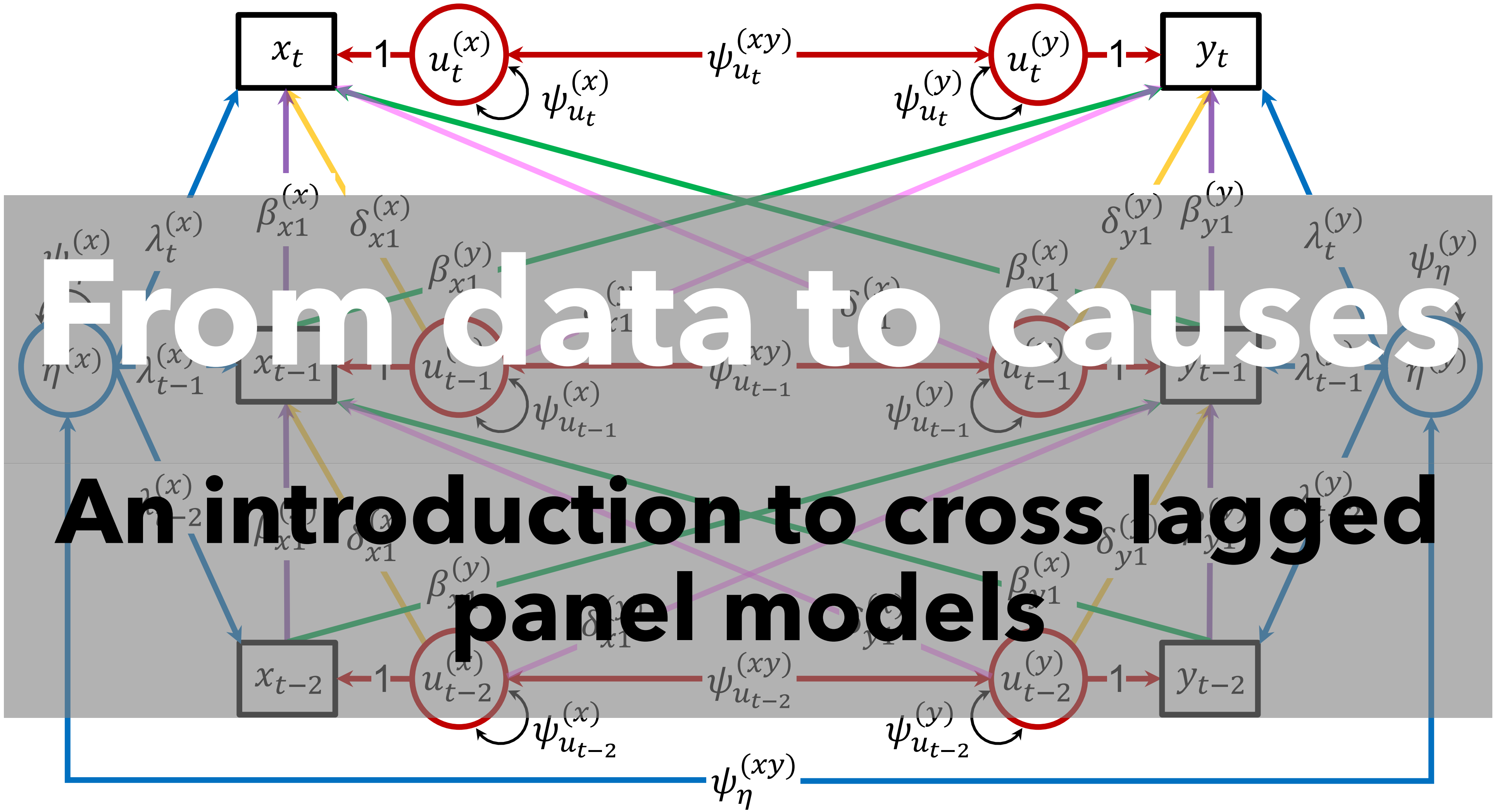


From data to causes

An introduction to cross lagged panel models

The problem

What we are interested in: **causality**

What we've got: **correlational** (or *observational*) data

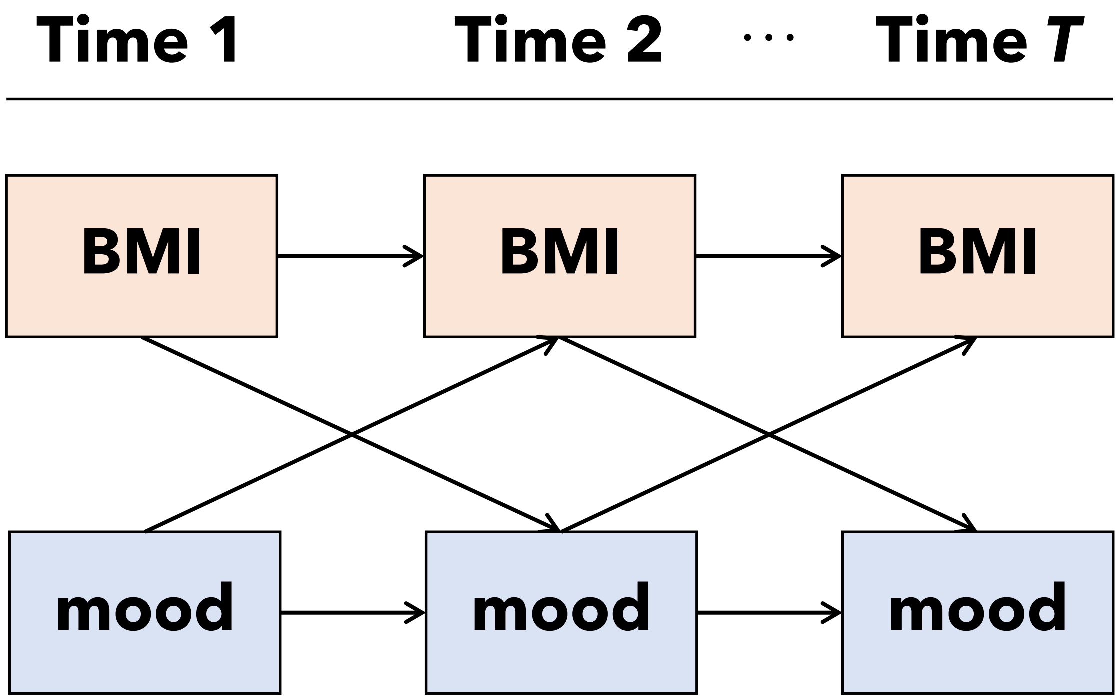
(One) solution

Take advantage of

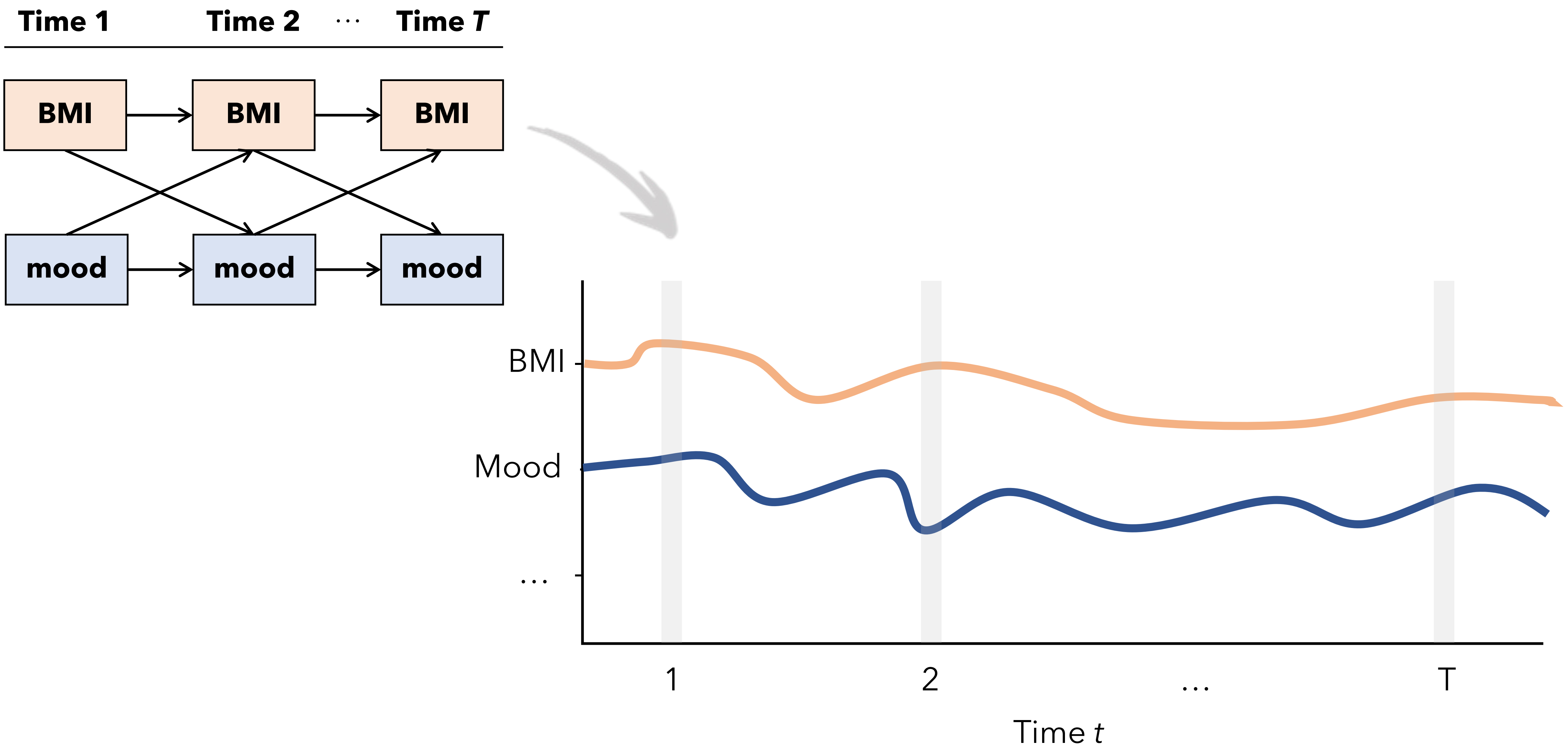
longitudinal panel data

= data collected for N units and T occasions

Panel data to the rescue



Panel data to the rescue



Panel data to the rescue

Panel data are useful because they help us do 3 things:

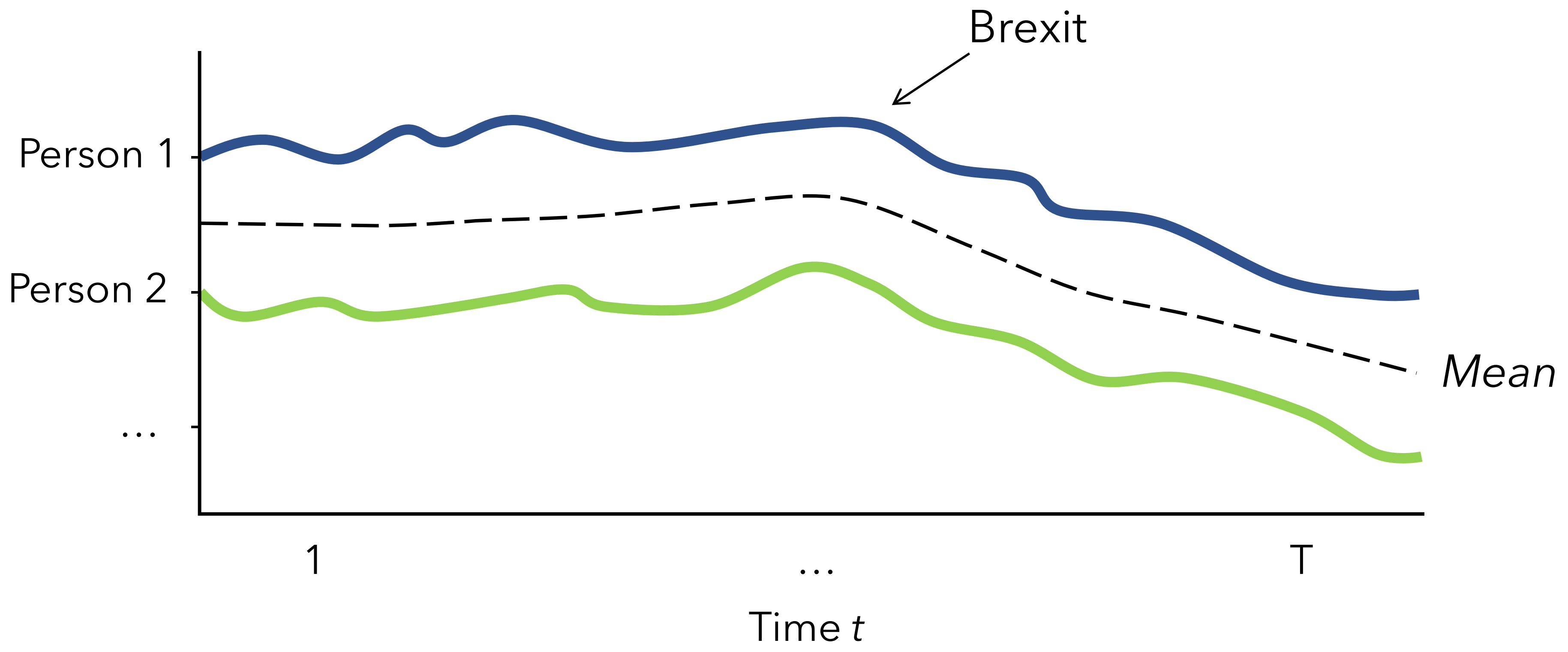
A. Model effects of the past on the future.

