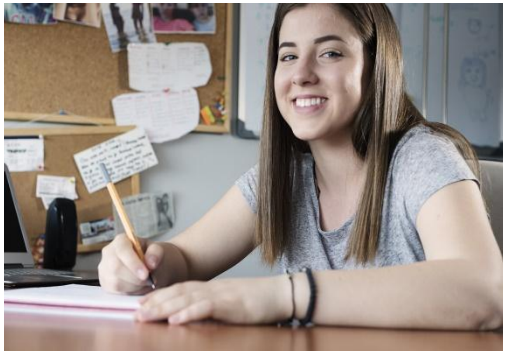

Growing Up in Ireland
National Longitudinal Study of Children

Time, Change and Causality
or
Getting the Most from GUI

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Introduction

- Time, change and causality
  - When is a cause, a cause?
  - The role of theory
- RCT's, observational data and longitudinal analysis
  - The problems of cross-sectional, panel and cohort studies
- Change in quantity and change in states
- The 'difference in difference' approach
- The fixed effects approach
  - Demeaning
  - First differences

Time, Cause and Statistics

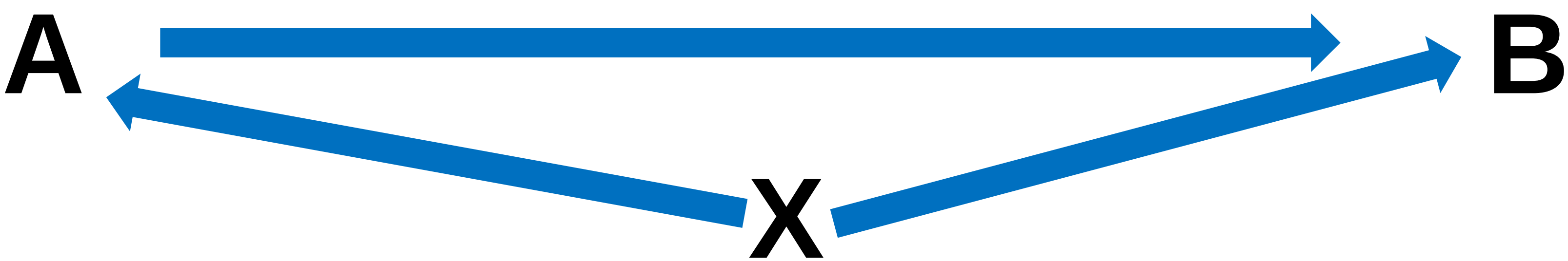
- Cause and effect are natural concepts
- Social scientists (part. Sociologists) can be queasy about ‘cause’
  - ‘Facts’ don’t speak for themselves
  - Invisible ‘social objects’ influence social behaviour
  - What are the causes of the causes?
    - Example, parenting in recession
- Empirical analysis needs to be guided by theory
- Have a model and hypotheses

Establishing Causality

- **The gold-standard of the randomised control trial:**
  - Isolation of ‘cause’ to one variable and manipulation
  - Random allocation to ‘intervention’ or ‘control’
  - Experimenter and subjects ‘blind’
- **Practical problems:**
  - Can we manipulate populations in natural settings
  - The issue of aggregates, e.g. communities
  - Lag periods, e.g. pensions, educational outcomes
- **Ethical problems:**
  - Can we expose individuals to ‘bads’?

