Analysing Comparative Longitudinal Survey Data Using Multilevel Models

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Barcelona Summer School in Survey Methodology · July 2016

University of BRISTOL

Centre for Multilevel Modelling

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The Plan

- course contents, structure, and timeline
  - lectures
  - labs
  - R
    - why I use it (principled and practical reasons)

- a bit about me

- my assumptions about what you do and don't know
  - multilevel models, including GLMMs (multilevel logit/probit, etc.)
  - not necessarily R (but how to fit GLMMs in some relevant software)

Agenda

1. motivation: the prevalence and promise of comparative longitudinal survey data (CLSD)
2. key features of multilevel models
3. fixed effects and random effects/multilevel/mixed models
4. within and between relationships and the “REWB” specification

Comparative Longitudinal Survey Data

Comparative Longitudinal Survey Data

- <u>comparative</u> survey data:
  - survey data on individuals nested in macro-social higher-level units
    - countries, or sub-national units:
      - states, provinces, regions, counties, cantons, cities, etc.
  - two levels of analysis

- comparative <u>longitudinal</u> survey data ("CLSD"):
  - <u>repeated cross-sectional</u> survey data, where individuals are observed only once -> <u>not</u> panel data
  - higher-level units are observed multiple times (albeit via observations on individuals) -> <u>panel data</u>

Why Use Comparative Longitudinal Survey Data?

Multilevel Analyses of Comparative Survey Data

ajps American Journal of Political Science

The Institutional Context of Tolerance for Ethnic Minorities: A Comparative, Multilevel Analysis of Western Europe

Steven A. Weldon

Article first published online: 29 MAR 2006

DOI: 10.1111/j.1540-5907.2006.00187.x

Issue

American Journal of Political Science

Volume 50, Issue 2, pages 331–349, April 2006

Multilevel Analyses of Comparative Survey Data

American Journal of Sociology Publication Info

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Published by: The University of Chicago Press
Article DOI: 10.1086/603536
Stable URL: http://www.jstor.org/stable/10.1086/603536

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Religious Attendance in Cross–National Perspective: A Multilevel Analysis of 60 Countries[1]

Stijn Ruiter
Radboud University Nijmegen

Frank van Tubergen
Utrecht University

Multilevel Analyses of Comparative Survey Data

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Impact Factor: 4.390 | **Ranking:** Sociology 1 out of 142

Workers of the Less Developed World Unite? A Multilevel Analysis of Unionization in Less Developed Countries

Nathan D. Martin

David Brady

Duke University

Multilevel Analyses of Comparative Survey Data

European Sociological Review VOLUME 29 | NUMBER 1 | 2013 32–47 32
DOI:10.1093/esr/jcr037, available online at www.esr.oxfordjournals.org
Online publication 12 May 2011

Childlessness and Psychological Well-Being in Context: A Multilevel Study on 24 European Countries

Tim Huijts[1,*], Gerbert Kraaykamp[1] and S. V. Subramanian[2]

Multilevel Analyses of Comparative Survey Data

Health & Place 18 (2012) 408–414

Contents lists available at SciVerse ScienceDirect

Health & Place

journal homepage: www.elsevier.com/locate/healthplace

Regional inequalities in the use of contraception in Spain: A multilevel approach ☆, ☆☆

Dolores Ruiz-Muñoz [a,b,c,*], Gloria Pérez [a,b,c,d], Mercè Gotsens [a,b,c], Maica Rodríguez-Sanz [a,b,c,

Comparative Survey Data

Country	Respondent	x	y
1	1	0	65
1	2	1	51
1	3	0	58
…	…		
2	1	1	30
2	2	1	43
2	3	1	51
…	…		
3	1	0	71
3	2	0	64
3	3	1	88
…	…		

Time Series Cross-Sectional ("TSCS") Data

Country	Year	x	y
1	1998	0	65
1	1999	1	51
…	…		
2	1998	0	58
2	1999	1	30
…	…		
3	1998	1	43
3	1999	1	51
…	…		

see:

Western, Bruce. 1998. "Causal Heterogeneity in Comparative Research: A Bayesian Hierarchical Modelling Approach." *American Journal of Political Science* 42[4]: 1233-59.

Longitudinal (Panel) Survey Data

Respondent	Wave	x	y
1	1	0	65
1	2	1	51
…	…		
2	1	0	58
2	2	1	30
…	…		
3	1	1	43
3	2	1	51
…	…		

see:

Bell, Andrew, and Kelvyn Jones. 2015. "Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data." *Political Science Research and Methods* 3: 133-153.

Comparative Longitudinal Survey Data

Country	Wave	Respondent	x	y
1	1	1	0	65
1	1	2	0	51
	…	…		
1	2	1	0	58
1	2	2	1	30
…	…	…		
2	1	1	1	43
2	1	2	1	51
	…	…		
2	2	1	1	71
2	2	2	0	64
…	…	…		

Comparative Longitudinal Survey Data

see:

Fairbrother, Malcolm. 2014. "Two Multilevel Modeling Techniques for Analyzing Comparative Longitudinal Survey Datasets." *Political Science Research and Methods* 2[1]: 119–140.

Schmidt-Catran, Alexander W., and Malcolm Fairbrother. 2016. "The Random Effects in Multilevel Models: Getting Them Wrong and Getting Them Right." *European Sociological Review* 32[1]: 23–38.

Comparative Longitudinal Survey Data

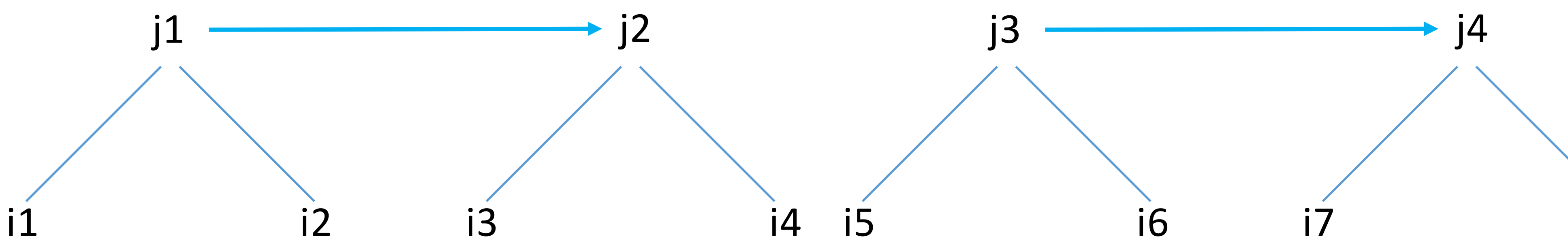
- examples of these datasets are increasingly prevalent:
    - European Social Survey, World Values Surveys, European Values Study, U.S. General Social Survey, German Socio-Economic Panel

- these datasets capture three kinds of variation:
    1. across individuals
    2. across countries/space
    3. across waves/time

Comparative Longitudinal Survey Data: Why Use Multilevel Models?

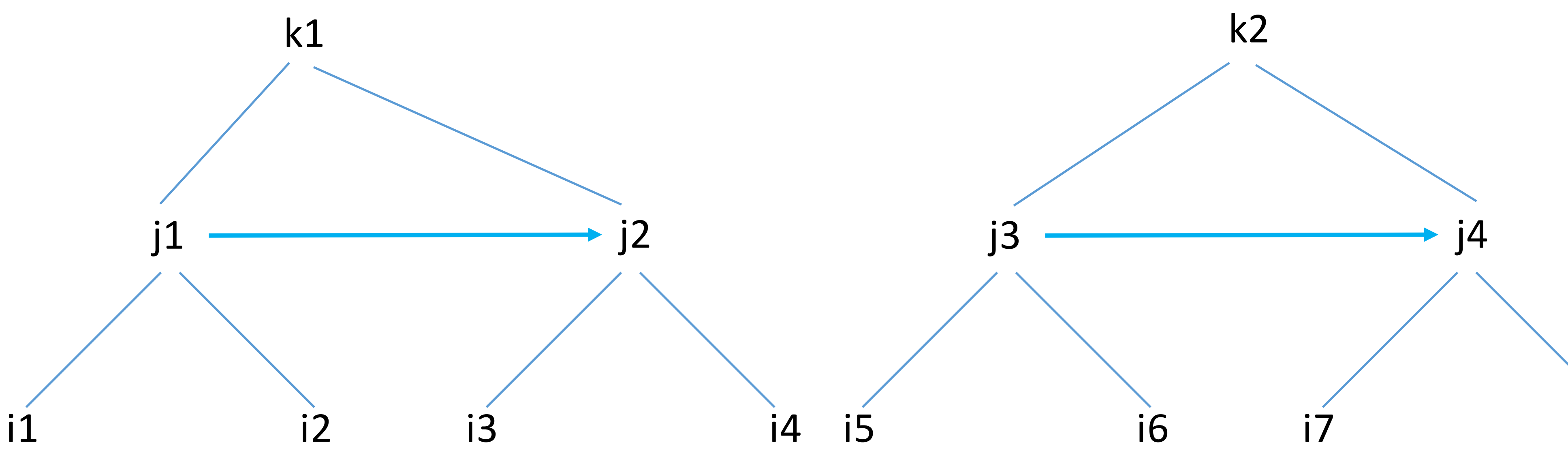
Comparative Longitudinal Survey Data

- individuals (i) are nested in country-years (j)