B. Overcome assumptions about the *direction* of effects.
   - all variables are allowed to impact all other variables

C. Control for some potential **confounds:**
   1) Occasion effect
   2) The past
   3) Co-movement

Confound 1: **occasion effects**

= a set of *shared events* or circumstances that everyone is subjected to, at any given occasion or period of measurement

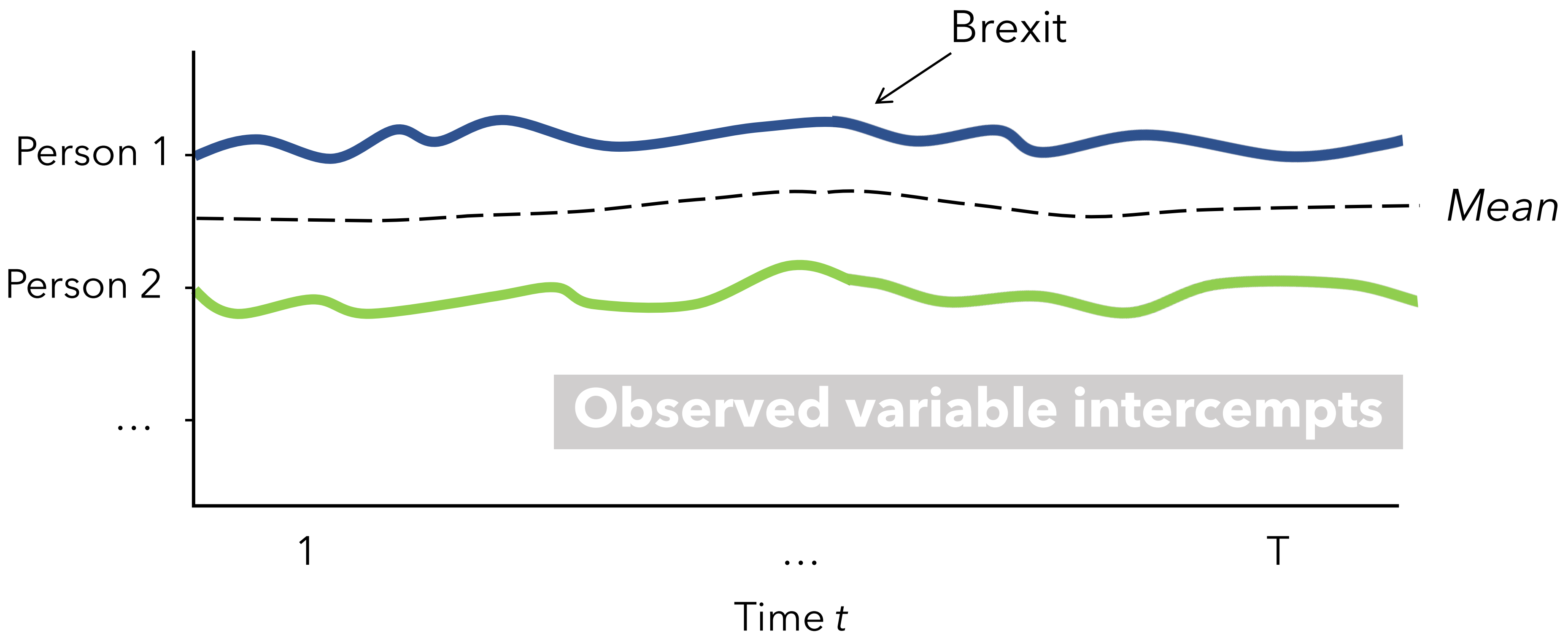


Solution: **demeaning**

Two things did not happen:

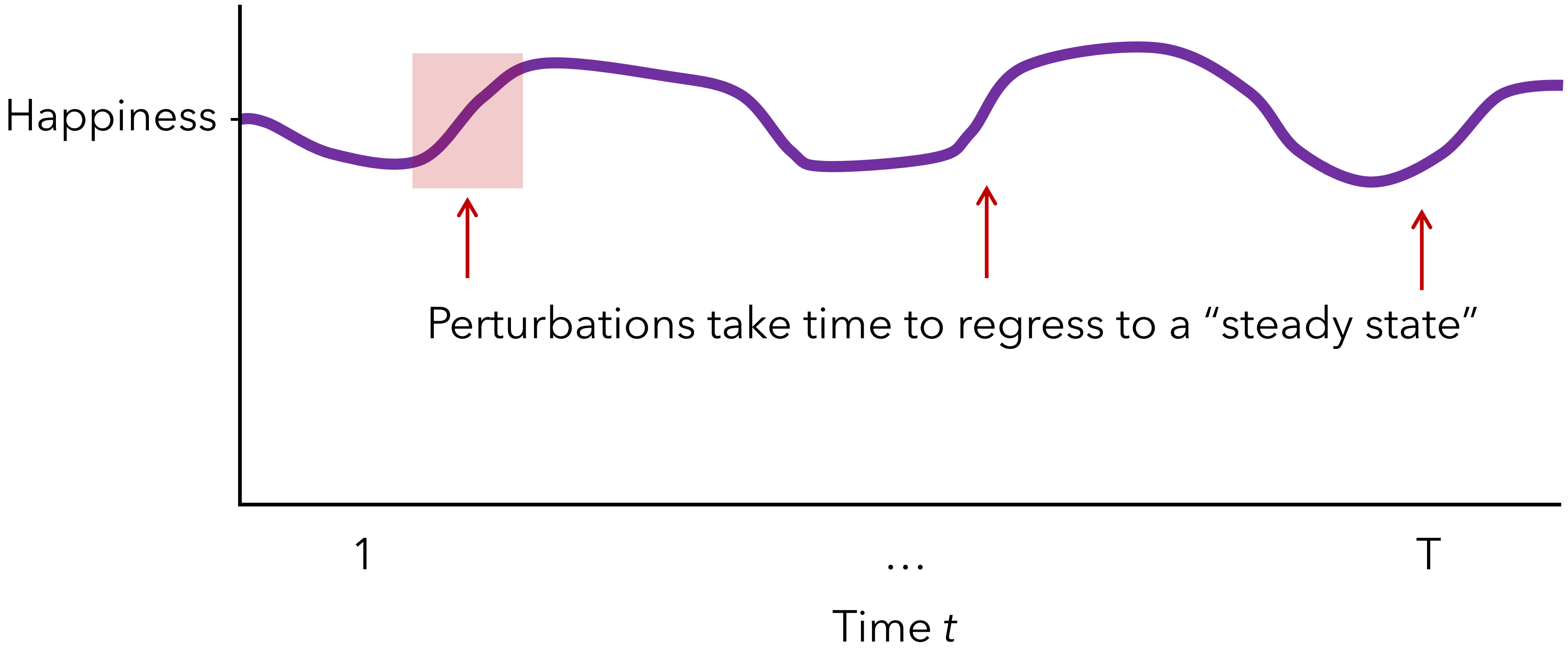
a) we haven't eliminated **differences between people**.

b) we also kept **deviations over time** (or perturbations)



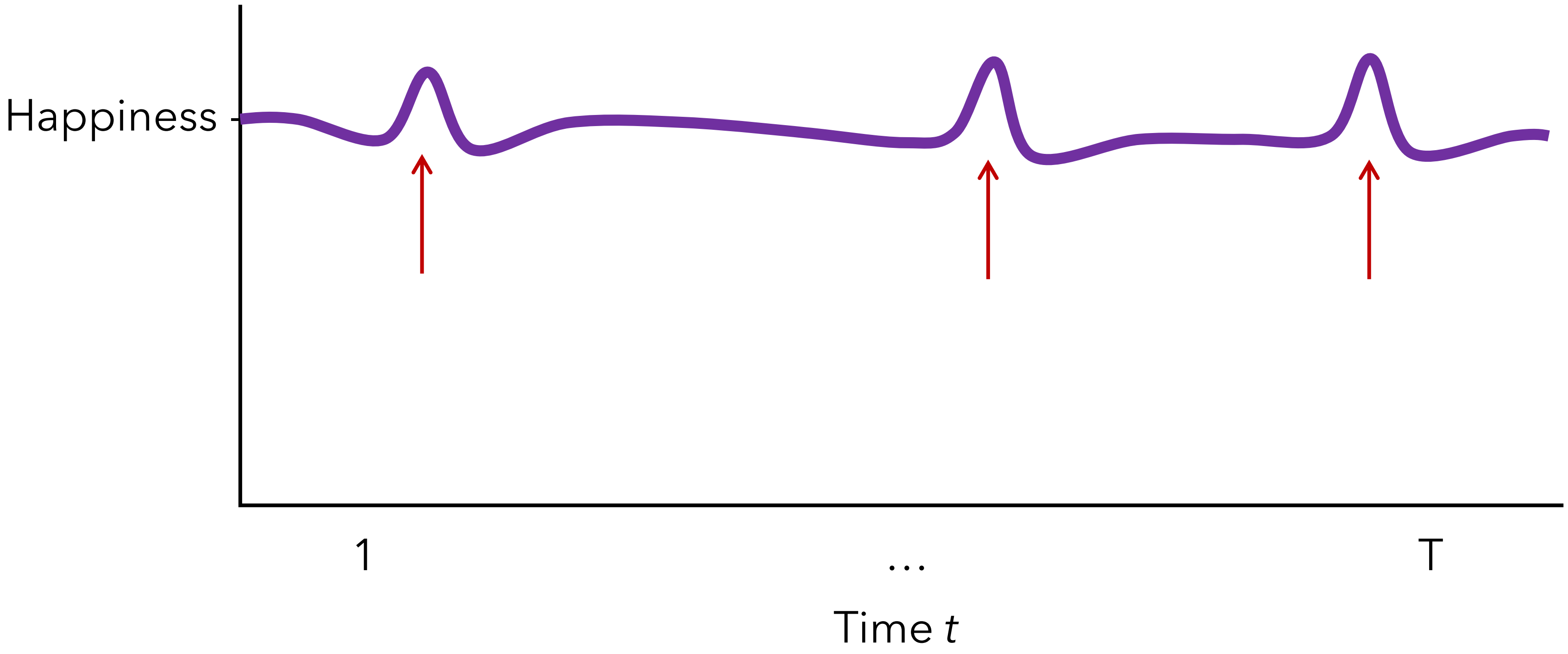
Confound 2: **the past**

= the *persistence* in a variable over time.



Solution: Autoregressive (AR) terms

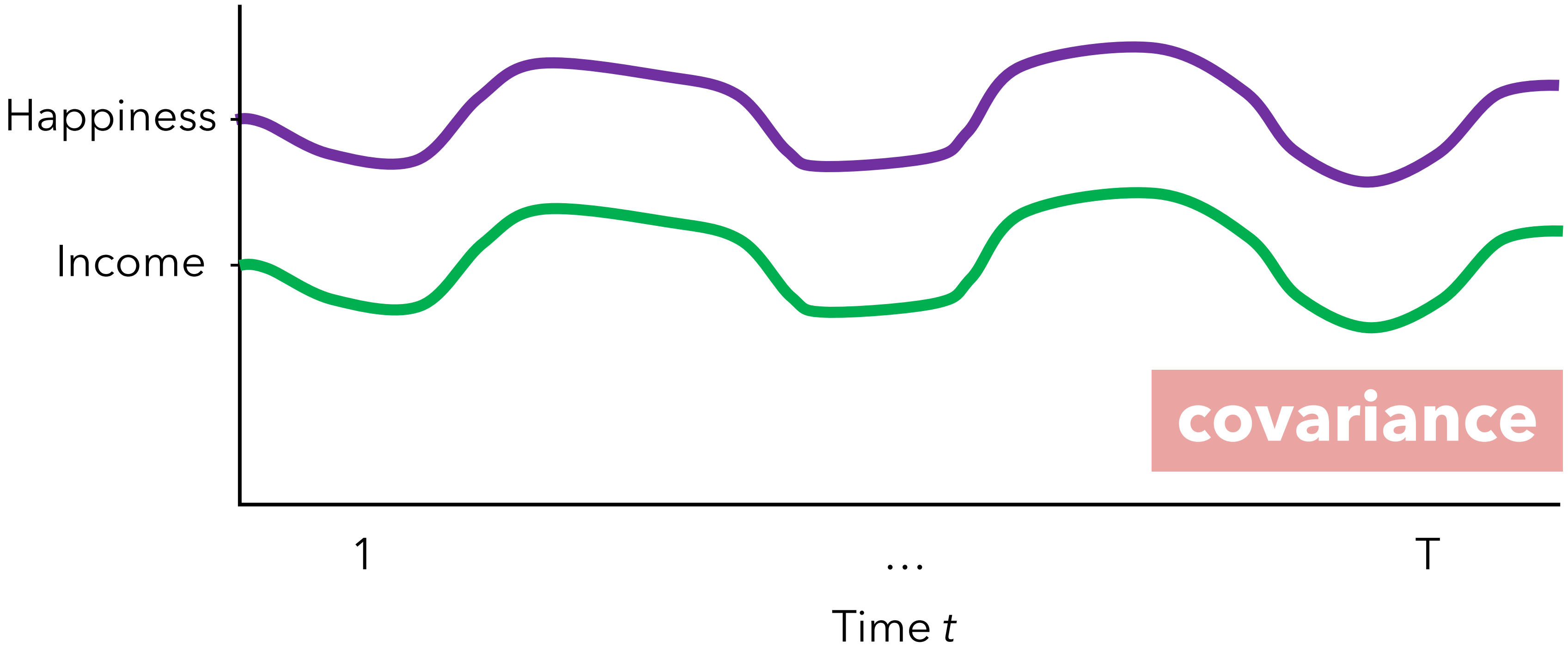
= *regression coefficients* reflecting the effect of the past on the future for the same variable.



