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The theory behind fixed-effects panel models
Fixed-effects panel models in practice

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Workshop LIVES Doctoral School, 1 November 2022

Content

1. Basics of longitudinal data and regression refresher

Data over time

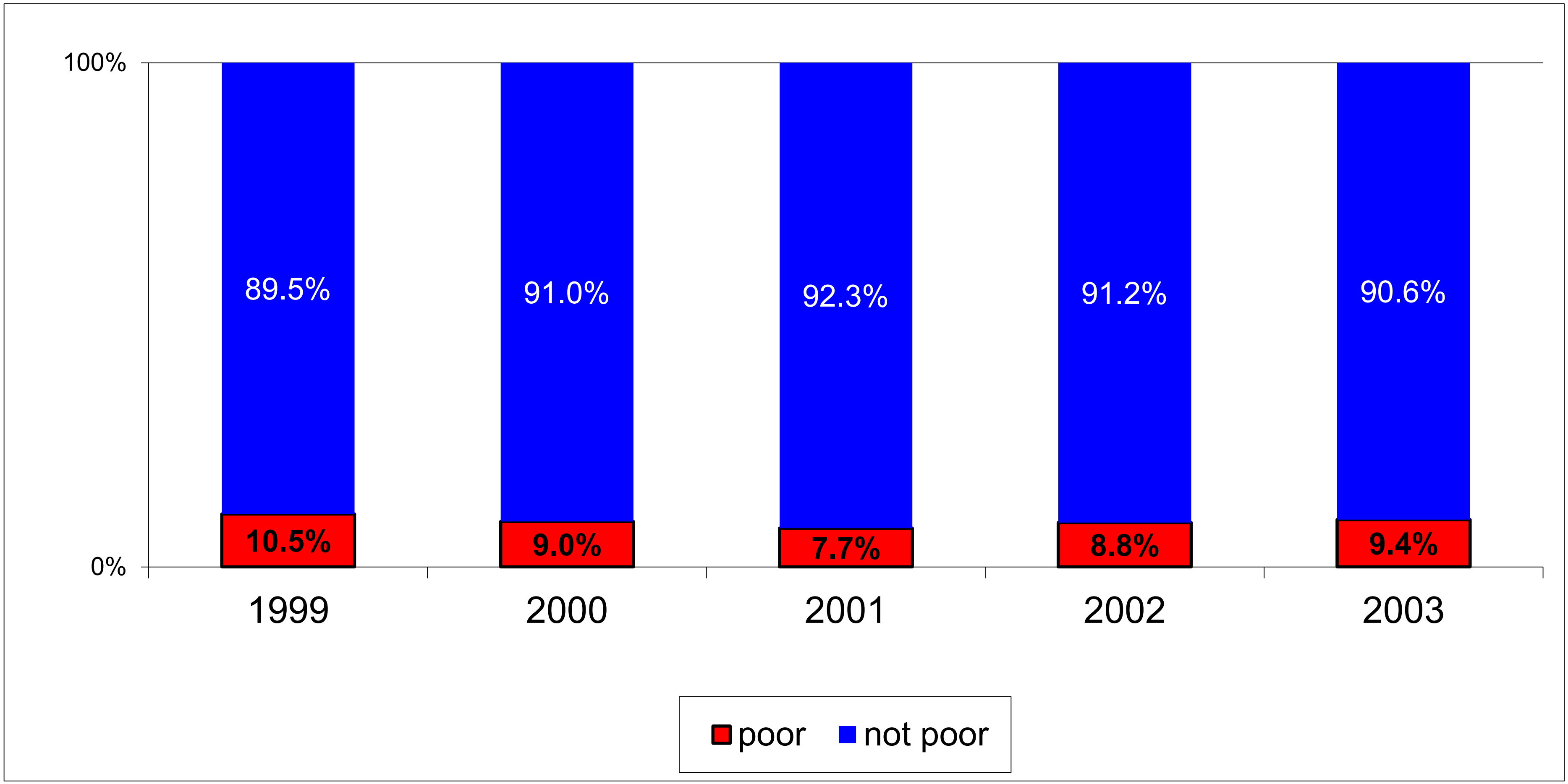
Cross-sectional data
(repeated cross-sections, e.g., ESS)

Time Series: N small (mostly=1), T large ($T \to \infty$)

→ time series models (finance, macro-economics, demography, …)

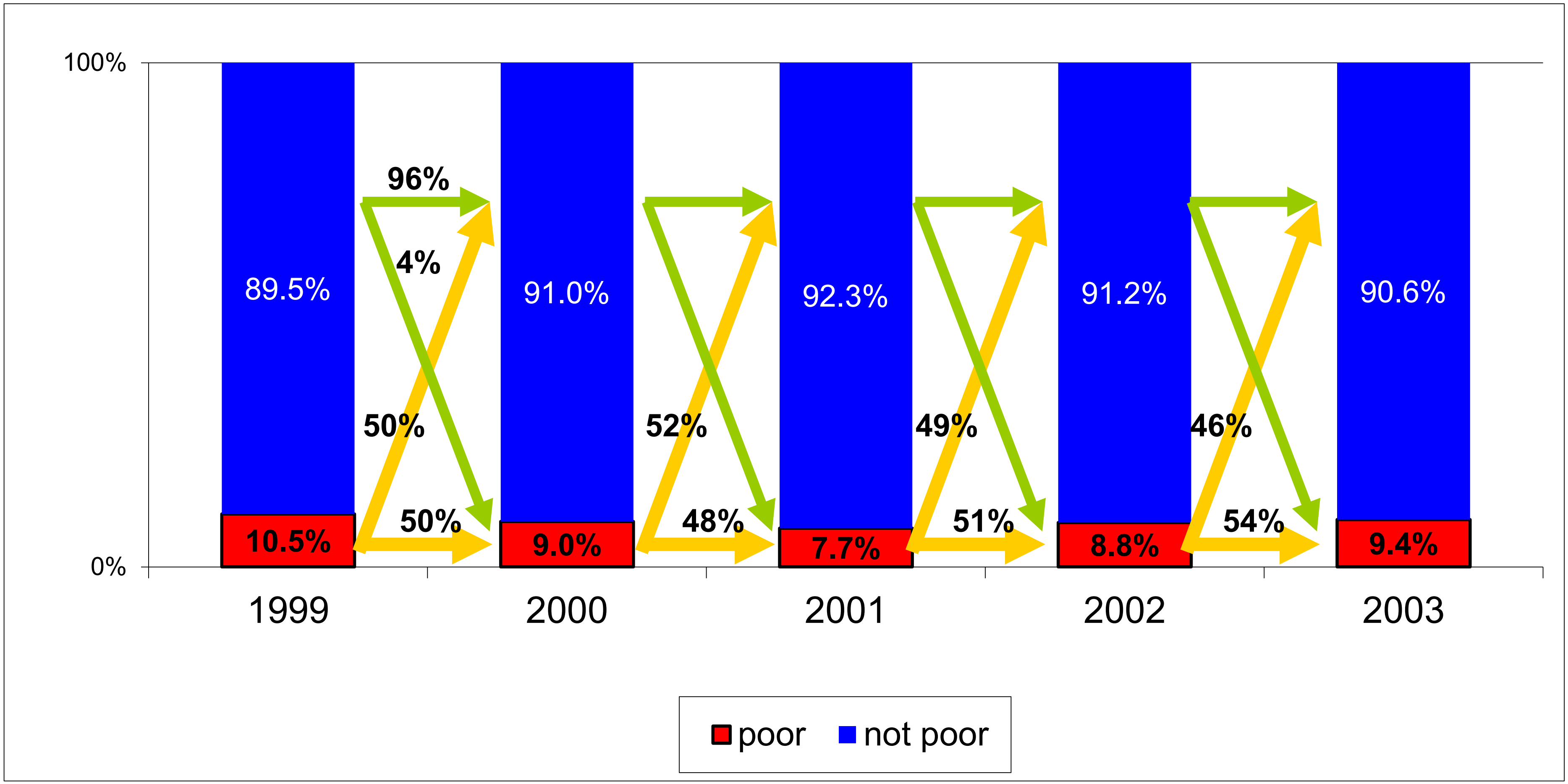
(Prospective) Panel data: N large ($N \to \infty$) , T small (2- < ca.100)
→ social science panel surveys (sociology, micro-economics, …)

Example: Transitions in and out of poverty
1. based on repeated cross-sectional data



-> poverty rate over time stable

Example: Transitions in and out of poverty
2. based on panel data



-> **individual dynamics** can only be measured with panel data!

Panel surveys increasingly important

Changing focus in social sciences

– Repeated observations of same unit:

→ Close to **experimental design**: *before and after* studies

Plus: Life course: social origin, biographical variables, expectations, social context (e.g., household, partner, peers), genetic data:

→ Understand mechanisms -> identify “**causal**” effects (not just correlates)

Panel data: Pros (+) and Cons (-)

+

- Less **measurement** issues than retrospectively collected data
- **Individual** trajectories
- (Better) identify **causal** effects than just correlations
- Close to **experimental design**: before and after studies

(Within-individual models)

-

- High **costs** (panel care, tracking households, incentives)
- Initial **non-response *and* attrition**
- Population **representativeness** (increasingly) challenged
- **Complex** design and analysis (e.g., combining waves, longitudinal weights)
- Design a panel for **next generation** of researchers
- **Panel conditioning** effects

Short regression refresher

(Important) assumptions of OLS regression

General

Random sample from clearly defined population → Inference on population

linear relationship dep./indep. variables → OLS estimation

Coefficient estimation

No endogeneity; Cov(x,e) = 0 → Coefficients unbiased

Error estimation

No autocorrelation $Cov(e_i,e_k)=0$

Constant variance (no heteroscedasticity)

→ Standard errors of coefficients unbiased

Reasons for endogeneity ($Cov(x,e) \neq 0$)

- **Omitted** (exogenous) variables
- **Simultaneity**
- **Nonlinearity** in parameters (can be tested)

Problems:

- Only **observed** variables controllable
- **Selection** process (mechanism of **who** experiences a change in the independent variable) largely unknown
- **Parametrization** necessary

Model with endogenous variables cannot be interpreted as causal

Poll 1: Panel surveys and repeated cross-sections

Which statements are correct? (all that apply)

1. Thanks to refreshment samples, panels are more representative of the population
2. Panels are better able to identify selection into the treatment
3. Repeated cross-sections cannot capture person-group trajectories

2. Causality and the counterfactual

Description vs. causality

We distinguish:

- **Descriptive statement** :

  Y for *individuals with D=1* (treatment) versus

  Y for *individuals with D=0* (control)

example: income of people with a master degree and people without

and

- **Causal statement (implying the counterfactual)**:

  Y for *individual i, had i D=1 instead of D=0*

  „effect“ of D on Y?

example: income of i, had i a master degree instead of no master degree.

The counterfactual

Group	Condition	Y^1	Y^0
Treatment group (D=1)		$\mathbf{y_1}$	counterfact
Control group (D=0)		counterfact	$\mathbf{y_0}$

- Each unit i has two *potential* outcomes: Y_i^1 and Y_i^0
- Question: «what if …»

- Fundamental Problem of Causal Inference (Holland 1986):
  never both potential results observable for the same unit
  -> treatment effect cannot be identified!

Identifying treatment effect 1: experiment

- Randomized experiment with treatment- and control group
  - gold standard: independence of treatment D and potential result Y
  - selection problem solved on design level (no self selection)

- Problem experiment in social sciences
  - often impossible, too expensive or ethically not feasible (death penalty!)
  - often difficult to conduct (e.g., effect of different class sizes: Star-experiment, smoking “experiment”)
  - often small sample sizes

Identifying treatment 2: „conditioning on observables“

- Control for a (categorical) variable is equivalent to analysis within categories of this variable

Methods:

- Stratification
- Regression
- Matching

Example treatment effect: master degree – income

Group Condition	$E[Y^1 \mid D]$	$E[Y^0 \mid D]$
Treatment group (D=1 = with master degree)	**10**	
Control group (D=0 = no master degree)		**5**

Fundamental Question:
which part of the mean difference of 5 is due to

- Additional qualifications from the master degree (**causal** effect)?
- Characteristics of people who earn a master degree, had they not earned it (**selection** effect)?

Example: master degree – income (with counterfactual)

Group	Condition	$E[Y^1 \mid D]$	$E[Y^0 \mid D]$
Treatment group (D=1 = with master degree)		**10**	6
Control group (D=0 = no master degree)		8	**5**

If 50% have a master degree:

⇨ Causal effect = 3.5 (= .5*4 + .5*3) =Average Treatment Effect (ATE)

⇨ Mean difference (=5) biased!
Error = 5 - 3.5 = 1.5

Error Components:

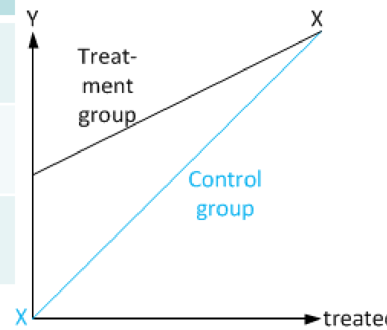
- *Baseline selection bias* = 6 - 5 = 1 (those with master earn more anyway; easy to calculate)
- *Treatment selection bias* = .5 (those with master benefit more from master)

Idea: partition sample into subsamples with no baseline and no treatment selection. Then condition on variables which identify such strata.

Example: baseline and treatment selection bias

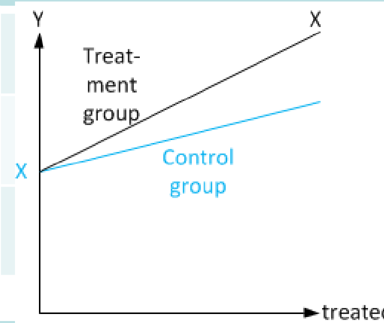
baseline bias (regression: y = 0 + **20** * d + error, correct for controls), ATE=**15**

	y_i^1	y_i^0	**y_i (observed)**	d_i	error
Treatment group	**20**	10	**20**	1	10
Control group	20	**0**	**0**	0	0



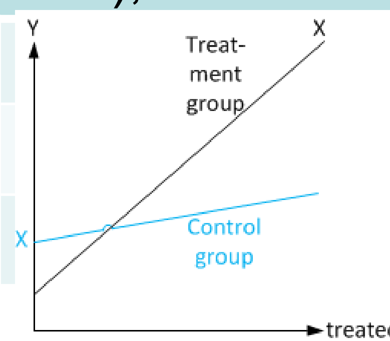
treatment bias (regression: y = 10 + **10** * d + error, correct for treated), ATE=**7.5**

	y_i^1	y_i^0	**y_i (observed)**	d_i	error
Treatment group	**20**	10	**20**	1	0
Control group	15	**10**	**10**	0	-5



Both types of bias (regression: y = 10 + **15** * d + error, correct for none), ATE=**12.5**

	y_i^1	y_i^0	**y_i (observed)**	d_i	error
Treatment group	**25**	5	**25**	1	-5
Control group	15	**10**	**10**	0	-10



Cov(d, e) ≠ 0 → all estimates of d biased (Cov(d, e)>0 → coefficients too large)

Example: control variable x eliminates bias

Regression: y = 5 + 5 * x + **10** * d (without x: 6.67+11.67*d+err. !) , ATE=**10**						
	y_i^1	y_i^0	**y_i (obs.)**	d_i	x_i	error (without x)
Treatment group	**20**	10	**20**	1	1	3.33+1.67=5
Treatment group	**20**	10	**20**	1	1	3.33+1.67=5
Treatment group	**15**	5	**15**	1	0	-1.67-3.33=-5
Control group	20	**10**	**10**	0	1	3.33+1.67=5
Control group	15	**5**	**5**	0	0	-1.67-3.33=-5
Control group	15	**5**	**5**	0	0	-1.67-3.33=-5

Because **Cov(d, e) | x = 0** (Cov(d,e)=0 within groups of x):
Estimate of **d unbiased**!

