

Dependent Interviewing

A Remedy or a Curse for
Measurement Error in Surveys?

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Paulina Pankowska, p.k.p.pankowska@vu.nl

Vrije Universiteit Amsterdam, Statistics Netherlands

Presentation outline

- Background
 - Longitudinal surveys & measurement error
 - Dependent interviewing (DI)
- Our research
 - Evaluating the effect of DI on:
 - Reliability of questions
 - Model estimates



Longitudinal surveys

- Collect data for same individuals over time
- Allow studying over-time change/ transitions

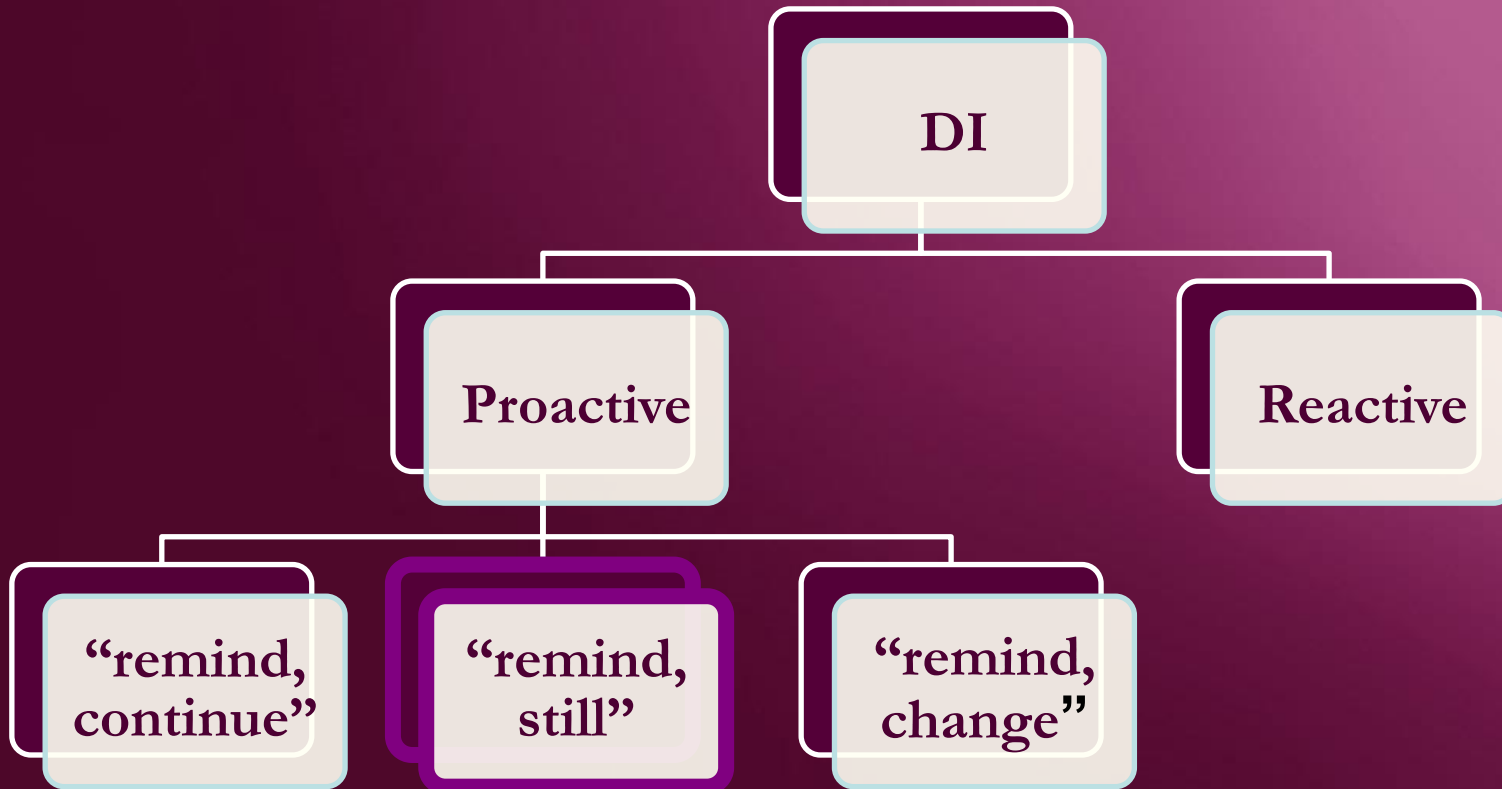
But...

