NATIONAL CENTRE FOR RESEARCH METHODS

Economic and Social Research Council

UNIVERSITY OF Southampton

MANCHESTER 1824 The University of Manchester

Longitudinal Data and Research

Day 1

http://bit.do/ncrm_longitudinal

Introduction to Longitudinal Data Analysis

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2022

Why Use Longitudinal Data?

- UK has an unparalleled collection
- These resources are critical for analysing social change (and social stability)
- But they need justification because they are costly in money and time

Longitudinal Social Surveys

- Cross-sectional data
  - Respondents surveyed at only one time point
- Longitudinal data
  - Repeated contacts (with the same individuals)
  - Respondents surveyed at multiple time points


DATA

Longitudinal Social Science Study Designs

Panel Study

The panel are the group and are repeatedly studied

- US (PSID)
- Germany (SOEP)
- Britain BHPS/UKHLS
- Australia (HILDA)
- Canada (SLID)
- Swiss (SHP); Korea (KLIPS); Russia (RLMS)

Longitudinal Social Science Study Designs

Cohort Study

- Repeated contacts data collection
 (simply a specific form of panel design in my view)

- Principally concerned with charting the development of a particular ‘group’ from a certain point in time

Longitudinal Social Science Study Designs

- Cohort Study

  - A birth cohort of babies born in a particular year (e.g. 1946; 1958; 1970; 2000-2)

  - A youth cohort, a group of pupils who completed compulsory education in the same year (YCS; LSYPE)

Research Using Longitudinal Social Survey Datasets

- For many social research projects cross-sectional data will be sufficient

- Most social research projects can be improved by the analysis of longitudinal data

- Some research questions require longitudinal data

Questions that Require Longitudinal Data

- Flows into and out of poverty
- The effects of family migration on the woman's subsequent employment activities
- Numerous policy intervention examples
- Numerous examples relating to 'individual' development

Key Messages (so far....)

- For many social research projects cross-sectional data will be sufficient

- Most social research projects can be improved by the analysis of longitudinal data

- *Researchers are likely to make more rapid progress using existing large-scale longitudinal data resources*

- Some research questions require longitudinal data

- Longitudinal data are not a panacea

'This longitudinal study suggests that notwithstanding the dominant effect of severity of intellectual impairment, a number of factors within and outside the family may also contribute to higher attainment in reading, writing and numeracy.

In particular mainstream schooling for those with less severe disabilities appears to have benefited the children in this study' (p.390).

Turner, S., Alborz, A. and **Gayle, V.** (2008) 'Predictors of academic attainments of young people with Down's syndrome', *Journal of Intellectual Disability Research*, 52(5), pp. 380-392.

Subjective Well-Being & Happiness

- Non-economic measures of social progress
- “Improving the quality of our lives should be the ultimate target of public policies” Angel Gurría, OECD Secretary-General
- UK commitment to developing wider measures of well-being
- Tailoring government policies to the things that matter

- Moving house itself causes a boost in happiness, and brings people back to their initial levels
- Moving and set-point theory
- Long-distance migrants are at least as happy as short-distance migrants despite the higher social and psychological costs involved
- Re-theorize moving within a conceptual framework that accounts for social well-being from a life-course perspective

Nowok, B., van Ham, M., Findlay, A. and **Gayle, V.** (2013) 'Does migration make you happy? A longitudinal study of internal migration and subjective wellbeing', *Environment and Planning A*, 45(4), pp. 986-1002.

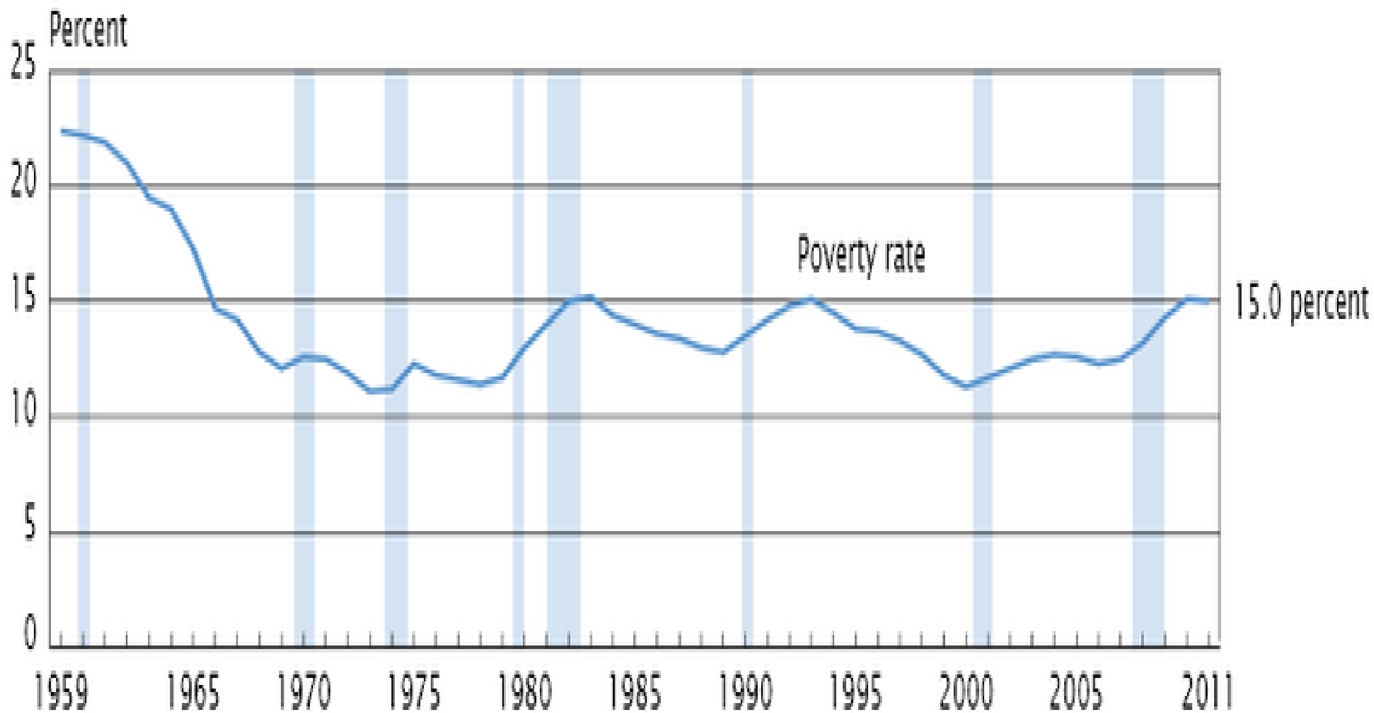
The Bigger Picture

- UKHLS is the largest living observatory of contemporary social life
- Contribution to the ‘evidence base’
- Contribution to empirically informed planning
- *Influencing behaviour and informing interventions*
- *Contributing to a fair and vibrant society*

Examples…

- Cohort studies - secondary smoking effects on children
- Whitehall Studies - influenced successive governments' thinking on social gradients in health
- Whitehall Studies -dispelled the myth that high status jobs have higher risk of heart disease

USA Poverty Rate 1959 - 2011



Note: The data points are placed at the midpoints of the respective years. For information on recessions, see Appendix A.

Source: U.S. Census Bureau, Current Population Survey, 1960 to 2012 Annual Social and Economic Supplements.

BHPS British Household Panel Survey

- Poverty rates flattened out in 1990s

- BHPS showed apparent cross-sectional stability but a hidden longitudinal flux
  - Substantial turnover or churning
  - The poor were not always poor

- Not detectable without panel data!

BHPS British Household Panel Survey

- UK Poverty rate approximately 18%
- In a 6 year periods one-third of individuals were poor at least once
- Only 2% were poor for all six years!
- Repeated short spells of poverty were more common than one long spell

The Consequences…

- Contributed to the ‘rubber band theory’
  - we are attached to an elastic tether
- Influenced the Labour government’s welfare reforms in the late 1990s
  - focussing on moving people into work and making work pay
- Now influences how living standards are measured in Britain
  - Official Statistics now include household panel based information

Summary Messages

- For many social research projects cross-sectional data will be sufficient
- Most social research projects can be improved by the analysis of longitudinal data
- Some research questions require longitudinal data

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The Research Value of Longitudinal Data

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A vignette…

The story of Jason Jones (aged 10) and his mum

Questions that Require Longitudinal Data

- Flows into and out of poverty
- The effects of family migration on the woman’s subsequent employment activities
- Numerous policy intervention examples
- Numerous examples relating to ‘individual’ development

Methodological Benefits of Longitudinal Social Science Data

- Micro-level social processes
- Temporal ordering of events
- Improving control for residual heterogeneity
- Improving control for state dependence

Micro-Level Social Processes

- Cross-sectional data = a snap shot
  - Good for studying the immediate
  - Several datasets can study macro / or gross changes

- Repeated contacts data allow the study of
  - The passage of time
  - Individual (or household) change/stability
  - Processes that occur at the micro-level of the individual (or family)
  - Surprises (or shocks)

Temporal Ordering of Events (Direction of Influence)

- Time moves in one direction so…
  - An event in 1990 comes before an event in 1995
  - Experiences at primary school could affect university entry
  - Teenage smoking could influence health in old age
- But not *vice versa*

  One sociology professor has argued with me suggesting that time does not move in only one direction

Temporal Ordering of Events (Direction of Influence)

- There is unequivocal evidence from cross-sectional data that, overall, the unemployed have poorer health

- This is consistent with both

  A. Unemployment causing ill health
  B. Ill health causing unemployment

- These two substantive stories are quite different

Month	Level of Health (20 = Good Health)	Employ Status
1	17	Employed
2	17	Employed
3	17	Employed
4	17	Unemployed
5	17	Unemployed
6	10	Unemployed
7	16	Unemployed
8	5	Unemployed
9	4	Unemployed
10	3	Unemployed
11	2	Unemployed
12	1	Unemployed

Person A

Became unemployed this has affected his level of health

Month	Level of Health (20 = Good Health)	Employ Status
1	17	Employed
2	1	Employed
3	1	Employed
4	1	Unemployed
5	1	Unemployed
6	1	Unemployed
7	1	Unemployed
8	1	Unemployed
9	1	Unemployed
10	1	Unemployed
11	1	Unemployed
12	1	Unemployed

Person B

Poor health led to unemployment

(because of poor job performance)

In a cross-sectional study (at month 12)

- Person A would have been unemployed for 9 months and have a health score of 1
- Person B would have been unemployed for 9 months and have a health score of 1
- This is an obvious example of how panel (i.e. repeated contacts) data can make an essential contribution to untangling social relationships

Improving Control for Omitted Explanatory Variables

- Residual Heterogeneity
  - Omitted explanatory variables
  - Unobserved heterogeneity
- The possibility of substantial variation between similar individuals due to unmeasured, and possibly immeasurable, variables is known as ‘*residual heterogeneity*’

Improving Control for Omitted Explanatory Variables

Because data collection instruments often fail to capture the detailed nature of social life there is, almost inevitably, considerable heterogeneity in response variables even amongst respondents that share the same characteristics across all of the explanatory variables

Improving Control for Omitted Explanatory Variables

As long as we make the assumption that (at least some of) these effects are enduring there are techniques for accounting for omitted explanatory variables if we have data at more than one time point

Improving Control for Omitted Explanatory Variables

- There are no routine methods of accounting for omitted explanatory variables in cross-sectional analysis

- It is sometimes claimed that the main advantage of longitudinal data is that it facilitates improved control for the plethora of variables that are omitted from any analysis

- Panel data won't completely sweep this problem away, but suitable models can improve control for, and estimate the effects of, residual heterogeneity

Improving Control for the Effects of Previous States (state dependence)

A frequently noted empirical regularity in the analysis of unemployment data is that those who were unemployed in the past or have worked in the past are more likely to be unemployed (or working) in the future

(Nobel Prize winner J.J. Heckman)

Improving Control for the Effects of Previous States (state dependence)

- Much of human behaviour is influenced by previous behaviour and outcomes (positive feedback)

- McGinnis (1968) ‘*axiom of cumulative inertia*’

Improving Control for the Effects of Previous States (state dependence)

- Working in May = more likely to be working in June
- Married this year = more likely to be married next year
- Own your own house this quarter
- Travel to work by car this week

Improving Control for the Effects of Previous States (state dependence)

With panel data we may be able to include past behaviour in the modelling process

Summary Message

There are methodological benefits…

but panel data are not a panacea!