Cov(d, e) > 0 (coefficient 11.67 too large)

When control variables?

All associations come from 3 elementary configurations:

- Chains: A → B or A → C→ B etc.

  controlling C blocks causal Path 💣 (“overcontrol”)

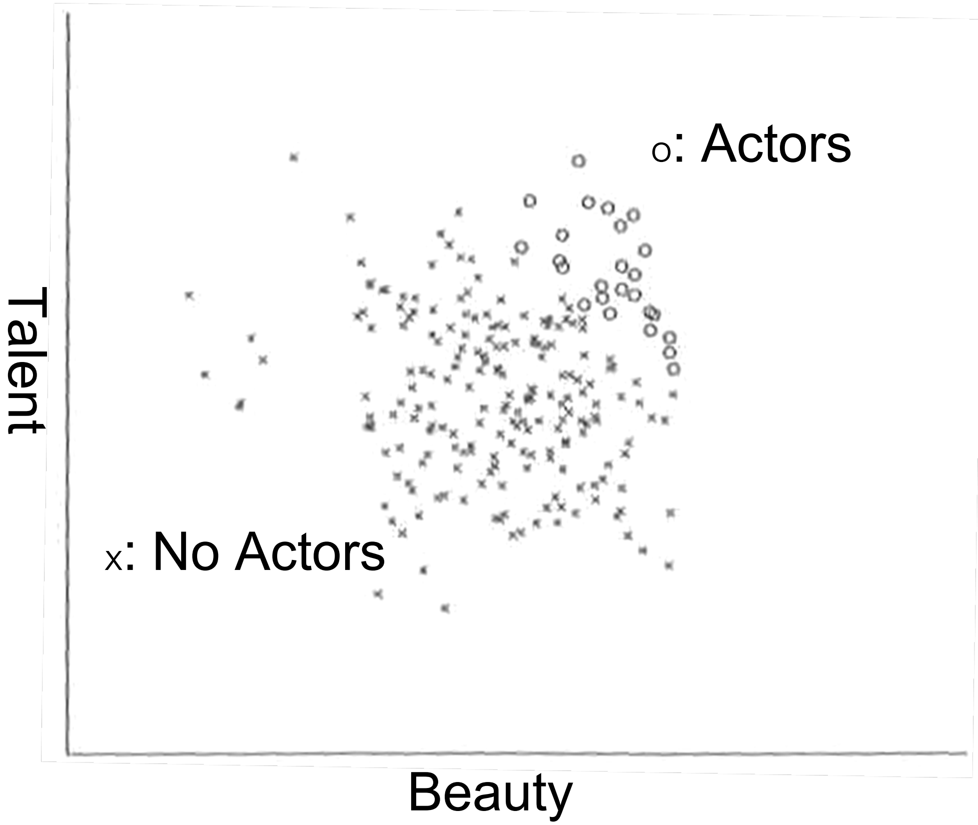
- Forks: A ← C→ B

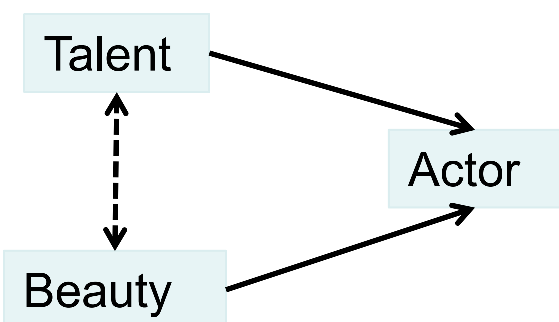
  controlling C solves Problem des «omitted variable bias» √ (confounding)

- inverted Forks: A → C ← B

  controlling C causes **collider variable bias** 💣 («endogenous selection bias»)

Collider bias: a hypothetical example





Beauty and talent independent among *applicants* to Hollywood (all)

Both are positively correlated with *becoming* a Hollywood actor (upper right)

However, beauty and talent are negatively correlated when the applicants are divided into admitted (upper right) and rejected applicants (lower left)

We create a spurious negative association between beauty and talent by controlling for a collider (Actor/No Actor)

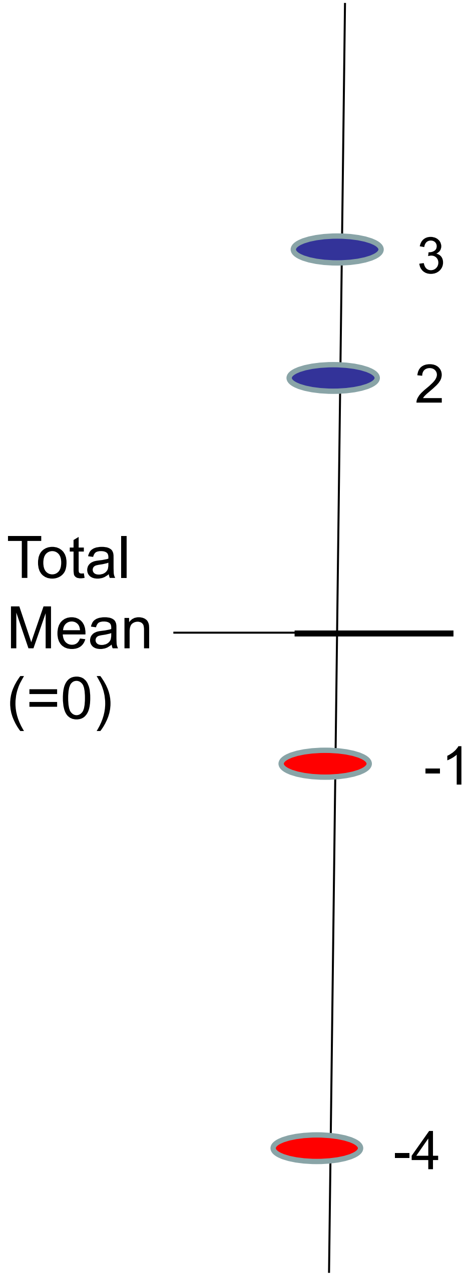
Poll 2: Causality and the counterfactual

Which statements are correct? (all that apply)

1. Panels include counterfactual values
2. error = difference between observed and counterfactual value (of the treatment conditions)
3. ATE = difference between observed and counterfactual value (of the treatment groups)

3. The mechanics of Fixed Effects (within) regression

Variance decomposition: total / within / between



$$\sum_{i=1}^{n}\sum_{t=1}^{T_i}(y_{it}-\bar{y})^2 = \sum_{i=1}^{n}\sum_{t=1}^{T_i}(y_{it}-\bar{y}_i)^2 + \sum_{i=1}^{n}\sum_{t=1}^{T_i}(\bar{y}_i-\bar{y})^2$$

$$T_{yy} = W_{yy} + B_{yy}$$

Total Variance

$\{(3-0)^2+(2-0)^2+(-1-0)^2+(-4-0)^2\} / 4$

$= (9+4+1+16)/4 = \mathbf{7.5}$

Between Variance

$((2.5-0)^2+(-2.5-0)^2)/2 = \mathbf{6.25}$

=82% of total variance (intra-class-correlation)

Within Variance

$((3-2.5)^2+(2-2.5)^2+(-1-(-2.5))^2+(-4-(-2.5))^2)/4 = \mathbf{1.25}$

=18% of total variance

Target: in regression equation: $y_{it} = \alpha + \beta x_{it} + e_{it}$

error decomposition $e_{it} = \alpha_i + \varepsilon_{it}$

-> Regression equation: $y_{it} = \alpha + \beta x_{it} + \alpha_i + \varepsilon_{it}$

Modeling variance in panel regression models

Total variance	Within Variance	Within and between variance
- **Pooled OLS**	- **Fixed effects (FE):** current value minus mean value - **DID (Difference in Difference):** FE with control for common trends - **First difference (FD)**: current value minus previous value	- **Random effects** (Multilevel): Weighted mean between OLS and FE - **Hybrid** Sum of FE and BE

The counterfactual and panel models

- Counterfactual in an **ideal world** : $Y_{i,t}^{Treat} - Y_{i,t}^{NonTreat}$
- Cross-sectional data: **selection effects!** $Y_{i,t}^{Treat} - Y_{j,t}^{NonTreat}$

Panel data I: within-estimator (FE)

$$Y_{i,t}^{TimesTreat(i)} - Y_{i,t}^{TimesNonTreat(i)}$$

Panel data II: "difference-in-difference" (DiD: i:treated, j:nontreated**):**

$$(Y_{i,t}^{TimesTreat(i)} - Y_{i,t}^{TimesNonTreat(i)}) - (Y_{j,t}^{TimesTreat(i)} - Y_{j,t}^{TimesNonTreat(i)})$$

=controls for common trend

Panel data III: first difference (FD):

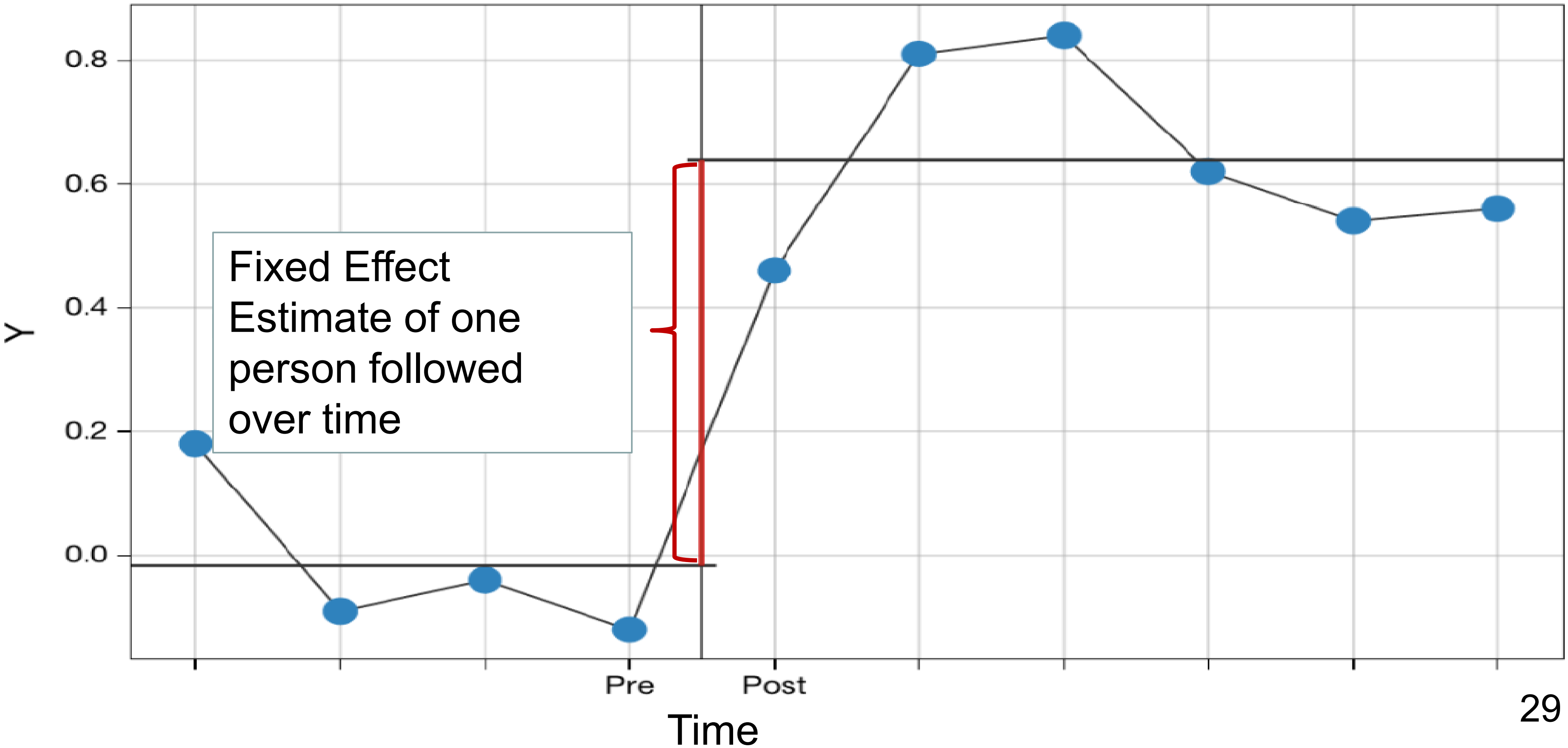
$$Y_{i,t+1} - Y_{i,t}$$

Fixed-effects Models (FE): Properties

FE model: **Only within-variance** (we hope that it is exogenous)

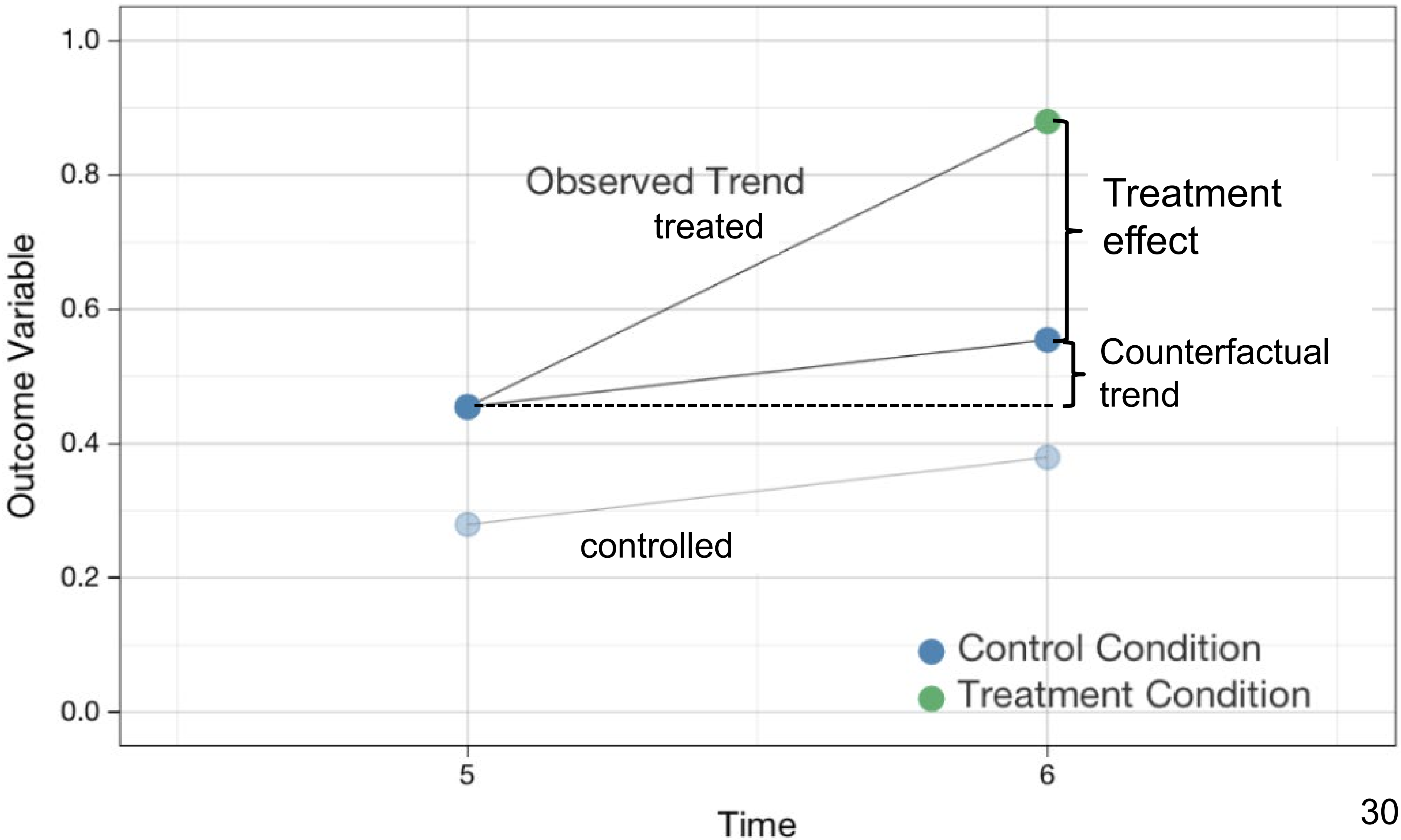
⇨ gets rid of all unobserved **time-invariant** individual heterogeneity