- Suffer from measurement error which affects transition estimates
 - Spurious change
- (Potential) solution- **DI**



Dependent interviewing (DI)

- Interviewing technique in which respondents are reminded of previous answers



DI & measurement error

- Expected to reduce (random) error
 - Assists recall → less spurious change
 - Reduces cognitive burden
- Might lead to systematic error
 - Satisficing → error carry-over
- Overall effect on reliability and estimates **uncertain**



Our research

- **Focus:** Evaluating the effect of DI on measurement error
- **Method:** Using latent class modelling to estimate misclassification rates and bias under DI and INDI
- **Data:**
 - Linked data from the Dutch LFS and ER
 - Main variable of interest- individuals' contract type (3 categories: permanent, temporary, other)



Our research

- **Temporary contracts**

- **DI:**

- In place until end of 2009
 - PDI- “remind, still”
 - Only if no job change occurred

“Last time you had a temporary contract. Is this still the case?”

- **INDI:**

- In place since 2010
 - Also in 2009 if job change occurred

“Do you currently have a permanent contract?”

Our research

- **Permanent contracts**
 - No job change occurred- value carried over
 - Job change occurred- question asked
- **A total of 3 scenarios:**

Job change occurred	2009	2010
Yes	(I) IND for temp and perm	
No	(II) DI for temp and value copied for perm	(III) INDI for temp and value copied for perm



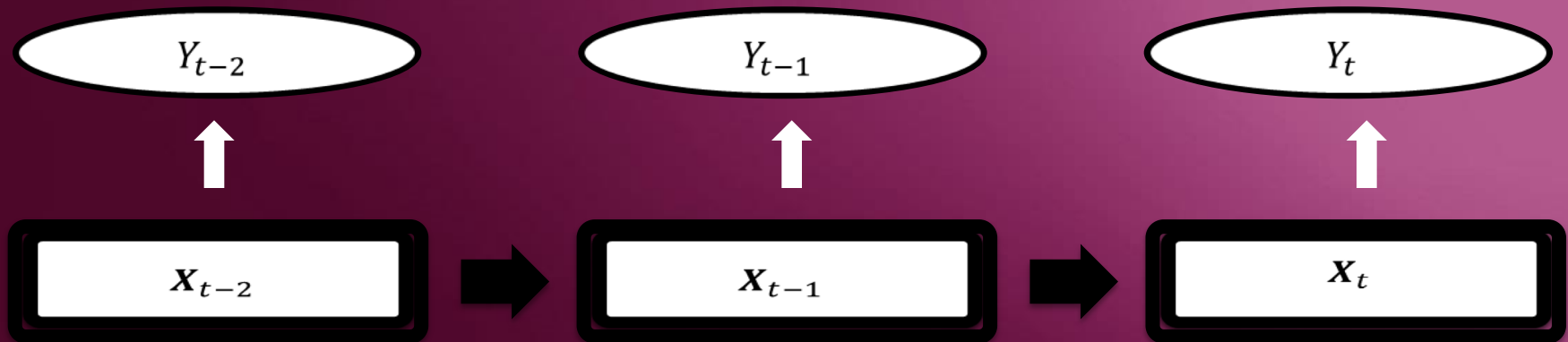
Latent Class Modelling (LCM)

- **Latent class analysis (LCA):**
 - Applied to categorical, cross-sectional data
 - Uses multiple conditionally independent indicators
 - Separates true value from error
- **Hidden Markov Models (HMMs):**
 - Applied to categorical, longitudinal data
 - Uses repeated measures over time
 - Separates true change from error