Tweet - Longitudinal data enhance our ability to investigate complicated processes in the social world

The Research Value of Longitudinal Data

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Sources of Longitudinal Data

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Repeated Cross-Sectional Surveys

- Often over-looked as a source of longitudinal information
- Many countries have cross-sectional surveys that are carried out on a regular basis
- They offer the possibility of pooling data for different years
- Not based on repeated contacts with the same individuals or households
- But offer opportunities to analyse general trends over time

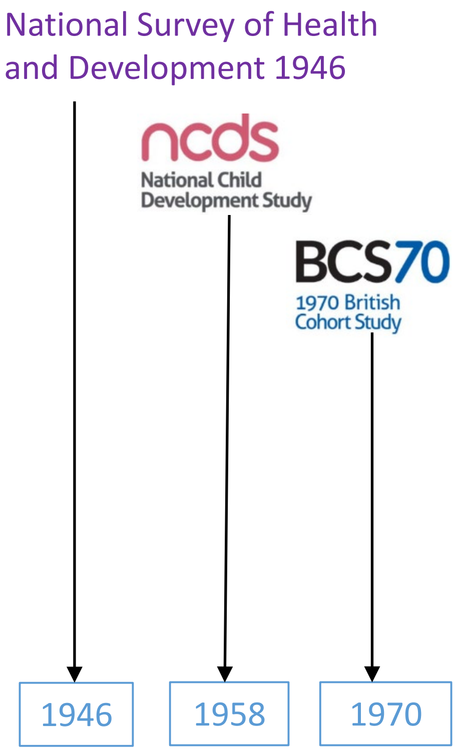
Studying Longer Term Trends

- Many sources of ‘repeated’ cross-sectional data
- Rapid progress can be made
- Standard statistical approached (e.g. regression models)

- Comparability (equivalence) is the central challenge
- How should time be represented

Cohort Studies

UK Birth Cohorts



UK Birth Cohorts

National Survey of Health and Development 1946

ncds
National Child Development Study

BCS70
1970 British Cohort Study

Millennium Cohort Study MCS

1946

1958

1970

2000/02

UK Birth Cohorts

National Survey of Health and Development 1946

ncds
National Child Development Study

BCS70
1970 British Cohort Study

Millennium Cohort Study MCS

??

1946

1958

1970

2000/02

2020

Avon Longitudinal Study of Parents and Children
Growing Up in Scotland
History of Next Steps (LSYPE) in England
Next Steps, formerly known as the Longitudinal Study of Young People in England (LSYPE), is a major survey of
people born between 1 September 1989 and 31 August 1990. Originally commissioned by the then
Children, Schools and Families (now Department for Education, DfE), the study was
affecting educational progress, attainment and transitions following the
The study began in 2004 when the young people were
independent schools, as well as Pupil Referral Units.
young people.
Youth Cohort Study
Abstract | Access | Get started | FAQ | Related | Links | Search
SERIES ABSTRACT
The Youth Cohort Study (YCS) began in 1985. It is a major programme of longitudinal research designed to monitor the behaviour and
decisions of representative samples of young people aged 16 years onwards as they make the transition from compulsory education to further
or higher education, or to the labour market. The YCS tries to identify and explain the factors which influence post-16 transitions, for example,
educational attainment, training opportunities, experiences at school. To date the YCS covers 13 cohorts and over 40 surveys.

Administrative Data

- ONS – Longitudinal Study (England and Wales)
- Northern Ireland Longitudinal Study (NILS)
- Scottish Longitudinal Study

  A panel study of 274k people based on Census records

  http://www.lscs.ac.uk/sls/

Panel Dataset Examples (Household Panel Studies)

- US Panel Study of Income Dynamics (PSID)
  - began in 1968
    http://psidonline.isr.umich.edu/

- Germany Socio-Economic Panel (SOEP)
  - began in 1984
    http://www.diw.de/en/soep

- British Household Panel Survey BHPS
  - (1991 onwards)
  - 5k households, 10k adults,
    http://www.iser.essex.ac.uk/survey/bhps

BHPS British Household Panel Survey

The British Household Panel Survey began in 1991 and is a multi-purpose study whose unique value resides in the fact that:

- it follows the same representative sample of individuals - the panel - over a period of years;
- it is household-based, interviewing every adult member of sampled households;
- it contains sufficient cases for meaningful analysis of certain groups such as the elderly or lone parent families.

The wave 1 panel consists of some 5,500 households and 10,300 individuals drawn from 250 areas of Great Britain. Additional samples of 1,500 households in each of Scotland and Wales were added to the main sample in 1999, and in 2001 a sample of 2,000 households was added in Northern Ireland, making the panel suitable for UK-wide research.

Nuisance calls claiming to be 'British Household Survey'

We have recently received a

BHPS Documentation - Volume B - the Codebook

You may access the codebook material in several ways:

- by consulting the **Subject Category Thesaurus** in order to find suitable index term(s).
- by selecting a specific **Index Term**
- by viewing a list of BHPS **Record Types**
- by Wave:
  - Wave One (A)
  - Wave Two (B)
  - Wave Three (C)
  - Wave Four (D)
  - Wave Five (E)
  - Wave Six (F)
  - Wave Seven (G)
  - Wave Eight (H)
  - Wave Nine (I)

Understanding Society
THE UK HOUSEHOLD LONGITUDINAL STUDY

Understanding Society: the UK Household Longitudinal Study

http://www.understandingsociety.org.uk/

- Understanding Society (US)
  - Also known as the UK Household Longitudinal Study (UKHLS)
- Began in January 2009
- Incorporates and extends the BHPS
- 40k UK households (4K Scottish households)
- 4k households in a special ethnic minorities sample
- Innovations include:
  - Linking to administrative data; spatial data; biometric data; qualitative data; child data (from age 10)

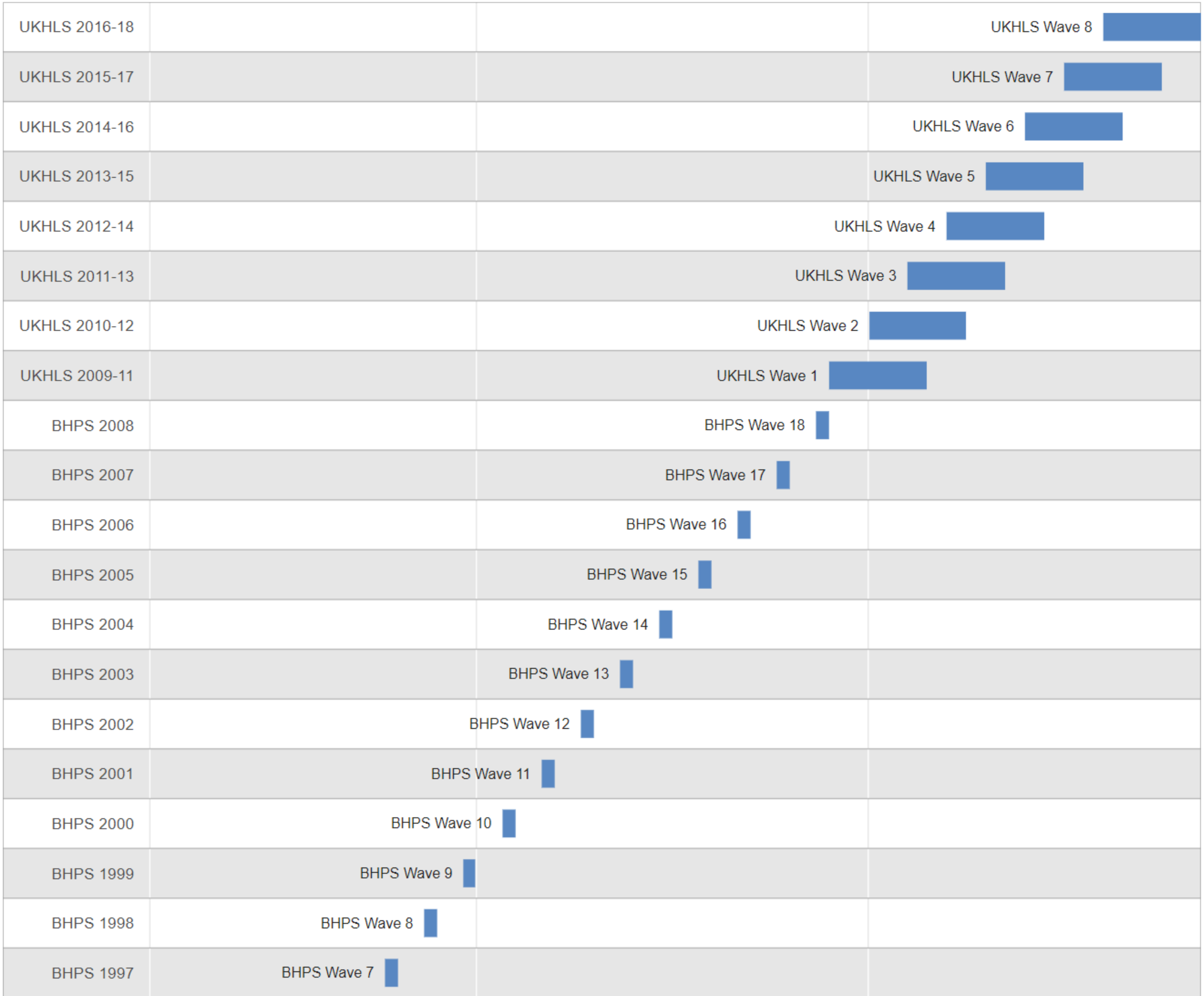
http://www.understandingsociety.org.uk/

Understanding Society Sample

- Approx. 27,000 households -
    - The fieldwork for this sample commenced in January 2009
- A boost ethnic minority sample,
    - focussed on five main ethnic minority groups, comprising 4,000 households
- Incorporating the BHPS sample of approximately 8,400 households
- An Innovation Panel of 1500 households to enable methodological research
    - (panel began in January 2008)

Understanding Society

- Focus on new research issues
- Opportunities for mixed methods:
  - Data linkage admin, organisation, spatial
  - Bio-markers and health indicators
  - Qualitative data
  - Other non-standard data: diaries, visual, audio


UKHLS 2016-18
UKHLS Wave 8
UKHLS 2015-17
UKHLS Wave 7
UKHLS 2014-16
UKHLS Wave 6
UKHLS 2013-15
UKHLS Wave 5
UKHLS 2012-14
UKHLS Wave 4
UKHLS 2011-13
UKHLS Wave 3
UKHLS 2010-12
UKHLS Wave 2
UKHLS 2009-11
UKHLS Wave 1
BHPS 2008
BHPS Wave 18
BHPS 2007
BHPS Wave 17
BHPS 2006
BHPS Wave 16
BHPS 2005
BHPS Wave 15
BHPS 2004
BHPS Wave 14
BHPS 2003
BHPS Wave 13
BHPS 2002
BHPS Wave 12
BHPS 2001
BHPS Wave 11
BHPS 2000
BHPS Wave 10
BHPS 1999
BHPS Wave 9
BHPS 1998
BHPS Wave 8
BHPS 1997
BHPS Wave 7

Dataset documentation

Understanding Society collects information from everyone aged 10 and over. Around 40,000 UK households have contributed to the Study. For more background information read our About Understanding Society Guide.