⇨ can only model **time-variant** control variables



DiD (Difference-in-Difference)-models

Use own pre-treatment *and* trend of control group as counterfactual



Poll 3: Panel regression models

Which statements are correct? (all that apply)

1. FE is unbiased, OLS is biased
2. OLS is unbiased, FE is biased
3. FE includes the individual trend

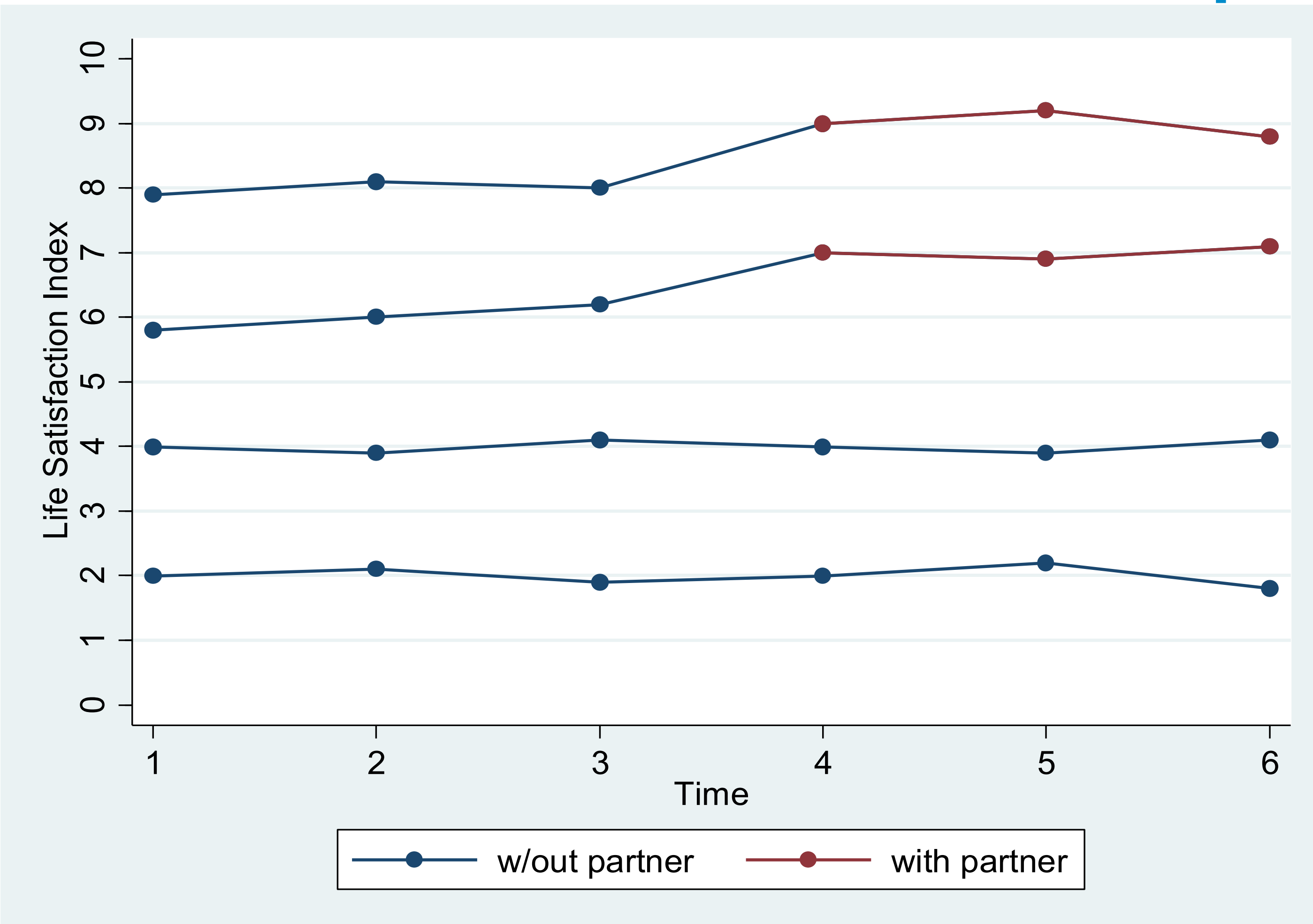
Small-N example: FE

Partner and Happiness: hypothetical data

```
. list id time satlife partner, separator(6)
```

	id	time	satlife	partner
1.	1	1	2	0
2.	1	2	2.1	0
3.	1	3	1.9	0
4.	1	4	2	0
5.	1	5	2.2	0
6.	1	6	1.8	0
7.	2	1	4	0
8.	2	2	3.9	0
9.	2	3	4.1	0
10.	2	4	4	0
11.	2	5	3.9	0
12.	2	6	4.1	0
13.	3	1	5.8	0
14.	3	2	6	0
15.	3	3	6.2	0
16.	3	4	7	1
17.	3	5	6.9	1
18.	3	6	7.1	1
19.	4	1	7.9	0
20.	4	2	8.1	0
21.	4	3	8	0
22.	4	4	9	1
23.	4	5	9.2	1
24.	4	6	8.8	1

Problem: self-selection into partnership

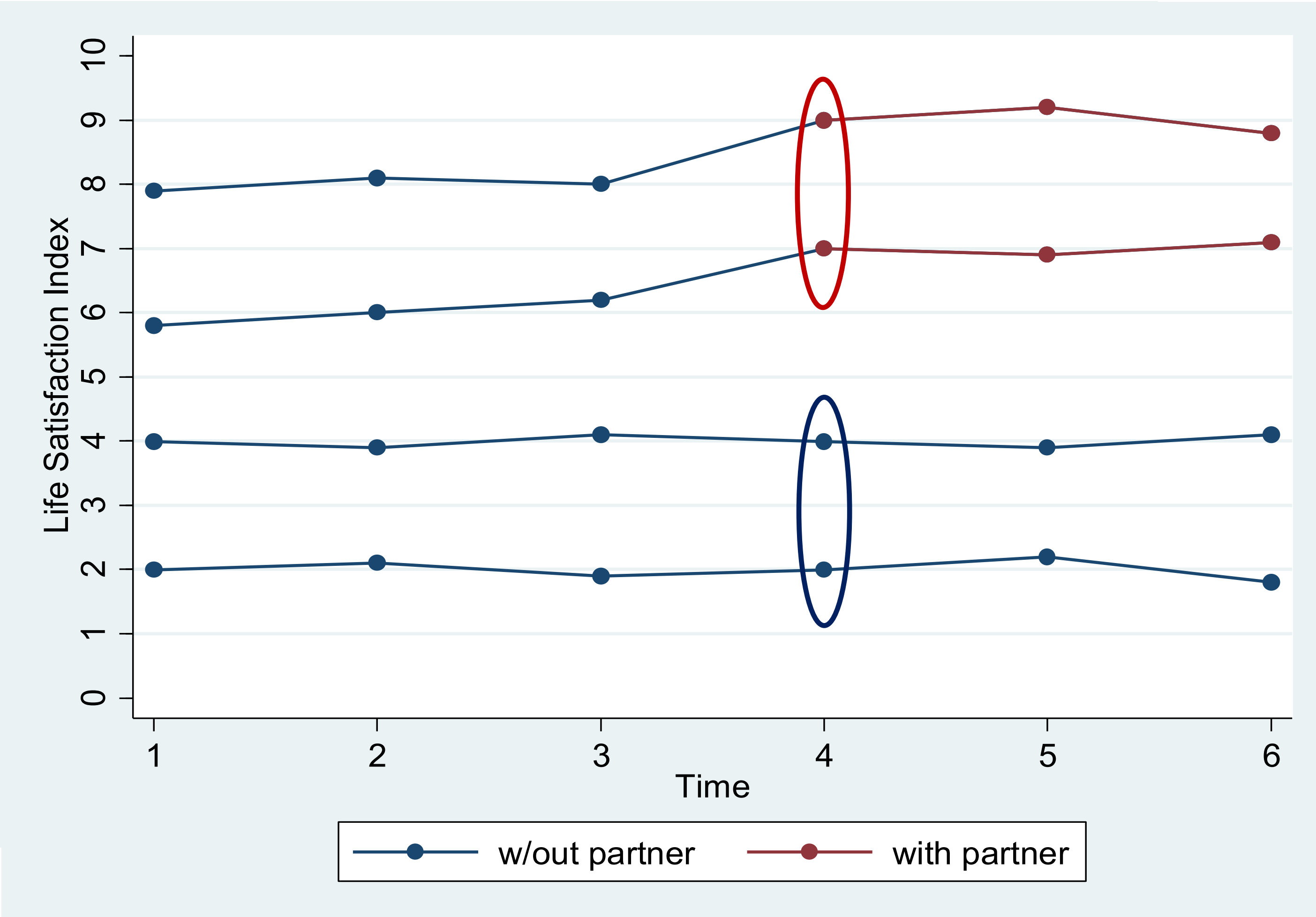


causal effect:
after-before (treat)
= sat(t=4,5,6)-
sat(t=1,2,3) | treat
=((7-6)+(9-8))/2 = **1**

Selectivity:
Only happier get a partner

Individuals with or without a partner differ by characteristics, which have effects on partnership AND happiness (confounders)

Cross-sectional regression?

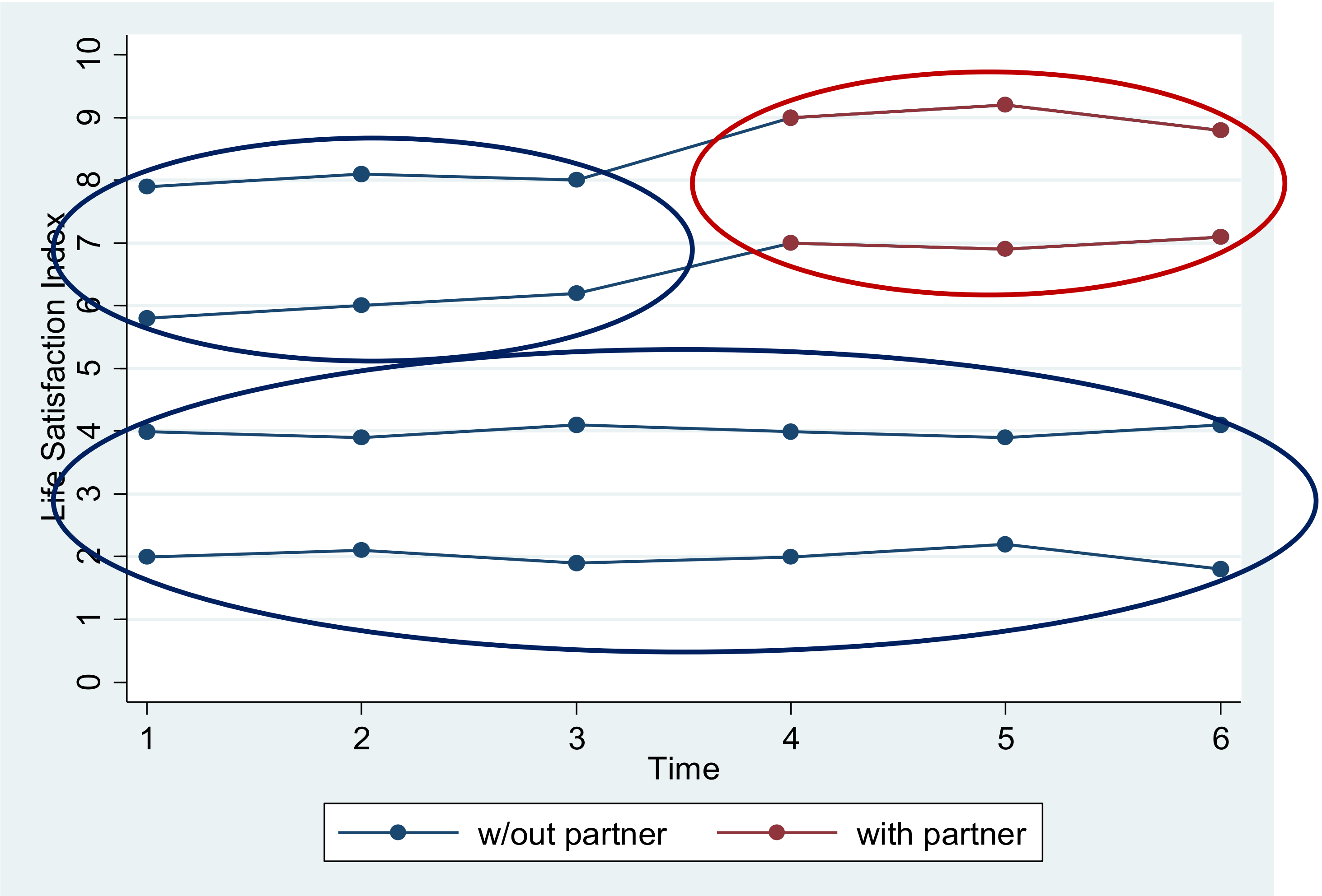


Mean value difference

$\beta_{t=4}$ = (9+7)/2 – (4+2)/2 = 8–3 = **5** is massively biased!