Confound 3: **co-movement**

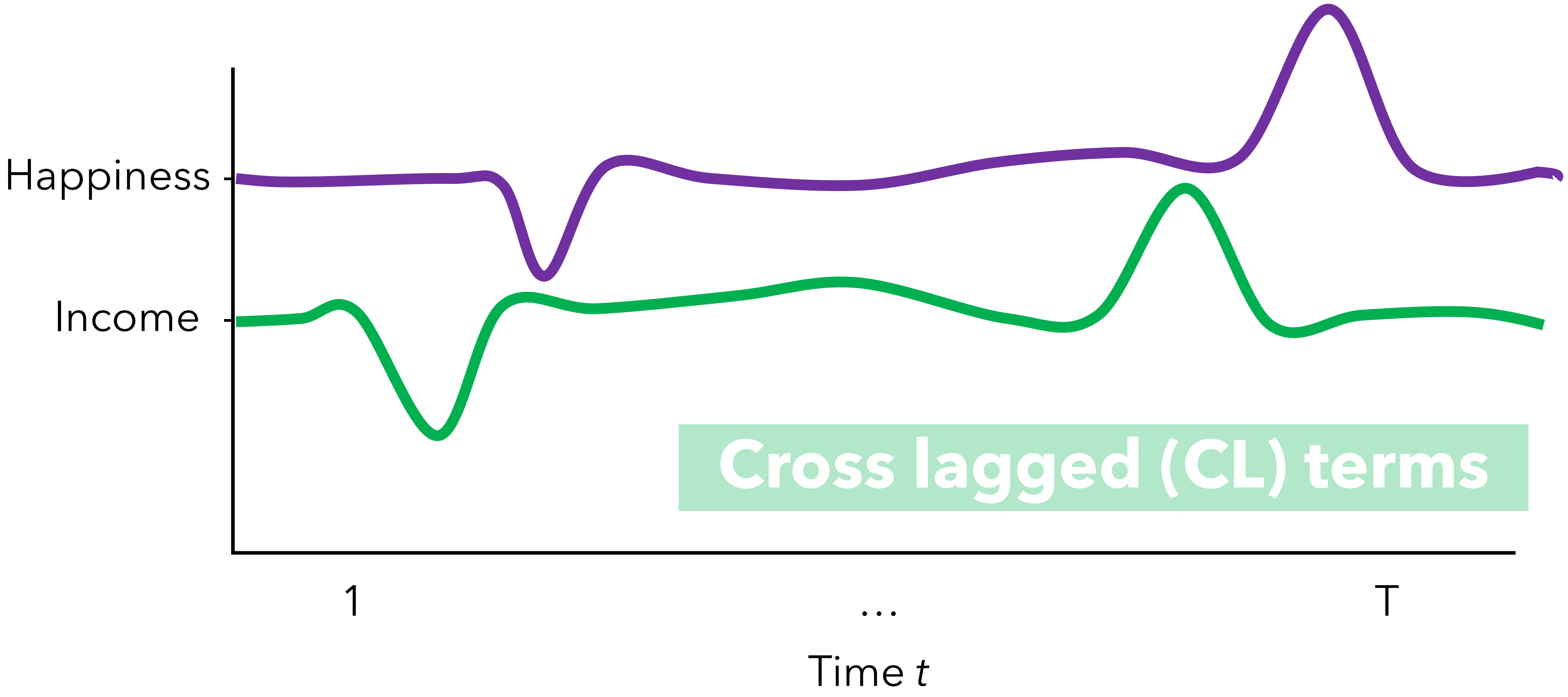
= the *contemporaneous correlation* (or covariance) among two variables.

⇢ is this *causality*?



So … what's left?

What (should be) left over after we eliminate these potential confounds is **causality**



What's left: Cross lagged (CL) terms

Attributes:

- *Temporal priority* for the predictors / causes
- *No directionality assumptions*

- ***Granger causality***

  = beyond all AR terms (and other controls) in the model, when including a predictor improves predictions, we have (preliminary) evidence for a causal effect.

The cross-lagged panel model

$\boxed{x_t}$ $\boxed{y_t}$

$x_{it} =$

$y_{it} =$

$\boxed{x_{t-1}}$ $\boxed{y_{t-1}}$

$\boxed{x_{t-2}}$ $\boxed{y_{t-2}}$

The cross-lagged panel model

x_t y_t

$$x_{it} = \alpha_t^{(x)}$$

$$y_{it} = \alpha_t^{(y)}$$

x_{t-1} y_{t-1}

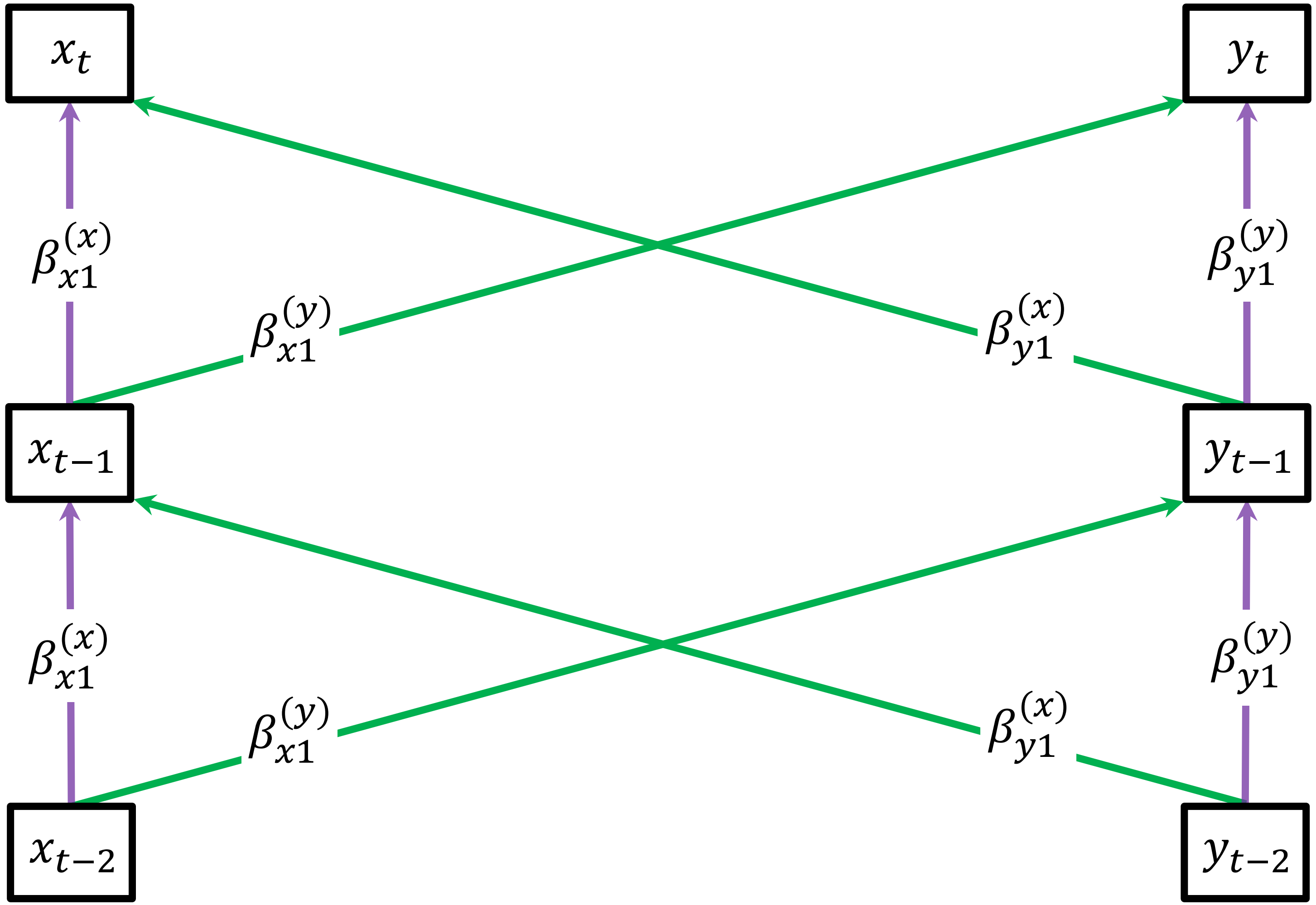
x_{t-2} y_{t-2}

The cross-lagged panel model

$$x_{it} = \alpha_t^{(x)} + \beta_{x1}^{(x)} x_{it-1}$$

$$y_{it} = \alpha_t^{(y)} + \beta_{y1}^{(y)} y_{it-1}$$

The cross-lagged panel model

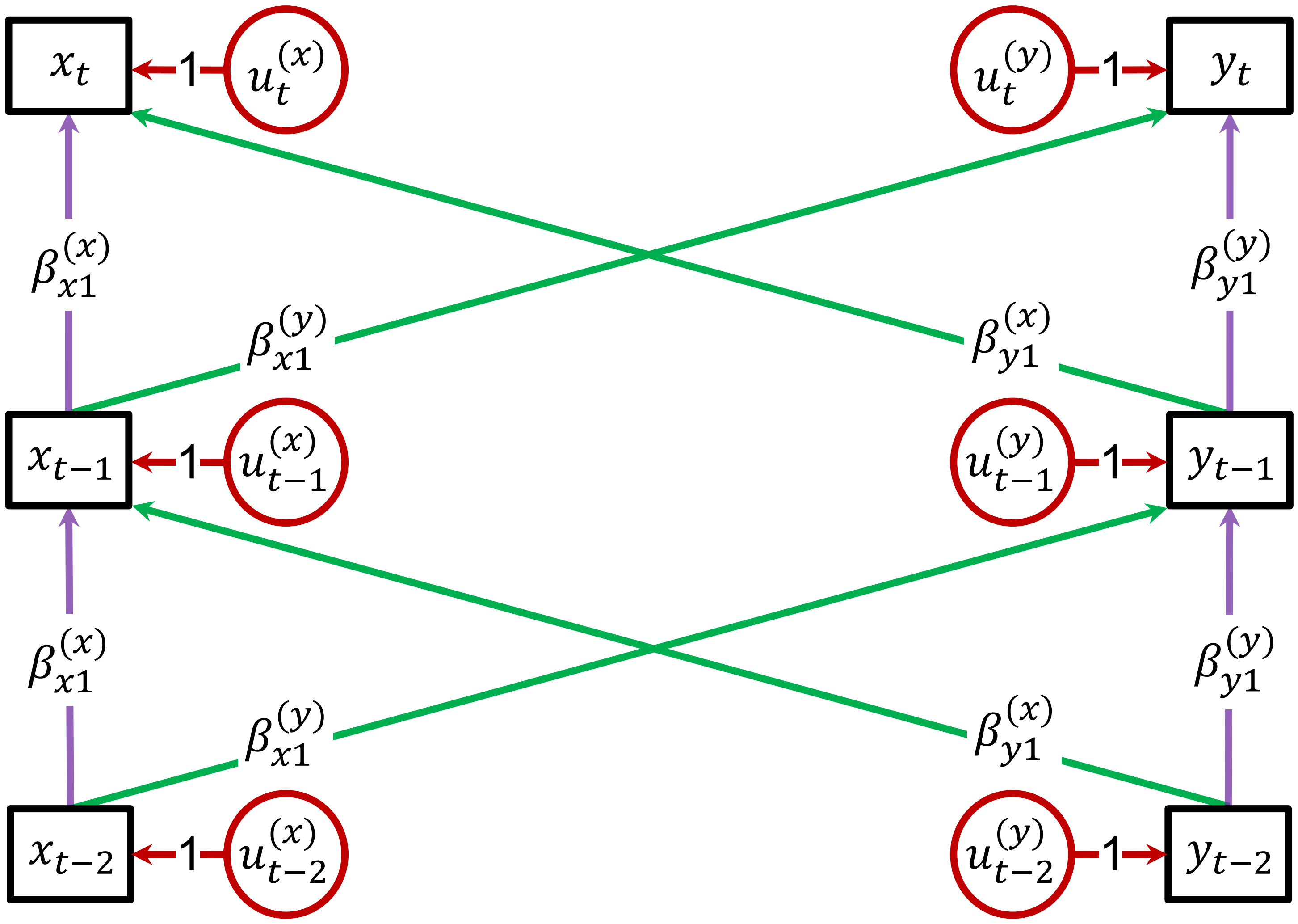


$$x_{it} = \alpha_t^{(x)} + \beta_{x1}^{(x)} x_{it-1} + \beta_{y1}^{(x)} y_{it-1}$$

$$y_{it} = \alpha_t^{(y)} + \beta_{y1}^{(y)} y_{it-1} + \beta_{x1}^{(y)} x_{it-1}$$

What's missing?