If you are new to using Understanding Society our Getting Started Guide will help you start working with the dataset. Our list of key variables for the analysis of individual response data may also help you.

search | Mainstage Variable ▾ | SEARCH

DATAFILES | QUESTIONNAIRE MODULES

ALL WAVES *(1991-2017)*
XWAVE *(1991-2017)*
WAVE 7 *(2015-2017)*
WAVE 6 *(2014-2016)*
WAVE 5 *(2013-2015)*
WAVE 4 *(2012-2014)*
WAVE 3 *(2011-2013)*
WAVE 2 *(2010-2012)*
WAVE 1 *(2009-2011)*
WAVE B18 *(2008)*
WAVE B17 *(2007)*

All Waves (284 Datafiles)

Datafile	Description	UKHLS	BHPS
indall	Information for all persons in household, incl. children and non-respondents	1, 2, 3, 4, 5, 6, 7	B1, B2, B3, B4, B5, B6, B7, B8, B9, B10, B11, B12, B13, B14, B15, B16, B17, B18
egoalt	Kin and other relationships between pairs of individuals in the household	1, 2, 3, 4, 5, 6, 7	B1, B2, B3, B4, B5, B6, B7, B8, B9, B10, B11, B12, B13, B14, B15, B16, B17, B18
hhresp	Substantive data from responding households	1, 2, 3, 4, 5, 6, 7	B1, B2, B3, B4, B5, B6, B7, B8, B9, B10, B11, B12, B13, B14, B15, B16, B17, B18
indresp	Substantive data for responding adults (16+),	1, 2, 3, 4, 5, 6, 7	B1, B2, B3, B4, B5, B6, B7, B8, B9, B10, B11, B12, B13,

OVERVIEW
SURVEY TIMELINE
USER GUIDES
DATASET DOCUMENTATION
INDEX TERMS
QUESTIONNAIRES
TECHNICAL REPORTS
FIELDWORK DOCUMENTS
LONG TERM CONTENT PLAN
QUALITY PROFILE

Sources of Longitudinal Data

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Duration Data and Models

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Alternative terminology

- Duration models
- Survival models
- Cox regression
- Cox models
- Failure time analysis
- Hazard models
- Event history analysis

Models for duration data allow the data analyst to assess the relative influence of a number of explanatory factors upon how long it takes for an event to occur

Original paper Cox (1972)

Applications

- Study the lifetimes of machine components in engineering
- Duration of unemployment in economics
- Time taken to complete cognitive tasks in psychology
- Lengths of tracks on a photographic plate in particle physics
- Survival times of patients in clinical trials

Research Examples

Heckman and Borjas (1980) used duration modelling approaches to study unemployment

Blossfeld and Hakim (1997) studied female part-time employment

Mulder and Smits (1999) investigated first time home ownership

Lillard et al. (1995) studied premarital cohabitation and subsequent marital dissolution

Research Examples

Kiernan and Mueller (1998) undertook an analysis of divorce using the BHPS and the NCDS

Boyle et al. (2008) examined union dissolution using the Austrian Family and Fertility Survey (FFS)

Chan and Halpin (2002) used BHPS to examine gender role attitudes and the domestic division of labour on divorce

Pevalin and Ermisch (2004) investigated mental health, union dissolution and re-partnering

Measuring a Duration

Three requirements for correctly determining a duration

1. A starting time must be unambiguously defined
2. Time must have a defined unit of measurement
3. The event must be clearly defined

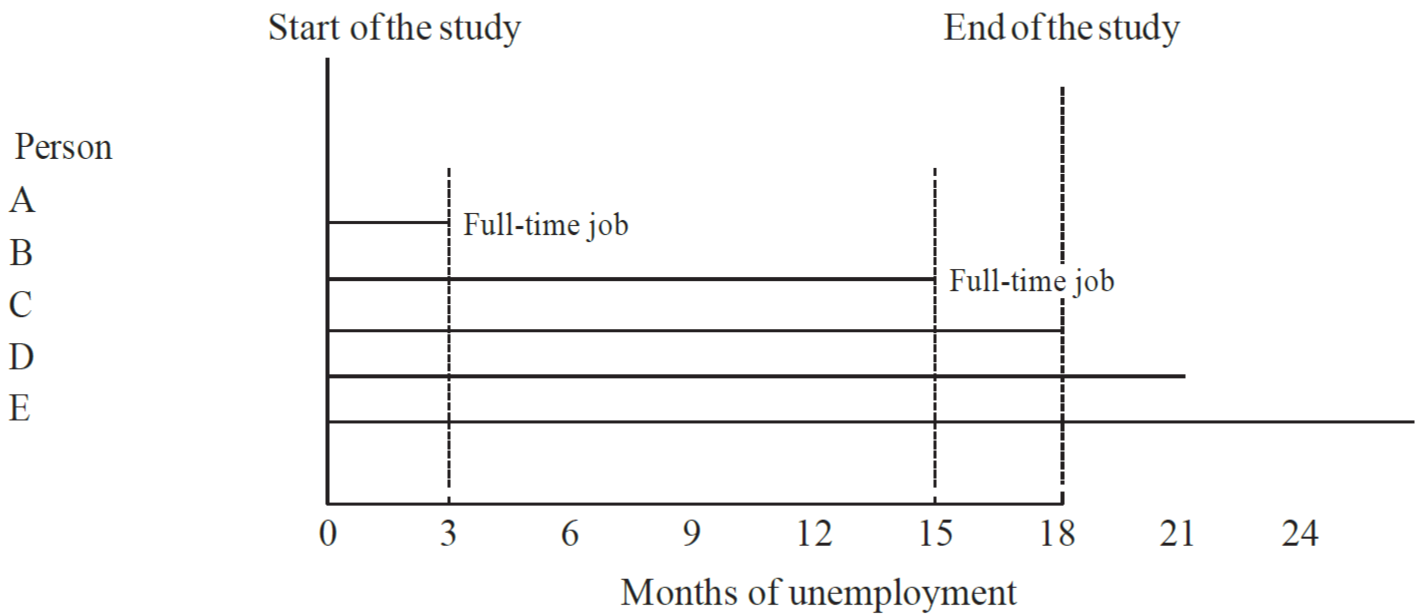


Figure 4 A diagram of a hypothetical study of unemployment

The Accelerated Life Model

Regression models can be estimated with duration data

Historically the log of the duration has been modelled

Censored Observations

- Censored observations affect regression model results
- The impact on the results on may sometimes be negligible
- Plewis (1997) states that when there is a very small proportion of censored cases they will have little effect, and an accelerated life model might still be suitable
- Supervisors, examiners and referees may not be convinced

Duration Modelling

- No longer directly modelling the duration
- The focus is on modelling the probability that an event occurs at time t , conditional on it not having occurred before t

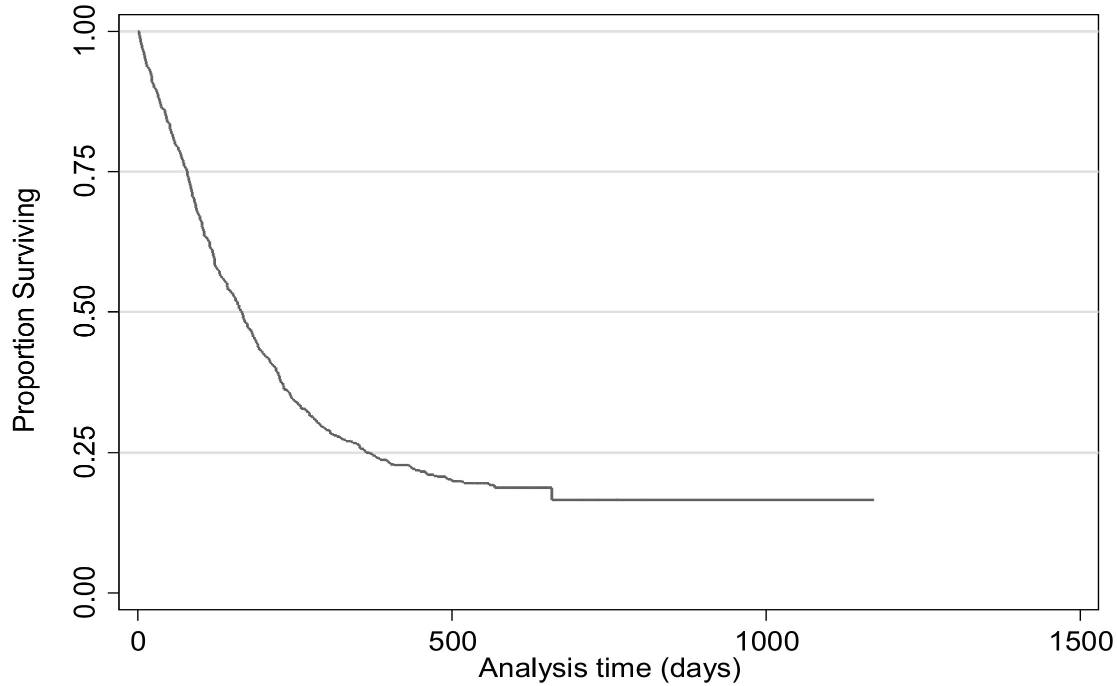
Stata Compact Codebook for the College Skills Program Dataset

Variable	Obs	Unique	Mean	Min	Max	Label
id	628	628	314.5	1	628	student id
time	628	338	234.7038	2	1172	number of days until test passed
test	628	2	.8089172	0	1	test passed (or censored)
age	623	31	32.36918	20	56	age at enrolment
no_jobs	611	28	4.574468	0	40	number of previous jobs
mooc	628	2	.4904459	0	1	taught by massive open online course
campus	628	2	.2929936	0	1	college campus
quals1	628	2	.4601911	0	1	no qualifications
quals2	628	2	.1815287	0	1	lower qualifications (below A'level)
quals3	628	2	.3582803	0	1	higher qualifications(above A'level)

Stata Output: stdes Command for the College Skills Program Data

```
         failure _d:  test
   analysis time _t:  time

                                   |-------------- per subject --------------|
Category                   total        mean         min     median        max
------------------------------------------------------------------------------
no. of subjects              628
no. of records               628           1           1          1          1

(first) entry time                         0           0          0          0
(final) exit time                   234.7038           2        166       1172

subjects with gap              0
time on gap if gap             0
time at risk              147394    234.7038           2        166       1172

failures                     508    .8089172           0          1          1
------------------------------------------------------------------------------
```

Stata Output: Kaplan-Meier Plot of Time to Passing the Test (College Skills Program Data)