Interpretation: Mean happiness of individuals with partner minus mean happiness of individuals without partner at time t=4

Pooled OLS no solution

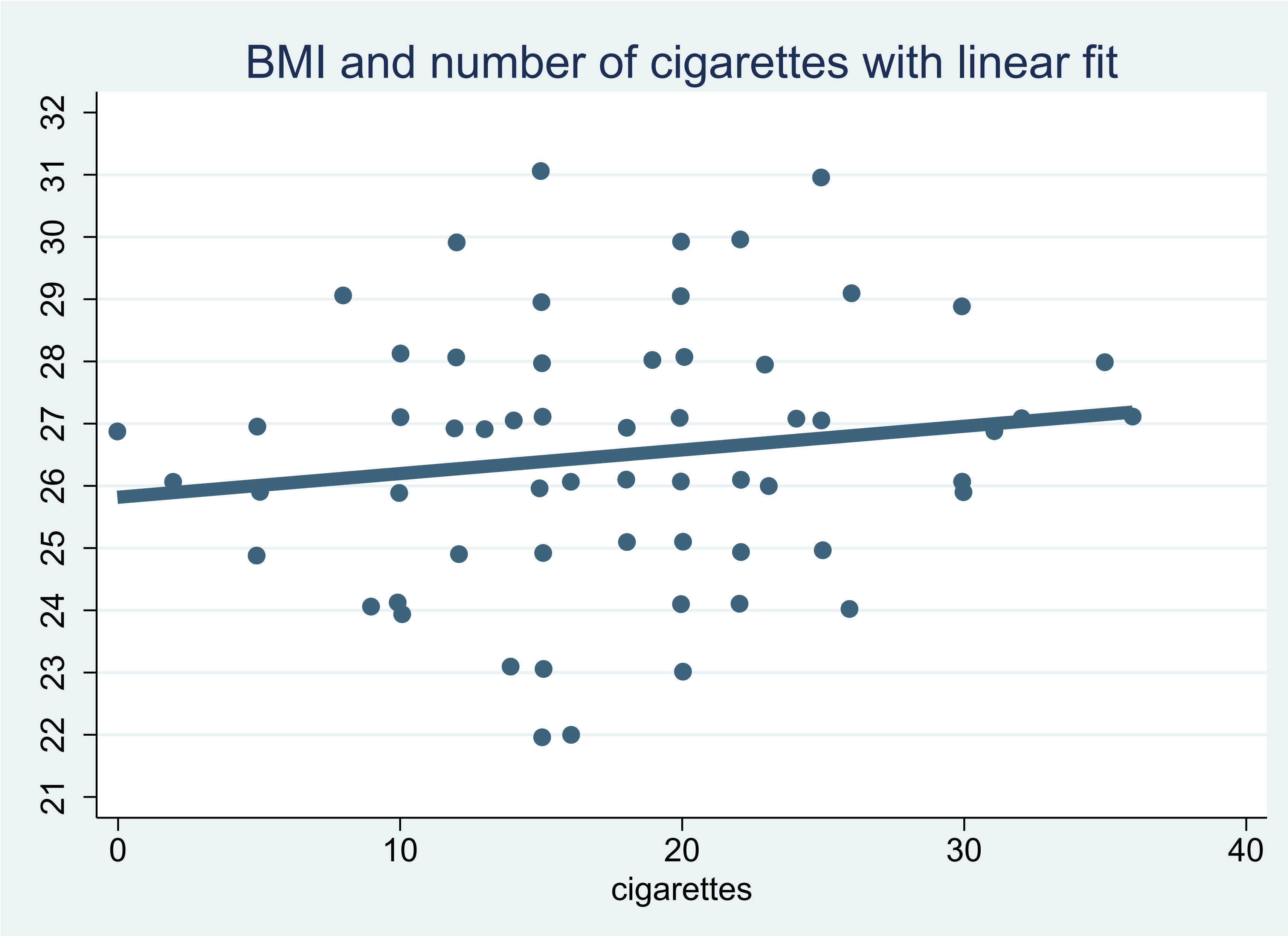


β_{pooled} = **3.67**

Example (continuous treatment): Omitted time-invariant variable bias BMI (Y) and smoking (X):

Hypothesis: smoking reduces BMI

Hypothetical data from 15 individuals: pooled OLS



Pooled OLS Regression (w/out and w/ cluster control)

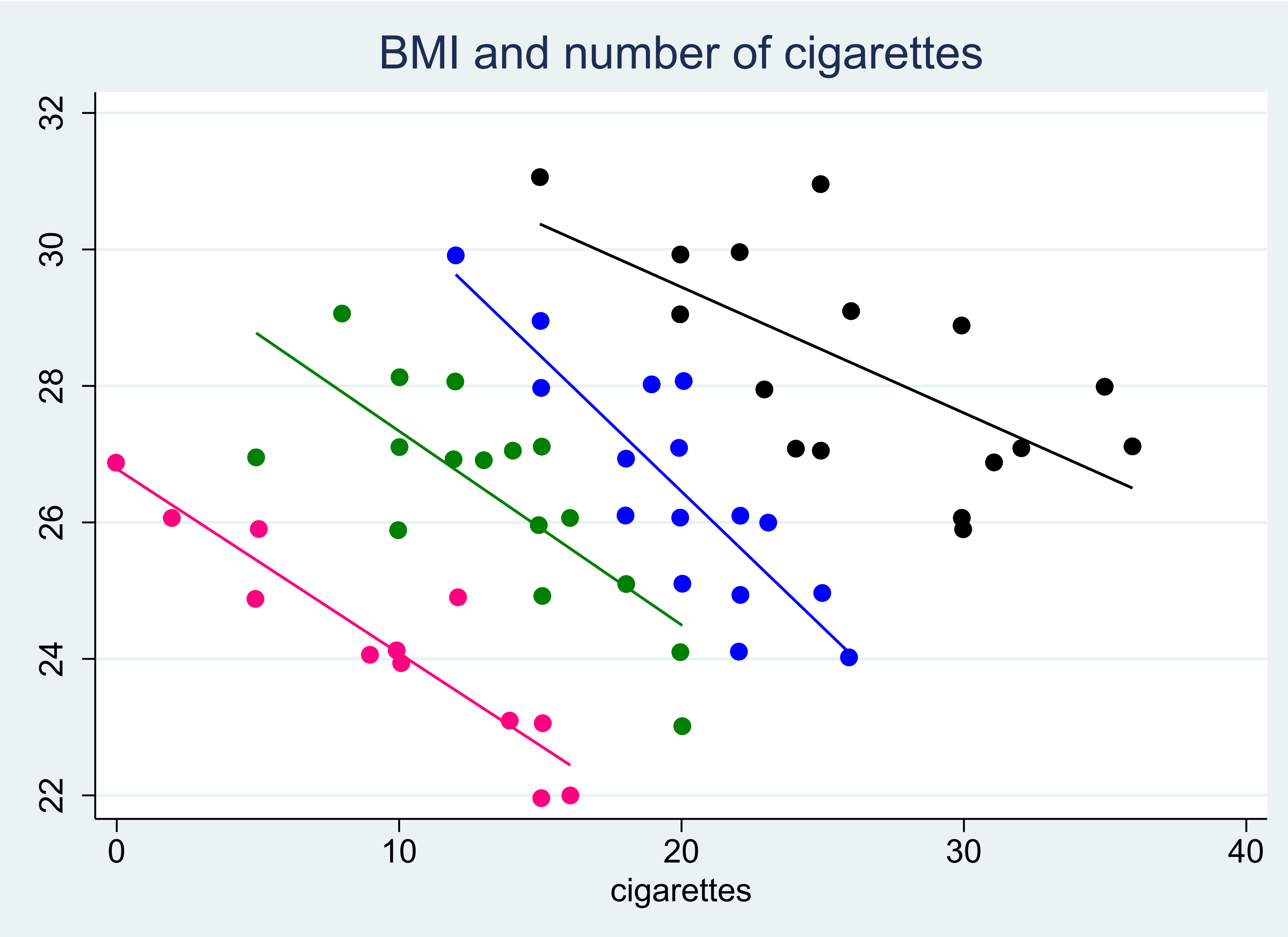
```
. reg bmi cigarettes
      Source |       SS           df       MS      Number of obs   =        60
-------------+----------------------------------   F(1, 58)        =      1.24
       Model |  5.40476902         1  5.40476902   Prob > F        =    0.2708
    Residual |  253.602348        58  4.37245428   R-squared       =    0.0209
-------------+----------------------------------   Adj R-squared   =    0.0040
       Total |  259.007117        59  4.38995114   Root MSE        =     2.091

------------------------------------------------------------------------------
         bmi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  cigarettes |   .0380385   .0342135     1.11   0.271    -.0304473    .1065243
       _cons |   25.81743   .6655684    38.79   0.000     24.48515    27.14971
```

```
. reg bmi cigarettes, vce(cl id)
Linear regression                               Number of obs     =         60
                                                F(1, 14)          =       1.19
                                                Prob > F          =     0.2947
                                                R-squared         =     0.0209
                                                Root MSE          =      2.091

                                    (Std. Err. adjusted for 15 clusters in id)
------------------------------------------------------------------------------
             |               Robust
         bmi |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  cigarettes |   .0380385   .0349433     1.09   0.295    -.0369073    .1129843
       _cons |   25.81743   .8002998    32.26   0.000     24.10096     27.5339
```

Omitted variable: Social class!



Regres-
sions
within
social
class
have
negative
slopes

Within Class Regression

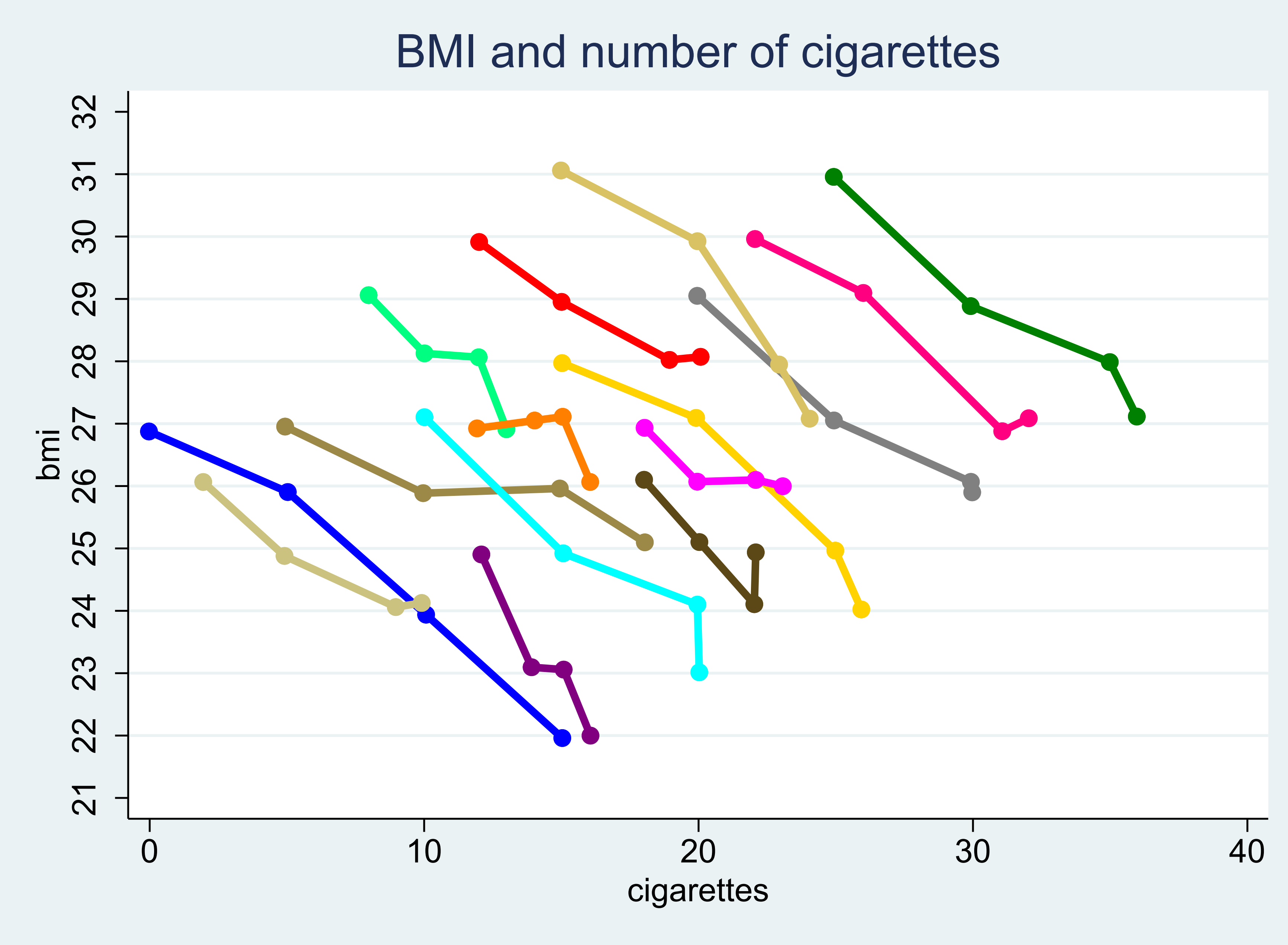
```
. reg bmi class##c.cigarettes, vce(cl id) noci

Linear regression                               Number of obs     =         60
                                                F(7, 14)          =      61.99
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7920
                                                Root MSE          =      1.018

                 (Std. Err. adjusted for 15 clusters in id)
-----------------------------------------------------------
                   |               Robust
               bmi |      Coef.   Std. Err.      t    P>|t|
-------------------+---------------------------------------
             class |
                2  |   1.273362   1.279048     1.00   0.336
                3  |  -2.958034   1.866086    -1.59   0.135
                4  |  -6.352585   .8561826    -7.42   0.000
                   |
        cigarettes |  -.1844306   .0440418    -4.19   0.001
                   |
class#c.cigarettes |
                2  |  -.2134357   .0638309    -3.34   0.005
                3  |  -.0996347   .1210344    -0.82   0.424
                4  |  -.0858862   .0536556    -1.60   0.132
                   |
             _cons |   33.13684    .797873    41.53   0.000
```

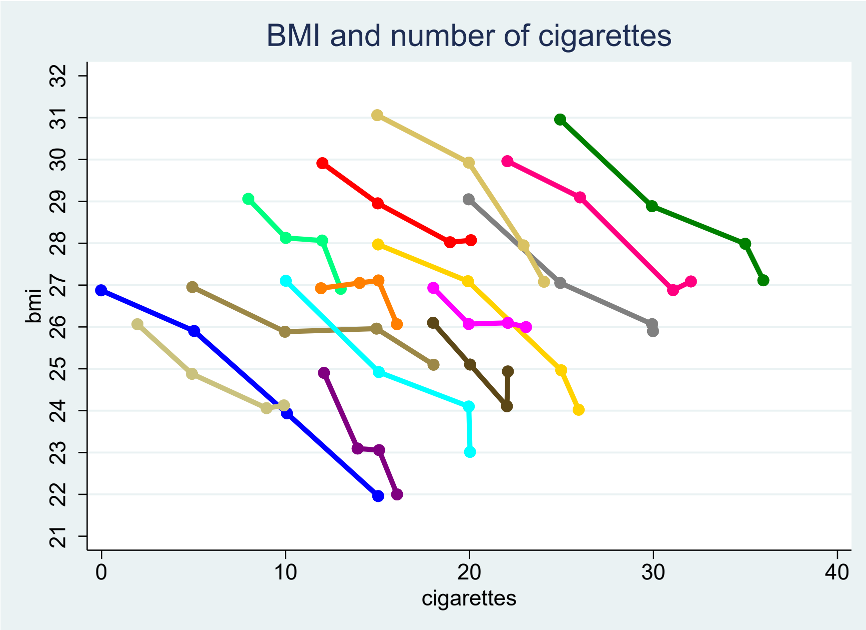
Within-individuals models
(FE and FD)