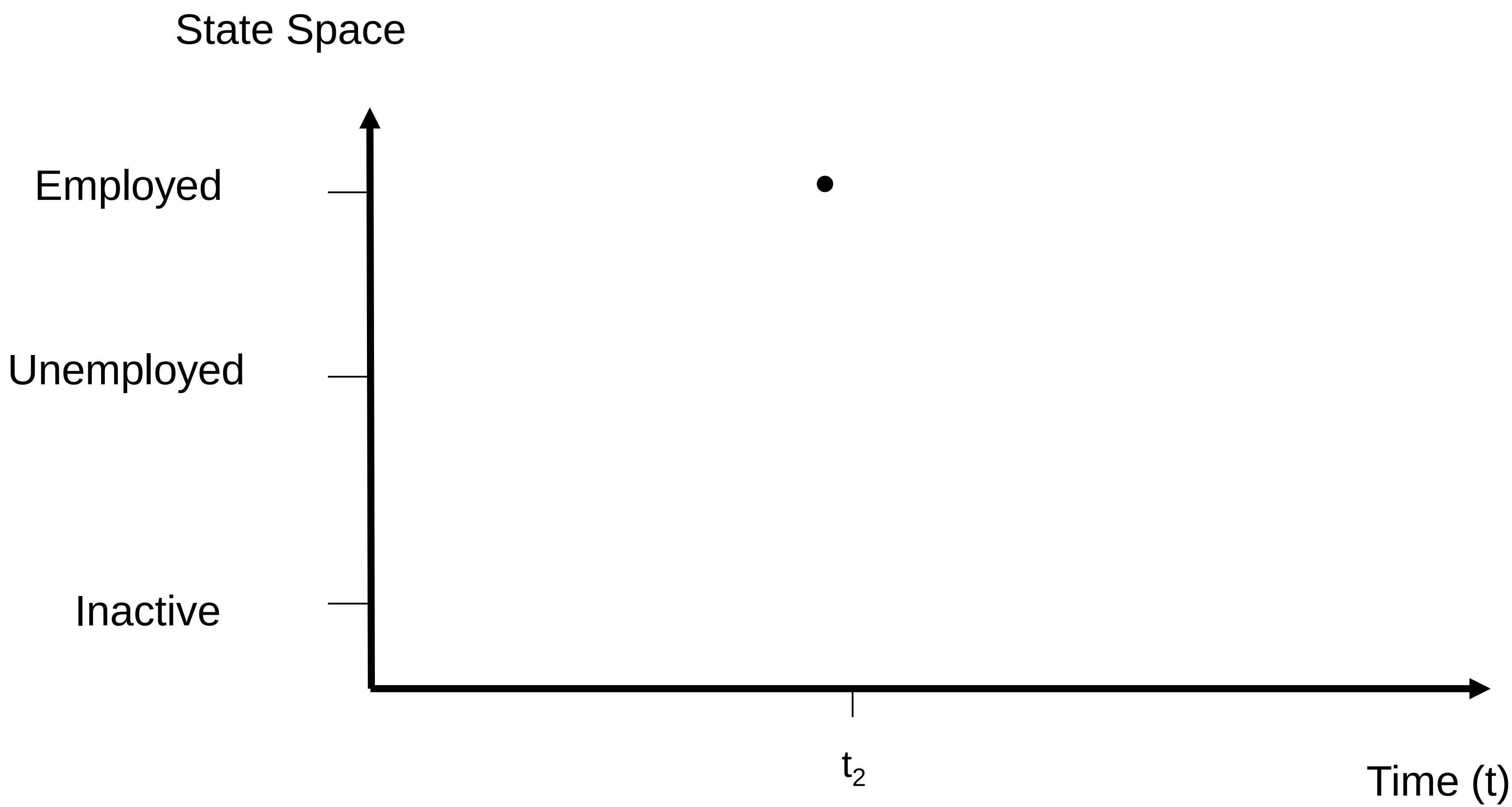
Longitudinal Studies

- The value of observational studies:
  - Naturalistic
  - Hopefully representative (variation)
- The problem of causality:



- Observing change over time – longitudinal studies
  - But how do we analyse these?