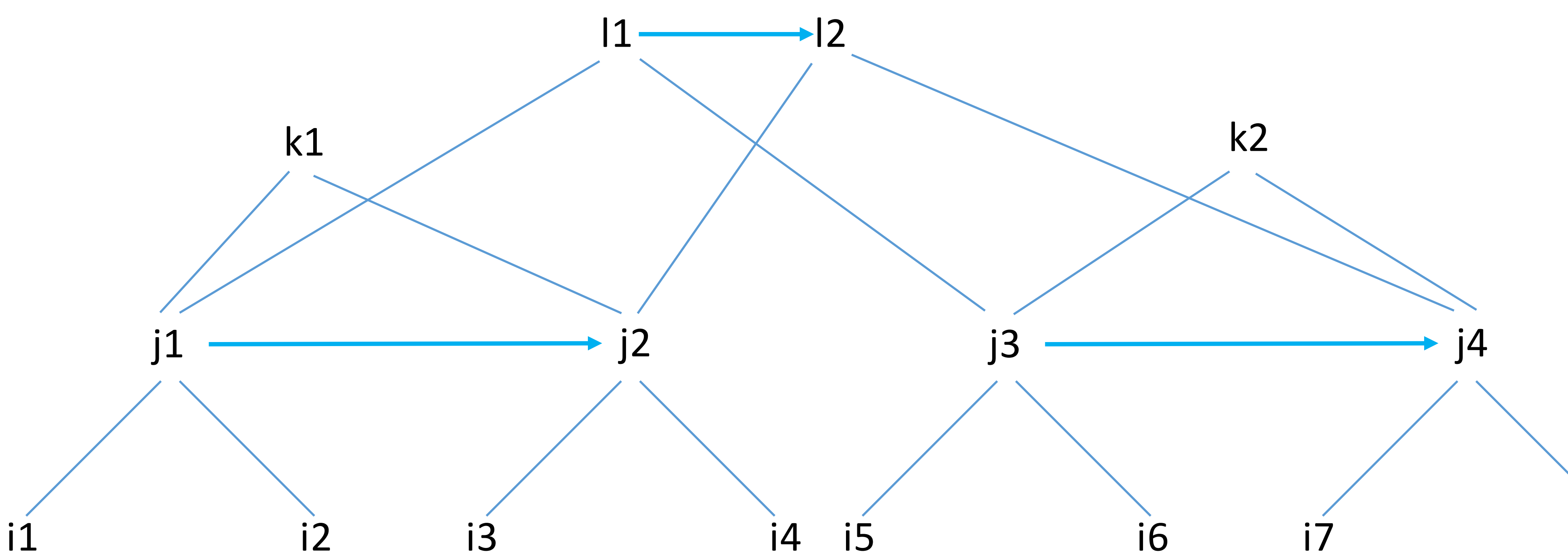
Comparative Longitudinal Survey Data

- individuals (i) are nested in country-years (j), which are separately nested in countries (k)



Comparative Longitudinal Survey Data

- individuals (i) are nested in country-years (j), which are separately nested in countries (k) and years (l)



Comparative Longitudinal Survey Data

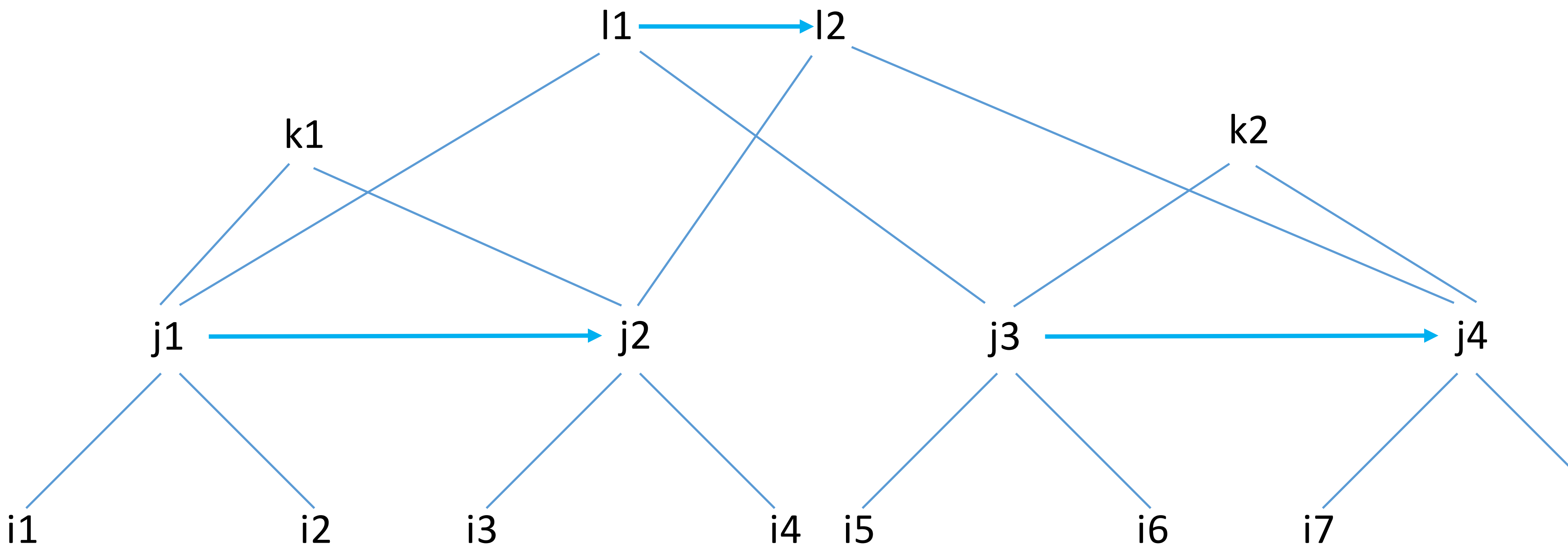
model: $y_{ijkl} = \beta_0 + \beta_1 x_{1ijkl} + \beta_2 x_{2jkl} + \beta_3 x_{3k} + u_j + u_k + u_l + e_{ijkl}$

$u_j \sim N(0, \sigma_{u_j}^2)$

$u_k \sim N(0, \sigma_{u_k}^2)$

$u_l \sim N(0, \sigma_{u_l}^2)$

$e_{ijkl} \sim N(0, \sigma_e^2)$



Comparative Longitudinal Survey Data

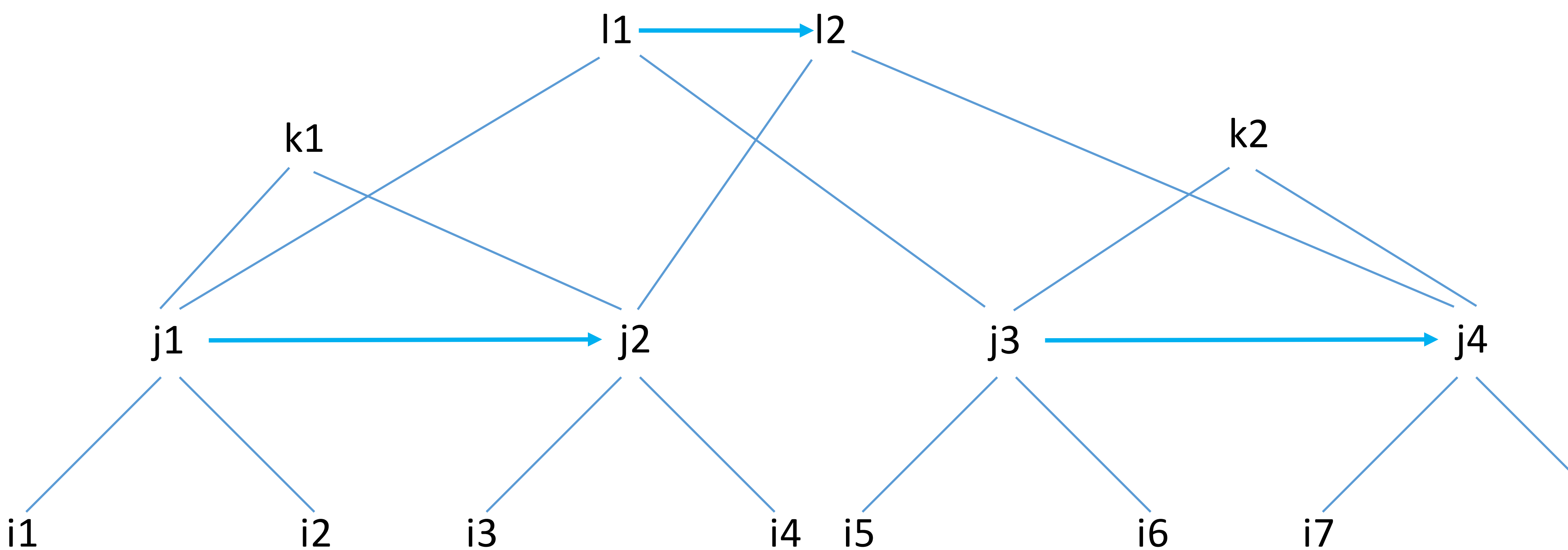
model: $y_{ijkl} = \beta_0 + \beta_1 x_{1ijkl} + \beta_2 x_{2jkl} + \beta_3 x_{3k} + u_j + u_k + u_l + e_{ijkl}$