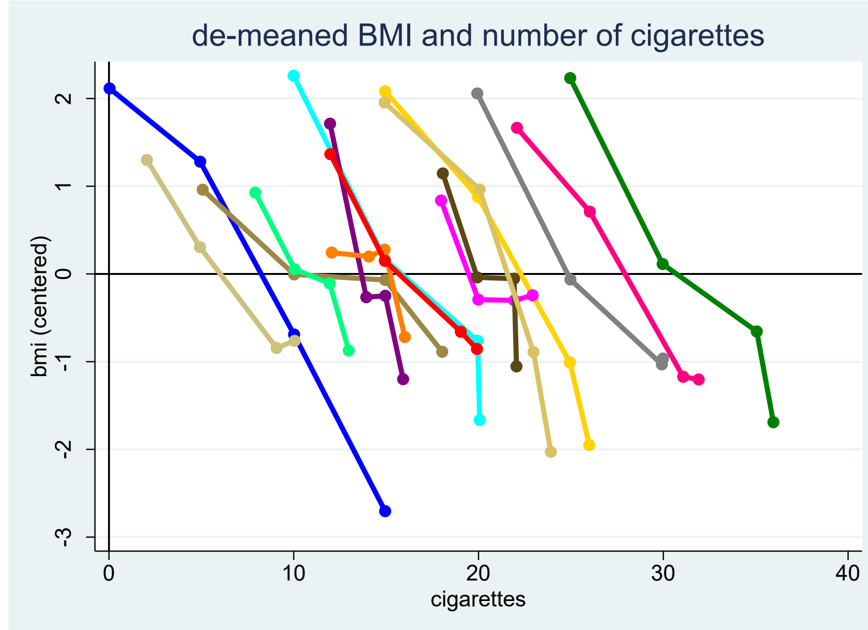
Panel: each individual separately

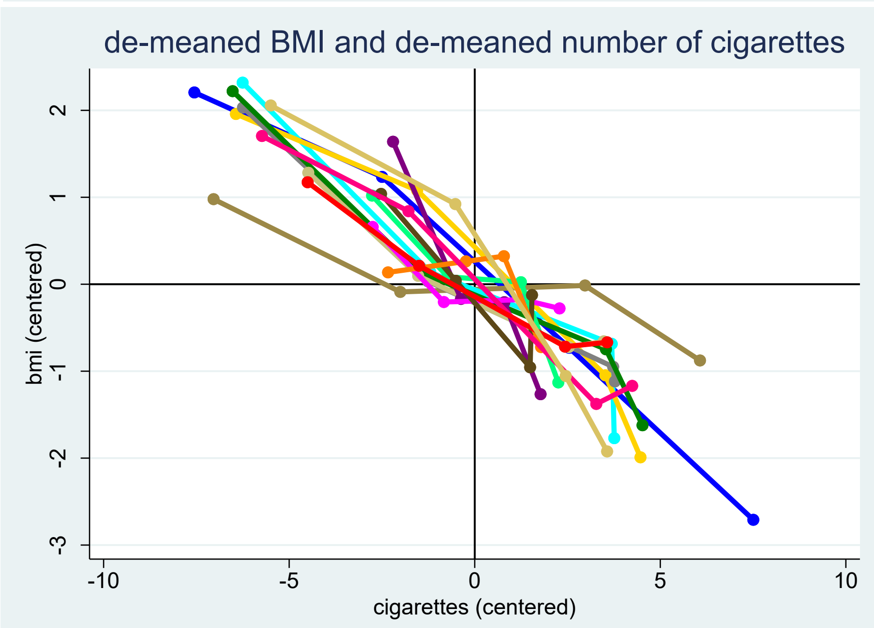


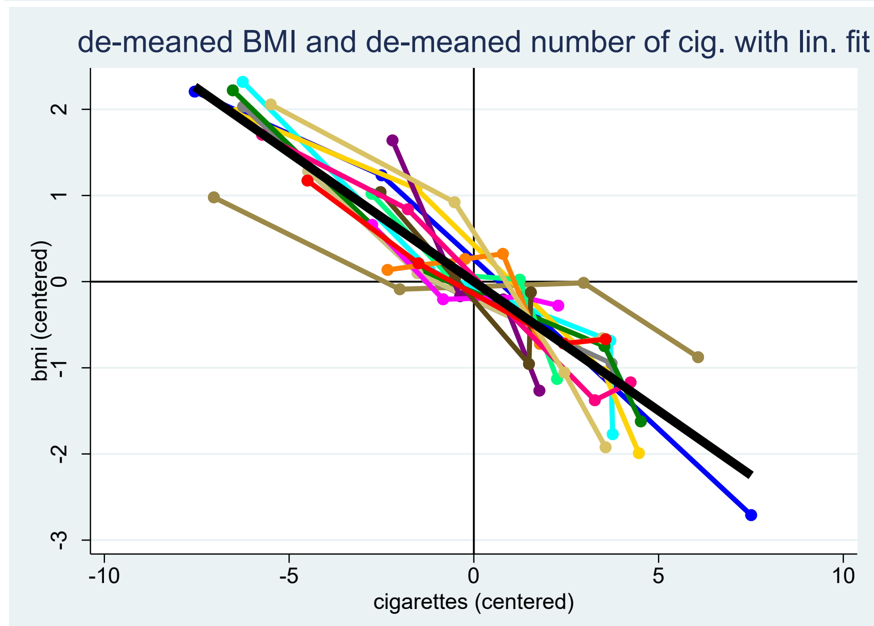
Regres-
sions
within
individuals
have
negative
slopes

Panel: FE transformation

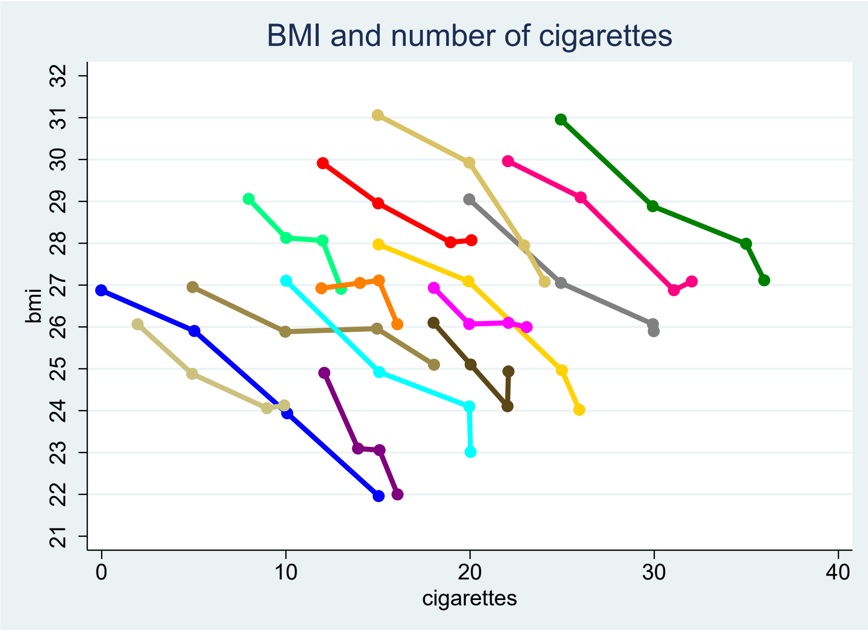


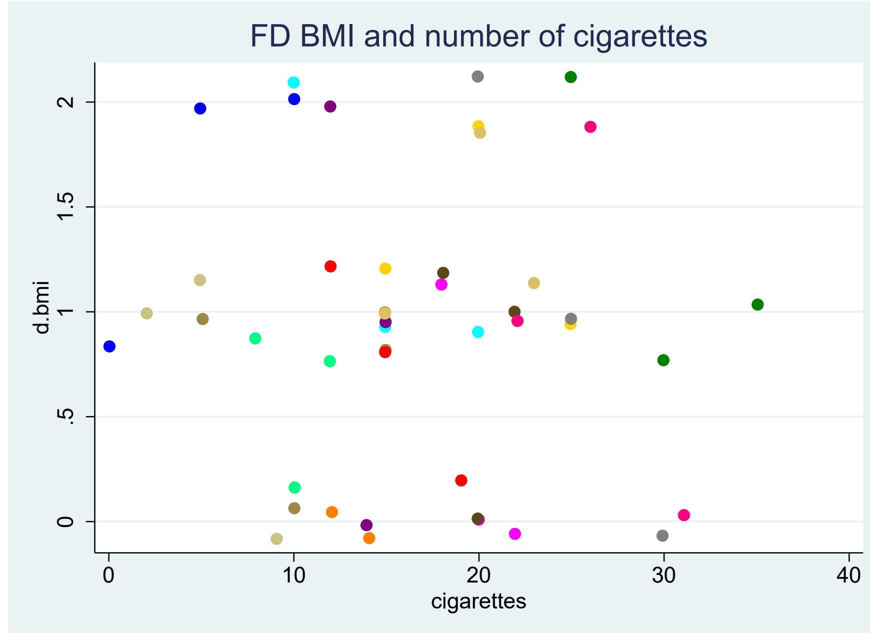


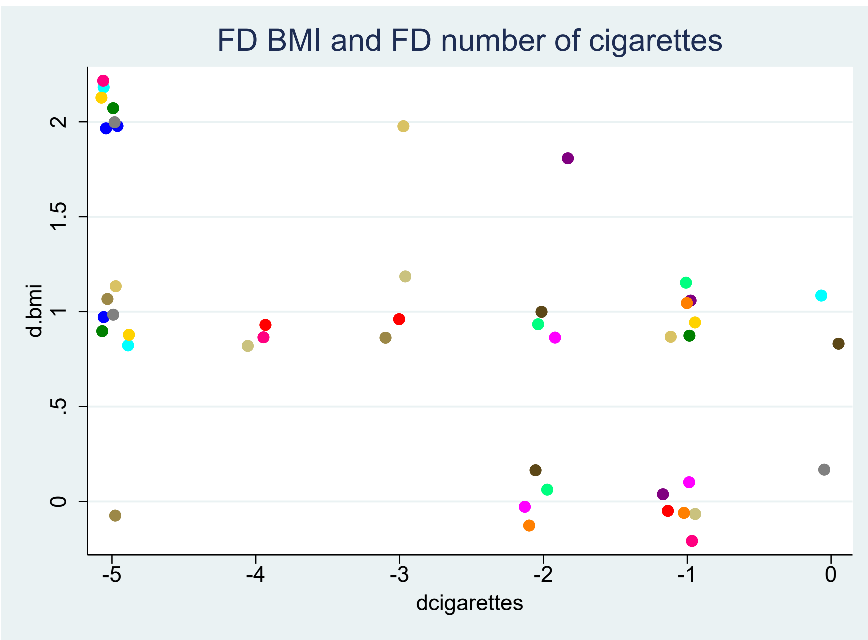


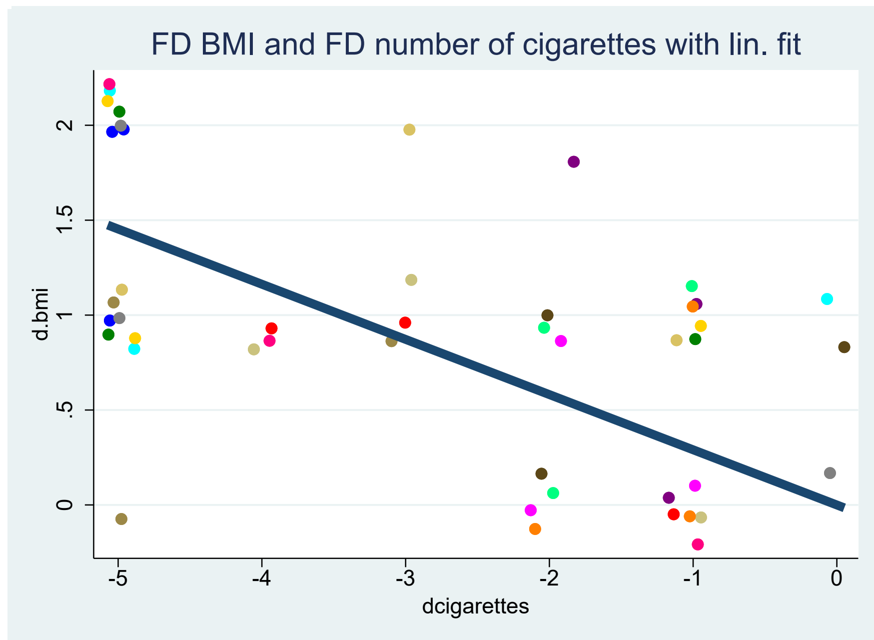


Panel: FD transformation









Calculation of the within-regression coefficients

FE: OLS of individually de-meaned data

De-meaning **and regress**ion:

```
bysort id: center bmi cigarettes
(result in c_bmi, c_cigarettes)

. reg c_bmi c_cigarettes i.time, noci // de-trended

      Source |       SS           df       MS      Number of obs   =        60
-------------+----------------------------------   F(4, 55)        =     89.42
       Model |  70.4049271         4  17.6012318   Prob > F        =    0.0000
    Residual |  10.8258727        55  .19683405    R-squared       =    0.8667
-------------+----------------------------------   Adj R-squared   =    0.8570
       Total |  81.2307998        59  1.37679322   Root MSE        =    .44366

------------------------------------------------------
       c_bmi  |      Coef.   Std. Err.      t    P>|t|
--------------+---------------------------------------
c_cigarettes  |  -.2569932   .0423276    -6.07   0.000
              |
        time  |
          5   |   .3979958   .1699408     2.34   0.023
         10   |   .3220262   .2611874     1.23   0.223
         15   |   .5693978   .3942911     1.44   0.154
              |
       _cons  |  -.3223549   .1918698    -1.68   0.099
```

FD: OLS of individually 1st differenced data

De-meaning **and regress**ion:

```
gen dcigarettes = cigarettes - l.cigarettes
gen dbmi = bmi - l.bmi


. reg dbmi dcigarettes, noci

      Source |       SS           df       MS      Number of obs   =        45
-------------+----------------------------------   F(1, 43)        =     17.80
       Model |  6.07890287         1  6.07890287   Prob > F        =    0.0001
    Residual |  14.6872578        43  .341564135   R-squared       =    0.2927
-------------+----------------------------------   Adj R-squared   =    0.2763
       Total |  20.7661607        44  .471958198   Root MSE        =    .58443

------------------------------------------------------
        dbmi |      Coef.   Std. Err.      t    P>|t|
-------------+----------------------------------------
 dcigarettes |  -.2042172   .0484079    -4.22   0.000
       _cons |   .3507921    .161779     2.17   0.036
```

FD is NOT invariant of measurement time !