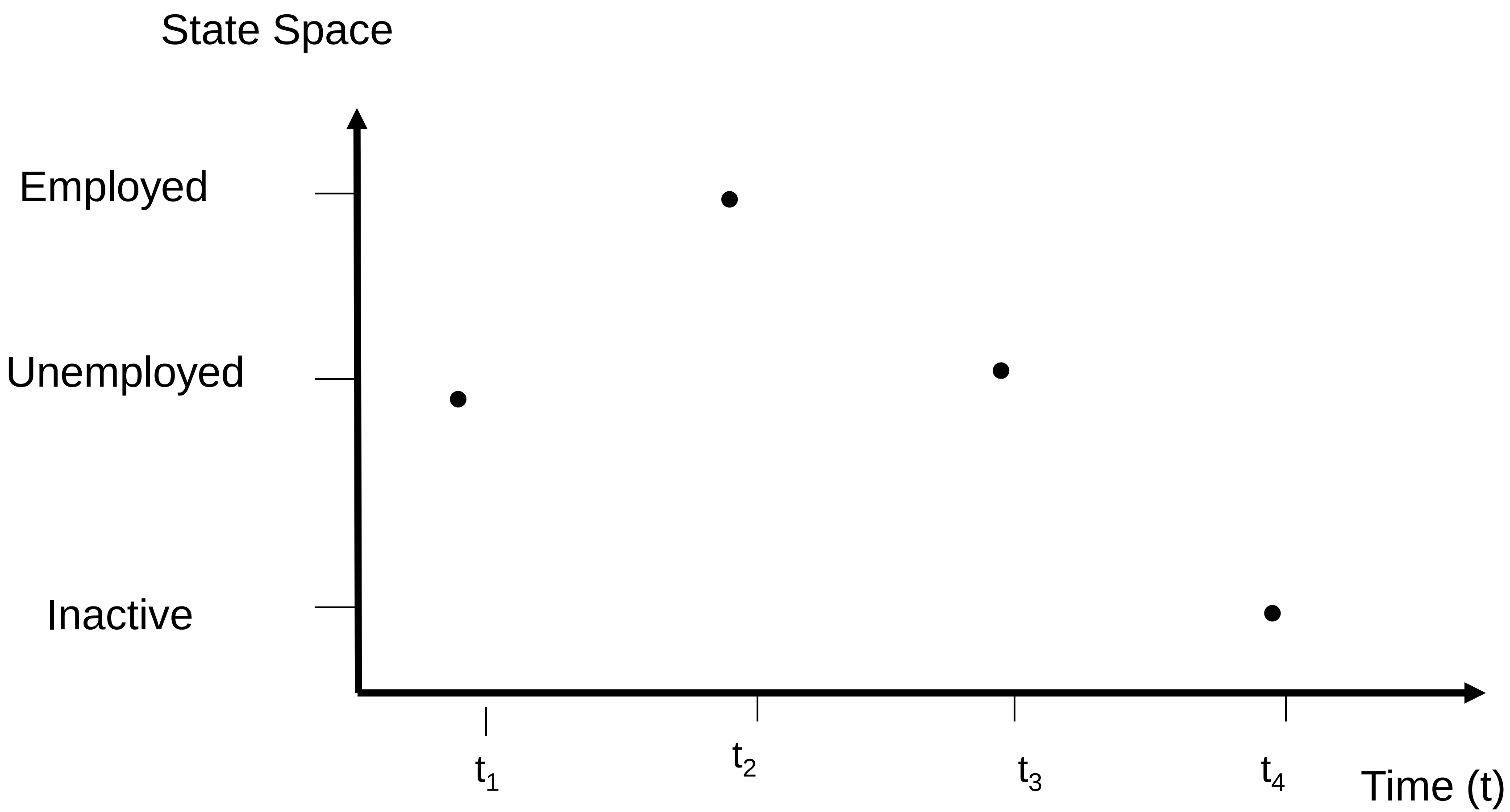
Cross-sectional Sample



Cross-Sectional Data

- CS analysis assume statistical equilibrium
- State probabilities are trend less and stable
- Coefficients express the net difference in the effects of predictors
- Cannot separate selection from causal effects
- Inferring causality is problematic – assume that predictors precede outcome and there are no feed backs

