Different methods for strengthening causal inference based on observational register data in the field of employment and health

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Introduction

Evaluation studies in the field of employment and health
- Effect of interventions and policy measures on employment participation and health

Availability of longitudinal register data
- Data linkage – large diversity of variables
- No selection bias
- Large study population

Challenges
- Interventions are not randomly occurring
- (Un)observed characteristics may differ between individuals who are / are not exposed

Different analytical strategies
- Anticipate on challenges of observational data & strengthen causal inference


Discussion paper

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Evaluation of occupational health interventions using a randomized controlled trial: challenges and alternative research designs

by Roosmarijn MC Schelvis, MSc,[1,2,3,4] Karen M Oude Hengel, PhD,[1,2,3] Alex Burdorf, PhD,[1] Birgitte M Blatter, PhD,[2,3] Jorien E Strijk, PhD,[2] Allard J van der Beek, PhD[3,4]

Overview of analytical strategies

- Propensity Score Matching
- Fixed effects model
- Within-between model
- Difference-in-Differences analysis
- Instrumental Variable (IV) model

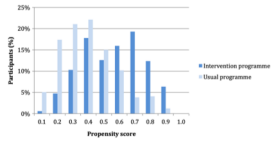
Propensity Score Matching

- Evaluation of an intervention in a non-randomized setting
- Takes into account differences in characteristics of intervention and control group
- Matching on the probability to be exposed to the intervention (=propensity score)

Best practice
- Stratified analyses based on propensity score

Disadvantage
- Reduction of sample size – lower power

Alternative strategy
- Include propensity score as independent variable in regression model



Propensity Score: an example

Aim: To investigate the influence of an interdisciplinary re-employment programme on health and (employment)participation among unemployed persons with mental health problems.

Study population
- Unemployed persons
- Mental health problems
- Intervention group (n=181)
- Control group (n=253)

Data
- Self-reported data
- ExIT cohort (2011-2014)

Results
- Increase in employment participation in intervention and control group (difference not statistically significant)

Table 2 Effect of participation in interdisciplinary re-employment programme and regular re-employment programmes on entering fulltime paid employment, any paid employment and voluntary work among unemployed persons

	Start of study % (N)	After 2 years % (N)	Difference in 2-year change intervention versus reference	
			Crude OR(95%CI)	Adjusted OR (95%CI)
Fulltime paid employment (GE36 h/week)				
Interdisciplinary re-employment programme	0%	9.8% (5/51)	1.50 (0.35–6.44)	1.65 (0.38–7.11)
Usual re-employment programme	0%	3.7% (4/107)		
Any paid employment				
Interdisciplinary re-employment programme	9.4% (17/181)	25.5% (13/51)	0.61 (0.26–1.43)	0.69 (0.25–1.87)
Usual re-employment programme	7.9% (20/253)	21.5% (23/107)		
Voluntary work (at least once a month)				
Interdisciplinary re-employment programme	18.8% (34/181)	35.3% (18/51)	1.25 (0.55–2.81)	1.15 (0.45–2.93)
Usual re-employment programme	26.1% (66/253)	42.1% (45/107)		

Adjusted propensity score in regression model, *Crude* propensity score *not* in regression model

Influence of an Interdisciplinary Re-employment Programme Among Unemployed Persons with Mental Health Problems on Health, Social Participation and Paid Employment

Beouwine E. Corbier[1] · Merel Schuring[1] · Alex Burdorf[1]

Propensity Score Matching: pros and cons

Strengths
- Takes into account differences in *observed* characteristics between groups
- Applicable to a wide range of situations

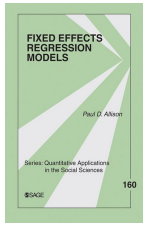
Limitation
- Propensity Score Matching – reduction of power for statistical analyses

Fixed effects model

Fixed effects models
- Within-individual changes
  - Each individual serves as its own control
  - Making comparisons within individuals over time
- Evaluation of the influence of events on outcome measures

Challenge
- Persons with an event may differ from those without an event in baseline characteristics
  → All time-constant variables are omitted from the analysis

Analytical procedure
- Include only time-varying variables in model
- Subtract the individual mean from each observation
- Perform regression analysis with deviation scores of all included variables



Fixed effects model: an example

Aims: To investigate associations of improvements/deteriorations in working conditions and health behavior and changes in work ability and health

Study population
- Employed persons (n=14.066)
- Aged 45-64 years

Data
- Self-reported data
- STREAM cohort (2010-2017)

Results
- Stronger associations for within-individual deteriorations in working conditions compared to within-individual improvements

Table 3 Within-individual deteriorations in working conditions, health behaviours and BMI in a given year and changes in work ability and self-rated health in the same year among 14 066 workers aged 45–63 years