With this data:

time	cigarettes	bmi
1	5	27
2	11	25
3	6	22
4	10	23

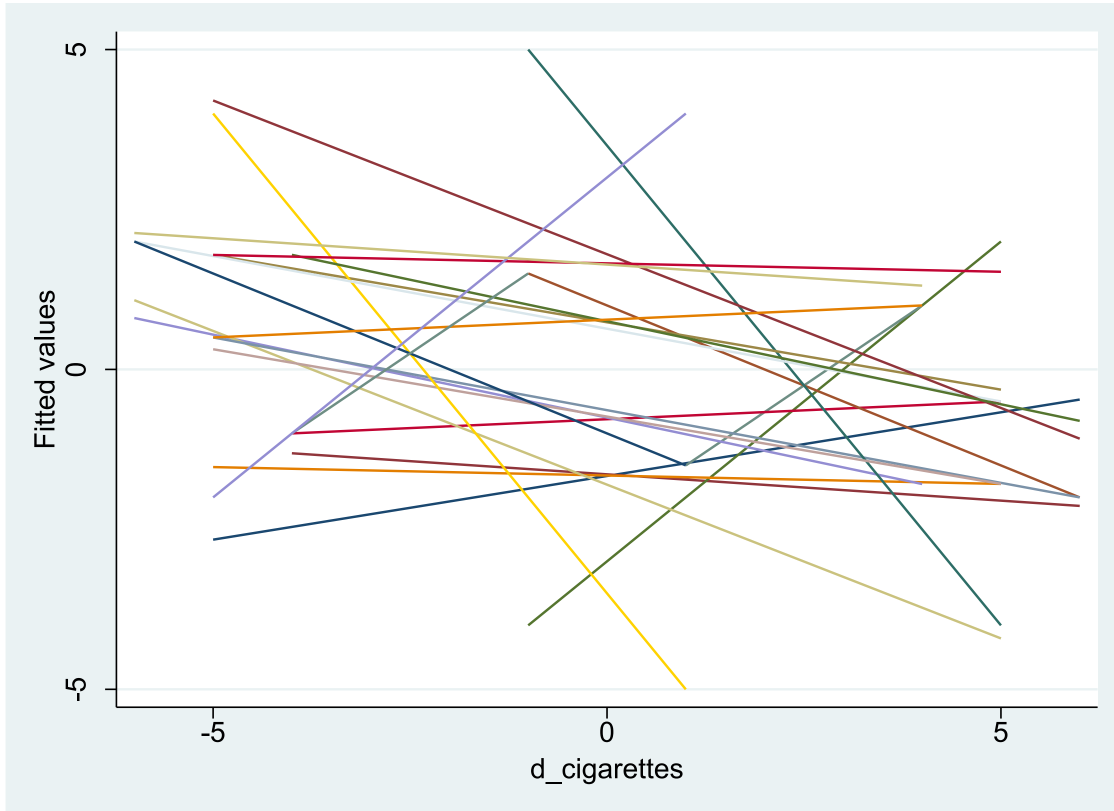
e.g.,: 1)

time	cig	d.cig	bmi	d.bmi
1	5	.	27	.
2	11	6	25	-2
3	6	-5	22	-3
4	10	4	23	1

2)

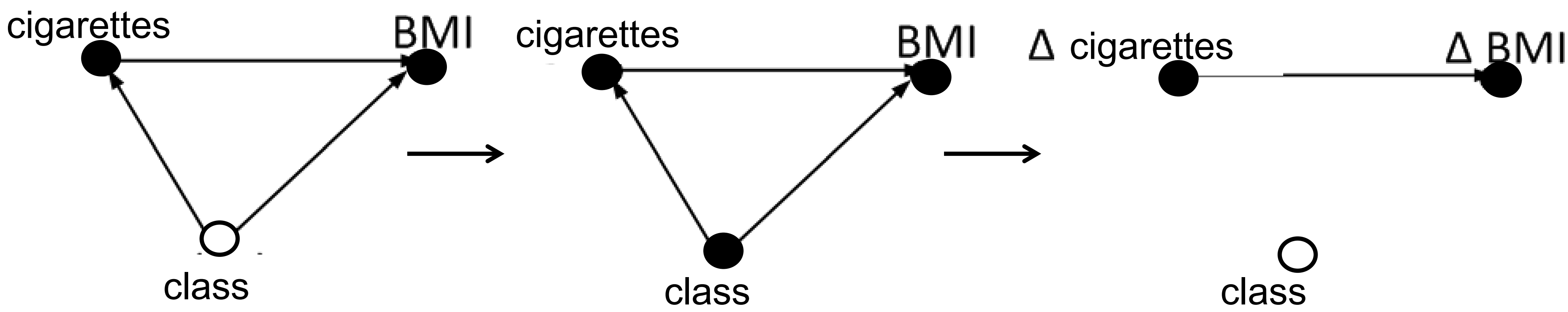
time	cig	d.cig	bmi	d.bmi
1	5	.	27	.
3	6	1	22	-5
2	11	5	25	3
4	10	-1	23	-2

We can produce these fitted lines:



Regression coefficient:
1): .09 2): .44

Graphical interpretation of within models



Regression w/o class Regression with class FE- regression

all α_i (including class!) eliminated

De-meaning identifies causal effect under weaker assumptions:
Cov(x,e) ≠ 0 *for time-invariant parts* α_i of e

Problems FE-Models

- Often (too) **little within-variance** -> check variance decomposition within/between/total!
- **Time-constant variables** (e.g., sex) cannot be modelled -> separate modeling or interaction
- **Co-varying (confounding) *changes*** must be controlled
- Only Average Treatment (effect of the)Treated, **not ATE**
- (**Selective) attrition** and panel conditioning

Poll 4: FE vs. OLS estimators

Which statements are correct? (all that apply)

1. FE is too low because it ignores between variance
2. OLS is too high because it includes between variance
3. OLS is better for time-constant independent variables

Excursus: Random effects regression (multilevel)

RE: weighted mean between FE and pooled OLS

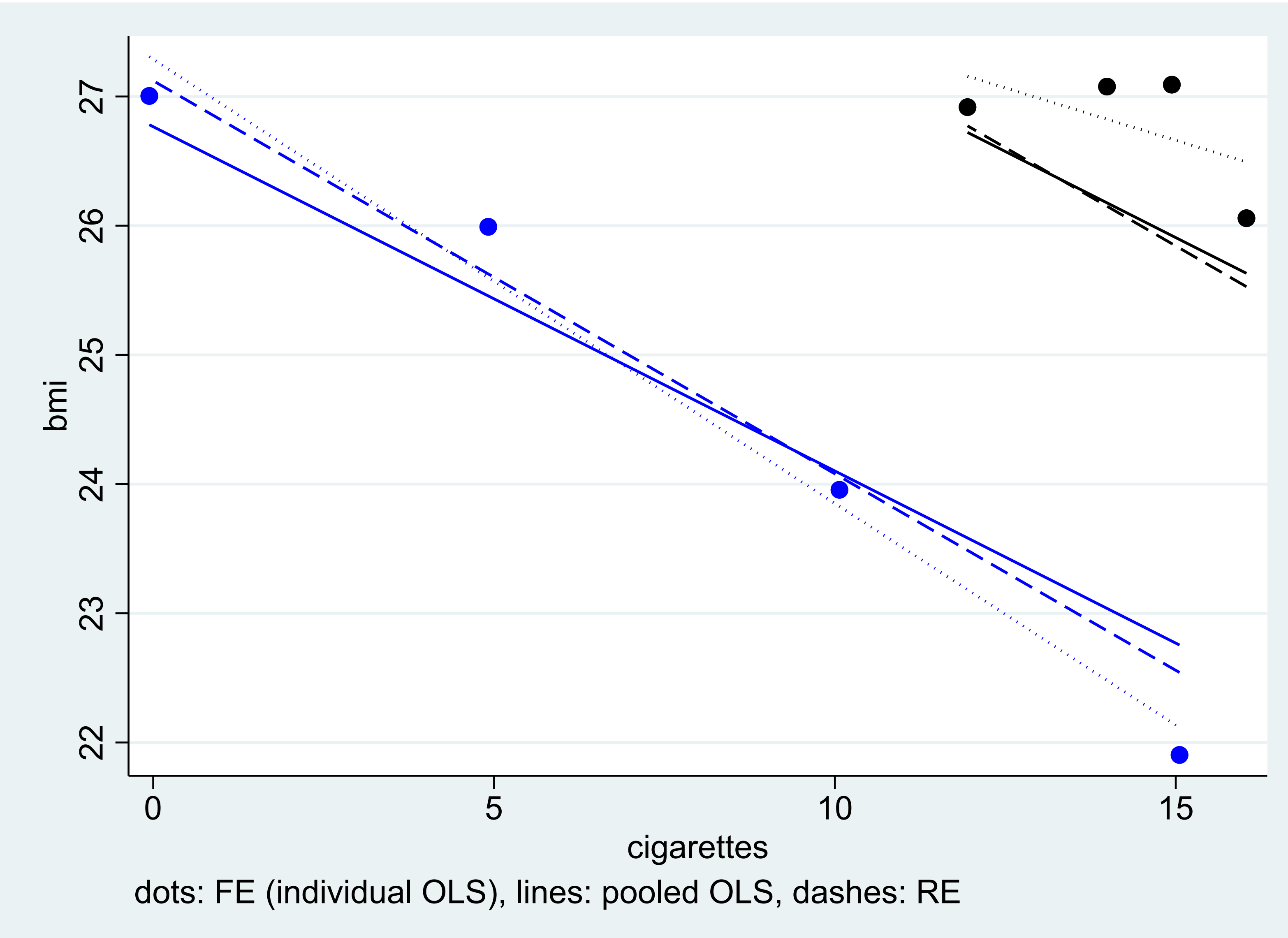
FE Regression	RE Regression	Pooled OLS
0	$\sigma_\varepsilon^2/(\sigma_\varepsilon^2+T\sigma_u^2)$	1
$\Theta = 1$		$\Theta = 0$

RE - Regression is equivalent to pooled OLS after the Transformation :

$$(y_{it} - \Theta\,\bar{y}_i) = \beta_0(1-\Theta) + \beta_1(x_{it} - \Theta\,\bar{x}_i) + (u_i(1-\Theta) + (\varepsilon_{it} - \Theta\,\bar{\varepsilon}_i))$$

with $\Theta = 1 - \sqrt{\dfrac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_u^2}}, \quad 0 < \Theta < 1$

RE example: BMI regressed on cigarettes and class



Weight class (lines)

→ high if indiv. OLS imprecise (black person)

RE “borrows strength” from OLS

Weight individual OLS (dots):

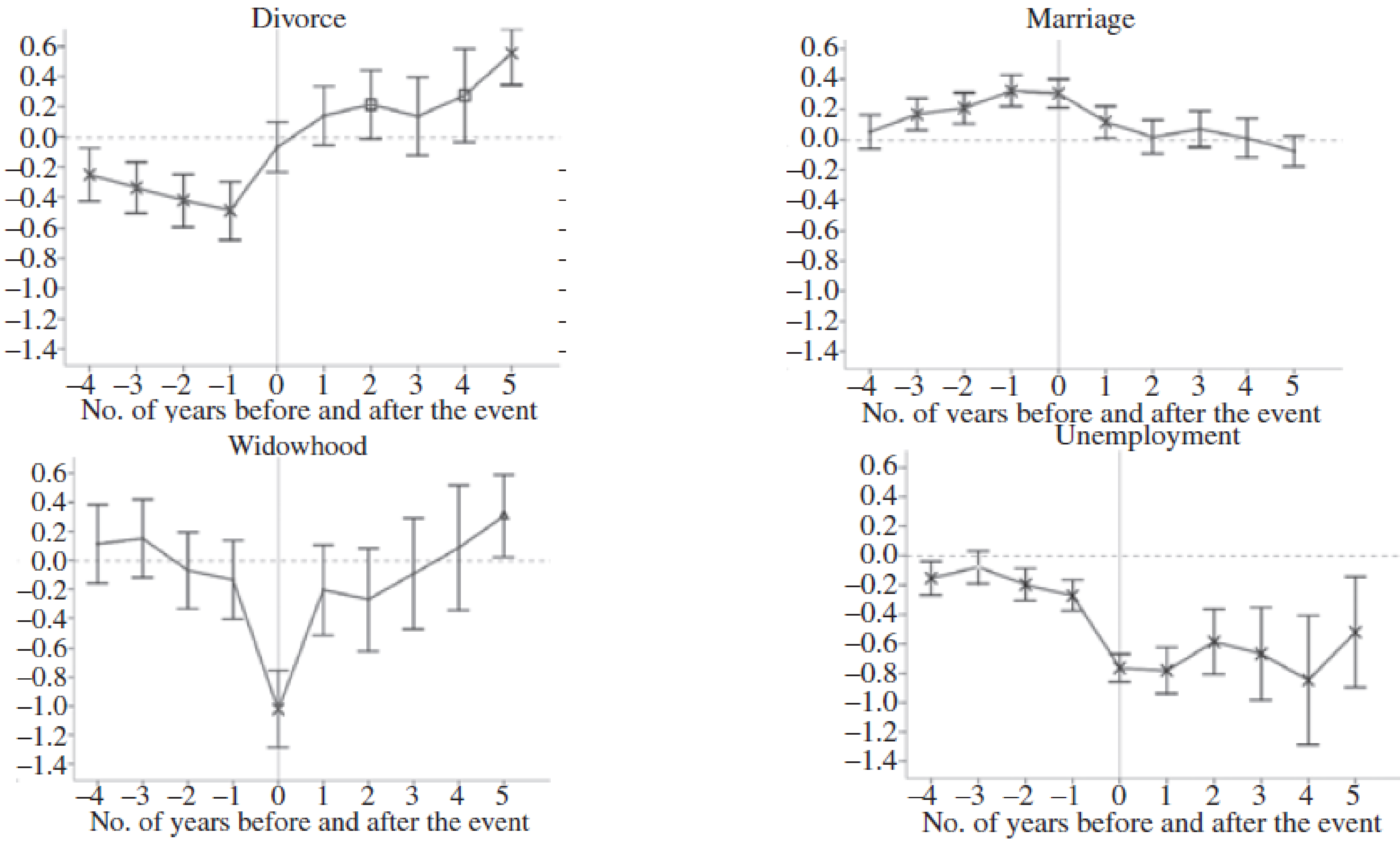
→ high if indiv. OLS precise (blue person)

Within estimators: Summary

Summary: within estimators

- Fixed effects (**FE**) transformation: $\tilde{y}_{it} = y_{it} - \bar{y}_i$ ("de-meaning")
  - Captures individual trend
- First difference (**FD**) estimator: $\Delta y_{it} = y_{it} - y_{i,t-1}$
  - Captures only **short-term change**, different from FE estimator if n>2
  - To model immediate effects
  - Measurement time is important
- Both **eliminate the individual effect α_i**
  -> control for heterogeneity, time-invariant characteristics cannot bias coefficients (omitted variables bias)
- Simple to compute (OLS)
- FE are preferred in social sciences

FE example with real data: Events and life satisfaction



Clark, A. E., E. Diener, Y. Georgellis, and R. E. Lucas. 2008. ‘Lags and leads in life satisfaction: A test of the baseline hypothesis’. *The Economic Journal* 118 (529): F222–43.

4. Comparison of models

Which model?

Research question: descriptive or causal

a.) descriptive: Are individuals with a partner more satisfied than those without a partner? (-> cross-sectional data)

b.) causal: How does **a change** in partnership status affect life satisfaction? (-> panel data)
Economist perspective:
-> Select the model which captures the **causal effect** best
-> Hausman test (**FE is the default**)

FE or RE ? The Hausman test

Hausman compares estimation coefficients $\hat{\beta}_{FE}$ and $\hat{\beta}_{RE}$

if $\hat{\beta}_{FE} = \hat{\beta}_{RE}$

-> use $\hat{\beta}_{RE}$, because $\hat{\beta}_{RE}$ is more efficient $\left(\text{var}(\hat{\beta}_{FE}) > \text{var}(\hat{\beta}_{RE})\right)$

if $\hat{\beta}_{FE} \neq \hat{\beta}_{RE}$

$->$ use $\hat{\beta}_{FE}$, because $\hat{\beta}_{FE}$ unbiased but $\hat{\beta}_{RE}$ not

Note:

- Very often $\hat{\beta}_{FE} \neq \hat{\beta}_{RE}$ (sample size high enough even with small differences)

- **Test is only formal and does *not* replace research question driven check for model appropriateness**

FE versus RE models

Fixed effects models

- **OLS**-estimated
- Only variance **within**-individuals used
- Controls for **unobserved heterogeneity** (consistent also if $Cov(\alpha_i, x) \neq 0$)
- Effects of **time-invariant characteristics cannot be estimated** (e.g., gender, cohort)

Random effect models

- **Maximum likelihood** estimated
- Uses both **within- and between-**individuals variance
- Assumes exogeneity: $\mathbf{Cov(\alpha_i, x)=0}$ (no effects from unobserved variables allowed)
- Effects **from time-invariant and time-varying covariates**

If research interest is **longitudinal or causal**

If research interest is on **variance on different levels**

The Hybrid (aka Mundlak) model

- FE-coefficients can be estimated within the multilevel (RE) framework
- The **same variable can be included in both levels**:

$$y_{it} = b_1 \bar{x}_i + b_2 (x_{it} - \bar{x}_i) + \alpha_i + e_{it}$$

- De-meaned coefficients equivalent to FE

Life satisfaction	Within		RE		Hybrid	
Partner	.282***	(.013)	.362***	(.012)	.282***	(.013)
Age	-.055***	(.003)	-.046***	(.002)	-.055***	(.003)
Age squared	.000***	(.000)	.000***	(.000)	.000***	(.000)
Partner: mean					.605***	(.024)
Age: mean					-.065***	(.002)
Age squared: mean					.001***	(.000)
Constant	9.510***	(.066)	8.869***	(.035)	8.958***	(.044)

5. FE example modeling happiness from a partner using the Swiss Household Panel

Research Question

Does living with the partner affect happiness in Switzerland?