The cross-lagged panel model

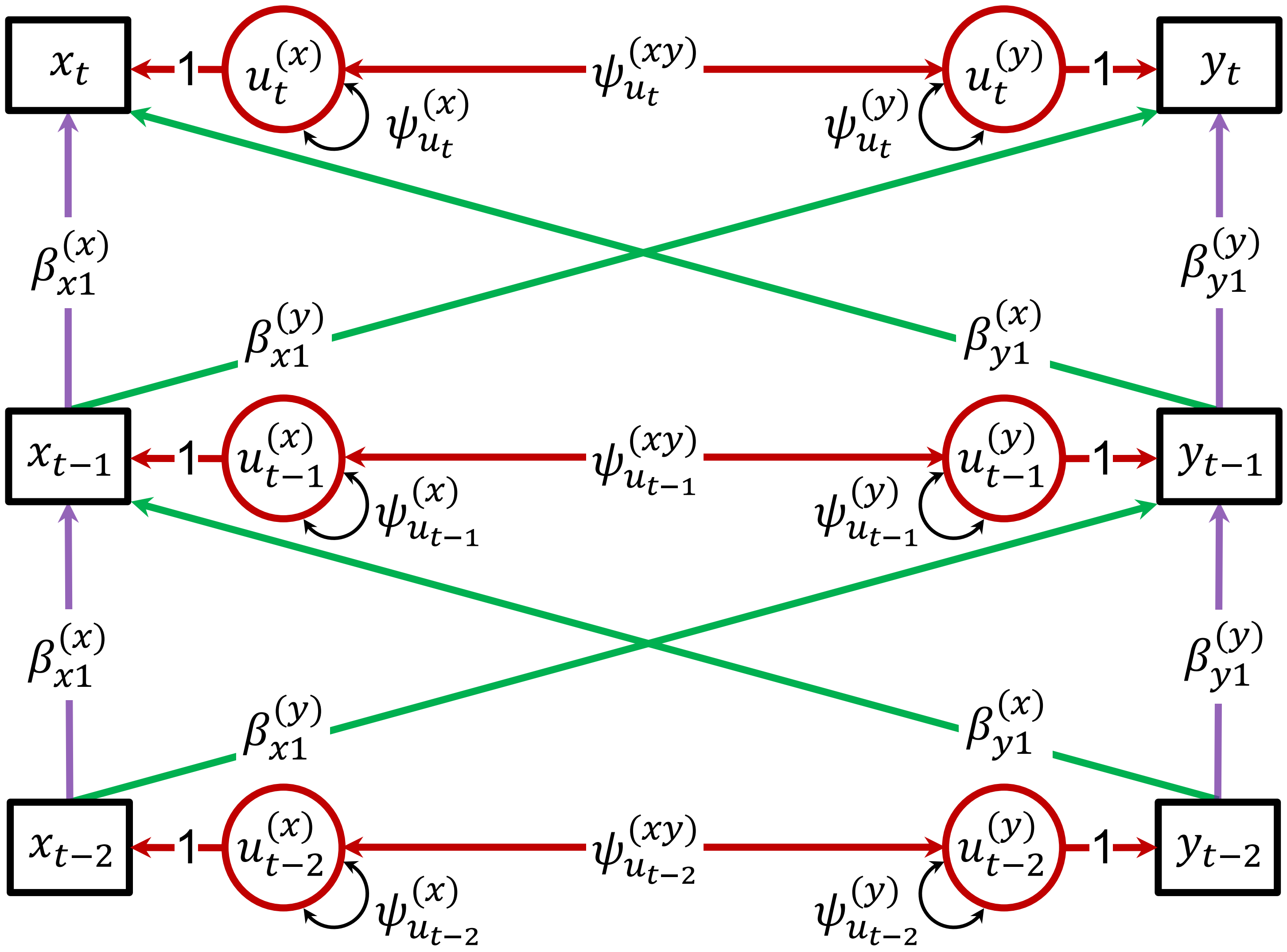


$$x_{it} = \alpha_t^{(x)} + \beta_{x1}^{(x)} x_{it-1} + \beta_{y1}^{(x)} y_{it-1} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \beta_{y1}^{(y)} y_{it-1} + \beta_{x1}^{(y)} x_{it-1} + u_{it}^{(y)}$$

Residuals
aka
"**impulses**"

The cross-lagged panel model



$$x_{it} = \alpha_t^{(x)} + \beta_{x1}^{(x)} x_{it-1} + \beta_{y1}^{(x)} y_{it-1} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \beta_{y1}^{(y)} y_{it-1} + \beta_{x1}^{(y)} x_{it-1} + u_{it}^{(y)}$$

Residuals
aka
"**impulses**"

Impulses as ***randomization devices***

The random change / perturbation can flow through the system along two possible paths:

1. **AR paths** ($\beta_{x1}^{(x)}$) = *persistence of an impulse* = the *ratio of the impulse that remains* from one occasion to the next.
2. **CL paths** ($\beta_{x1}^{(y)}$) = does the perturbation along one variable *uniquely* predict the future along the other variable? = the *ratio of the past impulse at gets communicated to the other variable in the future*.

Impulses as *randomization devices*

If impulses are random, they mimic random assignment and CL paths show us the ratio of the impulse affecting other variables.

Note:

- The *causal variables* are the impulses, not the observed variables!
- The assumption here is the typical *regression assumption*: that they are random.
- It's a specific kind of understanding of causality (*Granger-Sims causality*).

But...

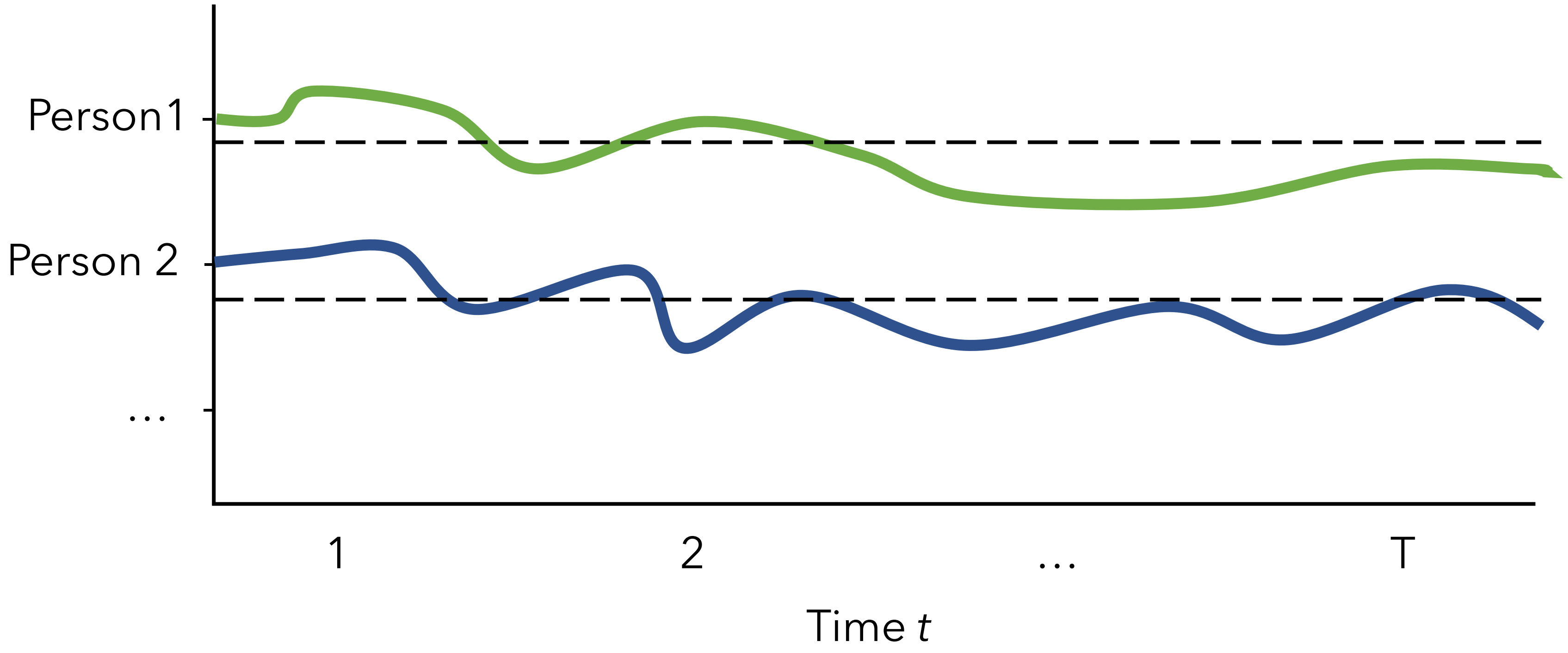
The cross-lagged model is common, but it has some limitations:

1. It does not control for ***stable factors*** over time that might bias AR and CL terms.
2. The range of dynamics in the model is limited by the multiplicative AR and CL form, along which past impulses have to “flow” = a very ***strict indirect-effects logic***.

So: we are going to modify the model to include terms that will control for **stable factors** and will allow to model both **short-term and long-term behavior** of impulses.

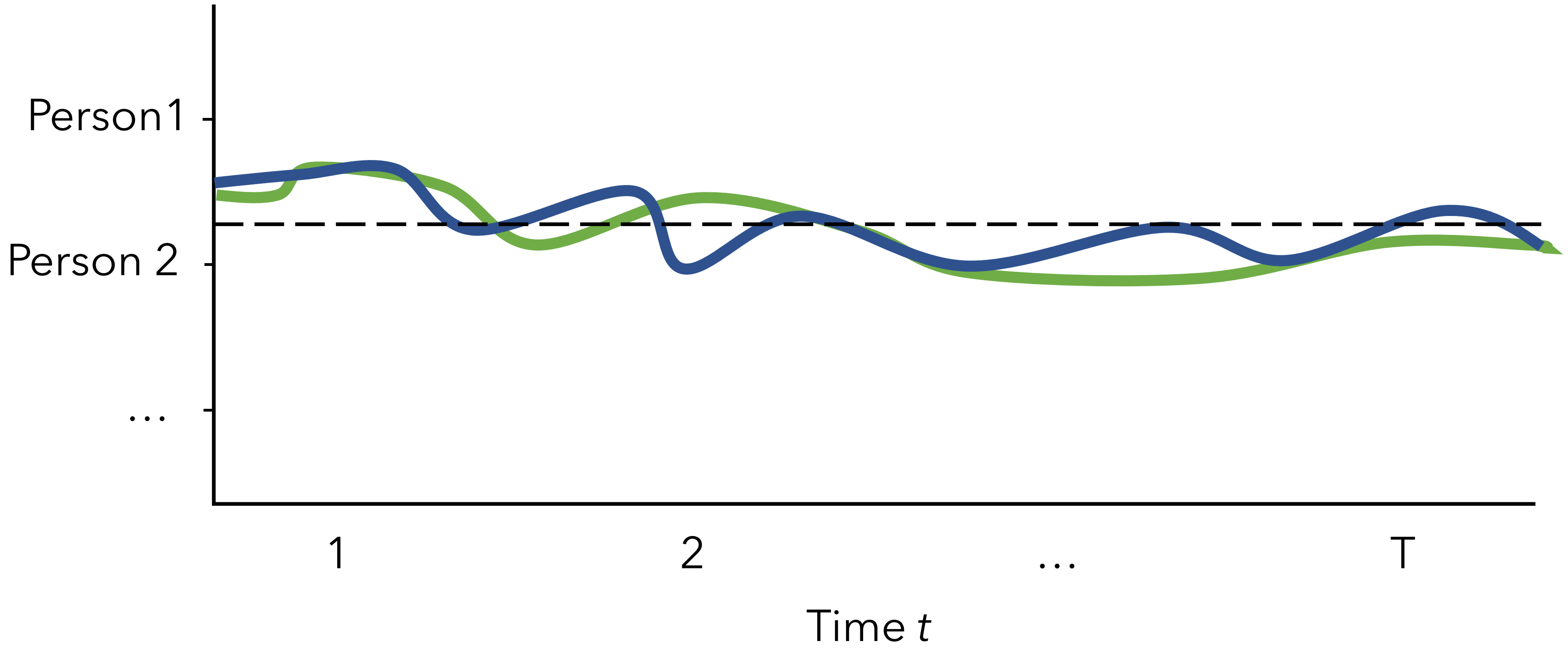
Unit effects

= *stable factors* that make people (or units of analysis) different from each other systematically over time.