Hidden Markov Models (HMMs)

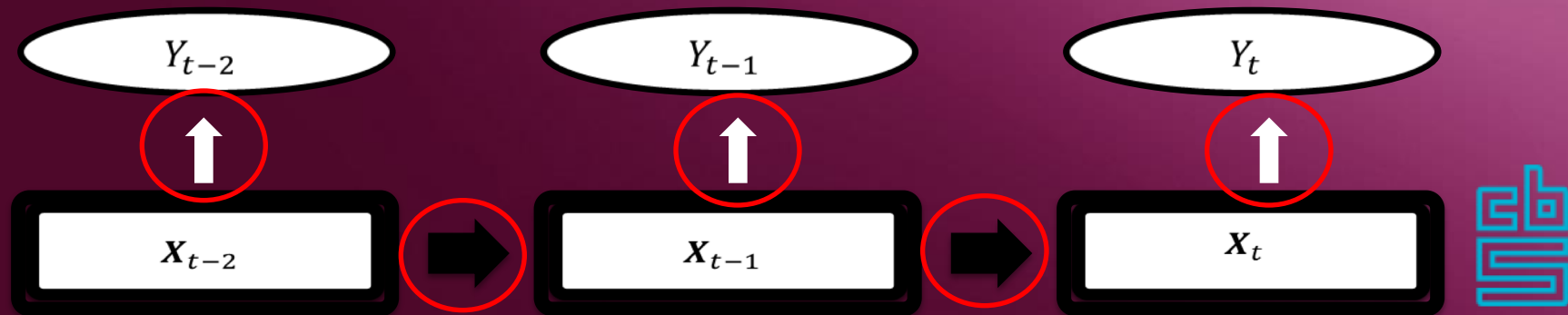
- HMMs consist of:
 - a structural part (latent/ true)
 - a measurement part (observed)



$$P(Y_i = y_i) = \sum_{x_0=1}^k \sum_{x_1=1}^k \dots \sum_{x_T=1}^k P(X_{i0} = x_0) \prod_{t=1}^T P(X_{it} = x_t | X_{i(t-1)} = x_{t-1}) \prod_{t=1}^T P(Y_{it} = y_t | X_{it} = x_t)$$

Hidden Markov Models (HMMs)

- HMMs assume that:
 - The latent state at time t only depends on the latent state at time $t-1$ - *the Markov assumption*
 - The observed state at time t only depends on the latent state at time t - *the local independence assumption*