	Change in self-reported work ability (0–10)		Change in self-rated health (1–5)	
	N*	b (95% CI)	N*	b (95% CI)
Working conditions				
Increase of psychological job demands (1–5)	15 375	**–0.23** (–0.27 to –0.19)	15 381	**–0.07** (–0.09 to –0.06)
Increase of emotional job demands (1–5)	13 996	**–0.25** (–0.29 to –0.21)	14 004	**–0.08** (–0.10 to –0.07)
Decrease of autonomy (1–5)	16 141	**–0.28** (–0.33 to –0.24)	16 148	**–0.10** (–0.12 to –0.08)
Decrease of social support (1–5)	16 594	**–0.21** (–0.25 to –0.18)	16 601	**–0.07** (–0.09 to –0.06)
Increase of physical workload (1–5)	12 551	**–0.26** (–0.31 to –0.20)	12 555	**–0.10** (–0.12 to –0.08)
Health behaviours and BMI				
Decrease in moderate physical activity (0–7)	12 900	**–0.04** (–0.05 to –0.03)	12 908	**–0.02** (–0.03 to –0.02)
Decrease in vigorous physical activity (0–7)	13 137	**–0.04** (–0.05 to –0.02)	13 142	**–0.02** (–0.03 to –0.02)
Start smoking (1=yes, 0=no)	599	–0.05 (–0.21 to 0.11)	597	0.02 (–0.04 to 0.08)
Increase in BMI (kg/m²)	17 757	**–0.05** (–0.06 to –0.03)	17 766	**–0.03** (–0.03 to –0.02)


BMJ Open

Associations of within-individual changes in working conditions, health behaviour and BMI with work ability and self-rated health: a fixed effects analysis among Dutch workers

Fixed effects model: pros and cons

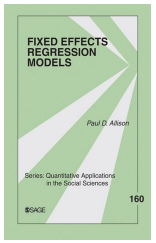
Strength

- Takes into account differences in characteristics between individuals, as long as these differences are constant over time

Limitations

- Reverse causality cannot be ruled out
  - Time lag can resolve this problem
- Only time-varying variables contribute to the model
  - Less statistical power

Within-between model



Also called 'hybrid model'

- *Within-individual changes* (among persons with an event)
  as well as *differences between individuals*

Analytical procedure

- Time-varying variables are split in two components
  - Time constant component (individual mean of all observations of each individual)
  - Time varying component (deviation of each observation from the individual mean)
- Time-constant variables as well as the two components of the time-varying variables are included in the regression model

Within-between model: an example

Aims: to investigate changes in health within individuals who entered paid employment, and differences in health between persons who entered employment or remained unemployed

Study population

- Unemployed persons
- Mental health problems

Data

- Self-reported data
- Fit4Work cohort

Results

- Improvement in health after entering employment
- Differences in health between (un)employed persons

Table 3. Within (change form unemployment to employment) and between (unemployed vs. employed persons) associations of employment status and health- and psychological measures among persons with common mental health problems (N=749). Hybrid model, adjusted for age, sex, and education. [b=regression coefficient, SE=standard error, OR=odds ratio, CI=confidence interval]

	Within-individual change				Between-individuals difference				Effect size within-individuals change
	b	SE	OR	95% CI	b	SE	OR	95% CI	
Mental health (0–100, higher is better)	16.34	3.40			26.74	5.08			0.68
Physical health (0–100, higher is better)	9.79	2.86			14.61	5.57			0.35
Self esteem (10–40, higher is better)	3.37	0.66			5.70	1.07			0.72
Mastery (6–18, higher is better)	1.69	0.38			2.74	0.64			0.58
Happiness (happy/very happy)			3.08	1.37–6.93			7.74	2.27–26.36	



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The benefits of paid employment among persons with common mental health problems: evidence for the selection and causation mechanism

by Schuring M, Robroek SJW, Burdorf A

Within-between model: pros and cons

Strength

- Not only time-varying, but also time-constant variables are included
- Variation of variables can be split in *differences between* individuals and *changes within* individuals

Limitation

- Reverse causality cannot be ruled out

Difference-in-differences model

Evaluation of an intervention/policy measure that is implemented in one specific region and not in another region

Challenge

- Individuals who are exposed to the intervention or policy measure may differ in baseline characteristics from those who are not exposed

Diff- in-diff approach

- Changes in trends over time before- and after exposure to the intervention, compared to those who are not exposed
- Differences in time-constant factors between regions are allowed

Assumption: No differences between regions in time-varying factors (except intervention)

Data requirements

- Observations before- and after implementation
- Observations in region where the intervention was (not) implemented

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Diff-in-Diff model: an example

Aim: To evaluate the influence of a job guarantee intervention on employment participation among secondary vocational education students

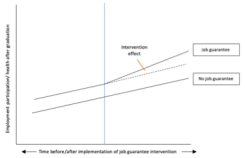
Study population

- Secondary vocational education students living in the City of Rotterdam who were (not) eligible for the job guarantee, based on
  - Their residential area
  - The study in which they were enrolled
  - The year of enrollment in education

Data

- Statistics Netherlands
  - Enrollment in education, type of education, graduation date
  - Residential area
  - Employment status per month

Study in progress



Evaluating a place-based job guarantee intervention on employment: a register-based cohort study among vocational education students