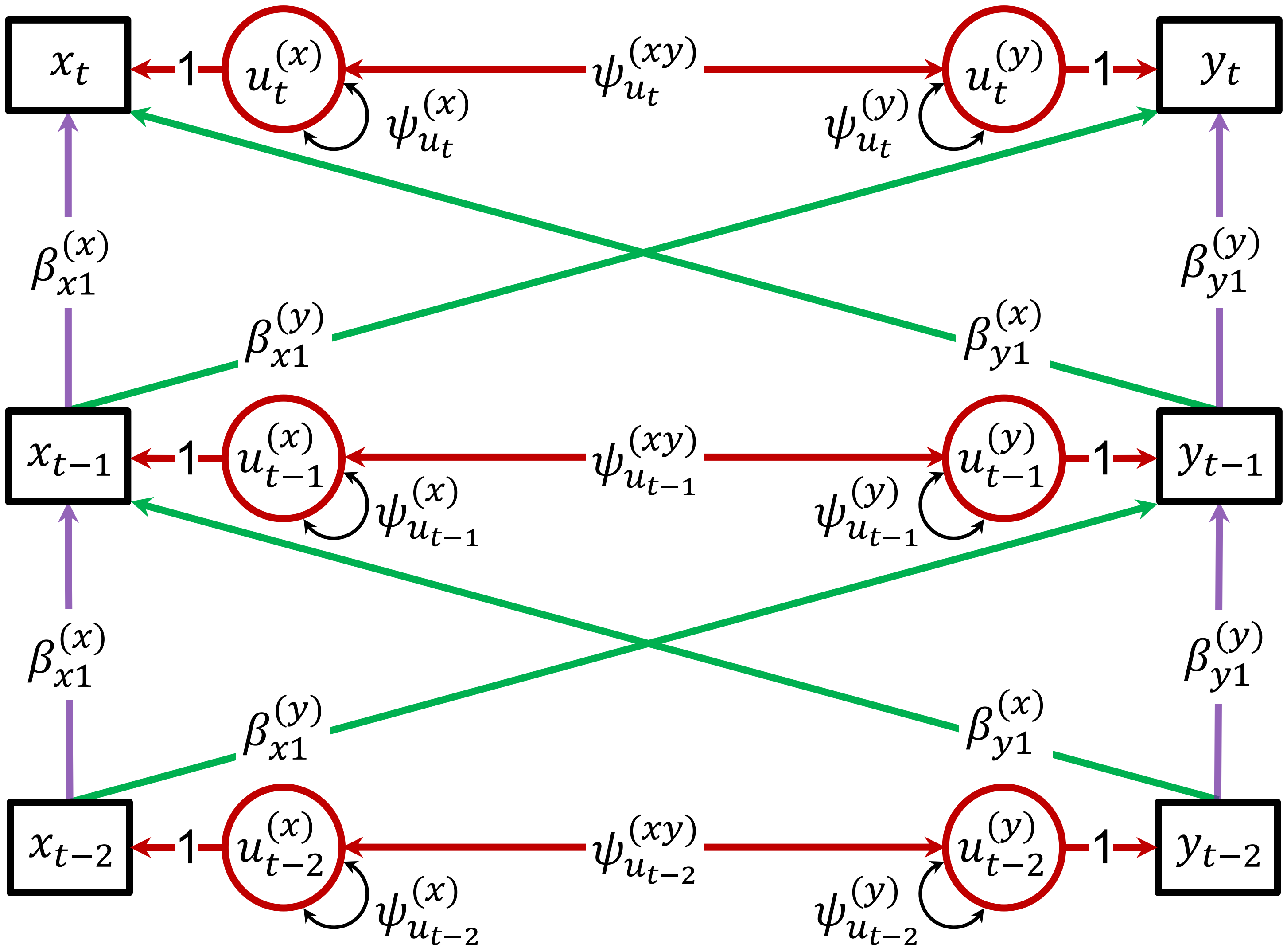


Unit effects

= *stable factors* that make people (or units of analysis) different from each other systematically over time.

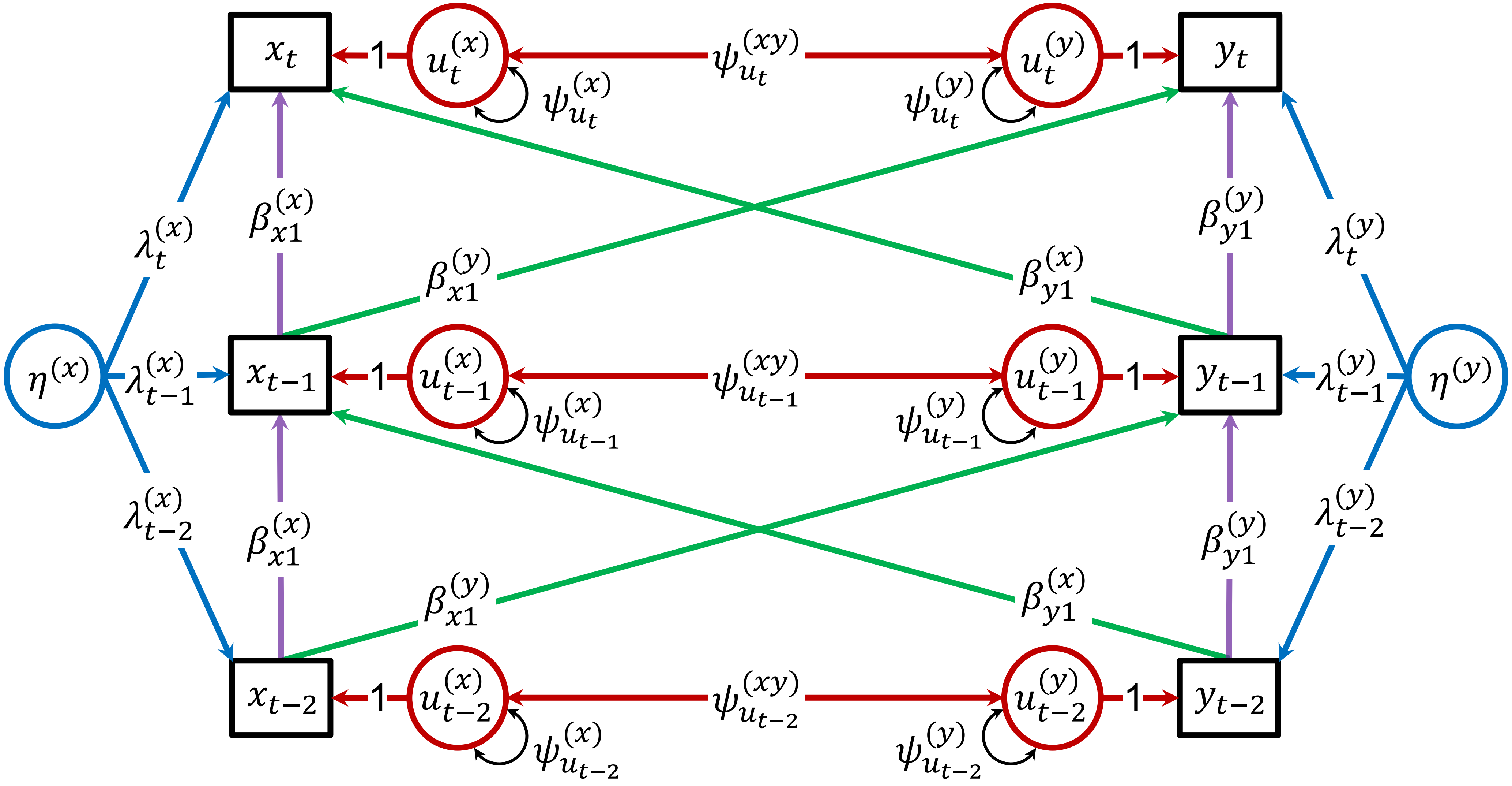


Back to our model...



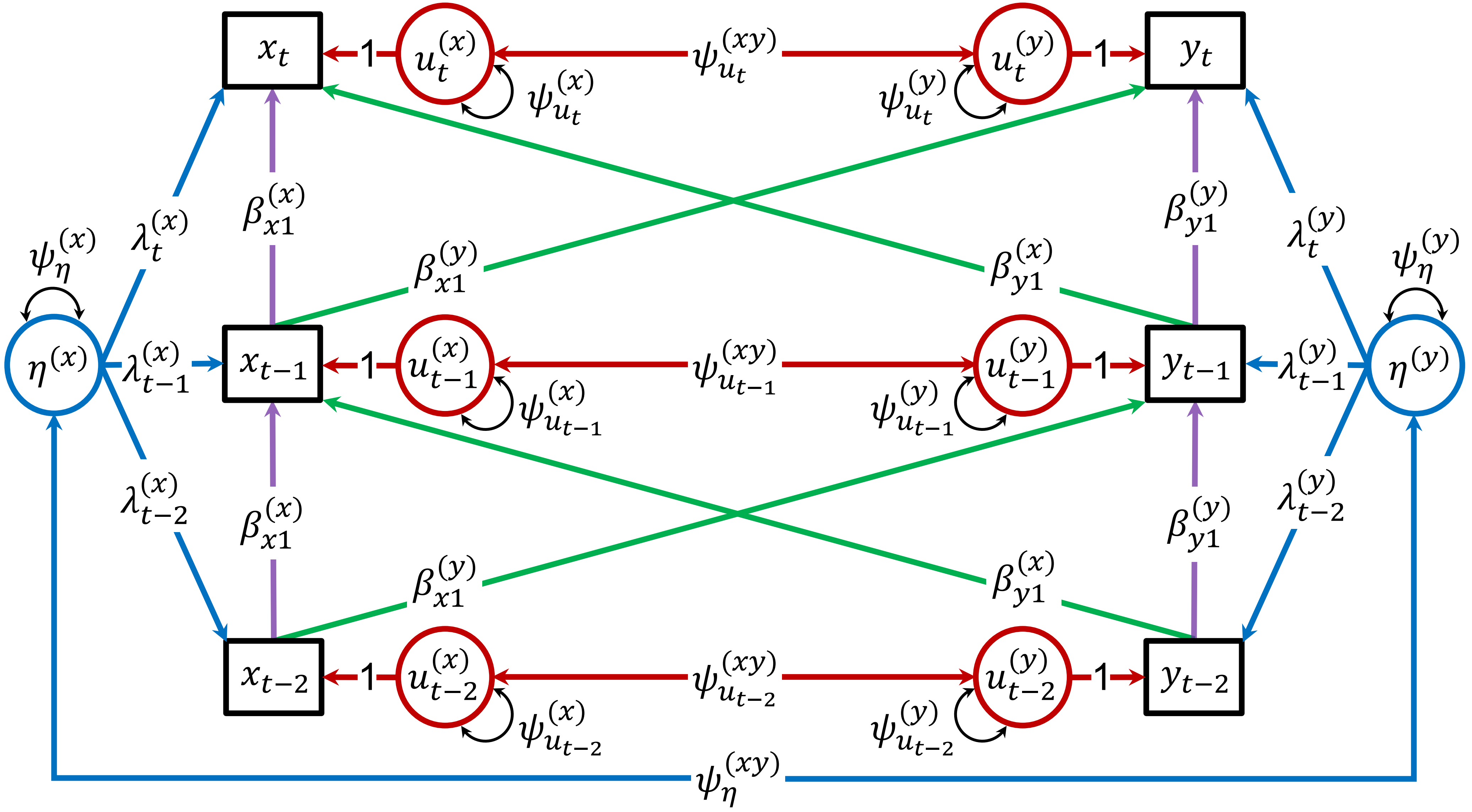
$$x_{it} = \alpha_t^{(x)} + \beta_{x1}^{(x)} x_{it-1} + \beta_{y1}^{(x)} y_{it-1} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \beta_{y1}^{(y)} y_{it-1} + \beta_{x1}^{(y)} x_{it-1} + u_{it}^{(y)}$$



$$x_{it} = \alpha_t^{(x)} + \lambda_t^{(x)}\eta_i^{(x)} + \beta_{x1}^{(x)} x_{it-1} + \beta_{y1}^{(x)} y_{it-1} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \lambda_t^{(x)}\eta_i^{(x)} + \beta_{y1}^{(y)} y_{it-1} + \beta_{x1}^{(y)} x_{it-1} + u_{it}^{(y)}$$