$u_j \sim N(0, \sigma_{u_j}^2)$

$u_k \sim N(0, \sigma_{u_k}^2)$

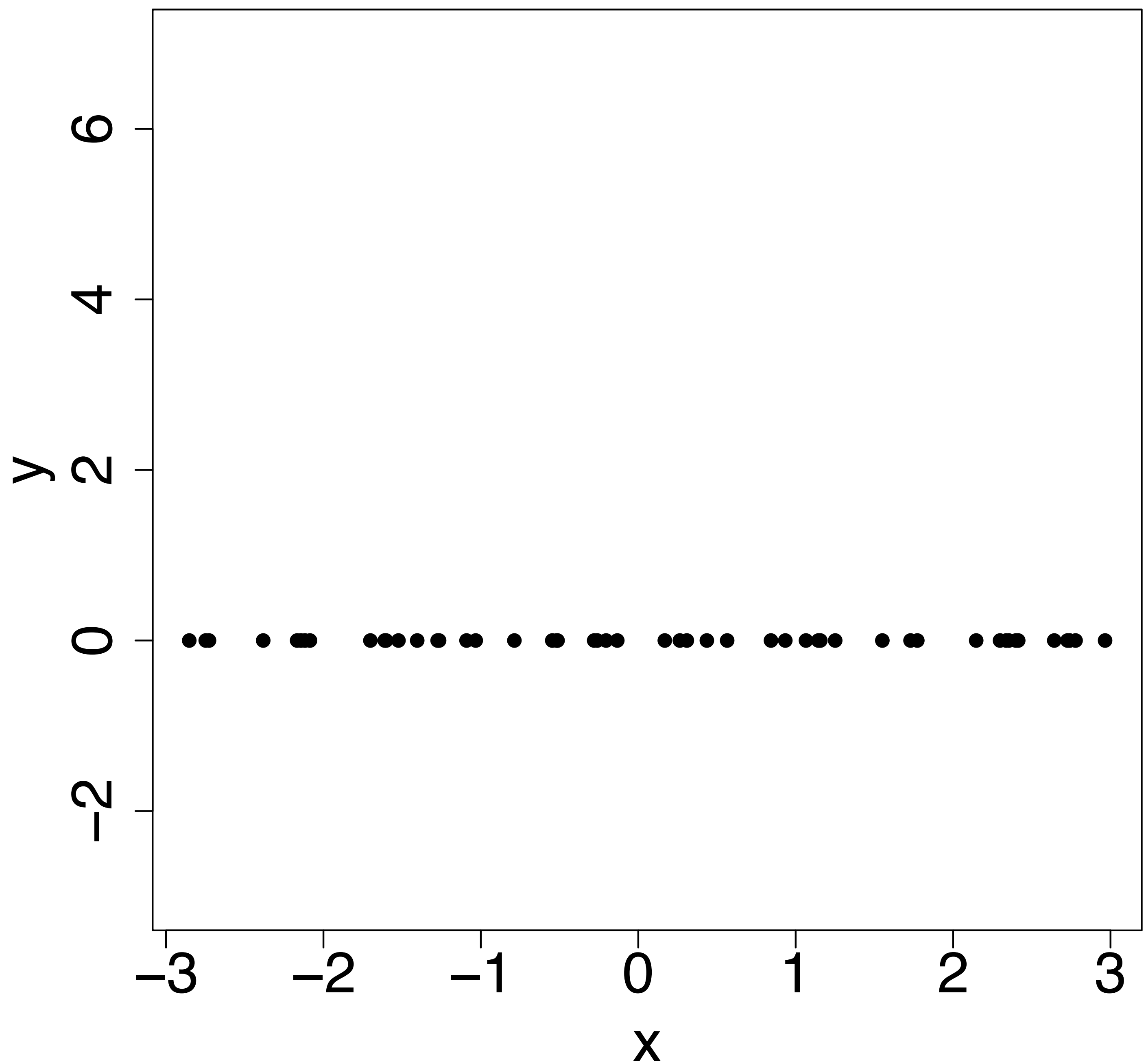
$u_l \sim N(0, \sigma_{u_l}^2)$ -> or fixed effects (dummies)