Data with Four Waves



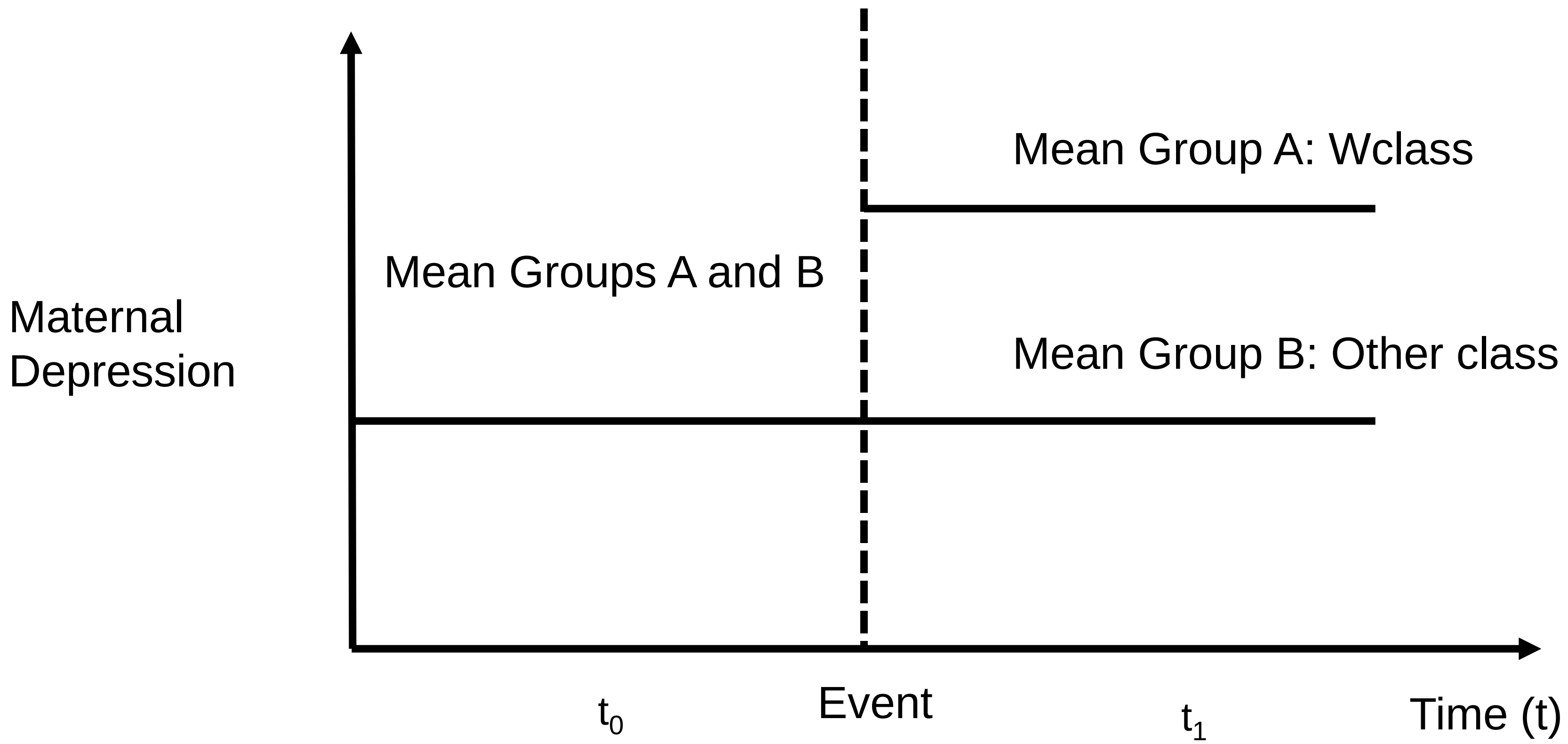
Change Over Two Time Points

- The addition of more observations permits analysis of quasi-causal relationships
- What predicts change from t_0 to t_1?
  - Change in whole population may just be coincidence
  - Change in a sub-population could be causal
- Leverage differential difference over time between groups: difference in difference
- Example: maternal depression, class and the impact of recession in 2010 compared to 2008

1. MD = α + Wclass + 2010 + error
2. MD = α + Wclass + 2010 + Wclass*2010 + error

Change Over Two Time Points

When analysing status change between two time points the classic approach is the 'difference in difference model':



Assumptions

- Outcome for both groups would be same in absence of ‘treatment’
- One group are not positively selected for the ‘treatment’
- If something else changed between t_0 and t_1, we can observe it and adjust for it
- There are no other, unobserved changes that will bias the estimate

Fixed Effects Models

- In the DinD estimate we assumed a great deal about changes that occurred between t_0 to t_1

$$MD = \alpha + Wclass + 2010 + Wclass{*}\underbrace{2010 + error}_{U_i}$$

- Multiple observations of the same individual allow us to control for individual differences
- Two approaches to ‘fixed-effects’:
    - Demeaning (sometimes called “within estimator)
    - First differencing