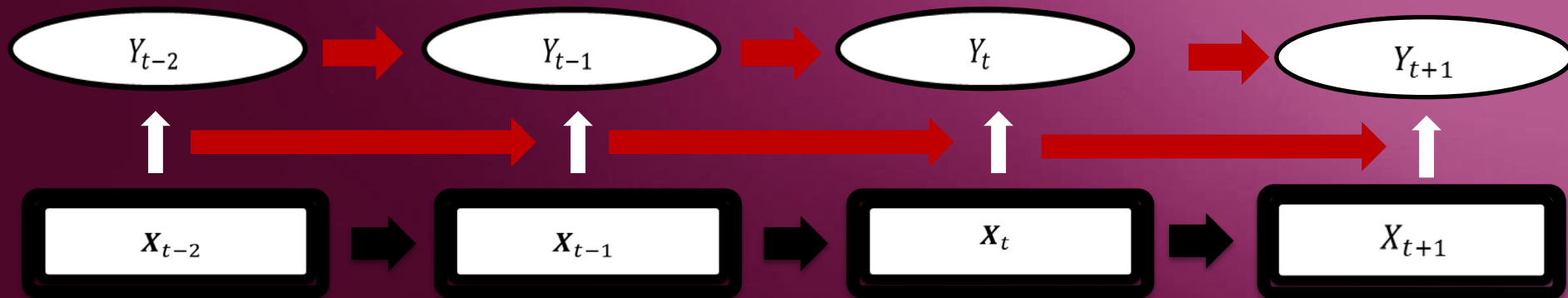


HMMs & DI

- DI (might) lead to autocorrelation of error



- Need to relax the local independence assumption

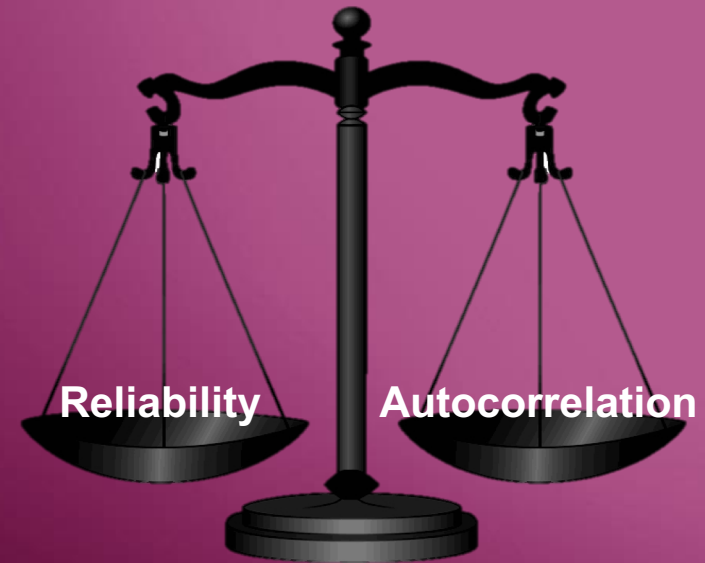


HMMs & DI

- Impossible to model autocorrelation and time-variant misclassification rates

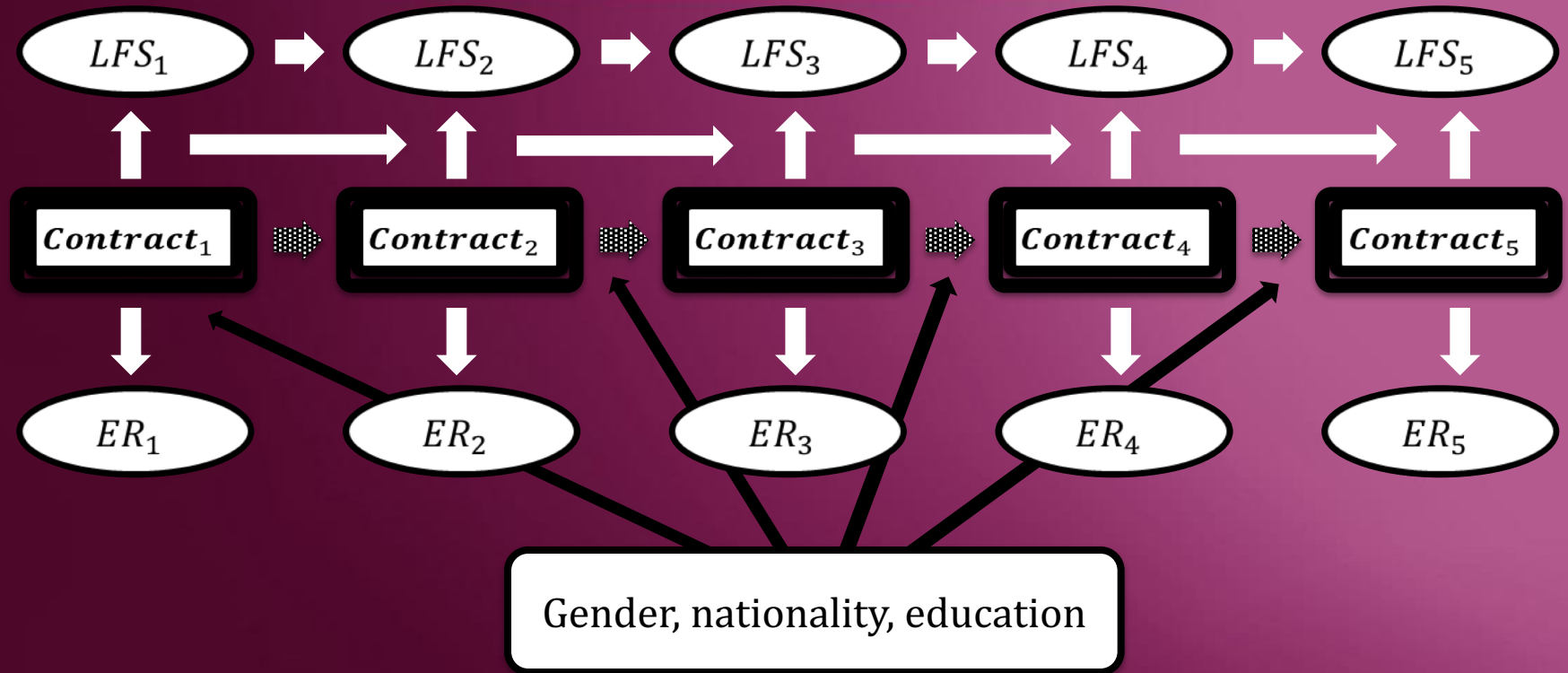


- Identifiability requires constant reliability



- **Unless** there are multiple indicators per time point (allow modeling both)

Our model



$$P(C_i = c_i, E_i = e_i | Z_i) = \sum_{x_0=1}^3 \sum_{x_1=1}^3 \dots \sum_{x_T=1}^3 P(X_{i0} = x_0 | Z_i)$$

$$\prod_{t=1}^T P(X_{it} = x_t | X_{i(t-1)} = x_{t-1}, Z_i)$$

$$P(E_{i0} = e_0 | X_{i0} = x_0)$$

$$\prod_{t=1}^T P(E_{it} = e_t | X_{it} = x_t, X_{i(t-1)} = x_{t-1}, E_{i(t-1)} = e_{t-1})$$

$$\prod_{t=1}^T P(C_{it} = c_t | X_{it} = x_t)$$

Data

- Linked dataset with information from LFS and ER
- Sample consists of 20,760 individuals aged 25 to 55 who
 - I. Started LFS in first quarter of 2009 (8,536)- *DI*
 - II. Started LFS in last quarter of 2010 (12,080)- *INDI*
- Dataset contains quarterly information on each individual for 5 time points



Results

- Misclassification (measurement error) rates

Scenario	Overall	Temporary contracts	% of cases