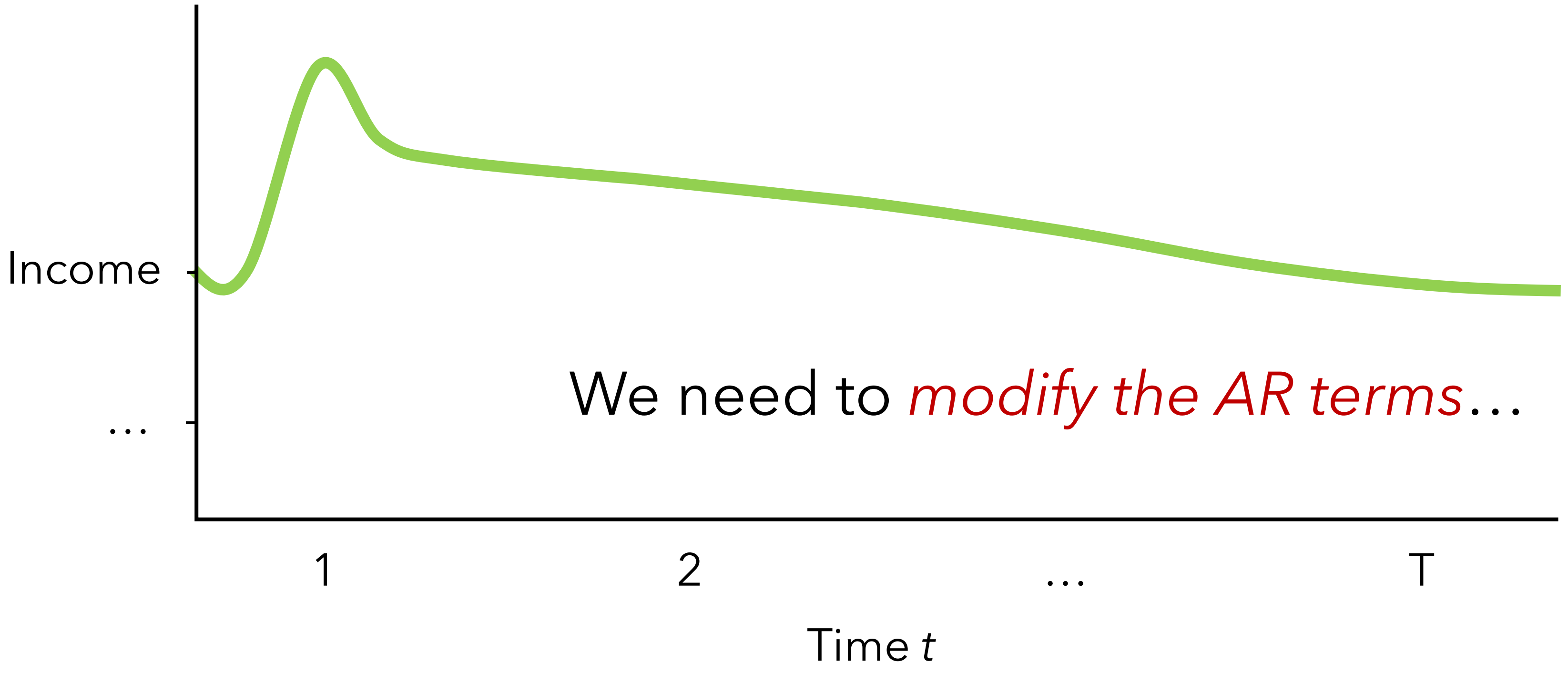


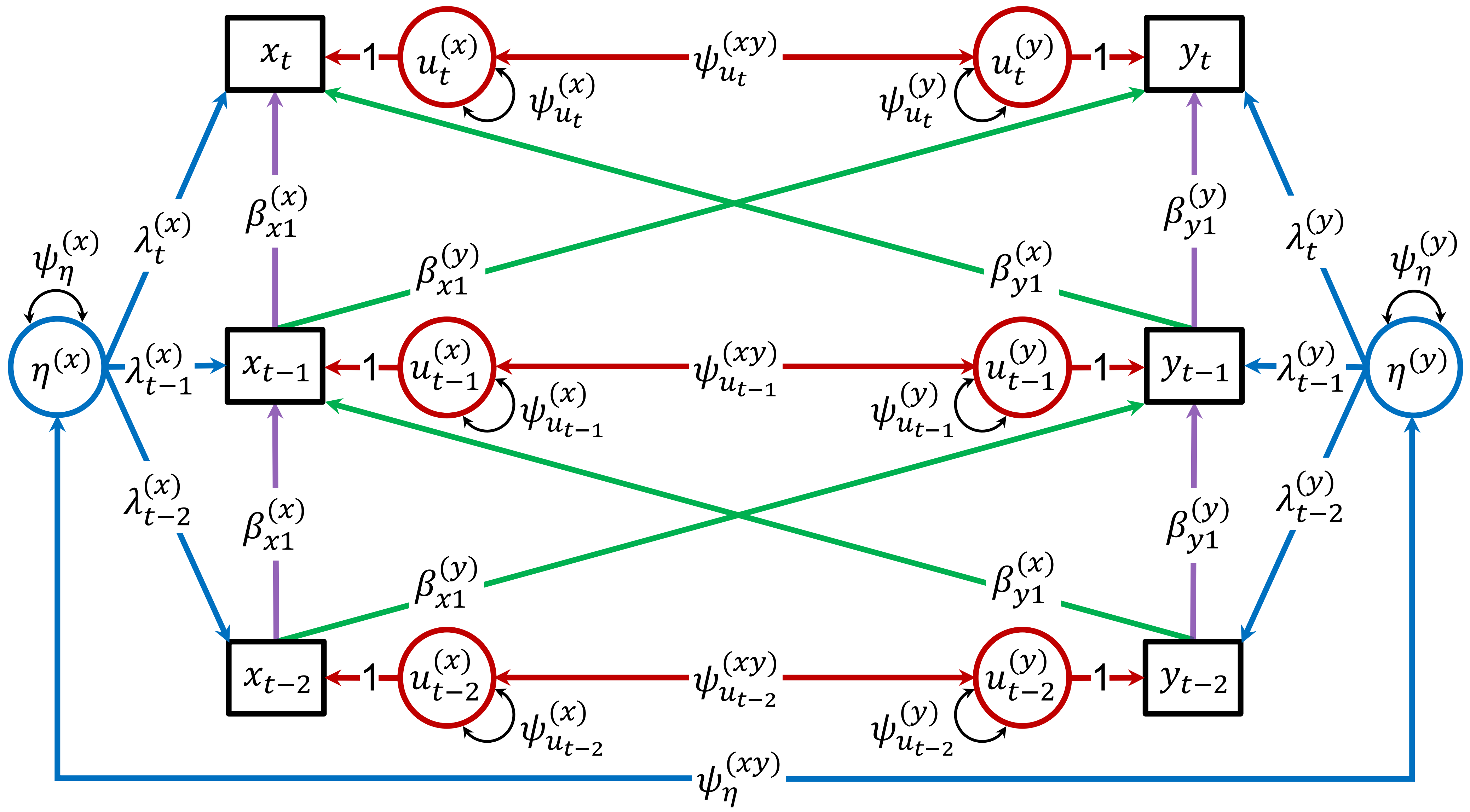
$$x_{it} = \alpha_t^{(x)} + \lambda_t^{(x)}\eta_i^{(x)} + \beta_{x1}^{(x)} x_{it-1} + \beta_{y1}^{(x)} y_{it-1} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \lambda_t^{(x)}\eta_i^{(x)} + \beta_{y1}^{(y)} y_{it-1} + \beta_{x1}^{(y)} x_{it-1} + u_{it}^{(y)}$$

Complex dynamics

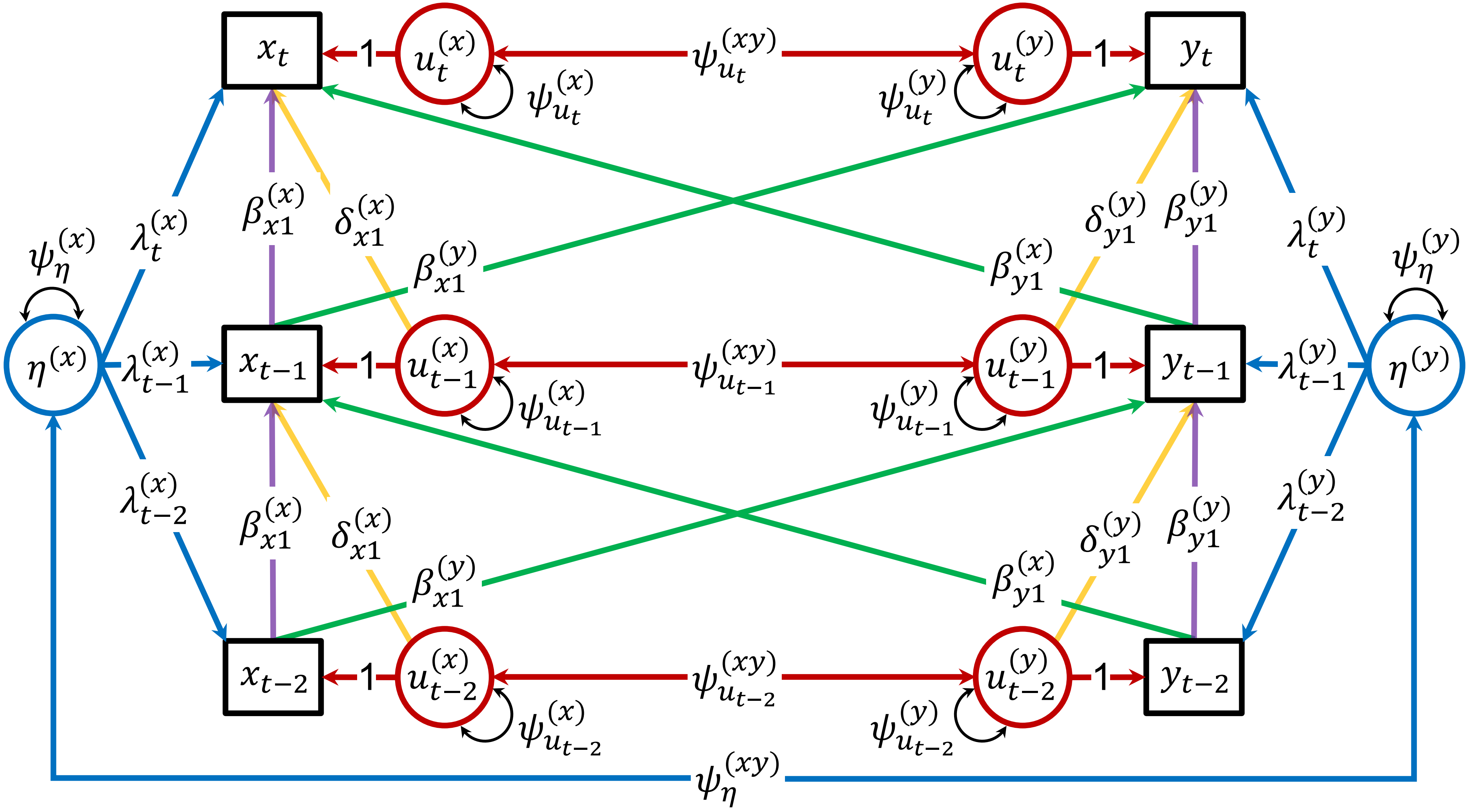
What if we have changing forms of *persistence* over time?





$$x_{it} = \alpha_t^{(x)} + \lambda_t^{(x)}\eta_i^{(x)} + \beta_{x1}^{(x)} x_{it-1} + \beta_{y1}^{(x)} y_{it-1} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \lambda_t^{(x)}\eta_i^{(x)} + \beta_{y1}^{(y)} y_{it-1} + \beta_{x1}^{(y)} x_{it-1} + u_{it}^{(y)}$$