$e_{ijkl} \sim N(0, \sigma_e^2)$

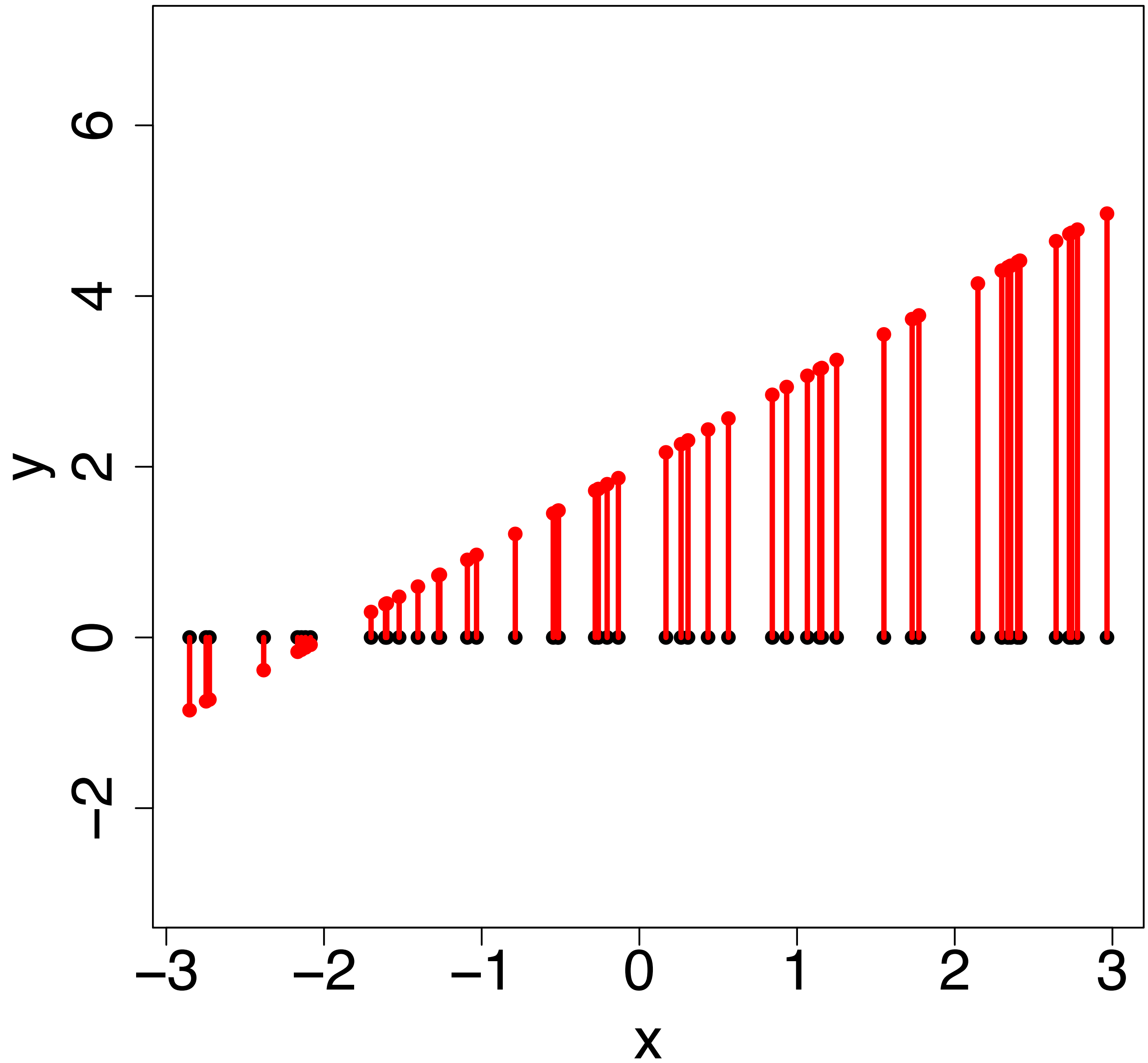


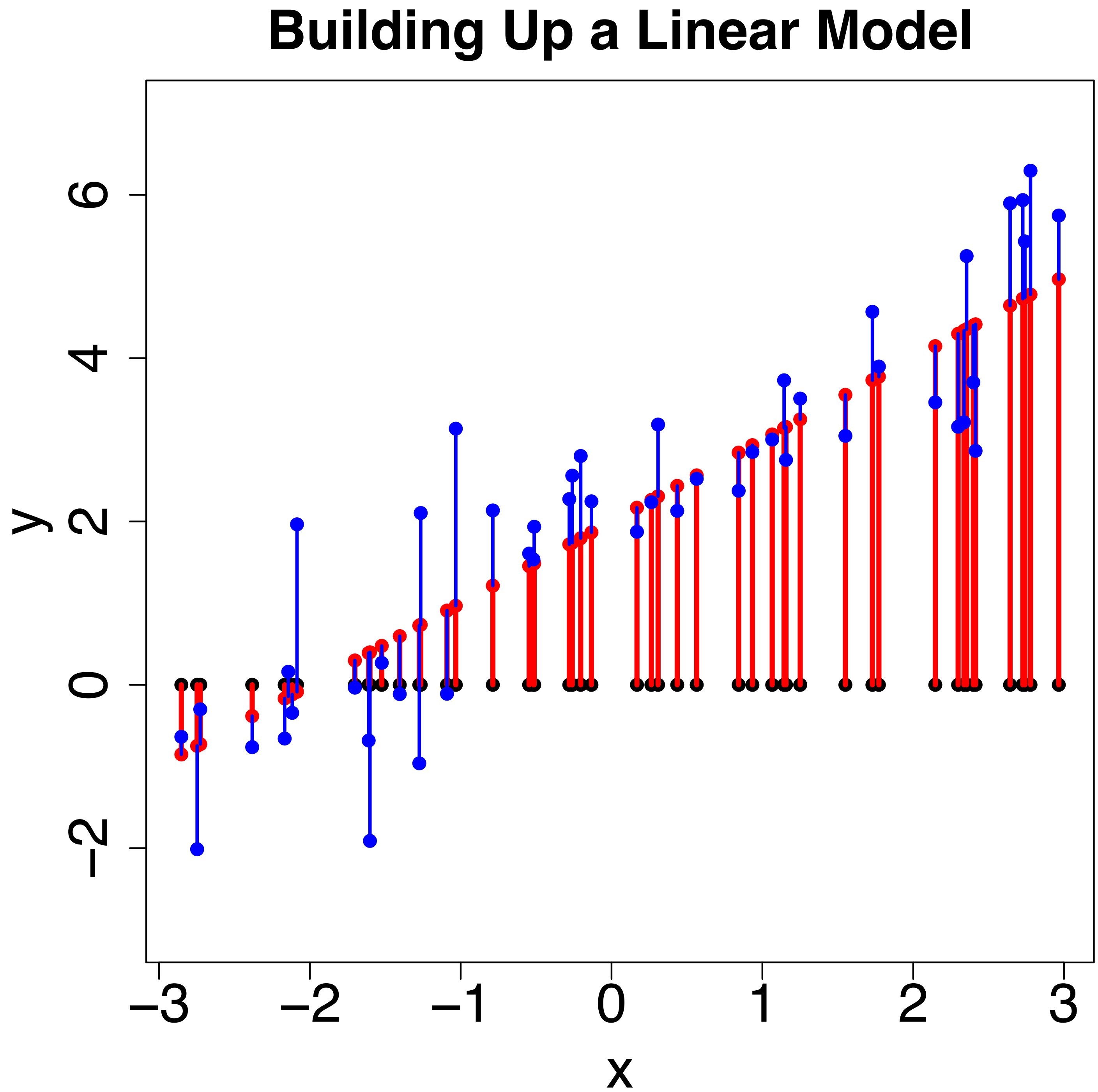
Key Features of Multilevel Models

Building Up a Linear Model

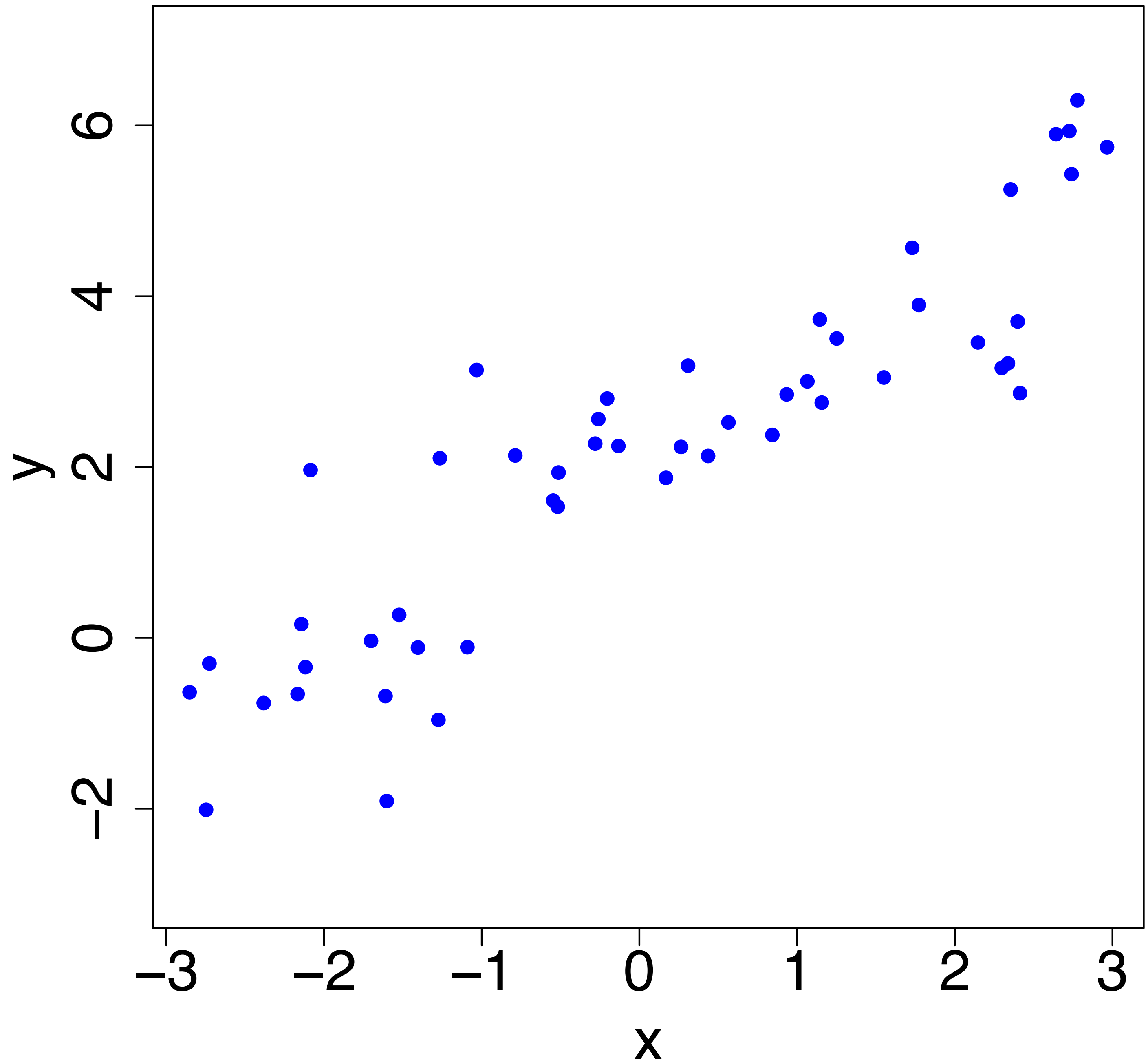


Building Up a Linear Model

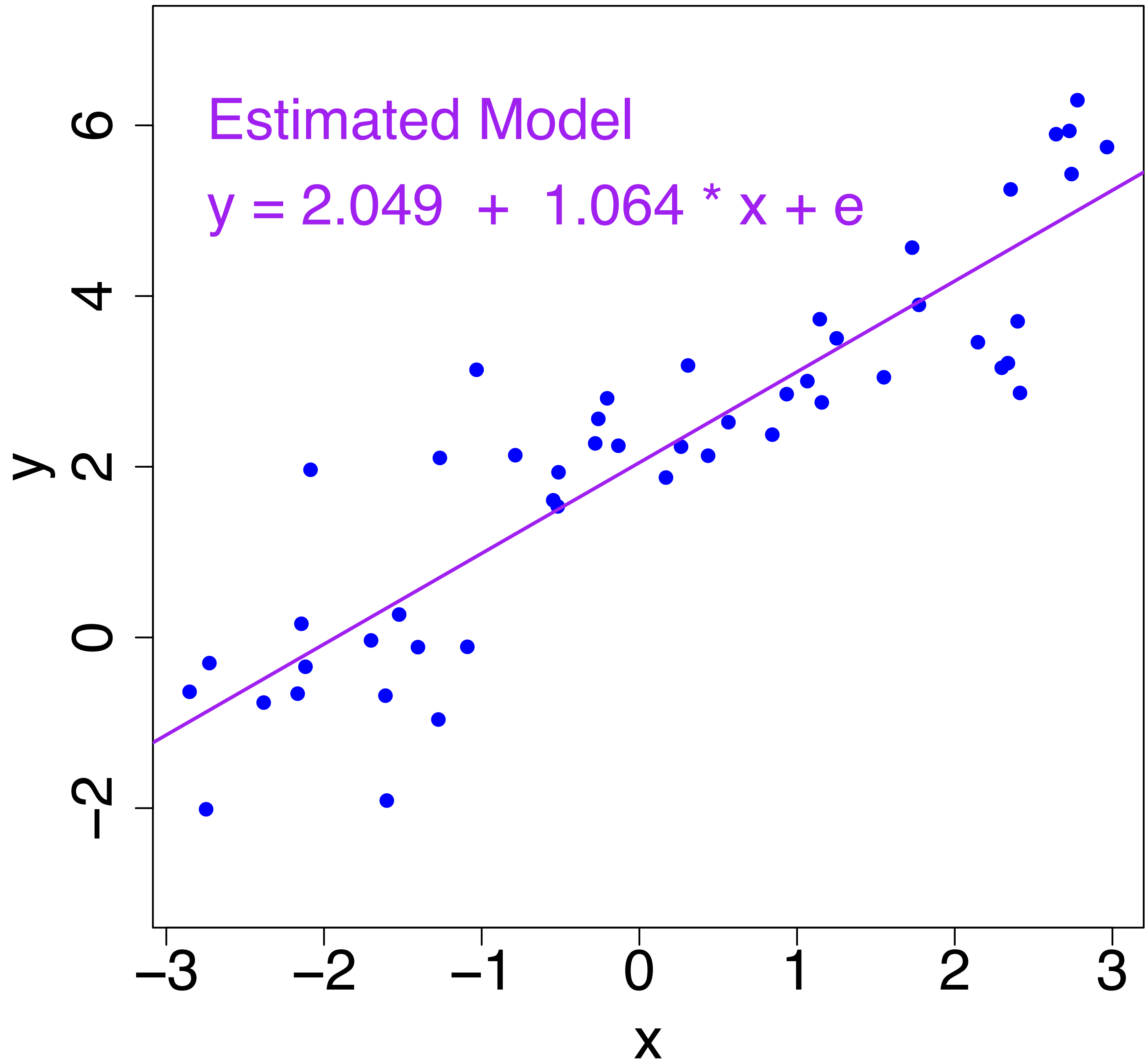


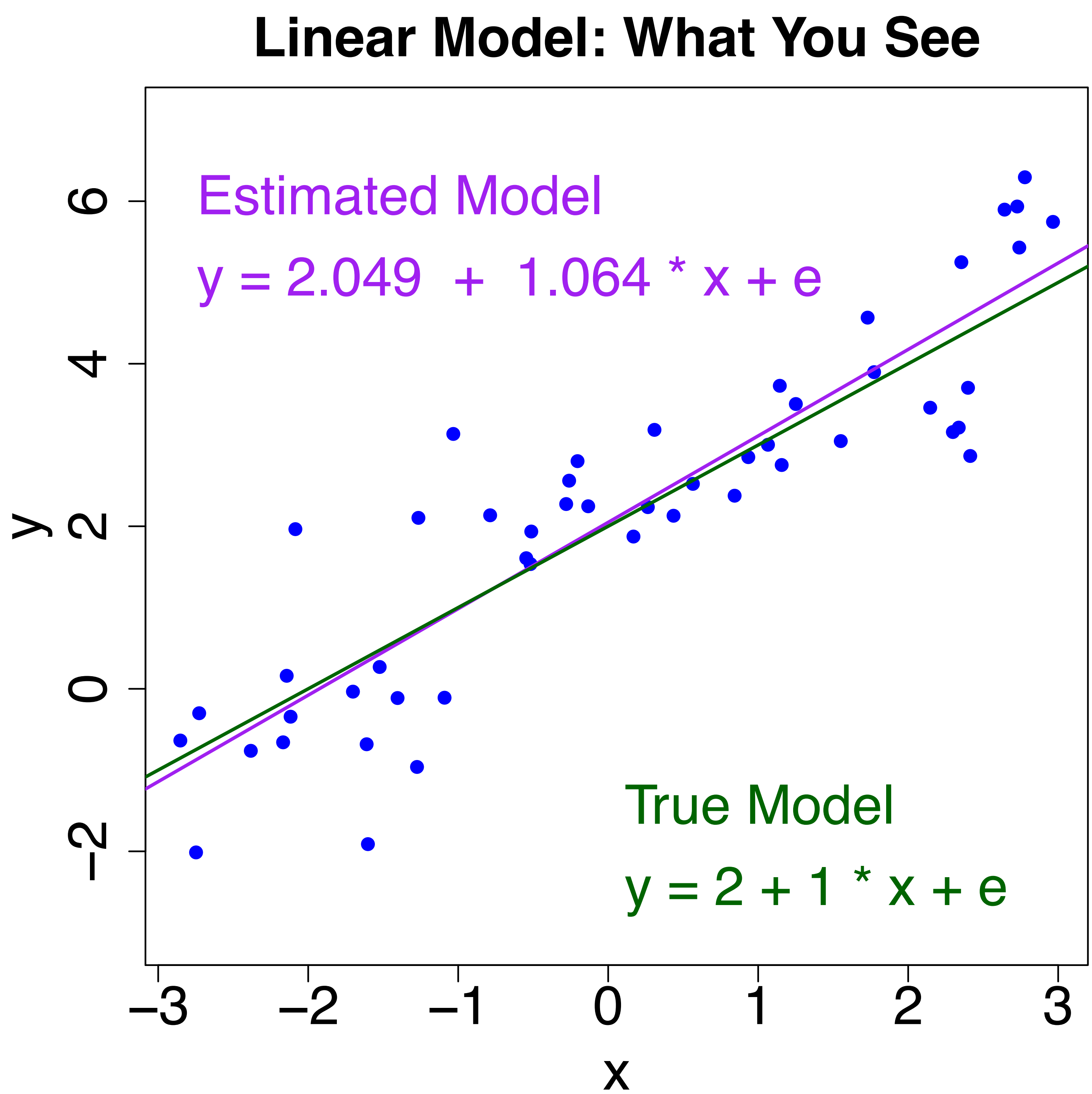

Building Up a Linear Model
y
x
−2
0
2
4
6
−3
−2
−1
0
1
2
3

Linear Model: What You See

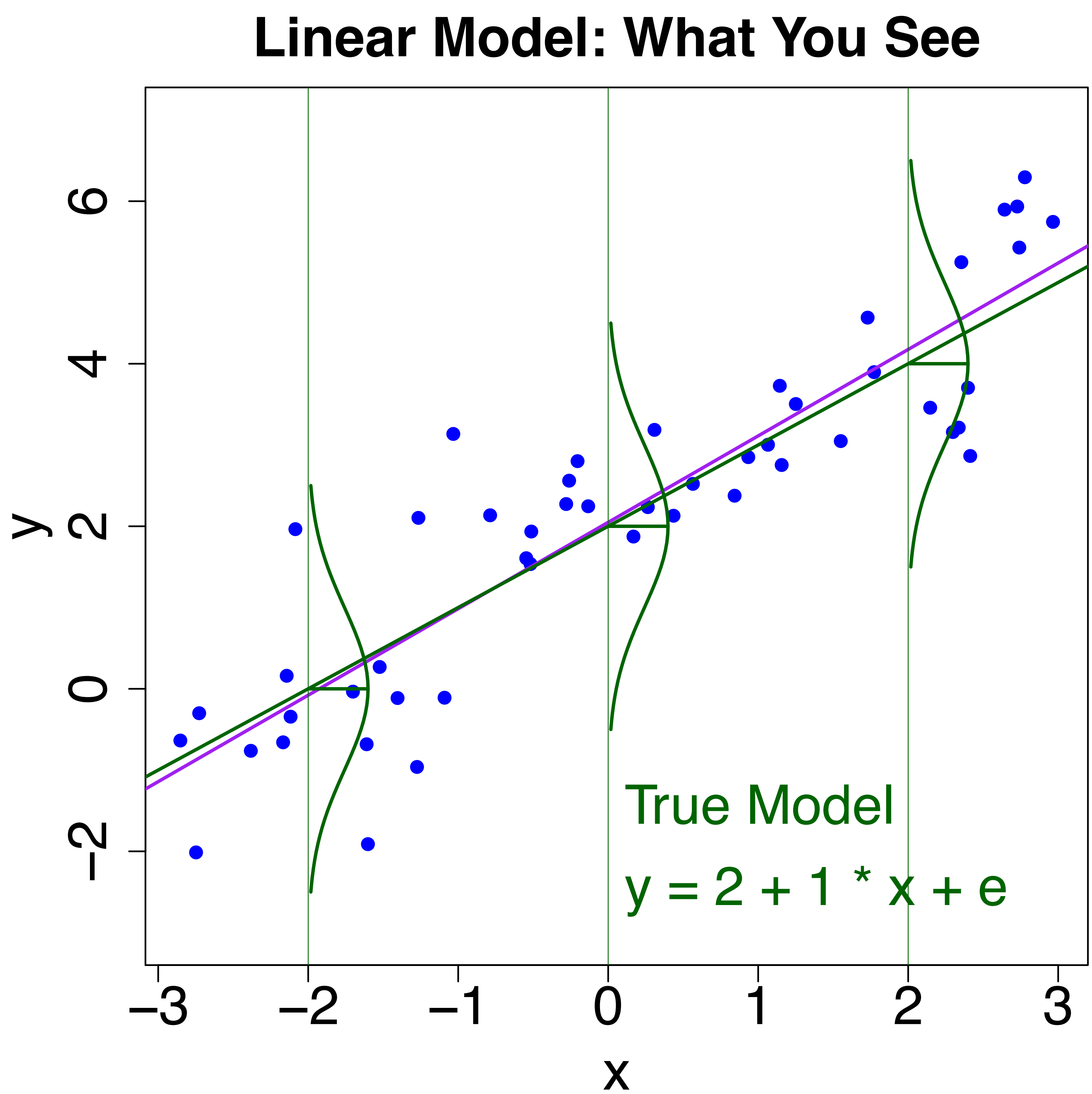


Linear Model: What You See

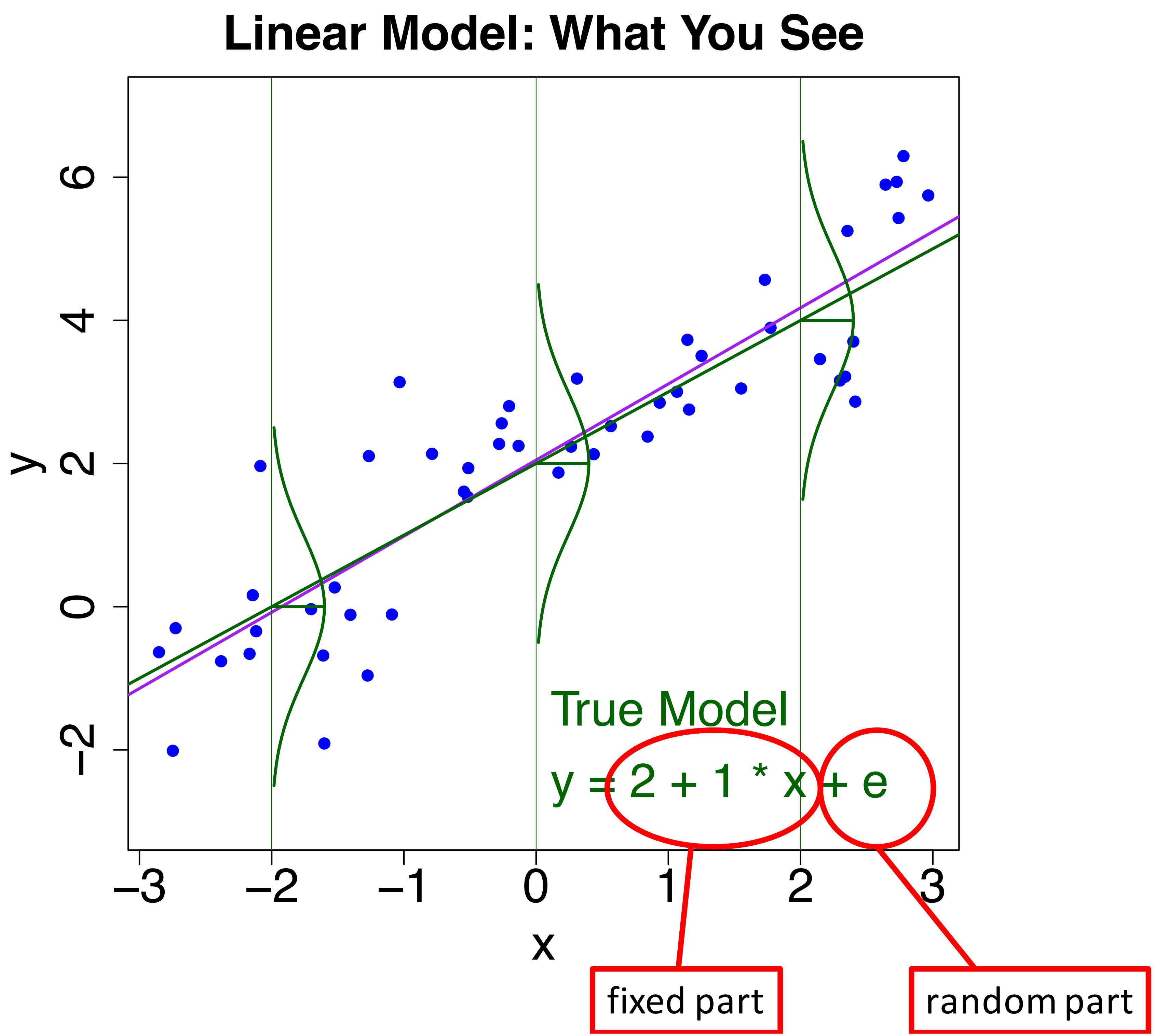




Linear Model: What You See
Estimated Model
y = 2.049 + 1.064 * x + e
True Model
y = 2 + 1 * x + e
−2
0
2
4
6
y
−3
−2
−1
0
1
2
3
x



Linear Model: What You See
True Model
y = 2 + 1 * x + e
y
x
−2
0
2
4
6
−3
−2
−1
0
1
2
3



Linear Model: What You See
True Model
y = 2 + 1 * x + e
fixed part
random part
x
y
−3
−2
−1
0
1
2
3
−2
0
2
4
6

Basic Theory

$$y_i = \beta_0 + \beta_1 x_{1i} + e_i$$
$$e_i \sim N(0,\sigma_e^2)$$

Basic Theory

$$y_i = \beta_0 + \beta_1 x_{1i} + e_i$$
$$e_i \sim N(0,\sigma_e^2)$$

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2j} + u_j + e_{ij}$$
$$u_j \sim N(0,\sigma_u^2)$$
$$e_{ij} \sim N(0,\sigma_e^2)$$