Famke J.M. Mölenberg, Alex Burdorf, Merel Schuring

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Diff-in-diff model: pros and cons

Strengths

- Causal effects from observational data
- (Time-constant) differences between groups are taken into account

Limitation

- We assume that there are no differences between regions in other time-varying factors
  - No other interventions/policies implemented

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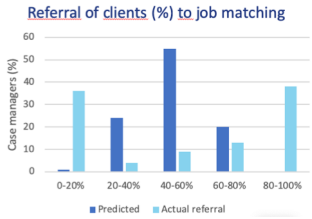
Instrumental variable (IV) model

Exploit the variation in exposure of persons to the intervention due to an exogenous factor

Example

Referral of clients by a case manager to job matching is influenced by

1. Individual characteristics of the client
2. Preference of the case manager (= instrument)



Assumptions

- Clients are randomly assigned to case managers
- Case managers are not involved in the employment services

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IV model: an example

Aim To evaluate the effect of 'job matching' on employment participation and health of welfare recipients

Study population

Welfare recipients in the city of Rotterdam

Instrument: preference of case manager

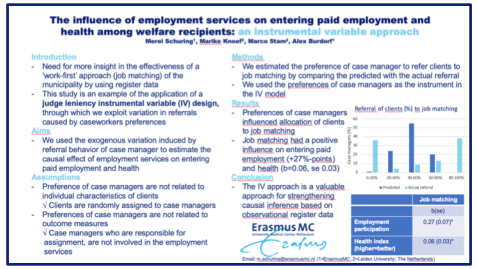
Data

Statistics Netherlands

(medication, employment)

Results

Job matching had a positive influence on employment participation and health



The influence of employment services on entering paid employment and health among welfare recipients: an instrumental variable approach

Morel Schuring[1], Marike Knoef[2], Marco Stam[1], Alex Burdorf[1]

Introduction
- Need for more insight in the effectiveness of a 'work-first' approach (job matching) of the municipality by using register data
- This study is an example of the application of a **judge leniency instrumental variable (IV) design,** through which we exploit variation in referrals caused by caseworkers preferences

Aims
- We used the exogenous variation induced by referral behavior of case manager to estimate the causal effect of employment services on entering paid employment and health

Assumptions
- Preference of case managers are not related to individual characteristics of clients
  √ Clients are randomly assigned to case managers
- Preferences of case managers are not related to outcome measures
  √ Case managers who are responsible for assignment, are not involved in the employment services

Methods
- We estimated the preference of case manager to refer clients to job matching by comparing the predicted with the actual referral
- We used the preferences of case managers as the instrument in the IV model

Results
- Preferences of case managers influenced allocation of clients to job matching
- Job matching had a positive influence on entering paid employment (+27%-points) and health (b=0.06, se 0.03)

Conclusion
- The IV approach is a valuable approach for strengthening causal inference based on observational register data

Referral of clients (%) to job matching

	Job matching
	b(se)
Employment participation	0.27 (0.07)*
Health index (higher=better)	0.06 (0.03)*

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IV model: pros and cons

Strength

- Causal effects from observational data

Limitations

- An exogenous factor that determines exposure to an intervention is difficult to find

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Conclusion

Different methods available to address the challenges of working with observational data.

- Differences between methods in strength of causal inference
- Applicable in different situations

Important to be aware of the strengths and limitations of each method

- Check (statistically test) the assumptions!

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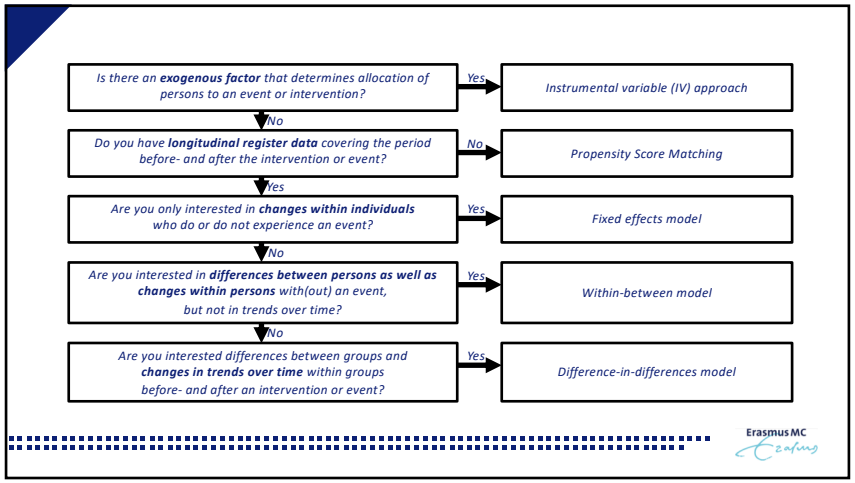
Questions

Which analytical strategy is best to strengthen causal inference in your research with observational register data?

What are the consequences of your analytical strategy for the interpretation of the findings?

Under which conditions is it justifiable to talk about causal effects based on research with observational register data?

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