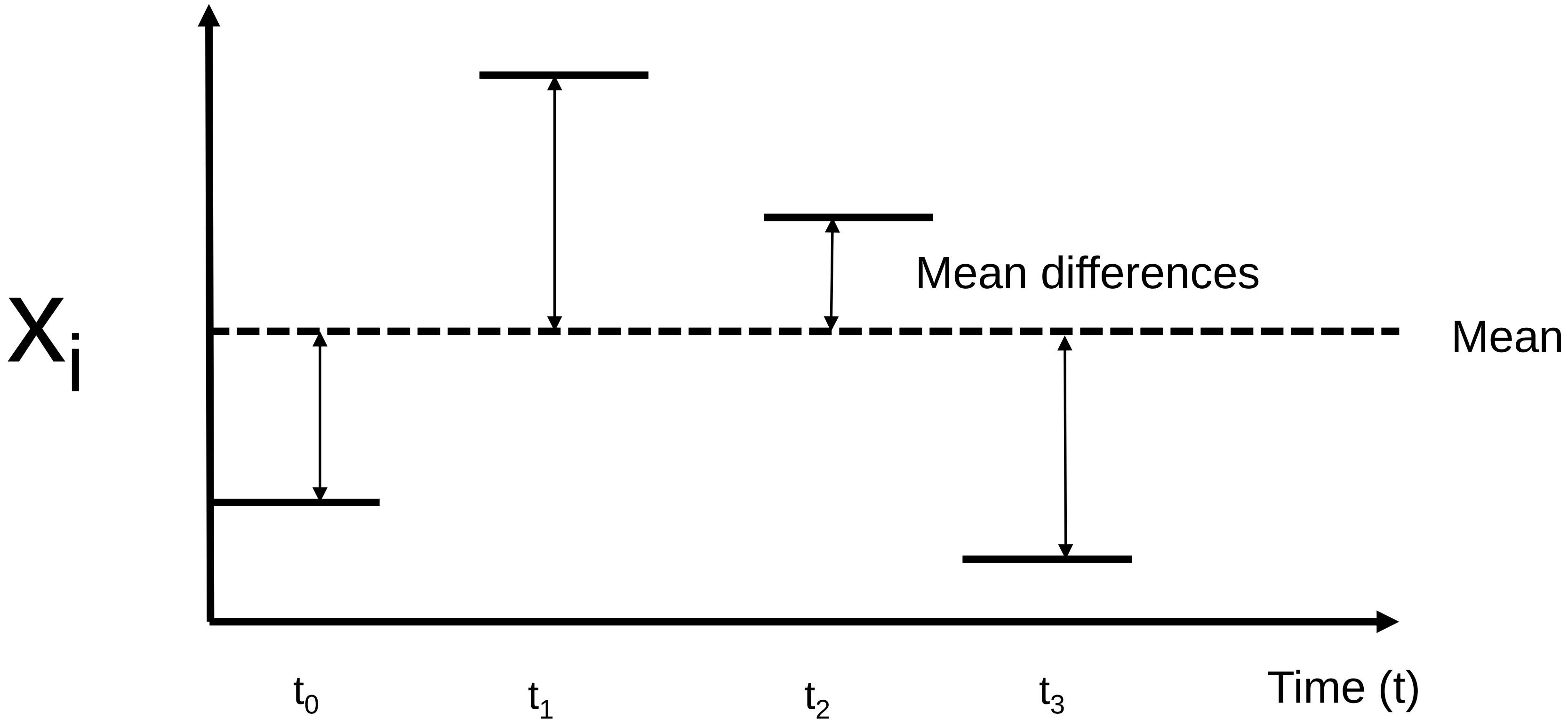
Demeaning

- With demeaning you (or computer) calculate individual averages of the dependent and explanatory variables
- You then subtract these averages from the regression equation:

$$\hat{y} = (yij - \bar{y}j) = \alpha + \beta(\chi ij - \bar{\chi}j) + \varepsilon ij$$

- So we are now predicting deviations from the individuals own mean rather than differences between individuals

Demeaning



First Differencing

- Alternative way of estimating the fixed effect is first differencing
- 'First differencing' subtracts the value of t_1 from the value of t_0 to produce the difference between the values
- We are thus explaining change at the individual level between periods
- Change can be explained by time constant (e.g. sex) and time-varying variables (e.g. income)
- First differencing can introduce serial correlation of the error terms so demeaning is usually a better option

Conclusion

- Longitudinal data offer a powerful tool for testing explanatory hypotheses
- Differential change across groups between periods useful even if the operative process unobserved
- Where operative variables observed, more powerful models can be estimated
- Explanatory analysis possible with two waves but more waves mean better estimates
- ‘Demeaning’ over 3 or more waves preferred