Basic Theory

$$y_i = \beta_0 + \beta_1 x_{1i} + e_i$$

$$e_i \sim N(0,\sigma_e^2)$$

fixed part

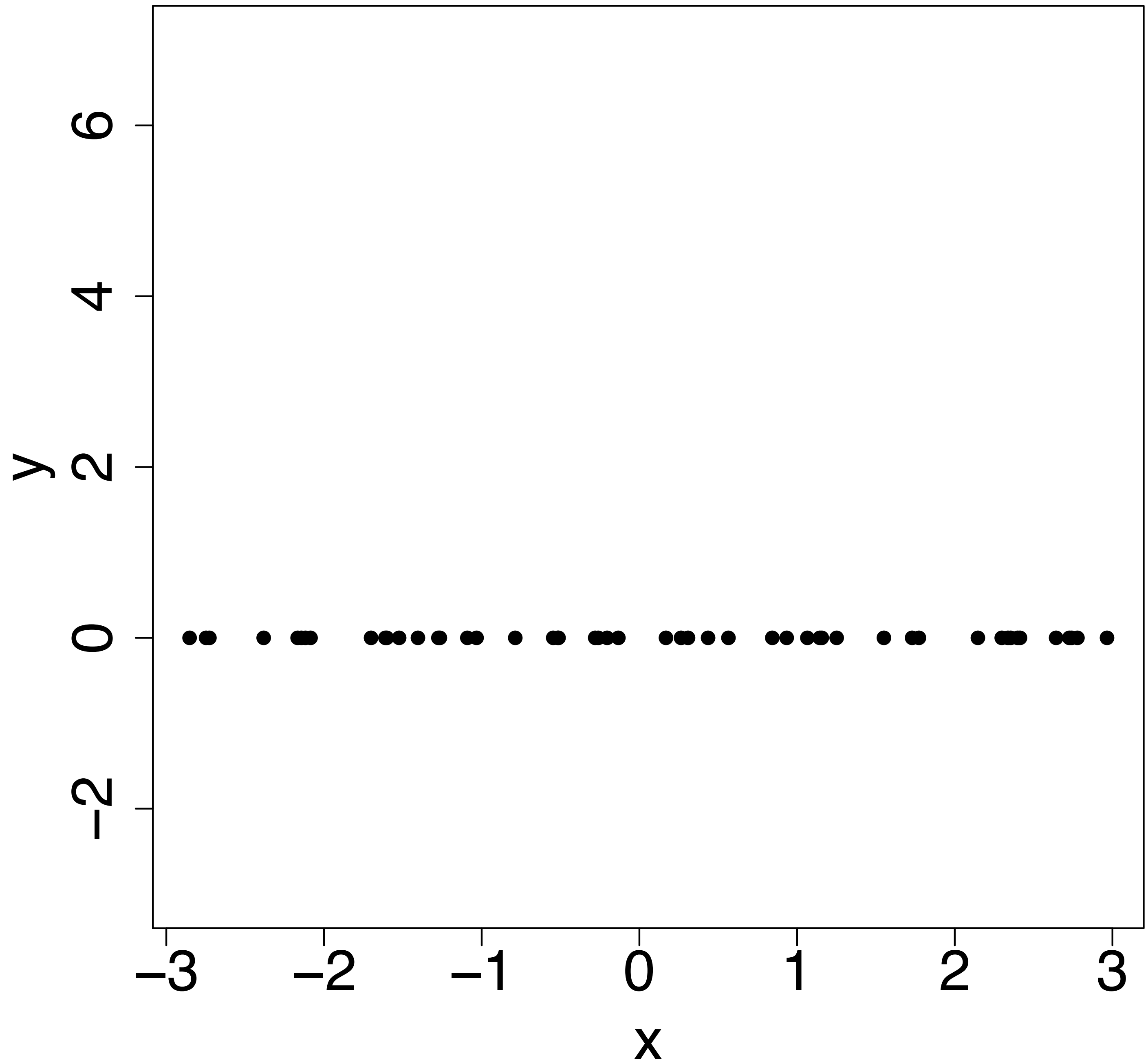
random part

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2j} + u_j + e_{ij}$$

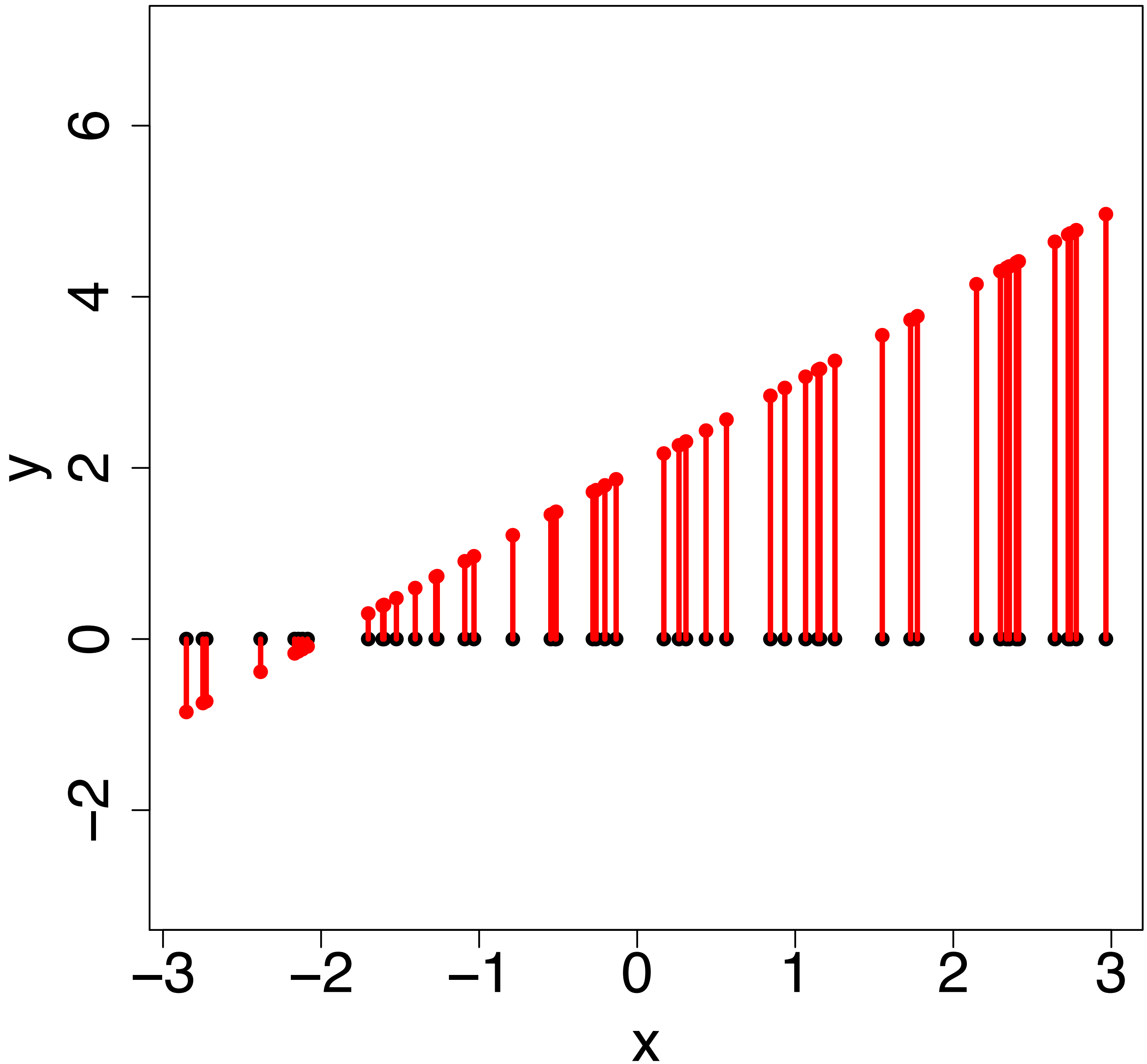
$$u_j \sim N(0,\sigma_u^2)$$

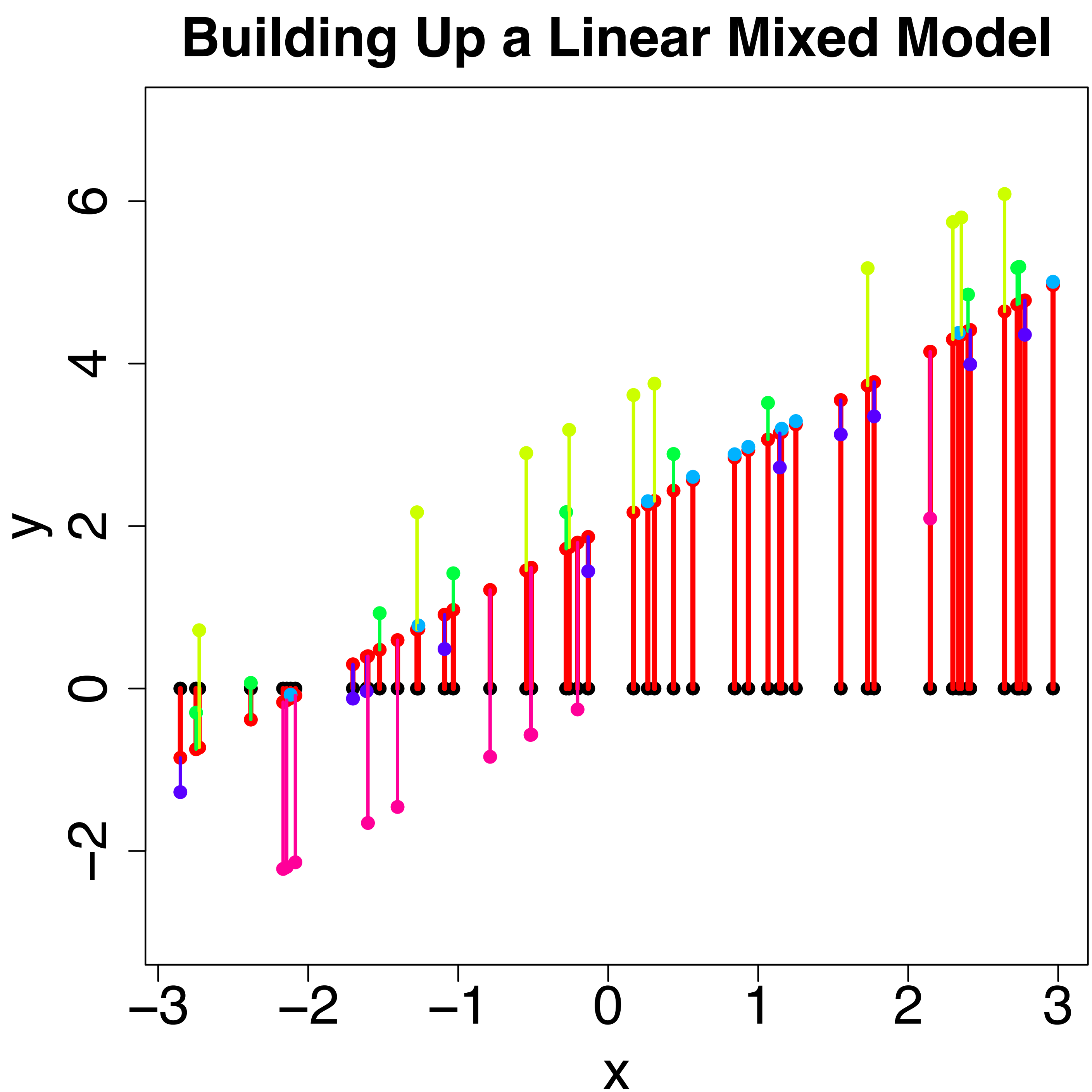
$$e_{ij} \sim N(0,\sigma_e^2)$$