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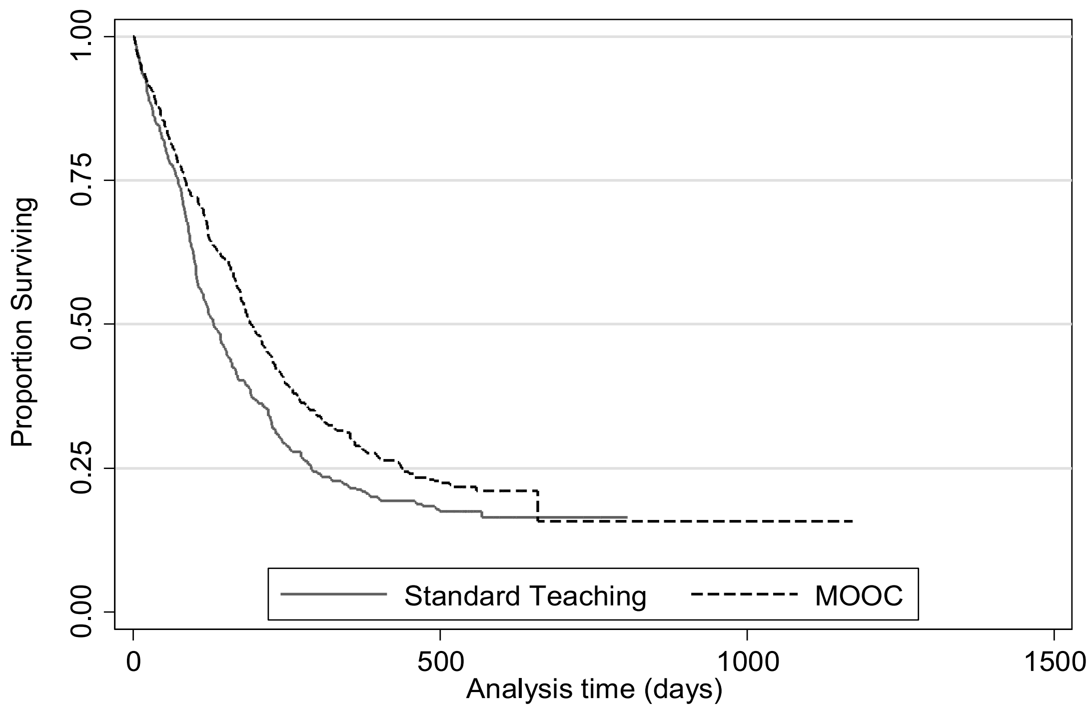


Stata Output: Log-Rank Test for Equality of Survivor Functions

```
 failure _d:  test

   analysis time _t:  time



Log-rank test for equality of survivor
functions


      |   Events          Events

mooc  |  observed        expected

------+-------------------------

0     |       265          235.80

1     |       243          272.20

------+-------------------------

Total |       508          508.00


            chi2(1) =       6.80

            Pr>chi2 =     0.0091
```

Stata Output: Cox Regression Model Time to Passing the Test (College Skills Program Data)

```
 failure _d:  test

   analysis time _t:  time


Iteration 0:   log likelihood =  -2868.555
Iteration 1:   log likelihood = -2851.6989
Iteration 2:   log likelihood = -2851.0884
Iteration 3:   log likelihood = -2851.0863
Refining estimates:
Iteration 0:   log likelihood = -2851.0863


Cox regression -- Breslow method for ties


No. of subjects =          610                Number of obs    =         610

No. of failures =          495

Time at risk    =       142994

                                              LR chi2(6)       =       34.94

Log likelihood  =   -2851.0863                Prob > chi2      =      0.0000


------------------------------------------------------------------------------

          _t |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

         age |  -.0237543   .0075611    -3.14   0.002    -.0385737   -.0089349

     no_jobs |    .034745   .0077538     4.48   0.000     .0195478    .0499422

        mooc |  -.2540169    .091005    -2.79   0.005    -.4323834   -.0756504

      campus |  -.1723881   .1020981    -1.69   0.091    -.3724966    .0277205

      quals2 |   .2467753   .1227597     2.01   0.044     .0061706    .4873799

      quals3 |    .125668   .1030729     1.22   0.223    -.0763513    .3276873

------------------------------------------------------------------------------
```

Stata Output: Test of the Effects of Previous Education in Cox Regression Model of Time to Passing the Test (College Skills Program Data)

```
( 1)  quals2 = 0
( 2)  quals3 = 0

          chi2(  2) =    4.36
        Prob > chi2 =    0.1130
```

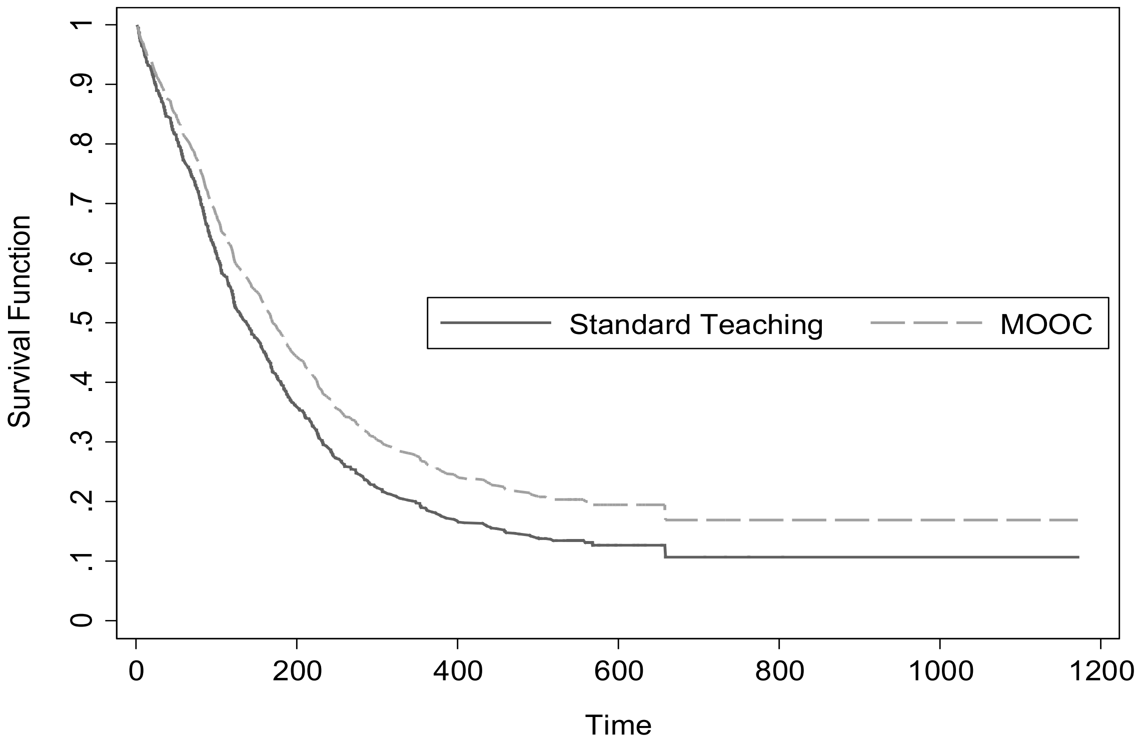
Stata Output: Hazard Ratios Cox Regression Model Time to Passing the Test (College Skills Program Data)

```
Cox regression -- Breslow method for ties

No. of subjects =          610                  Number of obs    =         610
No. of failures =          495
Time at risk    =       142994
                                                LR chi2(3)       =       27.76
Log likelihood  =   -2854.6735                  Prob > chi2      =      0.0000

------------------------------------------------------------------------------
          _t | Haz. Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |   .9794475   .0072674    -2.80   0.005     .9653067    .9937955
     no_jobs |   1.036128   .0078949     4.66   0.000     1.020769    1.051718
        mooc |   .7940896   .0716076    -2.56   0.011     .6654445    .9476047
------------------------------------------------------------------------------
```

Stata Output: Time to Passing the Test - Survival Functions Comparing Women Aged 30 with 5 Previous Jobs by Teaching Methods (College Skills Program Data)



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Longitudinal Data and Research

End of Day 1

http://bit.do/ncrm_longitudinal

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Gayle, V. (2022) Longitudinal Data Analysis
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Longitudinal Data and Research

Day 2

http://bit.do/ncrm_longitudinal

Analysing Panel Data (Part 1)

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2022

‘The making of a causal inference is not a simple affair that can be reduced to a formula applied mechanically to a set of panel data on two or more variables’
(Duncan, 1972 p.36)

Wide format dataset – single survey contact

id	age	female	working_hours
001	20	0	37
002	30	1	39
003	40	1	45

Wide format dataset - repeated contacts

id	female	age_1971	age_1972	age_1973	work_hours_1971	work_hours_1972	work_hours_1973
001	0	20	21	22	37	40	35
002	1	30	31	32	39	40	35
003	1	40	41	42	45	45	15

Snapshot of long format dataset

id	year	age	hours	ln_wage
3	68	22	40	1.49
3	69	23	40	1.70
3	70	24	40	1.45

id: personal identification number
year: year of the survey
age: respondent's age in years
hours: number of hours per week normally worked in main job
ln_wage: log of weekly wages (adjusted for inflation)

Pooled Cross-Sectional Model

- Panel are pooled together and standard statistical model used (e.g. OLS)
- A good place to start to explore
- Results provide some initial information

Pooled Cross-Sectional Model

- Overall limitation of the pooled cross-sectional model is that it assumes that each observation (i.e. row within a long format dataset) is independent of other observations

Pooled Cross-Sectional Model

- With panel data we know that individual respondents contribute many times to the data (usually once per wave for many waves)

- Pooling all of the data violates the standard regression modelling assumption that each observation is independent

Pooled Cross-Sectional Model

- In practice standard errors that are too small

- Think about what this means for significance?

