random intercept cross-lagged panel models that improve their realism for modeling psychological processes.

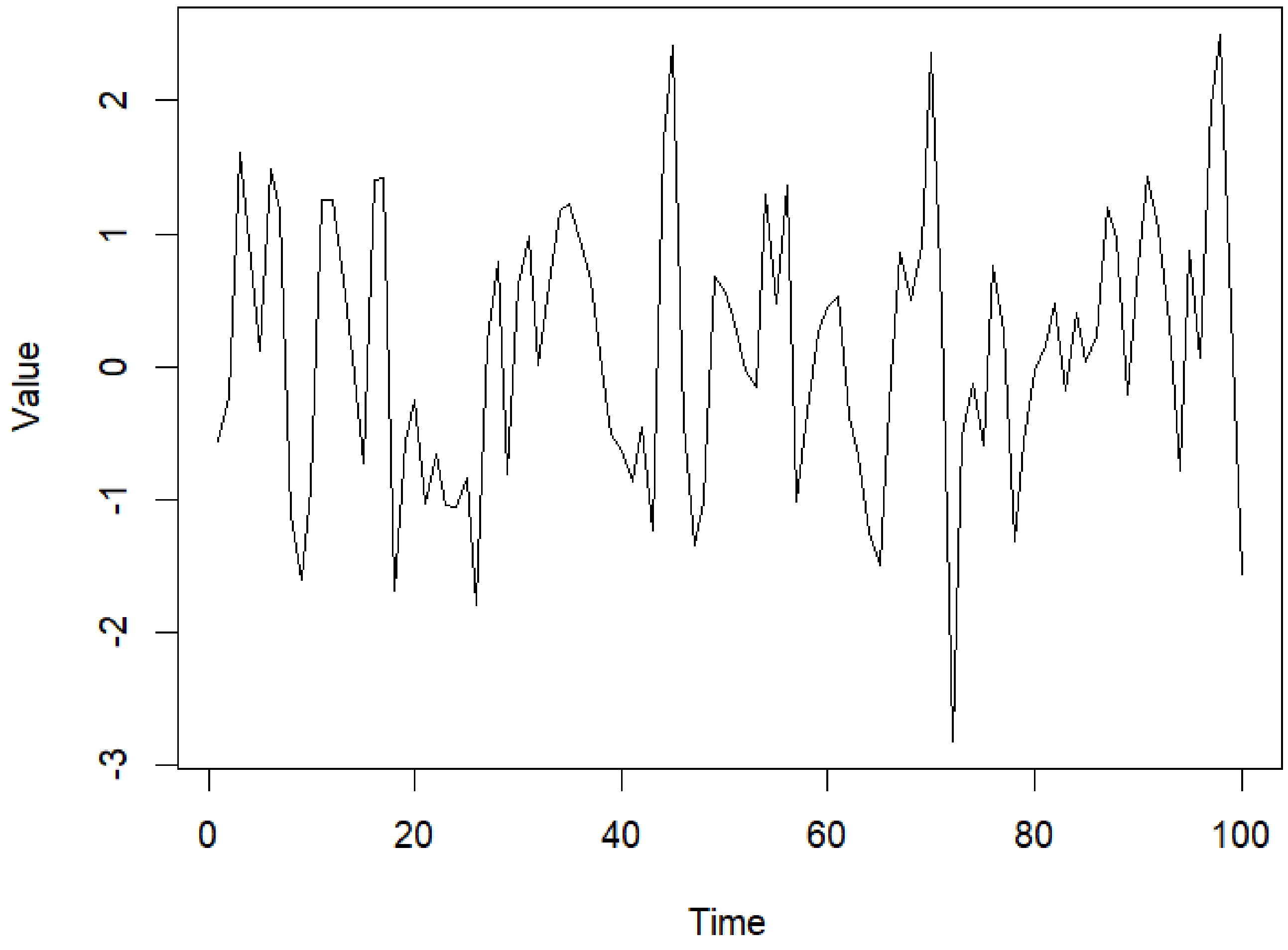
Study Questions

Question 4:

The plot to the right shows a simulated autoregressive process of order 2 (AR(2)):

a) Describe in your own words how an AR(2) process differs from an AR(1) process in terms of temporal dynamics.

b) What do the coefficients $\phi_1 = 0.5$ and $\phi_2 = -0.3$ suggest about the memory and oscillation of the process?



Simulated AR(2) process with $\phi_1 = 0.5$, $\phi_2 = -0.3$