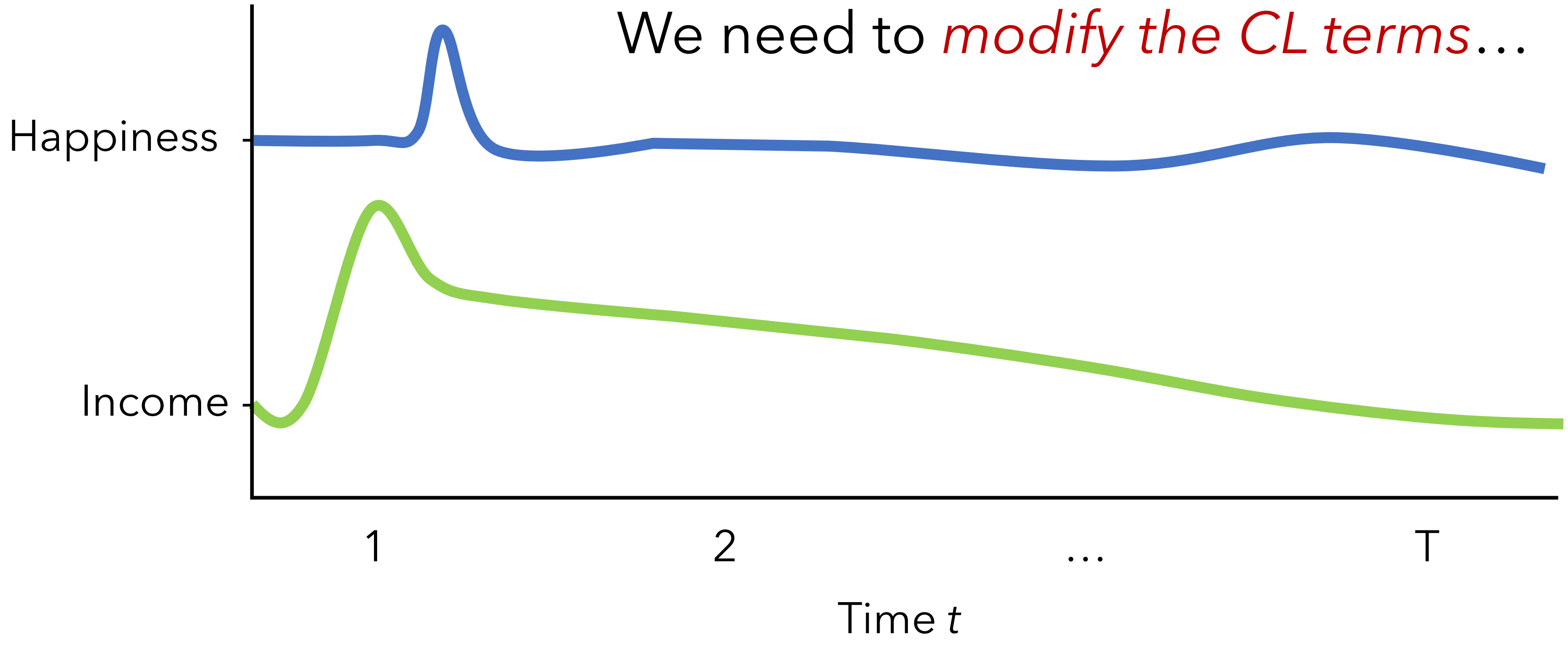


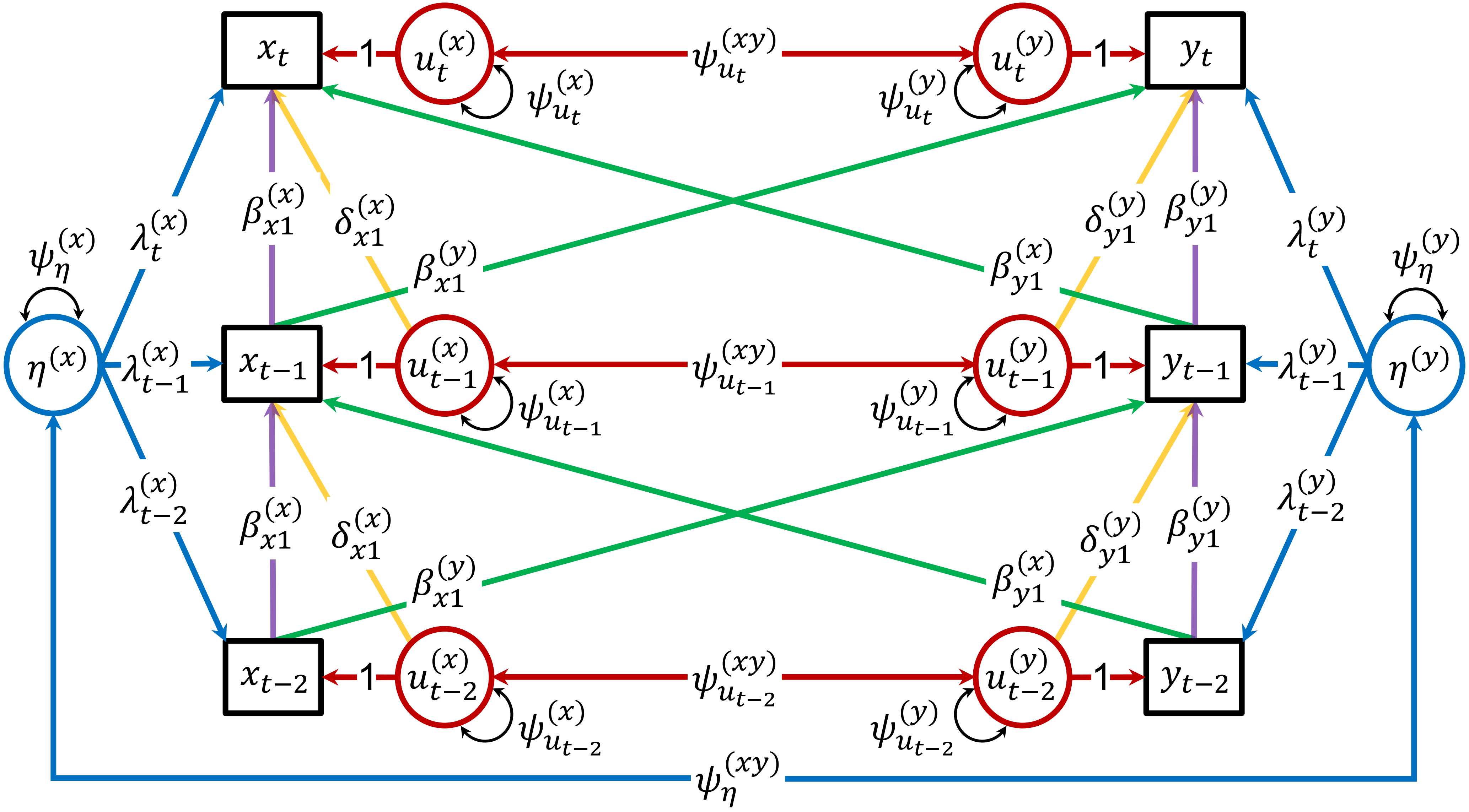
$$x_{it} = \alpha_t^{(x)} + \lambda_t^{(x)}\eta_i^{(x)} + \delta_{x1}^{(x)}u_{it-1}^{(x)} + \beta_{x1}^{(x)}x_{it-1} + \beta_{y1}^{(x)}y_{it-1} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \lambda_t^{(x)}\eta_i^{(x)} + \delta_{y1}^{(y)}u_{it-1}^{(y)} + \beta_{y1}^{(y)}y_{it-1} + \beta_{x1}^{(y)}x_{it-1} + u_{it}^{(y)}$$

Complex dynamics

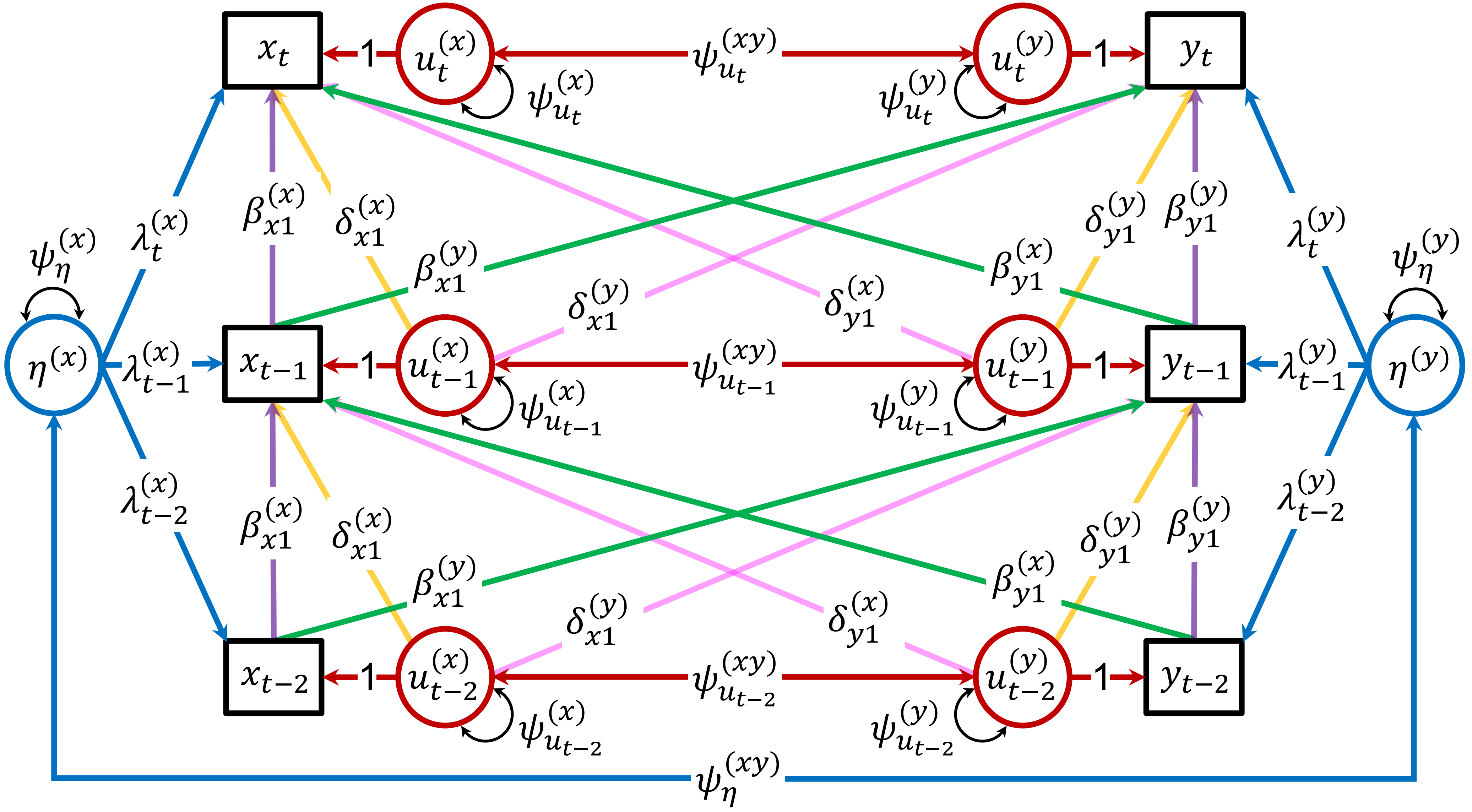
What if we have changing *effects* over time?





$$x_{it} = \alpha_t^{(x)} + \lambda_t^{(x)}\eta_i^{(x)} + \delta_{x1}^{(x)} u_{it-1}^{(x)} + \beta_{x1}^{(x)} x_{it-1} + \beta_{y1}^{(x)} y_{it-1} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \lambda_t^{(x)}\eta_i^{(x)} + \delta_{y1}^{(y)} u_{it-1}^{(y)} + \beta_{y1}^{(y)} y_{it-1} + \beta_{x1}^{(y)} x_{it-1} + u_{it}^{(y)}$$



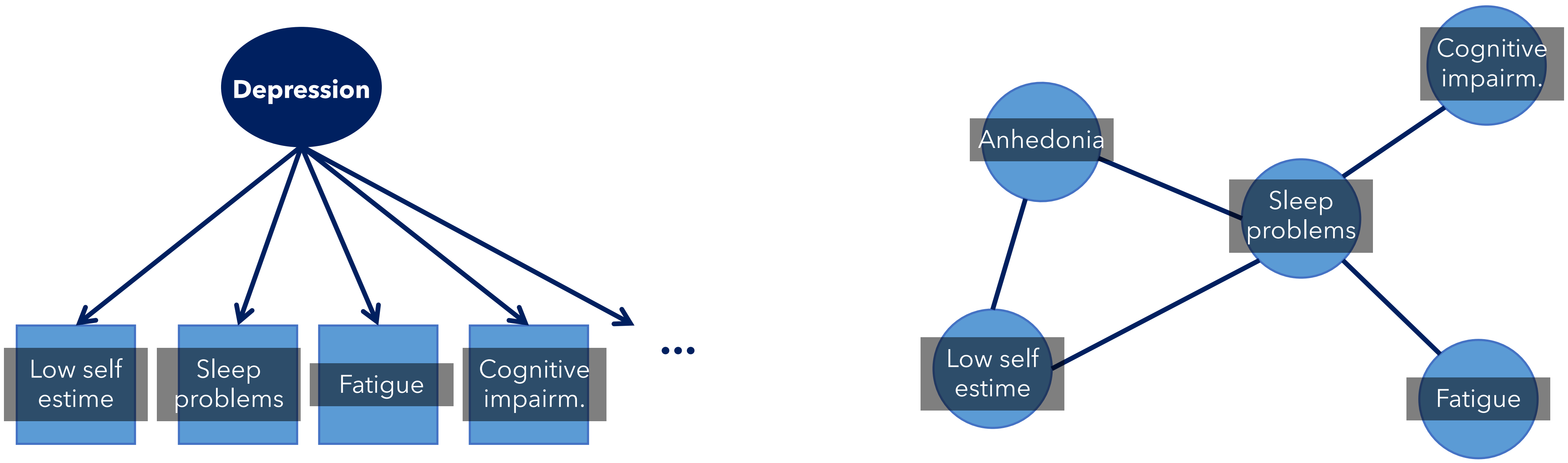
$$x_{it} = \alpha_t^{(x)} + \lambda_t^{(x)}\eta_i^{(x)} + \delta_{x1}^{(x)}u_{it-1}^{(x)} + \beta_{x1}^{(x)}x_{it-1} + \beta_{y1}^{(x)}y_{it-1} + \delta_{y1}^{(x)}u_{it-1}^{(y)} + u_{it}^{(x)}$$

$$y_{it} = \alpha_t^{(y)} + \lambda_t^{(x)}\eta_i^{(x)} + \delta_{y1}^{(y)}u_{it-1}^{(y)} + \beta_{y1}^{(y)}y_{it-1} + \beta_{x1}^{(y)}x_{it-1} + \delta_{x1}^{(y)}u_{it-1}^{(x)} + u_{it}^{(y)}$$