(I) Job change (2009/ 2010)- INDI	0,13	0,22	20%
(II) No job change & 2009- DI	0,11	0,28	24%
(III) No job change & 2010- INDI	0,11	0,25	17%

- Probability of carrying-over the same error for DI

Observed at t-1	Latent at t-1	Latent at t	Observed at t		
			Perm	Temp	Other
Temporary	Permanent	Permanent	0,10	0,90	0,00
Temporary	Other	Other	0,00	0,87	0,13



Results

- Misclassification rates for those who had or would have had DI (overall and by wave)

Scenario	Overall	Wave				
		1	2	3	4	5
(II) No job change & 2009- DI	0,301	-	0,301	0,290	0,307	0,306
(III) No job change & 2010- INDI	0,297	-	0,291	0,295	0,300	0,305

Results

- Latent and observed contract distributions

Type of contract	2009		2010	
	Observed	Latent	Observed	Latent
Permanent	0,69	0,61	0,68	0,60
Temporary	0,05	0,14	0,05	0,14
Other	0,26	0,25	0,27	0,26

- Latent and observed contract transition rates

Transition rate	2009		2010	
	Observed	Latent	Observed	Latent
Temp to perm	0,07	0,05	0,11	0,05

Conclusions

- Overall, DI appears to have a marginal effect on data quality
- DI associated with high probability of the copying of errors
- DI reduces random error (spurious change)



Thank you!

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- Dimitris Pavlopoulos, d.pavlopoulos@vu.nl