We use data from the SHP 2000-2021.
Happiness: In general, how satisfied are you with your life if 0 means "not at all satisfied" and 10 means "completely satisfied"?

- age range: 18-103
- N = 175,007 person-years (observations), 29,004 individuals

Mean values: people/times with and without partner

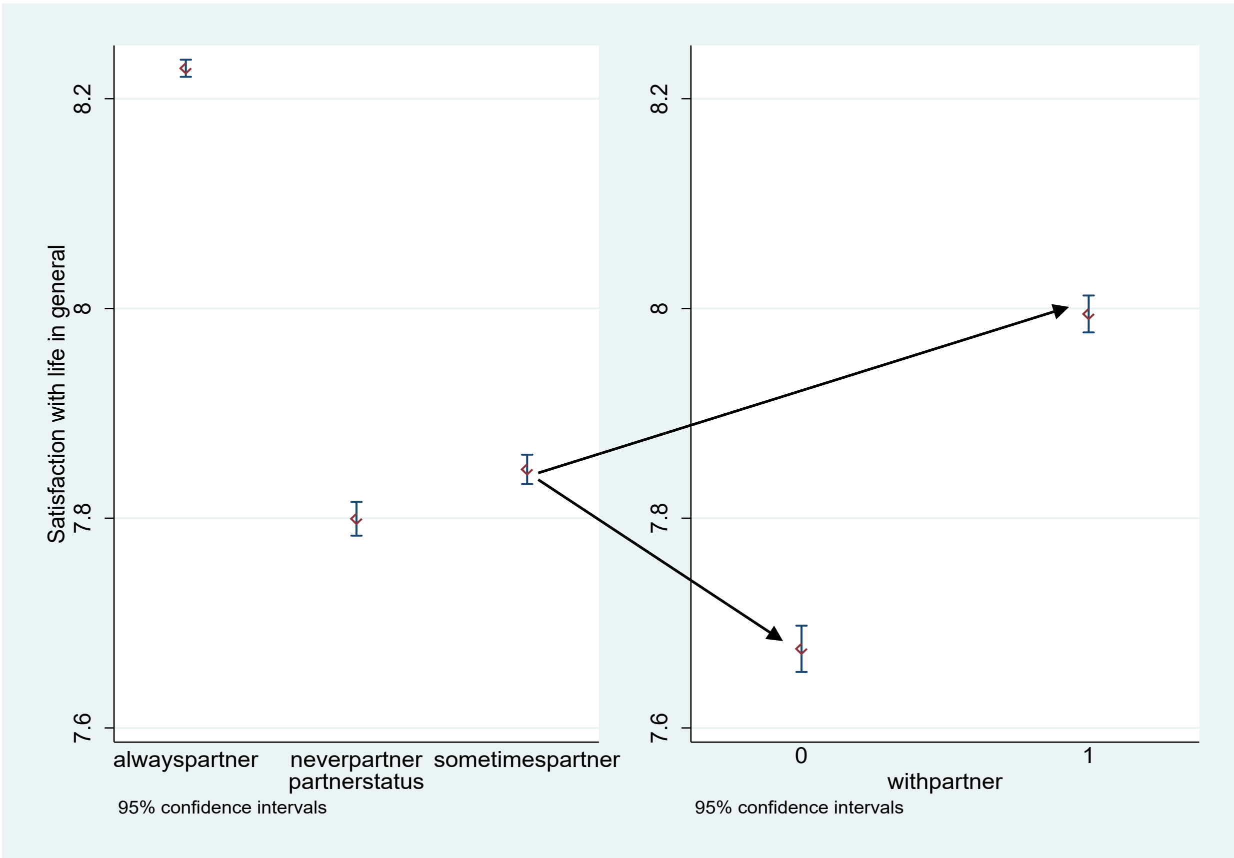
Individuals:

partnerstatus	Freq.	Percent	Cum.
alwayspartner	16,697	57.57	57.57
neverpartner	8,518	29.37	86.94
sometimespartner	3,789	13.06	100.00
Total	29,004	100.00	

Observations:

partnerstatus	Freq.	Percent	Cum.
alwayspartner	96,550	55.17	55.17
neverpartner	36,565	20.89	76.06
sometimespartner	41,892	23.94	100.00
Total	175,007	100.00	

Mean Happi-ness:



First indicator for within/causal effect from FE model: 7.99 – 7.68 = 0.31

Challenge

- adequate model (OLS, FE, (FD), RE)

- correct statistical confounding (covariate selection):

No undercontrol bias: we include as controls:

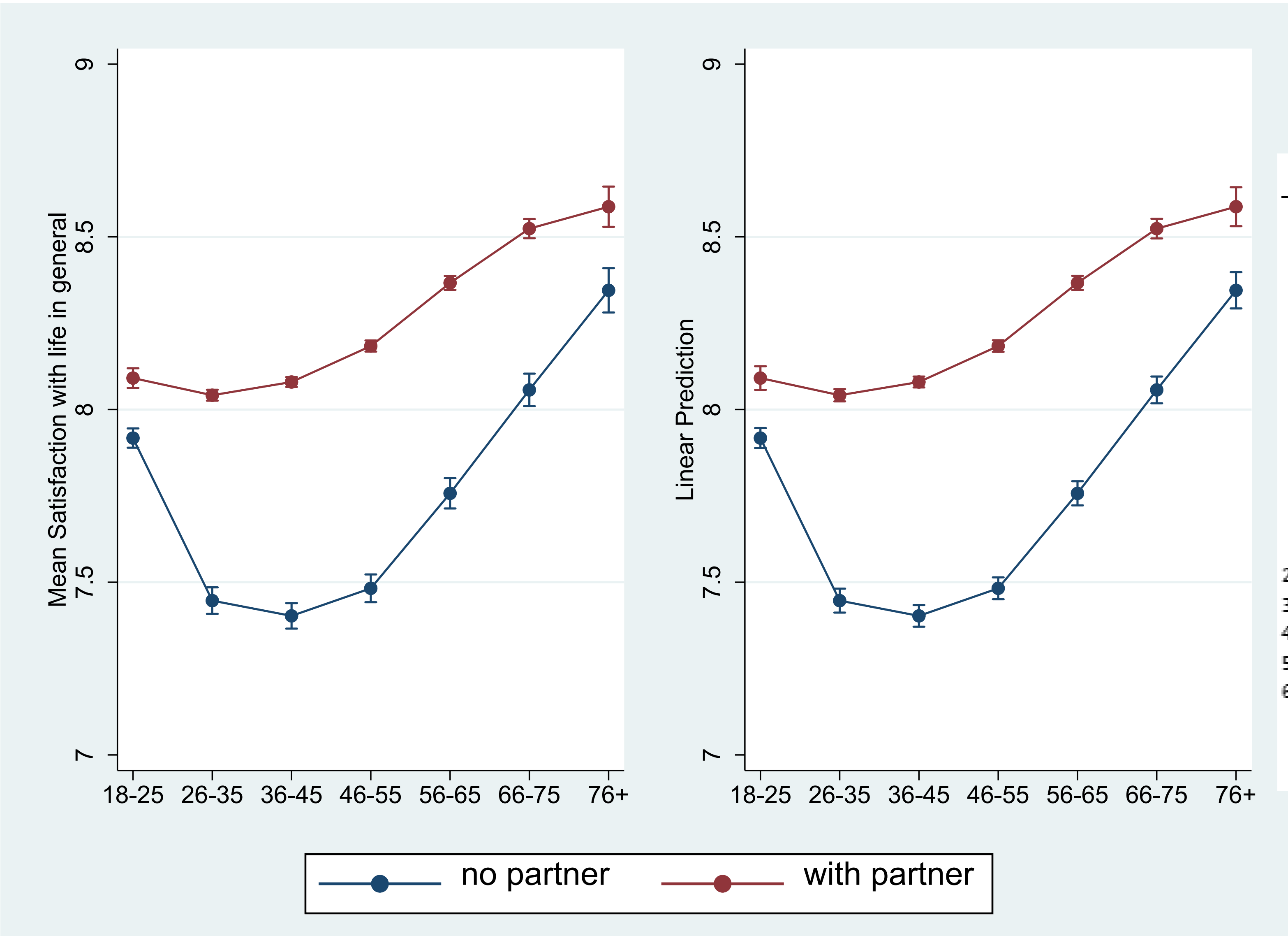
- 1st wave (technical confounder: too high report of happiness)
- survey year: period and fieldwork effects (techn./exog. conf.)
- agecat, 18-25, 26-35, …., 66-75, 76+ (exogenous confounder)

No overcontrol bias. We do *not* include:

- health: part of partnership that affects happiness through health (mediator) would be lost.
- income/wealth (same reason)

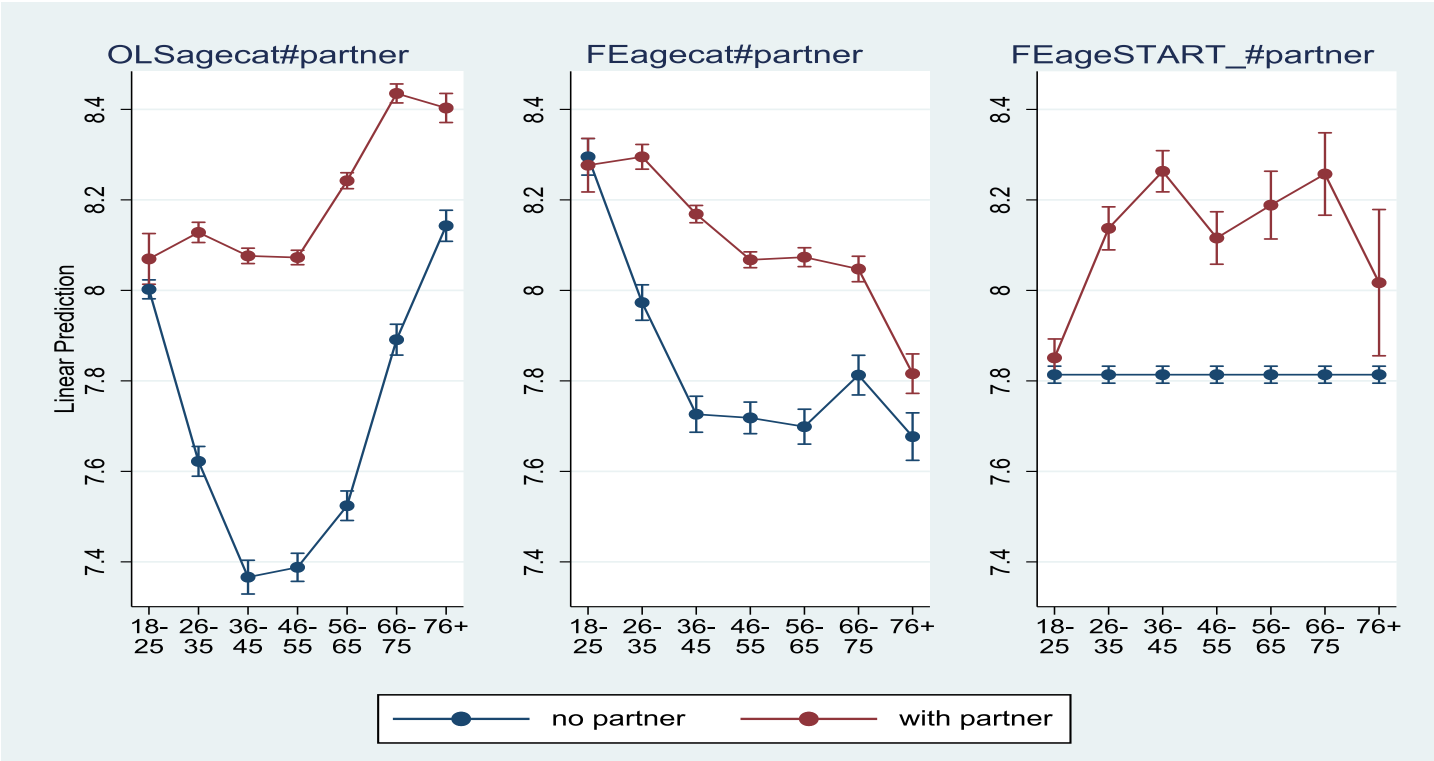
Raw values = OLS with interactions

“raw” relationship = Predicted values from OLS regression:



satlife	Coef.
agestart	
26-35	-.4842095
36-45	-.5264061
46-55	-.4453997
56-65	-.1747879
66-75	.1277996
76+	.4155071
partner	
with partner	.1669308
agestart#partner	
26-35#with partner	.4294541
36-45#with partner	.5101651
46-55#with partner	.533239
56-65#with partner	.4453144
66-75#with partner	.3080402
76+#with partner	.0759715
_cons	7.92908

Adequate model / time-varying covariates



Panels 2 and 3: Care with agecat X partner: We want the effect from partner, not from aging!
-> keep age constant within individuals (ageSTART).
-> only effect from partner at different ages estimable.