Cross lagged *network* models

From data to systems

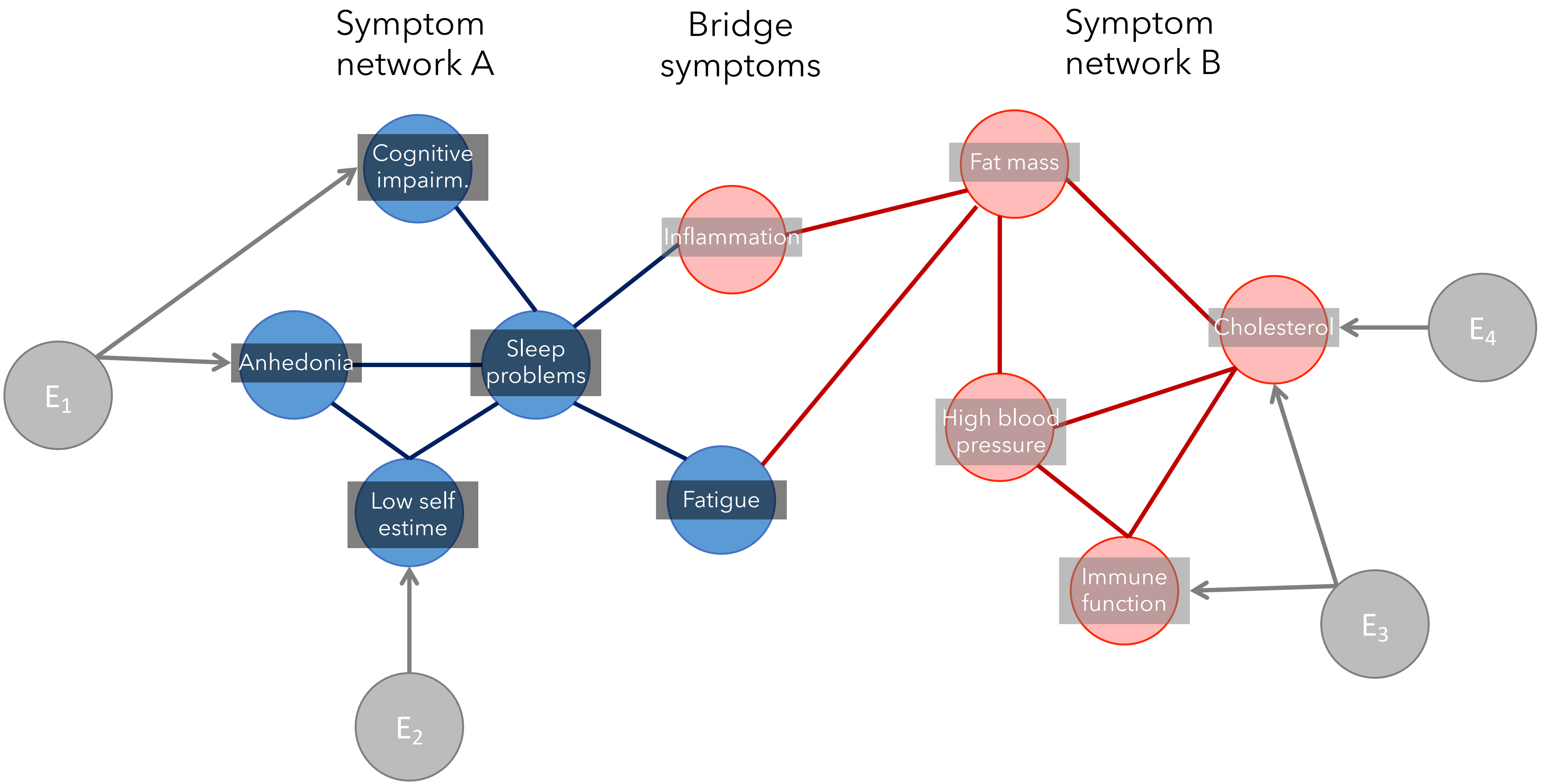
Health is complicated...



Cramer, A. O. J., Waldorp, L., van der Maas, H., & Bors- boom, D. (2010). Comorbidity: A Network Perspective. *Behavioral and Brain Sciences*, *33*(2-3), 137– 150. doi: 10.1017/S0140525X09991567

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, 16(1):5–13.

Network models of comorbidity



Consequences of the Network Perspective

- Co-occurrence of symptoms, moods, personality aspects understood as emergent behavior
  - Implication: symptom-based interventions possible
- Every person is a different system
  - Implication: personalized modeling and treatment

ALSPAC data

10.6 years	12.8	13.8	16.7	17.8	23.8
SMFQ	SMFQ	SMFQ	SMFQ	SMFQ	SMFQ
CMR	CMR	CMR	CMR	CMR	CMR

2.2 1 2.9 1.1 6

	SMFQ	9.6 yrs	10.6 yrs	11.7 yrs	12.8 yrs	13.1 yrs	13.8 yrs	15.4 yrs	16.6 yrs	16.7 yrs	17.8 yrs	18.7 yrs	21.9 yrs	22.9 yrs	23.8 yrs	
1	Felt miserable or unhappy	ku660	fddp110	kw6000	ff6500	ta5020	fg7210	DAWBA	tc4030	ccs4500	CCXD900	cct2700	YPA2000	YPB5000	YPC1650	
2	Had fun		fddp111		ff6501		fg7211			ccs4501	CCXD901					
3	Didn't enjoy anything at all	ku661	fddp112	kw6001	ff6502	ta5021	fg7212		tc4031	ccs4502	CCXD902	cct2701	YPA2010	YPB5010	YPC1651	
4	Felt so tired they just sat around and did nothing	ku662	fddp113	kw6002	ff6503	ta5022	fg7213		tc4032	ccs4503	CCXD903	cct2702	YPA2020	YPB5030	YPC1653	
5	Was very restless	ku663	fddp114	kw6003	ff6504	ta5023	fg7214		tc4033	ccs4504	CCXD904	cct2703	YPA2030	YPB5040	YPC1654	
6	Felt they were no good any more	ku664	fddp115	kw6004	ff6505	ta5024	fg7215		tc4034	ccs4505	CCXD905	cct2704	YPA2040	YPB5050	YPC1655	
7	Cried a lot	ku665	fddp116	kw6005	ff6506	ta5025	fg7216		tc4035	ccs4506	CCXD906	cct2705	YPA2050	YPB5060	YPC1656	
8	Felt happy		fddp117		ff6507		fg7217			ccs4507	CCXD907				YPC1661	
9	Found it hard to think properly or concentrate	ku666	fddp118	kw6006	ff6508	ta5026	fg7218		tc4036	ccs4508	CCXD908	cct2706	YPA2060	YPB5080	YPC1658	
10	Hated themselves	ku667	fddp119	kw6007	ff6509	ta5027	fg7219		tc4037	ccs4509	CCXD909	cct2707	YPA2070	YPB5090	YPC1659	
11	Enjoyed doing lots of things		fddp120		ff6510		fg7220			ccs4510	CCXD910					
12	Felt they were a bad person	ku668	fddp121	kw6008	ff6511	ta5028	fg7221		tc4038	ccs4511	CCXD911	cct2708	YPA2080	YPB5100	YPC1660	
13	Felt lonely	ku669	fddp122	kw6009	ff6512	ta5029	fg7222		tc4039	ccs4512	CCXD912	cct2709	YPA2090	YPB5120	YPC1662	
14	Thought nobody really loved them	ku670	fddp123	kw6010	ff6513	ta5030	fg7223		tc4040	ccs4513	CCXD913	cct2710	YPA2100	YPB5130	YPC1663	
15	Thought they would never be as good as other people	ku671	fddp124	kw6011	ff6514	ta5031	fg7224		tc4041	ccs4514	CCXD914	cct2711	YPA2110	YPB5150	YPC1665	
16	Felt they did everything wrong	ku672	fddp125	kw6012	ff6515	ta5032	fg7225		tc4042	ccs4515	CCXD915	cct2712	YPA2120	YPB5170	YPC1667	
17	Had a good time		fddp126							ccs4516	CCXD916					
19	Laughed a lot													YPB5020	YPC1652	
20	Looked forward to the day ahead										CIS-R			YPB5140	YPC1664	CIS-R
21	Felt really positive about the future													YPB5160	YPC1666	
22	Felt valued													YPB5070	YPC1657	
23	Felt unhappy													YPB5110		

		9.6 / 9.8 yrs	10.7 / 10.6 yrs	11.7 yrs	12.8 yrs	13.1 yrs	13.8 yrs	15.4 yrs	16 yrs	17 yrs	17.8 yrs					24.5 yrs
Anthropometry	**Height (cm)**	pub203	pub303	pub403	ff2000	pub503	fg3100	fh3000	pub803	pub903	FJMR020					FKMS1000
	Weight (kg)	pub204 / f9dx	pub304	pub404 / fedx	ff2030	pub504	fg3207	fh3010 / fh2209	pub804	pub904	FJMR022					FKMS1030
	Waist circumference (cm)	f9ms018	fdms018	fems018	ff2020		fg3120	fh4020								fkms1052 (mm)
	Hip circumference (cm)	f9ms020		fems020												fkms1062 (mm)
Fat distribution	**Total body fat mass (g)**	f9dx135		fedx135			fg3254	fh2254			FJDX135					FKDX1001
	Android fat mass (g)						fg3257	fh2257			FJDX138					FKDX1041
	Gynoid fat mass (g)						fg3260	fh2260			FJDX141					FKDX1051
	Trunk fat mass (g)	f9dx126		fedx126			fg3245	fh2245			FJDX126					FKDX1031
	Fat percentage (impedence)			fems028a	ff2036		fg3136	fh3016			FJMR025a					
	Liver fat (scan)										FJLI100					FKLI1010
Cardio-vascular health	**Systolic BP**	f9sa021	fdar117	fesa021	ff2620 & ff2625		fg6120-25	fh2030 & fh2035			FJEL032-36-40					FKBP1030
	Diastolic BP	f9sa022	fdar118	fesa022	ff2621 & ff2626		fg6121-26	fh2031 & fh2036			FJEL033-37-41					FKBP1031
	Pulse rate	f9sa023		fesa023	ff2622 & ff2627		fg6122-27	fh2032 & fh2037			FJEL024					FKBP1032
	Heart rate						fg1020	fh2006 (max)			FJEL116					FKSP1837
	Pulse wave velocity		fdar114								FJAR083d / FJAR088d					FKCV4200
	Ejection duration										FJEL115					FKSP1804
	IMT										FJAR079d					FKCV1131-21
	Heart echo										FJGR031-57					FKEC5050-190
Metabolites	**Total cholesterol (fasting)**	CHOL_F9						chol_TF3			CHOL_TF4					Chol_F24
	HDL cholesterol (fasting)	HDL_f9						hdl_TF3			HDL_TF4					HDL_F24
	LDL cholesterol (fasting)	LDL_f9						ldl_TF3			LDL_TF4					LDL_F24
	Insulin (fasting)	insulin_F9						insulin_TF3			insulin_TF4					Insulin_F24
	Triglyceride (fasting)	trig_f9						trig_TF3			TRIG_TF4					Trig_F24
	Glucose (fasting)							glucose_TF3 / Glc_TF3 (metab)			glucose_TF4 / Glc_TF4 (metab)					Glucose_F24
Inflammation	**CRP**	CRP_f9						crp_TF3			CRP_TF4					CRP_F24
	IL-6	IL6_f9														IL6_F24