Robust Standard Errors

- Robust standard errors are sometimes known as Huber/White sandwich estimates of variance (see White, 1984, Huber, 1967)

id	year	age	hours	ln_wage
3	68	22	40	1.49
3	69	23	40	1.70
3	70	24	40	1.45

Collapsed dataset of the mean values

Id	year $\overline{x}$	age $\overline{x}$	hours $\overline{x}$	ln_wage $\overline{x}$
3	60	23	40	1.55

id: personal identification number

year $\overline{x}$: mean year of the survey

age $\overline{x}$: mean of respondent's age in years

hours $\overline{x}$: mean number of hours per week normally worked in main job

ln_wage $\overline{x}$: mean log of weekly wages (adjusted for inflation)

Between Effects Model

Estimates a standard cross-sectional model on the data

A regression model with *Y* the mean of the log of weekly wages (adjusted for inflation)

X vars

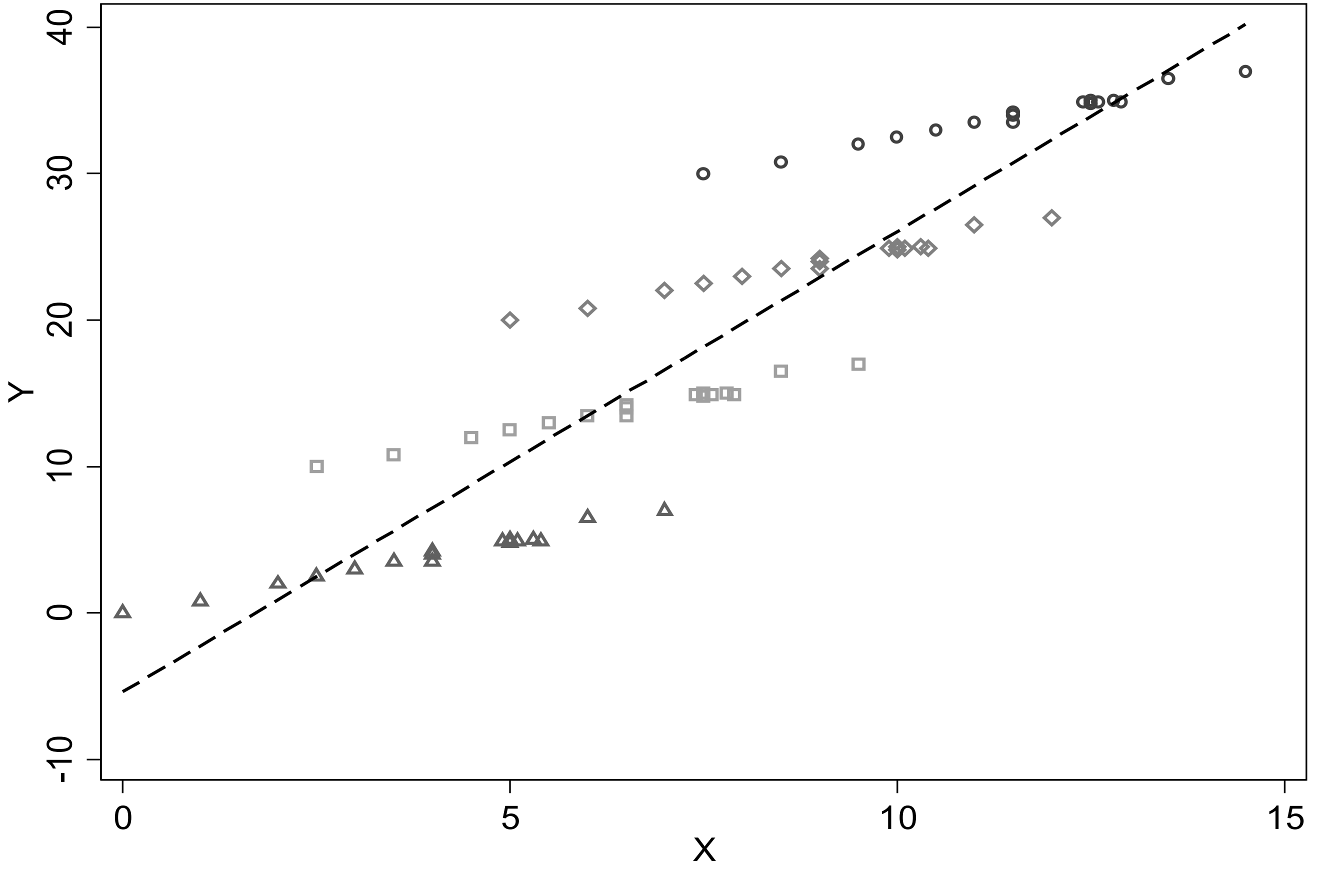
- mean hours per week normally worked in the respondent's main job
- mean age across the three waves of the survey

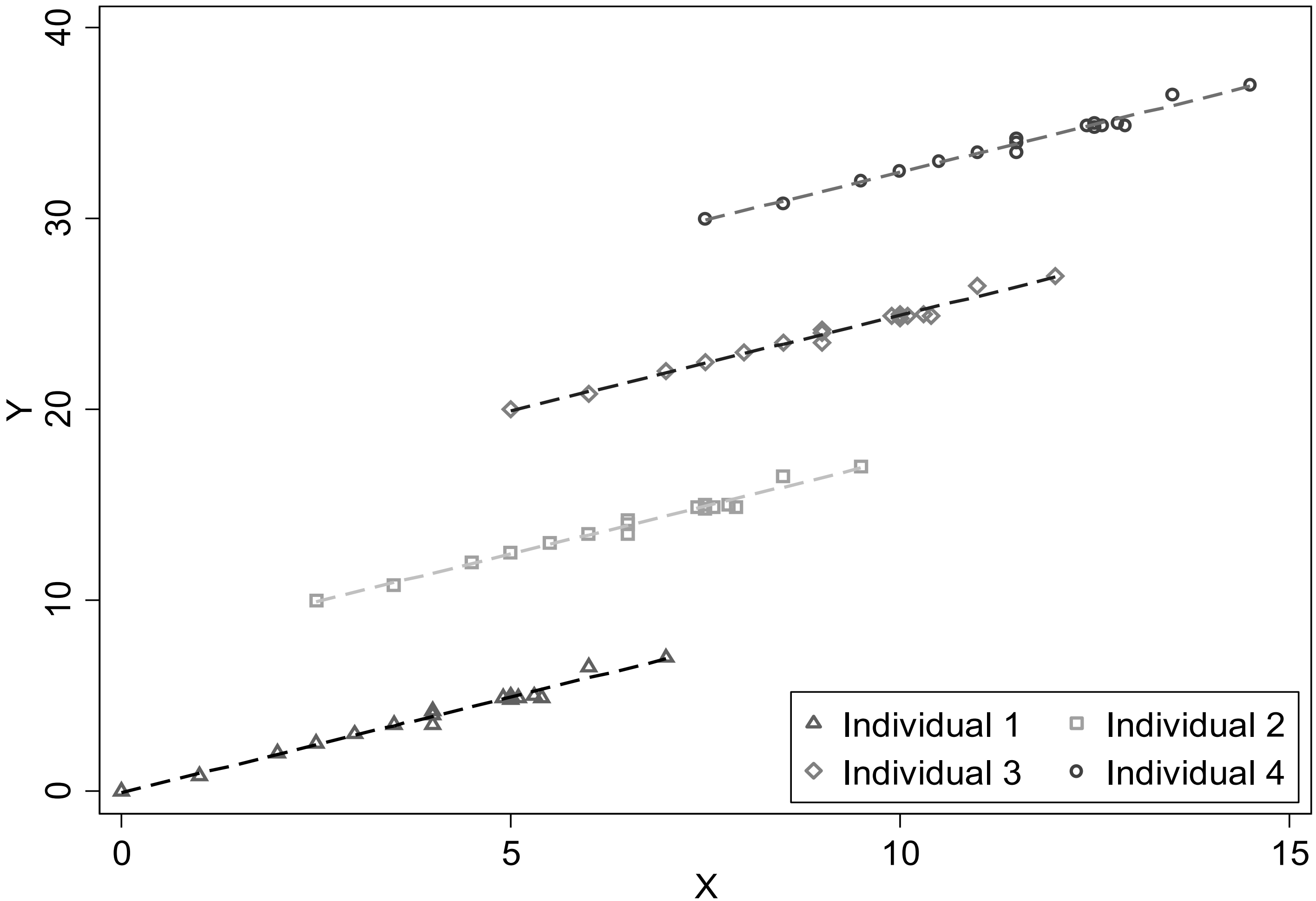
Between Effects Model

Because now there is only one row of data per respondent the problem of non-independence of observations in the original (long format) panel data is sidestepped

What might the limitation of this approach be?

A Thought Experiment…





Y
X
0
10
20
30
40
0
5
10
15
Individual 1
Individual 2
Individual 3
Individual 4

The Fixed Effects Panel Model

- Concentrates on change over time within an individual respondent
- Can include explanatory variables that, for the individual respondent, change over time (e.g. age, monthly income and body mass index)
- In general cannot include explanatory variables that, for the individual respondent, are time-constant (e.g. town of birth, birth weight, father's occupation when respondent was aged 14)
- Has the potentially attractive property of providing robust estimates when observed explanatory variables are correlated with the unobserved effects

The Random Effects Panel Model

- Analyses both change within an individual respondent’s outcomes, and differences between respondents’ outcomes
- Can include explanatory variables that, for the individual respondent, change over time (e.g. age, monthly income and body mass index)
- Can include explanatory variables that, for the individual respondent, are time-constant (e.g. town of birth, birth weight, father’s occupation when respondent was aged 14)
- Makes the assumption that observed explanatory variables are not correlated with the unobserved effects

Notation

Pooled Cross-Sectional Regression Model

(1) $Y_{it} = \beta_0+\beta_1 X_{1it} +\ldots+ \beta_k X_{kit} + \varepsilon_{it}$

Fixed Effects Panel Regression Model

(2) $Y_{it} = \beta_0 + \lambda_i + \beta_1 X_{1it} +\ldots+ \beta_k X_{kit} + \varepsilon_{it}$

Random Effects Panel Regression ('random intercepts' version)

(3) $Y_{it} = \beta_0 + \beta_1 X_{1it} +\ldots+ \beta_k X_{kit} + \upsilon_i + \varepsilon_{it}$

A Toy Example

Variable	Obs	Mean	Min	Max	Label
y	32	5.38	1	11	y outcome variable
id	32	4.50	1	8	id
female	32	.50	0	1	female
wave2	32	.25	0	1	wave 2
wave3	32	.25	0	1	wave 3
wave4	32	.25	0	1	wave 4

OLS Regression

y	Coef.	Std. Err.	t	P|t|	[95% Conf.	Interval]
female	.625	.4187448	1.49	0.147	-.2341934	1.484193
wave2	.75	.5921946	1.27	0.216	-.465083	1.965083
wave3	3.5	.5921946	5.91	0.000	2.284917	4.715083
wave4	6.25	.5921946	10.55	0.000	5.034917	7.465083
_cons	2.4375	.4681709	5.21	0.000	1.476893	3.398107

Between Effects Model

```
Between regression (regression on group means)  Number of obs      =         32
Group variable: id                              Number of groups   =          8

R-sq:                                           Obs per group:
     within  =      .                                          min =          4
     between = 0.2500                                          avg =        4.0
     overall = 0.0133                                          max =          4

                                                F(1,6)             =       2.00
sd(u_i + avg(e_i.))=      .625                  Prob  F           =     0.2070

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      female |       .625   .4419417     1.41   0.207    -.4563925    1.706392
       wave2 |          0  (omitted)
       wave3 |          0  (omitted)
       wave4 |          0  (omitted)
       _cons |     5.0625      .3125    16.20   0.000      4.29784     5.82716
------------------------------------------------------------------------------
```

Fixed Effects Model

```
Fixed-effects (within) regression               Number of obs     =         32
Group variable: id                              Number of groups  =          8

R-sq:                                           Obs per group:
     within  = 0.8722                                         min =          4
     between =      .                                         avg =        4.0
     overall = 0.8259                                         max =          4

                                                F(3,21)           =      47.77
corr(u_i, Xb)  = -0.0000                        Prob   F         =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      female |          0  (omitted)
       wave2 |        .75   .5824824     1.29   0.212    -.4613384    1.961338
       wave3 |        3.5   .5824824     6.01   0.000     2.288662    4.711338
       wave4 |       6.25   .5824824    10.73   0.000     5.038662    7.461338
       _cons |       2.75   .4118772     6.68   0.000     1.893454    3.606546
-------------+----------------------------------------------------------------
     sigma_u |   .6681531
     sigma_e |  1.1649647
         rho |  .24752475   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(7, 21) = 1.32                       Prob   F = 0.2914
```