Panels 1 and 2: Happiness drops with age (Kratz & Brüderl 2021) -> FE

Problem in OLS:

- older age groups increasingly positively selected (health, satisfaction)
- older age cohorts happier (FE ok)
- omitted variables: e.g., migrants (unhappier, rather partnered) (FE ok)

Overcontrol: health

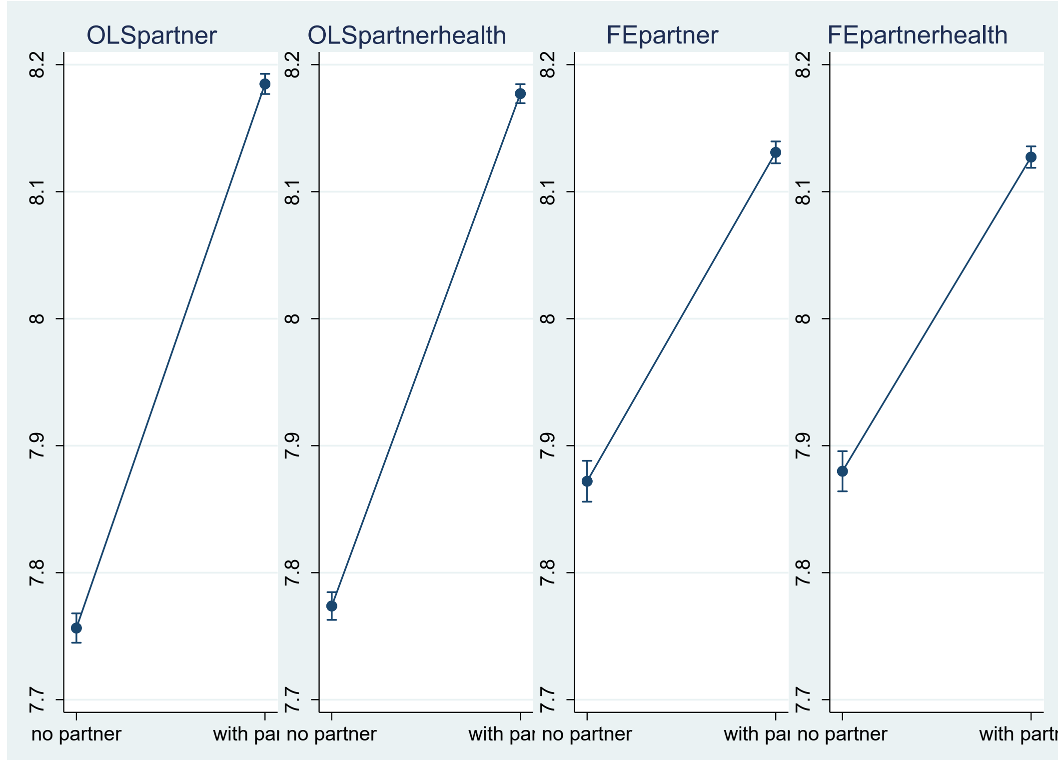
OLS Regression:

OLSpartner:

satlife	Coef.
partner	
with partner	.4284237
_cons	7.75641

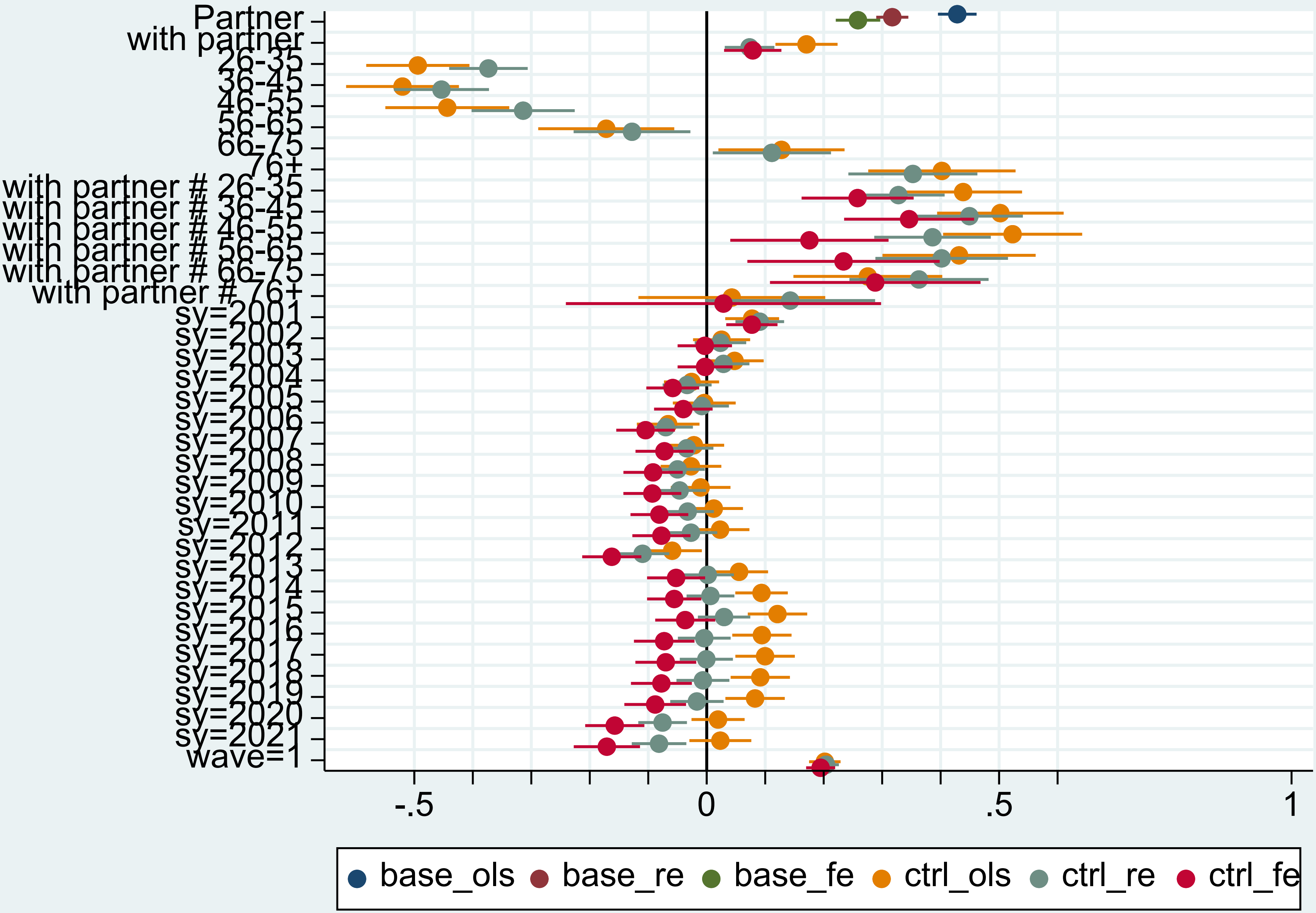
OLSpartnerhealth:

satlife	Coef.
health	
1	1.388222
2	2.48981
3	3.254251
4	3.74775
partner	
with partner	.4034427
_cons	4.558023



The part of partnership that affects happiness through health (mediator) is lost

Coefficient plot: OLS, RE, FE

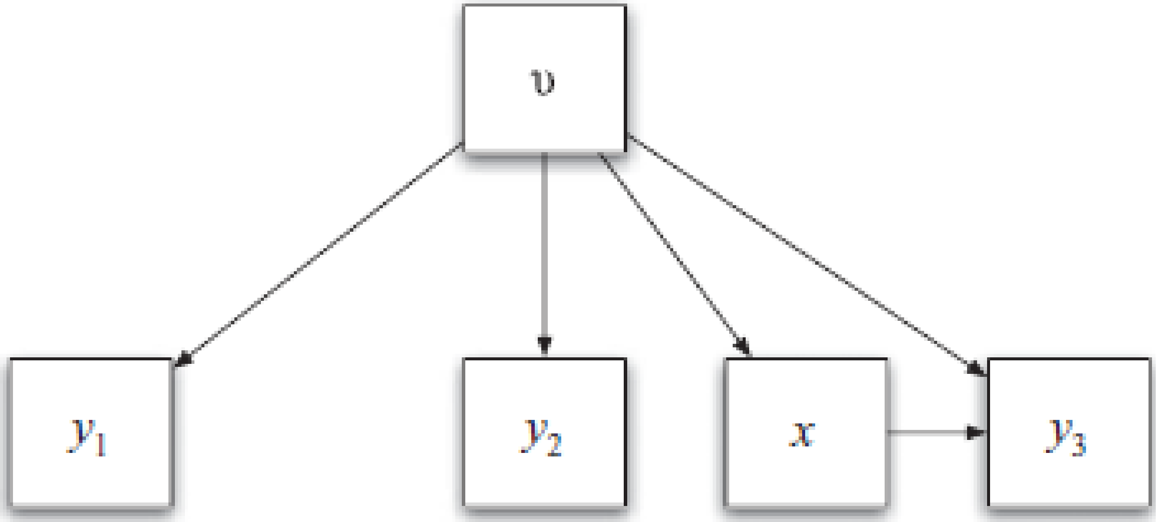


re between ols and fe

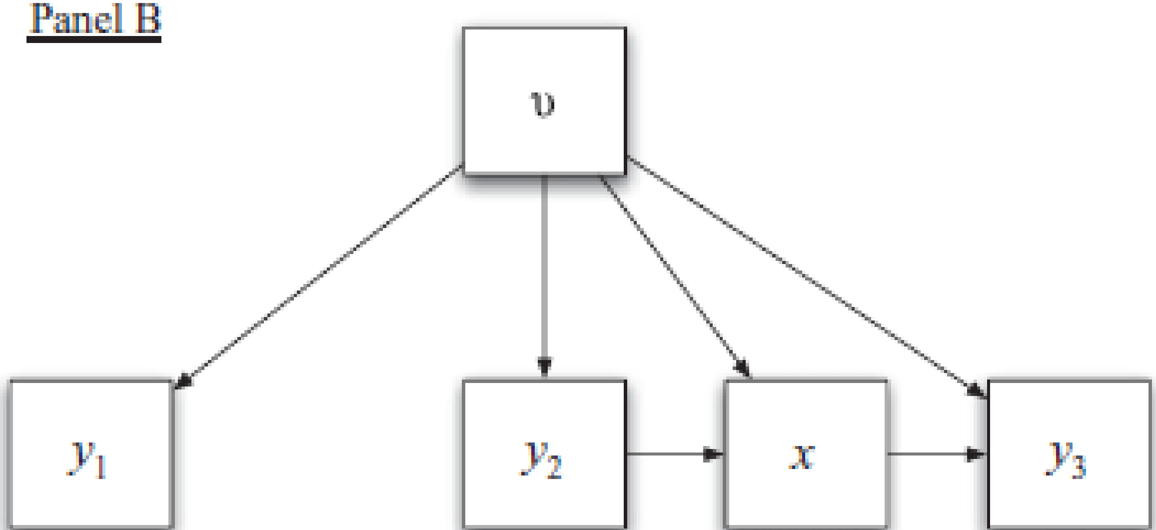
6. Test assumptions of FE models

1.Treatment selection effect (Vaisey & Miles, 2017, Fig.2)

Panel A



Panel B



Panel A: classic FE case: y_t are functions of an unobserved time-constant fixed effect (u), selection into the treatment (x) is based on u, and y_3 is affected by both u and x

Panel B makes the treatment x a function of the previous wave's outcome variable. Controlling for u alone does not prevent the effect of y_2 on y_3 through x from "leaking through" into the estimate of the effect of x.

1. Test Treatment selection effect

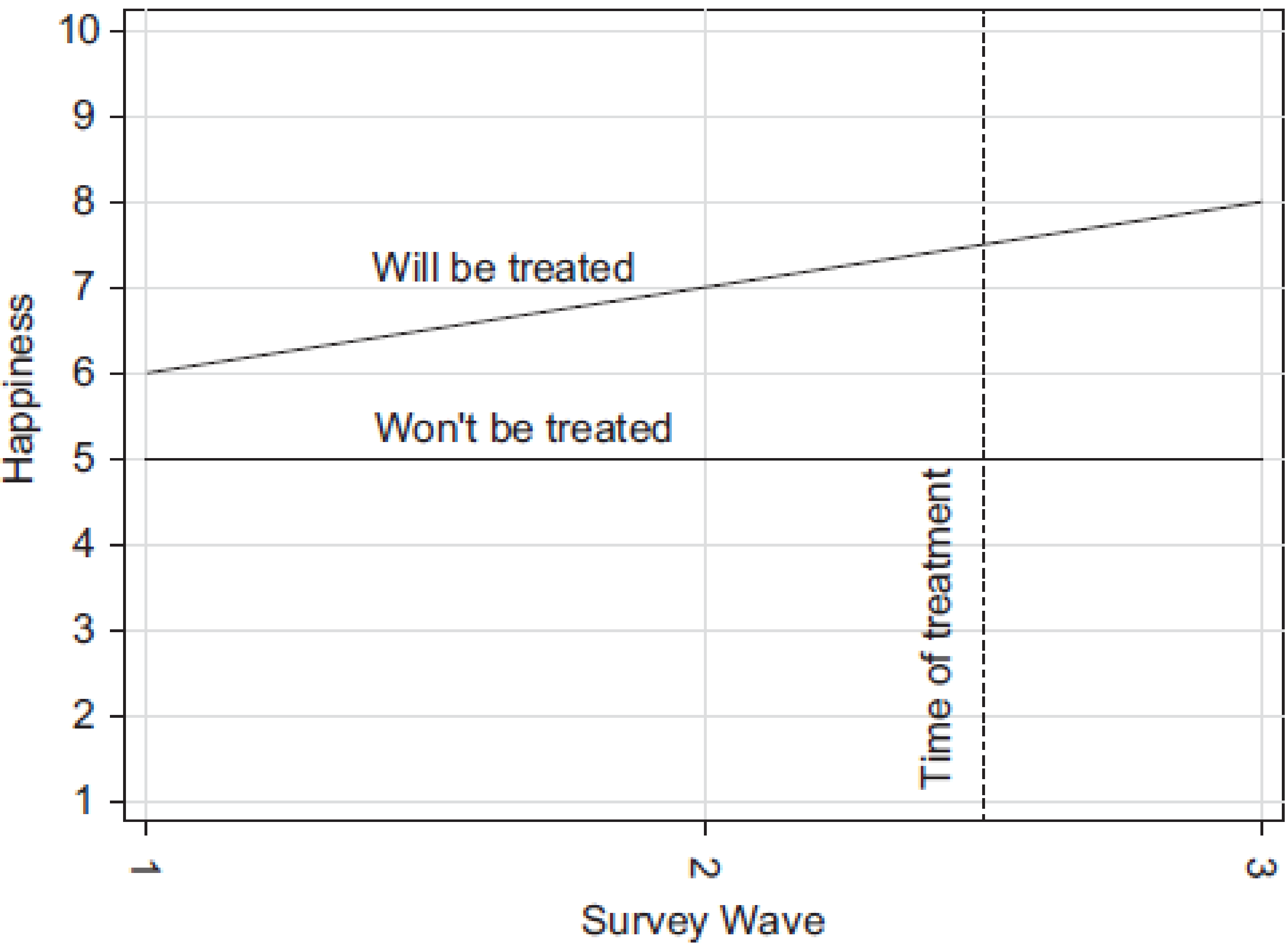
The test checks, if x_t can be predicted by y_{t-1} net of a proxy for the (time-constant) fixed effect?

We proxy the fixed effect by the sum $y_{t-1} + y_{t-2}$
So we regress $partner_t$ on $happy_{t-1}$ and on $(happy_{t-1} + happy_{t-2})$

partner	Coef.	Std. Err.	t	P>|t|	
satlife					
L1.	.0013211	.0013265	1.00	0.319	insignificant
l12satlife	.0326805	.0015419	21.19	0.000	
_cons	.1623415	.0235284	6.90	0.000	

-> no evidence of treatment selection

2. Parallel trajectories (Vaisey & Miles, 2017, Fig.5)



If treated and untreated have different time trends, FE coefficients will be biased, because **FE fails to account for time trends that differ between will-be-treated and won't-be-treated** groups prior to the treatment.

1. Test Treatment selection effect

We use a model that allows different treatment groups to have different time slopes. In the modified hybrid model:

$$y_{it} = b_1\bar{x}_i + b_2(x_{it} - \bar{x}_i) + c\,t + d(t\bar{x}_i) + \alpha_i + e_{it}$$

we allow respondents with different average levels of x to have different time trajectories (re model)

satlife	Coef.	Std. Err.	z	P>|z|
c_partner	.2571382	.0192564	13.35	0.000
m_partner	9.925261	3.879543	2.56	0.011
sy	-.0037778	.0016657	-2.27	0.023
c.sy#c.m_partner	-.0047139	.0019269	-2.45	0.014

Interaction term indicates small endogenous selection.

Note: b_2 is in FE models not biased by potential differences in time slopes for those with different mean values of x.

Literature

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Andreß, H., Golsch, K., & Schmidt, A. (2013). Applied panel data analysis for economic and social surveys. Springer Science & Business Media.

Brüderl, J. & Ludwig, V. (2015). Fixed-effects panel regression. In: SAGE Handbook of regression analysis and causal inference (eds: Best and Wolf), 327-357.

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Short (2-3 wave) panels:

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