Random Effects Model

```
Random-effects GLS regression                   Number of obs     =         32
Group variable: id                              Number of groups  =          8

R-sq:                                           Obs per group:
     within  = 0.8722                                         min =          4
     between = 0.2500                                         avg =        4.0
     overall = 0.8392                                         max =          4

                                                Wald chi2(4)      =     145.32
corr(u_i, X)   = 0 (assumed)                    Prob  chi2       =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      female |       .625   .4419417     1.41   0.157    -.2411899     1.49119
       wave2 |        .75   .5824824     1.29   0.198    -.3916445    1.891644
       wave3 |        3.5   .5824824     6.01   0.000     2.358356    4.641644
       wave4 |       6.25   .5824824    10.73   0.000     5.108356    7.391644
       _cons |     2.4375    .474224     5.14   0.000     1.508038    3.366962
-------------+----------------------------------------------------------------
     sigma_u |  .22658174
     sigma_e |  1.1649647
         rho |  .03645008   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Comparing Models

	BE	FE	RE
	b(se)	b(se)	b(se)
female	0.625	0.000	0.625
	(0.442)	(.)	(0.442)
wave2	0.000	0.750	0.750
	(.)	(0.582)	(0.582)
wave3	0.000	3.500***	3.500***
	(.)	(0.582)	(0.582)
wave4	0.000	6.250***	6.250***
	(.)	(0.582)	(0.582)
_cons	5.063***	2.750***	2.438***
	(0.313)	(0.412)	(0.474)
n	32	32	32

BE: Between Effects Model

FE: Fixed Effects Panel Model

RE: Random Effects Panel Model

Concluding Thoughts

Random effects panel model is using (or borrowing) some information from the fixed effects panel model

At the same time it is borrowing some information from the between effects model

This should illustrate why econometricians often make oral statements such as ‘the random effects panel model is a matrix weighted average of the within-effects (fixed effects) and the between effects’

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Example: A BHPS Panel Data File

Example: A BHPS Panel Data File

first 10 years;
25 - 35 year olds;
'essex originals‘;
males;
working full-time;

yvar is wPAYNU2 Usual net pay per month: current job (now adjusted for inflation)

Variable	Obs	Unique	Mean	Min	Max	Label
pid	8412	1324	1.99e+07	1.00e+07	1.07e+08	cross-wave person identifier
wave	8412	10	5.382668	1	10	wave of the BHPS
zhid	8412	8332	5794920	1000381	1.07e+07	household identification number
zpno	8412	7	1.497147	1	7	person number
zdoby	8412	9	1960.981	1957	1965	year of birth
zpaynu2	6098	3898	1050.62	50.14124	9741.704	(deflated 1991)usual net pay per month...
zjbhrs	6435	60	40.47677	0	99	no. of hours normally worked per week
zjbcssm	7503	558	34.75936	.56	90.32	cambridge scale males: present job
pacssm	6827	347	30.12809	.56	85.04	cambridge scale males : father's job
graduate	7924	2	.1680969	0	1	Graduates (zqfachi)
zregage	8412	19	9.178673	0	18	age at interview-25

Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
pid	8,412	19933161	15557954	10004531	107127271
wave	8,412	5.382668	2.883692	1	10
zhid	8,412	5794920	2814730	1000381	10677259
zpno	8,412	1.497147	.8551585	1	7
zdoby	8,412	1960.981	2.607186	1957	1965
zpaynu2	6,098	1050.62	488.2907	50.14124	9741.704
zjbhrs	6,435	40.47677	7.895388	0	99
zjbcssm	7,503	34.75936	19.10313	.56	90.32
pacssm	6,827	30.12809	19.00986	.56	85.04
graduate	7,924	.1680969	.3739759	0	1
zregage	8,412	9.178673	3.853988	0	18

Pooled Cross-Sectional Model

```
. reg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav

      Source |       SS           df       MS      Number of obs   =     5,097
-------------+----------------------------------   F(14, 5082)     =    128.85
       Model |   325506963        14  23250497.3   Prob > F        =    0.0000
    Residual |   917001747     5,082  180441.115   R-squared       =    0.2620
-------------+----------------------------------   Adj R-squared   =    0.2599
       Total |  1.2425e+09     5,096  243820.391   Root MSE        =    424.78
```

Pooled Cross-Sectional Model (Continued)

zpaynu2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
zjbhrs	9.559008	.8714275	10.97	0.000	7.850635	11.26738
zjbcssm	8.709623	.370681	23.50	0.000	7.982928	9.436317
pacssm	2.099019	.354503	5.92	0.000	1.40404	2.793998
graduate	195.6784	17.63807	11.09	0.000	161.1001	230.2566
zregage	6.51771	2.257654	2.89	0.004	2.091734	10.94368
wave						
2	32.02204	26.09955	1.23	0.220	-19.14433	83.1884
3	47.53042	26.53109	1.79	0.073	-4.481953	99.5428
4	32.50858	27.03488	1.20	0.229	-20.49144	85.5086
5	37.20393	27.6692	1.34	0.179	-17.03963	91.44749
6	83.98088	28.31416	2.97	0.003	28.47293	139.4888
7	72.86194	28.92154	2.52	0.012	16.16326	129.5606
8	96.8642	29.82545	3.25	0.001	38.39346	155.3349
9	139.523	31.31379	4.46	0.000	78.13451	200.9116
10	138.2166	32.437	4.26	0.000	74.62611	201.8071
_cons	135.0271	43.56656	3.10	0.002	49.61787	220.4363

Pooled Cross-Sectional Model
With robust standard errors

```
. reg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav, cluster(pid)

Linear regression                               Number of obs     =      5,097
                                                F(14, 824)        =      23.09
                                                Prob > F          =     0.0000
                                                R-squared         =     0.2620
                                                Root MSE          =     424.78

                                   (Std. Err. adjusted for 825 clusters in pid)
------------------------------------------------------------------------------
```

Pooled Cross-Sectional Model
With robust standard errors

zpaynu2	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
zjbhrs	9.559008	1.943735	4.92	0.000	5.743753	13.37426
zjbcssm	8.709623	.7934006	10.98	0.000	7.152299	10.26695
pacssm	2.099019	1.115752	1.88	0.060	-.0910308	4.289069
graduate	195.6784	59.72225	3.28	0.001	78.45271	312.904
zregage	6.51771	4.515835	1.44	0.149	-2.346185	15.3816
wave						
2	32.02204	13.90313	2.30	0.022	4.732323	59.31175
3	47.53042	18.75842	2.53	0.011	10.71052	84.35033
4	32.50858	20.47166	1.59	0.113	-7.674154	72.69131
5	37.20393	25.89333	1.44	0.151	-13.62072	88.02857
6	83.98088	30.03699	2.80	0.005	25.02286	142.9389
7	72.86194	34.50542	2.11	0.035	5.133077	140.5908
8	96.8642	37.73043	2.57	0.010	22.80514	170.9233
9	139.523	43.37522	3.22	0.001	54.3841	224.662
10	138.2166	46.56261	2.97	0.003	46.82133	229.6119
_cons	135.0271	76.33256	1.77	0.077	-14.80204	284.8562

The Fixed Effects Panel Model

- Concentrates on change over time within an individual respondent
- Can include explanatory variables that, for the individual respondent, change over time (e.g. age, monthly income and body mass index)
- In general cannot include explanatory variables that, for the individual respondent, are time-constant (e.g. town of birth, birth weight, father's occupation when respondent was aged 14)
- Has the potentially attractive property of providing robust estimates when observed explanatory variables are correlated with the unobserved effects

The Random Effects Panel Model

- Analyses both change within an individual respondent's outcomes, and differences between respondents' outcomes
- Can include explanatory variables that, for the individual respondent, change over time (e.g. age, monthly income and body mass index)
- Can include explanatory variables that, for the individual respondent, are time-constant (e.g. town of birth, birth weight, father's occupation when respondent was aged 14)
- Makes the assumption that observed explanatory variables are not correlated with the unobserved effects

Notation

Pooled Cross-Sectional Regression Model

(1) $Y_{it} = \beta_0 + \beta_1 X_{1it} + \ldots + \beta_k X_{kit} + \varepsilon_{it}$

Fixed Effects Panel Regression Model

(2) $Y_{it} = \beta_0 + \lambda_i + \beta_1 X_{1it} + \ldots + \beta_k X_{kit} + \varepsilon_{it}$

Random Effects Panel Regression ('random intercepts' version)

(3) $Y_{it} = \beta_0 + \beta_1 X_{1it} + \ldots + \beta_k X_{kit} + \upsilon_i + \varepsilon_{it}$

```
. xtreg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav, fe
note: pacssm omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,097
Group variable: pid                             Number of groups  =        825

R-sq:                                           Obs per group:
     within  = 0.0973                                         min =          1
     between = 0.0047                                         avg =        6.2
     overall = 0.0151                                         max =         10

                                                F(13,4259)        =      35.30
corr(u_i, Xb)  = -0.0716                        Prob > F          =     0.0000
```

```
. xtreg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav, fe

note: pacssm omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,097
Group variable: pid                             Number of groups  =        825

R-sq:                                           Obs per group:
     within  = 0.0973                                         min =          1
     between = 0.0047                                         avg =        6.2
     overall = 0.0151                                         max =         10

                                                F(13,4259)        =      35.30
corr(u_i, Xb)  = -0.0716                        Prob > F          =     0.0000
```

```
. xtreg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav, fe
note: pacssm omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,097
Group variable: pid                             Number of groups  =        825

R-sq:                                           Obs per group:
     within  = 0.0973                                         min =          1
     between = 0.0047                                         avg =        6.2
     overall = 0.0151                                         max =         10

                                                F(13,4259)        =      35.30
corr(u_i, Xb)  = -0.0716                        Prob > F          =     0.0000
```

```
. xtreg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav, fe
note: pacssm omitted because of collinearity

Fixed-effects (within) regression               Number of obs     =      5,097
Group variable: pid                             Number of groups  =        825

R-sq:                                           Obs per group:
     within  = 0.0973                                        min =          1
     between = 0.0047                                        avg =        6.2
     overall = 0.0151                                        max =         10

                                                F(13,4259)        =      35.30
corr(u_i, Xb)  = -0.0716                        Prob > F          =     0.0000
```

zpaynu2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
zjbhrs	3.162216	.7598803	4.16	0.000	1.672455	4.651978
zjbcssm	.7083871	.4688331	1.51	0.131	-.2107702	1.627544
pacssm	0	(omitted)				
graduate	-68.42179	58.82074	-1.16	0.245	-183.7411	46.89752
zregage	9.779486	18.59062	0.53	0.599	-26.66781	46.22679
wave						
2	33.77626	23.69473	1.43	0.154	-12.67775	80.23027
3	50.54727	39.7453	1.27	0.204	-27.37422	128.4688
4	36.4279	57.69603	0.63	0.528	-76.68639	149.5422
5	38.07226	75.6673	0.50	0.615	-110.2751	186.4196
6	85.96321	93.47347	0.92	0.358	-97.2935	269.2199
7	87.99939	111.601	0.79	0.430	-130.7967	306.7955
8	115.7779	130.037	0.89	0.373	-139.1623	370.7181
9	161.5511	148.3231	1.09	0.276	-129.2394	452.3416
10	172.5317	167.0504	1.03	0.302	-154.9742	500.0375
_cons	751.7321	98.72638	7.61	0.000	558.177	945.2873

```
-------------+----------------------------------------------------------------
     sigma_u |  436.52027
     sigma_e |  251.17185
         rho |  .75126958   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(824, 4259) = 12.59                  Prob > F = 0.0000
```

areg

```
. areg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav, absorb(pid)
note: pacssm omitted because of collinearity

Linear regression, absorbing indicators         Number of obs     =      5,097
                                                F(  13,   4259)   =      35.30
                                                Prob > F          =     0.0000
                                                R-squared         =     0.7838
                                                Adj R-squared     =     0.7413
                                                Root MSE          =   251.1718

------------------------------------------------------------------------------
     zpaynu2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      zjbhrs |   3.162216   .7598803     4.16   0.000     1.672455    4.651978
     zjbcssm |   .7083871   .4688331     1.51   0.131    -.2107702    1.627544
      pacssm |          0  (omitted)
    graduate |  -68.42179   58.82074    -1.16   0.245    -183.7411    46.89752
     zregage |   9.779486   18.59062     0.53   0.599    -26.66781    46.22679
             |
        wave |
          2  |   33.77626   23.69473     1.43   0.154    -12.67775    80.23027
          3  |   50.54727    39.7453     1.27   0.204    -27.37422    128.4688
          4  |    36.4279   57.69603     0.63   0.528    -76.68639    149.5422
          5  |   38.07226    75.6673     0.50   0.615    -110.2751    186.4196
          6  |   85.96321   93.47347     0.92   0.358     -97.2935    269.2199
          7  |   87.99939    111.601     0.79   0.430    -130.7967    306.7955
          8  |   115.7779    130.037     0.89   0.373    -139.1623    370.7181
          9  |   161.5511   148.3231     1.09   0.276    -129.2394    452.3416
         10  |   172.5317   167.0504     1.03   0.302    -154.9742    500.0375
             |
       _cons |   751.7321   98.72638     7.61   0.000      558.177    945.2873
-------------+----------------------------------------------------------------
         pid |      F(824, 4259) =     12.593   0.000          (825 categories)
```

xtreg , re (random effects)

```
. xtreg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav, re

Random-effects GLS regression                   Number of obs     =      5,097
Group variable: pid                             Number of groups  =        825

R-sq:                                           Obs per group:
     within  = 0.0875                                         min =          1
     between = 0.2458                                         avg =        6.2
     overall = 0.2291                                         max =         10

                                                Wald chi2(14)     =     688.95
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
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```

zpaynu2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
zjbhrs	4.095316	.7257752	5.64	0.000	2.672823	5.51781
zjbcssm	3.190851	.4147334	7.69	0.000	2.377988	4.003713
pacssm	3.949381	.7204518	5.48	0.000	2.537321	5.36144
graduate	202.0455	30.88336	6.54	0.000	141.5152	262.5758
zregage	9.659352	4.59312	2.10	0.035	.6570023	18.6617
wave						
2	32.94832	16.59421	1.99	0.047	.4242625	65.47238
3	48.03321	18.53548	2.59	0.010	11.70434	84.36207
4	31.86777	21.25793	1.50	0.134	-9.797011	73.53255
5	31.99669	24.47987	1.31	0.191	-15.98297	79.97635
6	78.77641	27.94861	2.82	0.005	23.99814	133.5547
7	77.89485	31.66425	2.46	0.014	15.83407	139.9556
8	100.9134	35.62999	2.83	0.005	31.07988	170.7469
9	144.7248	39.838	3.63	0.000	66.64376	222.8058
10	153.3713	44.0223	3.48	0.000	67.08919	239.6534
_cons	441.8567	45.78108	9.65	0.000	352.1274	531.5859

```
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Group variable: pid                             Number of groups  =        825

R-sq:                                           Obs per group:
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corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

------------------------------------------------------------------------------
     zpaynu2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      zjbhrs |   4.095316   .7257752     5.64   0.000     2.672823     5.51781
     zjbcssm |   3.190851   .4147334     7.69   0.000     2.377988    4.003713
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     zregage |   9.659352    4.59312     2.10   0.035     .6570023     18.6617
             |
        wave |
          2  |   32.94832   16.59421     1.99   0.047     .4242625    65.47238
          3  |   48.03321   18.53548     2.59   0.010     11.70434    84.36207
          4  |   31.86777   21.25793     1.50   0.134    -9.797011    73.53255
          5  |   31.99669   24.47987     1.31   0.191    -15.98297    79.97635
          6  |   78.77641   27.94861     2.82   0.005     23.99814    133.5547
          7  |   77.89485   31.66425     2.46   0.014     15.83407    139.9556
          8  |   100.9134   35.62999     2.83   0.005     31.07988    170.7469
          9  |   144.7248     39.838     3.63   0.000     66.64376    222.8058
         10  |   153.3713    44.0223     3.48   0.000     67.08919    239.6534
             |
       _cons |   441.8567   45.78108     9.65   0.000     352.1274    531.5859
-------------+----------------------------------------------------------------
     sigma_u |  331.89925
     sigma_e |  251.17185
         rho |  .63584801   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

The total error variance can be considered as

$$(\text{sigma\_u})^2 + (\text{sigma\_e})^2$$

Rho (random effects)

the fraction of the variance that is due to *u_i* is

$$\frac{(\text{sigma\_u})^2}{((\text{sigma\_u})^2 + (\text{sigma\_e})^2)}$$

Rho in this example…

(331.89925^2)/((331.89925^2)+(251.17185^2))

Rho = 0.64

64 per cent of the error variance is at the panel level

Rho in this example…

$(331.89925^2)/((331.89925^2)+(251.17185^2))$

Rho = 0.64

64 per cent of the error variance is at the panel level

Rho is analogous to an intra-class correlation, or ICC, as it is known in other areas such as the literature on multilevel modelling

Rho

When rho is zero the panel-level variance component is unimportant and the panel estimator is not different from the pooled (i.e. cross-sectional) estimator

In our experience it is almost never the case that rho is zero when estimating a model using a genuine panel dataset

One notable exception is reported in Exeter (2004), where the units in the panel were geographical areas

Formal test of random effects

```
Breusch and Pagan Lagrangian multiplier test for random
effects

        zpaynu2[pid,t] = Xb + u[pid] + e[pid,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                 zpaynu2 |   243820.4       493.7817
                       e |    63087.3       251.1718
                       u |   110157.1       331.8993

        Test:   Var(u) = 0
                             chibar2(01) =  6525.74
                          Prob > chibar2 =   0.0000
```

Analysing Panel Data (Part 2)

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Analysing Panel Data (Part 3)

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Which Model Should We Use?

Gelman and Hill (2007), two leading statisticians, comment that the statistical literature is full of confusing and contradictory advice

Searle, Casella and McCulloch (1992) assert that because of conflicting definitions, it is no surprise that clear answers to the question ‘fixed or random effects?’ are unusual

- Researchers routinely ask, ‘Should I choose a fixed effects panel model or a random effects panel model?’
- The answer depends on what the data analyst is attempting to model
- The fixed effects panel model focuses upon the within-subject change
- The random effects panel model is influenced by both within-subject and between-subject patterns
- Both have potential advantages and limitations

```
.hausman fe re

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       fe           re         Difference          S.E.
-------------+----------------------------------------------------------------
        logq |    .9192846     .9066805        .0126041        .0153877
        logf |    .4174918     .4227784       -.0052867        .0058583
          lf |   -1.070396    -1.064499       -.0058974        .0255088
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        2.12
                Prob>chi2 =      0.5469
                (V_b-V_B is not positive definite)
```

Which Model Should We Use?

See Gayle and Lambert (2018)

Comparing fixed effects panel models and random effects panel models

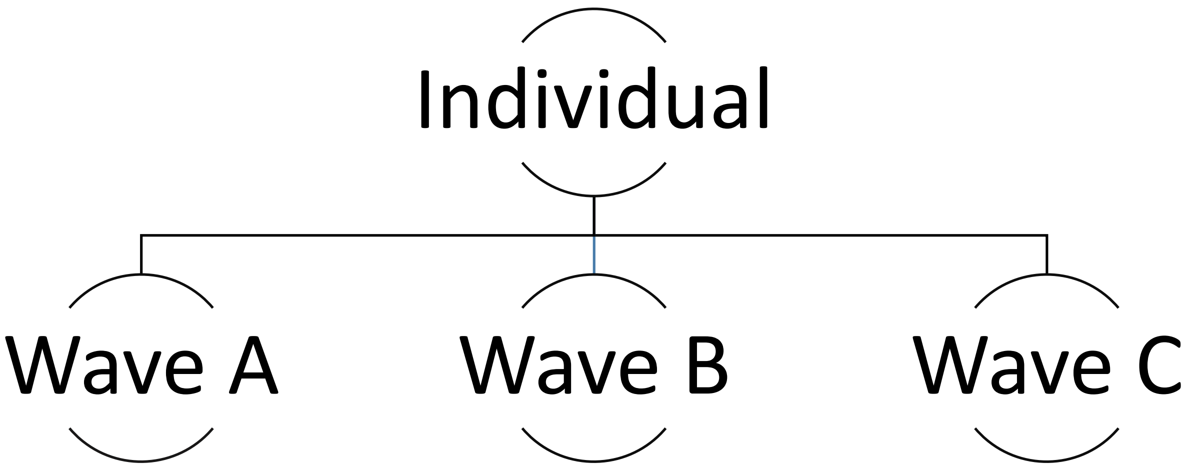
Alternative Literatures

- Econometrics

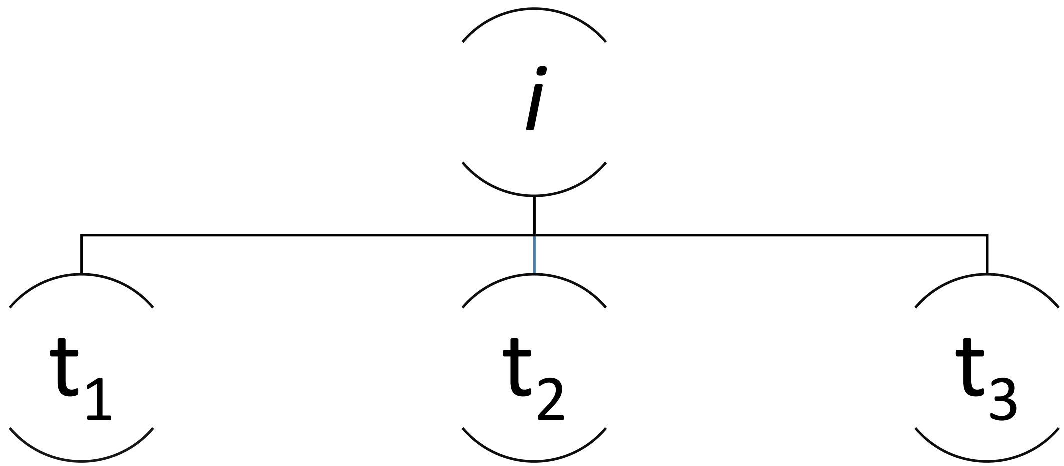
- Multilevel modelling (e.g. in the education literature)

- Epidemiology and biostatistics (e.g. public health)

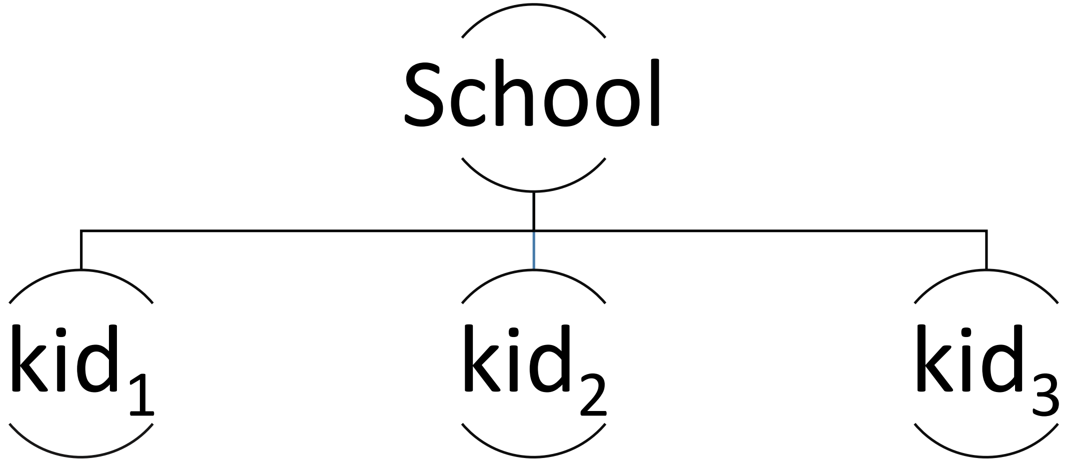
Panel Data Structure



Panel Data Structure



Hierarchical Data Structure



Stata Code

Panel Model

```
xtreg zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav, re mle
```

Multilevel Model

```
xtmixed zpaynu2 zjbhr zjbcssm pacssm graduate zregage i.wav|| pid:, mle
```

	(1) Panel RE	(2) Multilevel
Zpaynu2		
zjbhrs	3.983***	3.983***
	(0.723)	(0.721)
zjbcssm	2.975***	2.975***
	(0.425)	(0.415)
pacssm	4.075***	4.075***
	(0.759)	(0.757)
graduate	195.5***	195.5***
	(32.05)	(31.91)
zregage	9.742*	9.742*
	(4.820)	(4.820)

```
_cons                    449.7***         449.7***
                        (46.94)          (46.84)
--------------------------------------------
sigma_u
_cons                    358.2***
                        (10.18)
--------------------------------------------
sigma_e
_cons                    251.9***
                        (2.734)
--------------------------------------------
lns1_1_1
_cons                                     5.881***
                                        (0.0284)
--------------------------------------------
lnsig_e
_cons                                     5.529***
                                        (0.0109)
--------------------------------------------
N                          5097             5097
--------------------------------------------
Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001
```

Stata logs the sigma_u and sigma_e in the standard xtmixed output

Mundlak-Chamberlain

In a nutshell…

The inclusion of means of the time-varying covariates within the random effects model

Table 6 Coefficients (β) and their standard errors (se) from the fixed effects panel model, the random effects panel model with Mundlak adjustment, and the random effects panel model – log wages

	(1) Fixed effects β_{fe} (s.e.)		(2) Random effects with Mundlak β_{mre} (s.e.)		(3) Random effects β_{re} (s.e.)	
Ft work experience (years)	0.097	***	0.097	***	0.057	***
	(0.001)		(0.001)		(0.001)	
Weeks worked	0.001	*	0.001	*	0.002	**
	(0.001)		(0.001)		(0.001)	
Blue-collar occupation	−0.021		−0.021		−0.108	***
	(0.014)		(0.014)		(0.016)	
Individual's mean ft work experience (years)			−0.090	***		
			(0.002)			
Individual's mean weeks worked			0.010	**		
			(0.004)			
Individual's mean blue-collar occupation			−0.316	***		
			(0.034)			
Constant	4.709	***	6.164	***	5.523	***
	(0.038)		(0.212)		(0.047)	
n	4165		4165		4165	

Table 7 Coefficients (β) and their standard errors (se) from the fixed eff ects panel model, the random eff ects panel model with Mundlak adjustment, and the random eff ects panel model – Log total cost (per $1000)

	(1) Fixed eff ects β_{fe} (s.e.)		(2) Random eff ects with Mundlak β_{mre} (s.e.)		(3) Random eff ects β_{re} (s.e.)	
Log output revenue index (passenger miles)	0.919	***	0.919	***	0.907	***
	(0.030)		(0.030)		(0.026)	
Log price of fuel	0.417	***	0.417	***	0.423	***
	(0.015)		(0.015)		(0.014)	
Load factor (average capacity of the fleet)	−1.070	***	−1.070	***	−1.064	***
	(0.202)		(0.202)		(0.200)	
Airline mean log output revenue index (passenger miles)			−0.137			
			(0.113)			
Airline mean log price of fuel			−5.941			
			(4.479)			
Airline mean Load factor (average capacity of the fleet)			−0.681			
			(2.751)			
Constant	9.714	***	85.808		9.628	***
	(0.230)		(56.482)		(0.210)	
n	90		90		90	

Data from Greene (1999).

Other Panel Models

Binary Outcomes
xtlogit
xtprobit
clogit

Ordinal Outcomes

xtologit	random-effects ordered logistic models
xtoprobit	random-effects ordered probit models

Count Data

xtpoisson	panel data poisson models
xtnbreg	panel data negative binomial models

Dynamic Models

- Dynamic panel models extend panel models
- Appeal to the idea of using panel data to better understand ‘state dependence’
- Lagged dependent variables as X vars
- Complicated because the lagged dependent variables will themselves be influenced by unobserved effects

Dynamic Models

- Standard panel estimation procedures will be inconsistent with lagged dependent variables
- Arellano and Bond (1991) derived a suitable estimator which is available using the Stata command *xtabond*
- Stewart (2006) *redprob*

Further Topics to Consider…

- The estimation and interpretation of interaction effects in statistical models (see Ai and Norton, 2003; Norton, Wang and Ai, 2004; Mitchell and Chen, 2005)

- Post-estimation measures and model evaluation (see Long and Freese, 2014)

- Missing data (see Carpenter and Kenward, 2012)

- Sample attrition, panel conditioning, interviewer effects and data collection modes (see Lynn, 2009)

Analysing Panel Data (Part 3)

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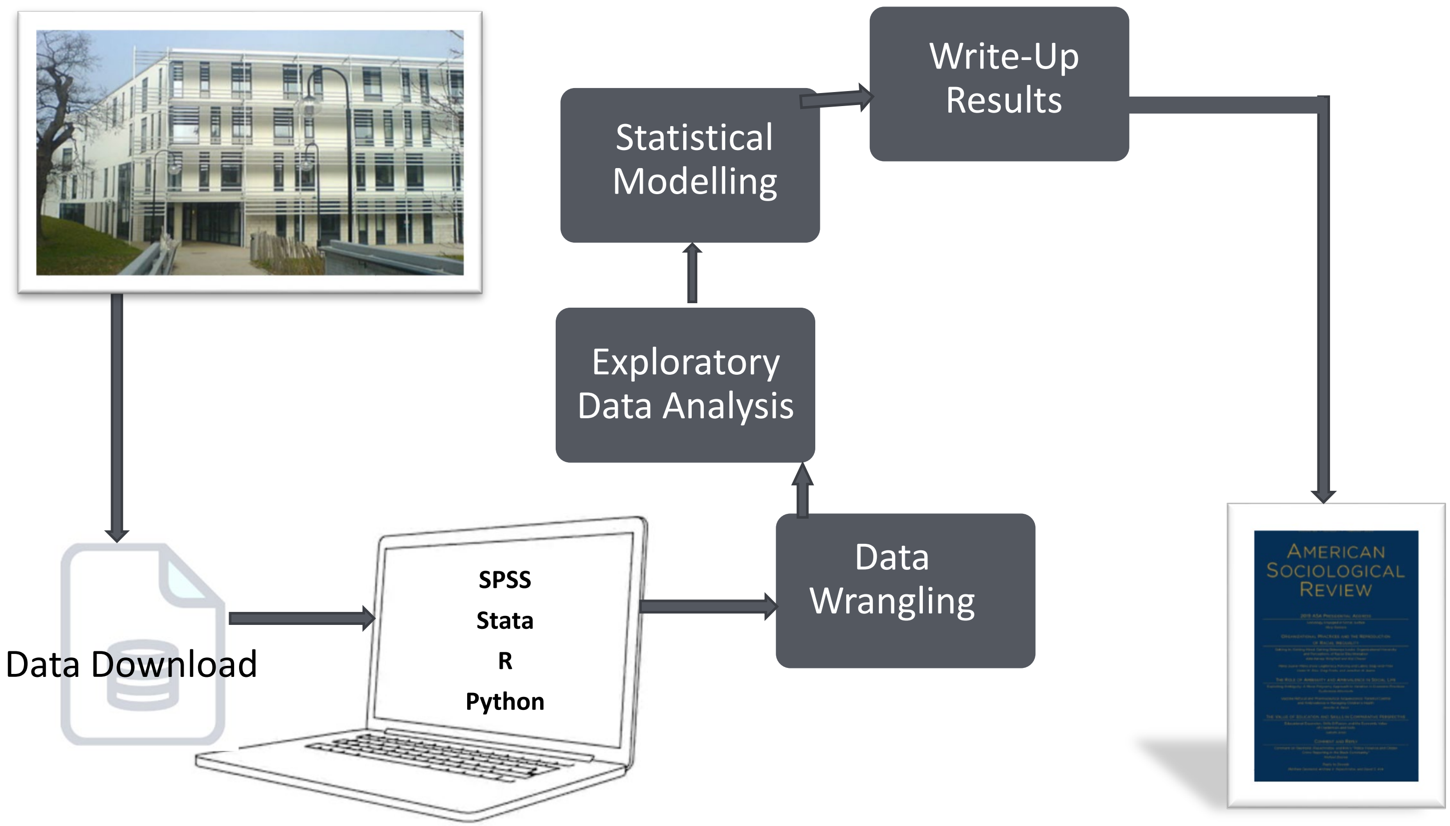
Statistical Modelling

Software

Tools of the Trade



Write-Up Results
Statistical Modelling
Exploratory Data Analysis
Data Wrangling
SPSS
Stata
R
Python
Data Download
American Sociological Review

Considerations

1. Supervisor’s expertise
2. Peer group (e.g. other PhD students)
3. Departmental access and support
4. University licenses
5. Data format and meta data (e.g. UK Data Service)
6. Academic subject area
7. Academic job market
8. Non-academic job market

DON'T PANIC !

Stata

```
logit admit gre gpa
```

SPSS

```
logistic regression admit with gre gpa.
```

SAS

```
proc logistic data="c:\data\binary" descending;
 class rank / param=ref ;
 model admit = gre gpa;
 run ;
```

R

```
mylogit <- glm(admit ~ gre + gpa, data = mydata, family = "binomial")
```

Python

```
independentVar = [`gre’, `gpa’,`Int’]
logReg = sm.Logit(df[`admit’] , df[independentVar])
answer = logReg.fit( )
```

NATIONAL CENTRE FOR RESEARCH METHODS

Statistical Modelling

Software

Concluding Remarks

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- Some research questions require longitudinal data

- Longitudinal data are not a panacea

- For many social research projects cross-sectional data will be sufficient

- Most social research projects can be improved by the analysis of longitudinal data

- *Researchers are likely to make more rapid progress using existing large-scale longitudinal data resources*

Final Comment…

Angrist and Pischke (2008) playfully remarked that if applied research was easy then theorists would do it!

They also reassure readers that applied research is not as hard as the dense pages of Econometrica might lead us to believe

How to cite this file

Gayle, V. (2022) Longitudinal Data and Research
Available at: https://www.ncrm.ac.uk (Accessed: day month year)

Longitudinal Data and Research

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