Building Up a Linear Mixed Model

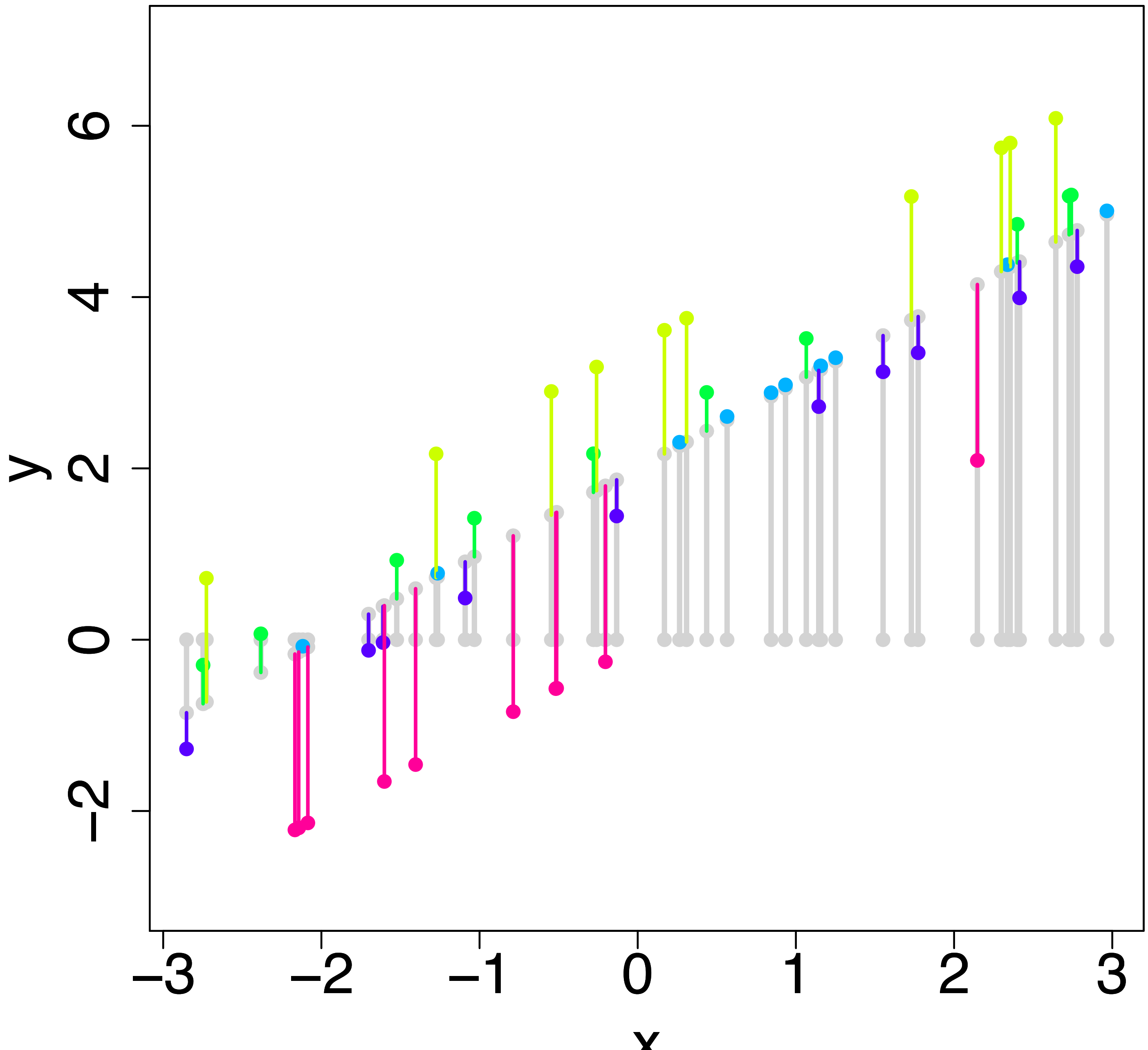


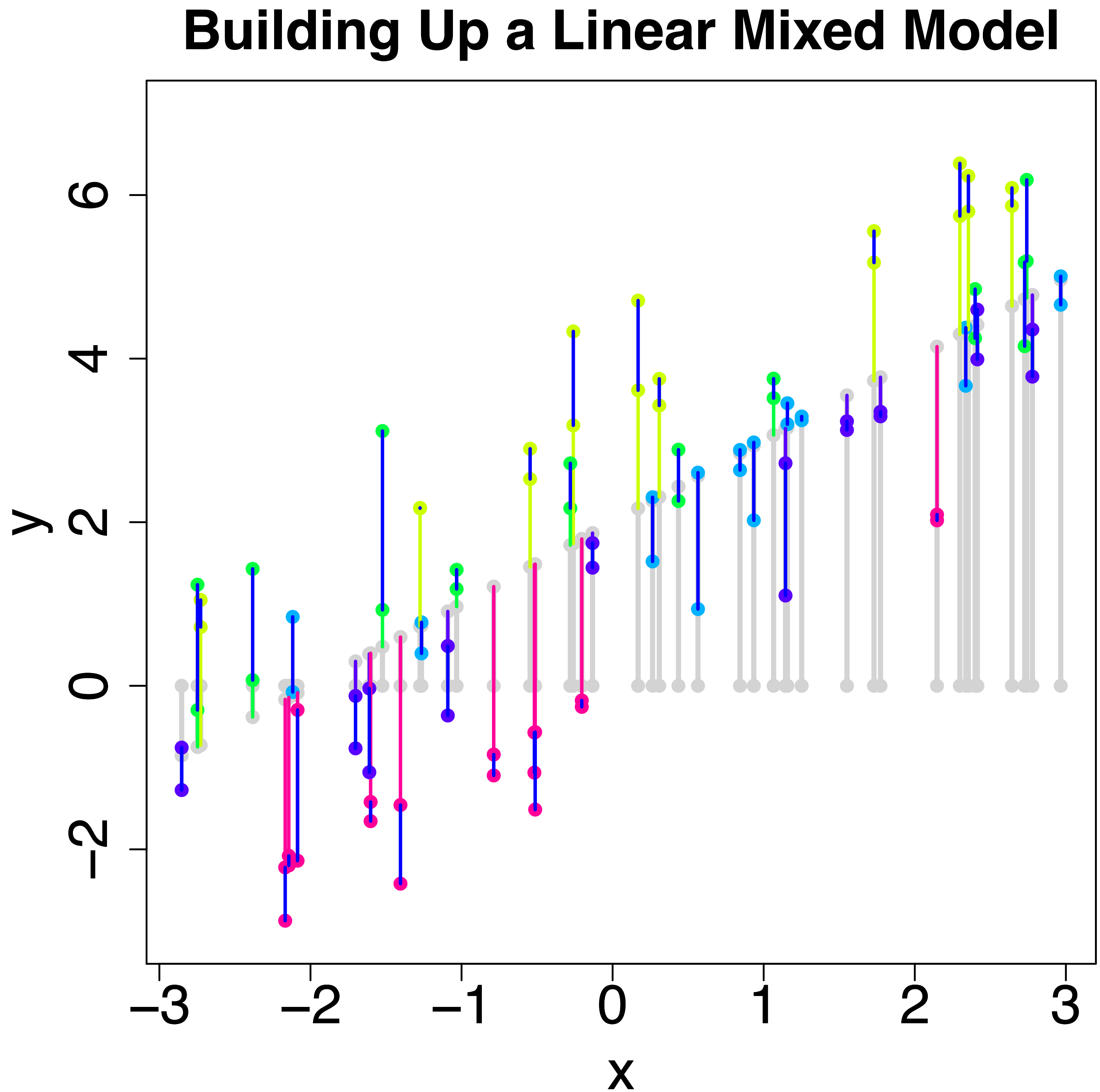
Building Up a Linear Mixed Model



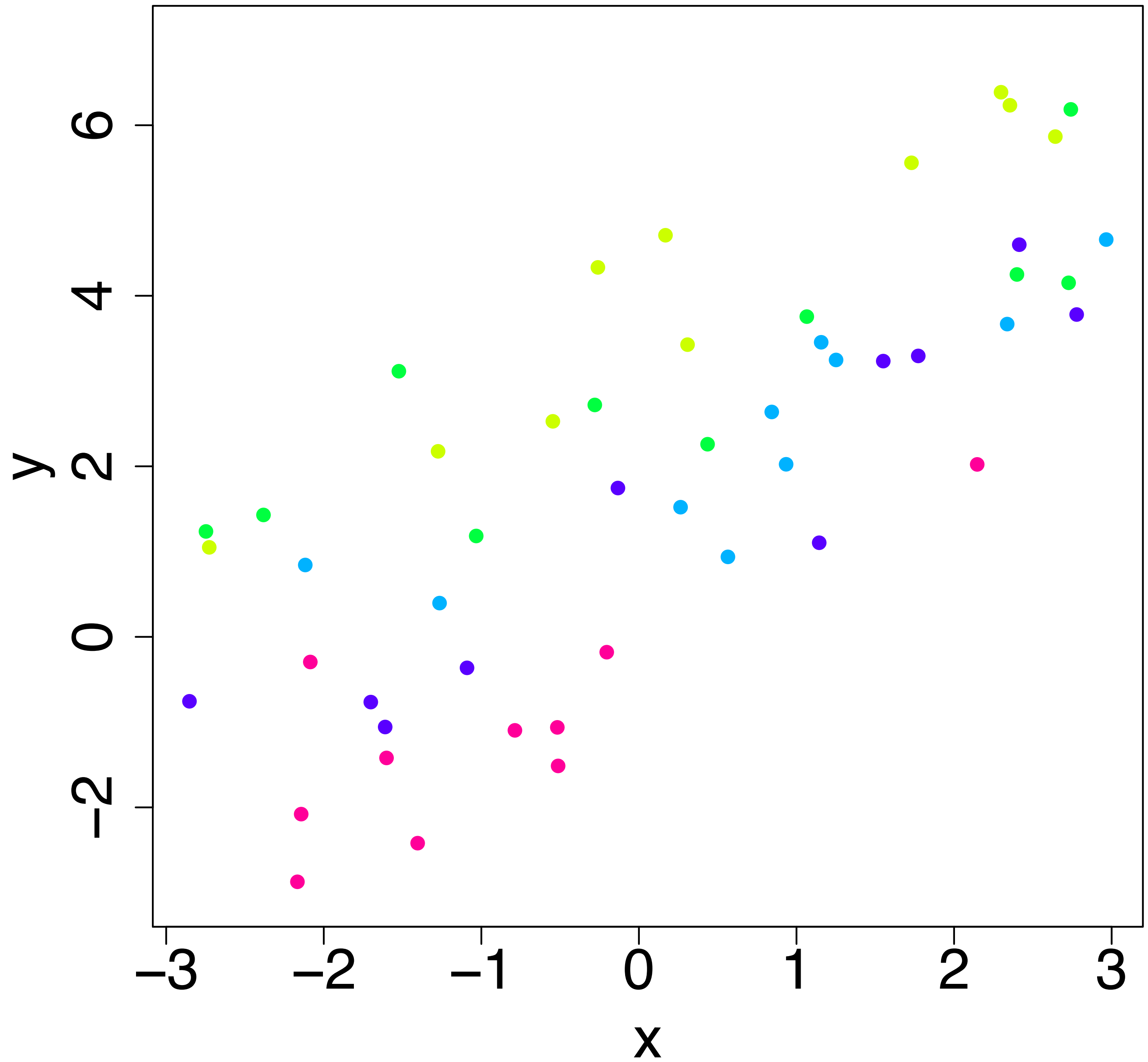

Building Up a Linear Mixed Model
y
x
−2
0
2
4
6
−3
−2
−1
0
1
2
3

Building Up a Linear Mixed Model

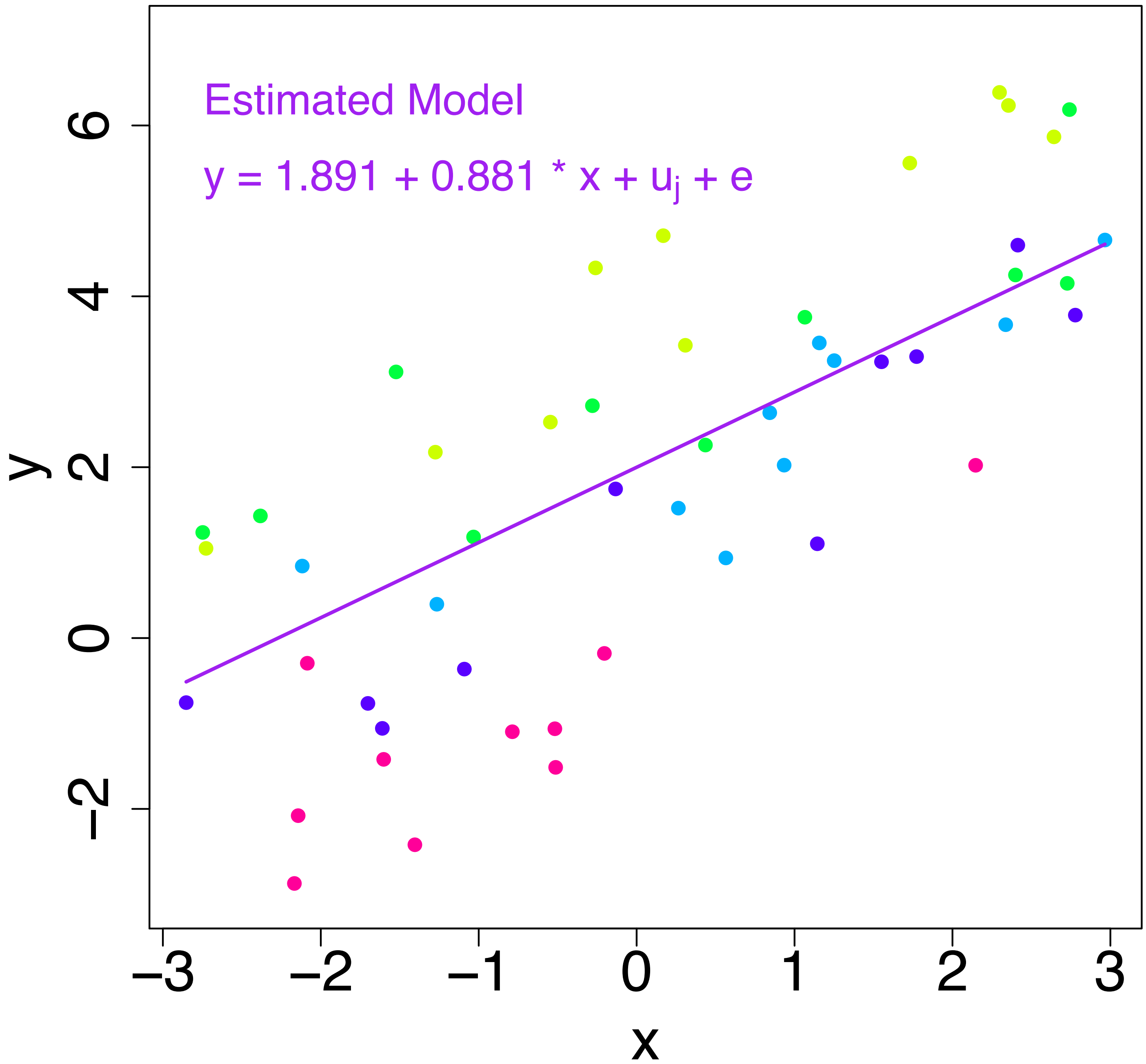


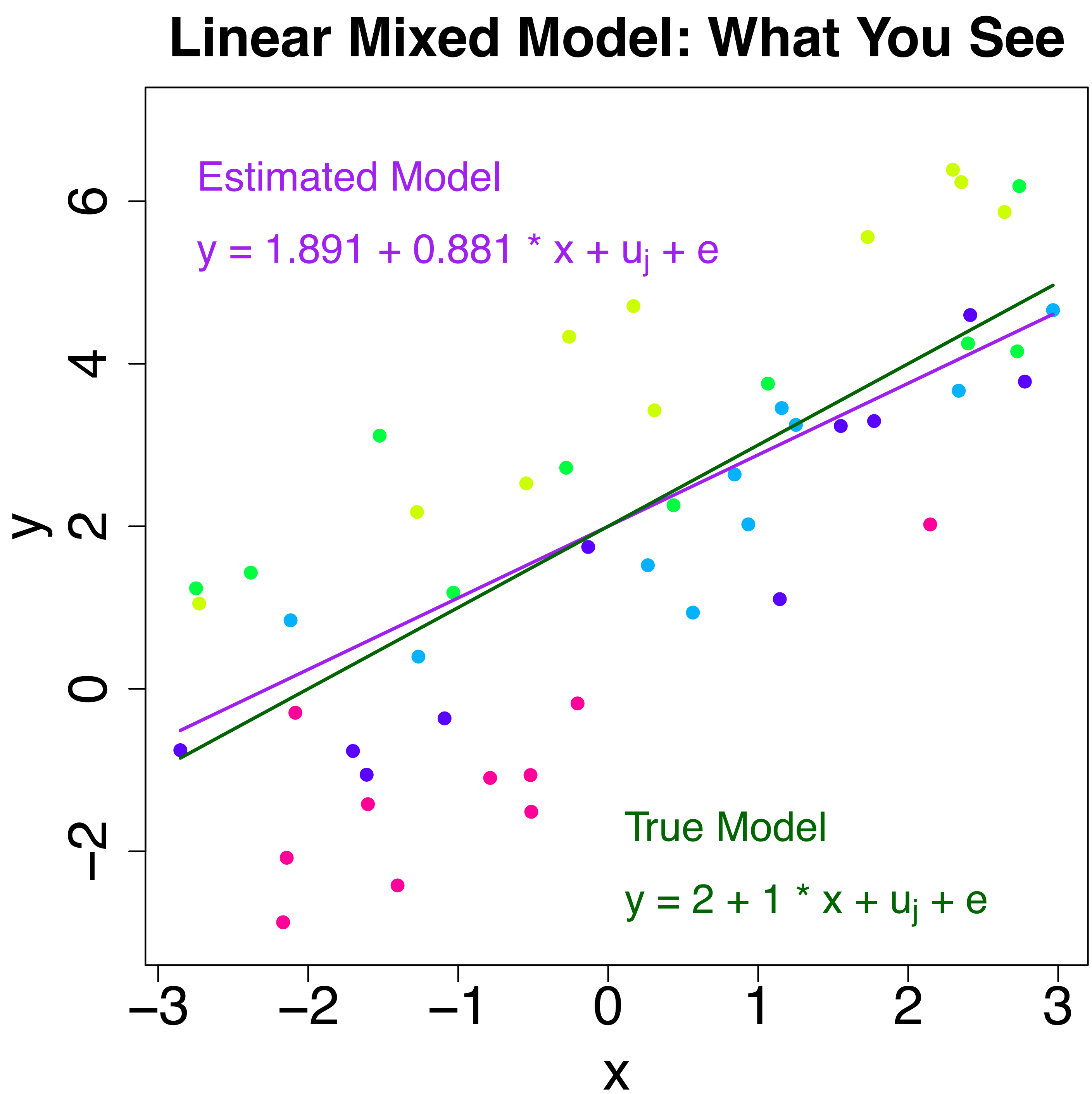

Building Up a Linear Mixed Model
y
x
−3
−2
−1
0
1
2
3
−2
0
2
4
6

Linear Mixed Model: What You See



Linear Mixed Model: What You See





Linear Mixed Model: What You See
Estimated Model
y = 1.891 + 0.881 * x + u_j + e
True Model
y = 2 + 1 * x + u_j + e
y
x
−3
−2
−1
0
1
2
3
−2
0
2
4
6

Random Effects

- coefficient on *x* (RE model, with SE):

  0.88051 (0.06565)

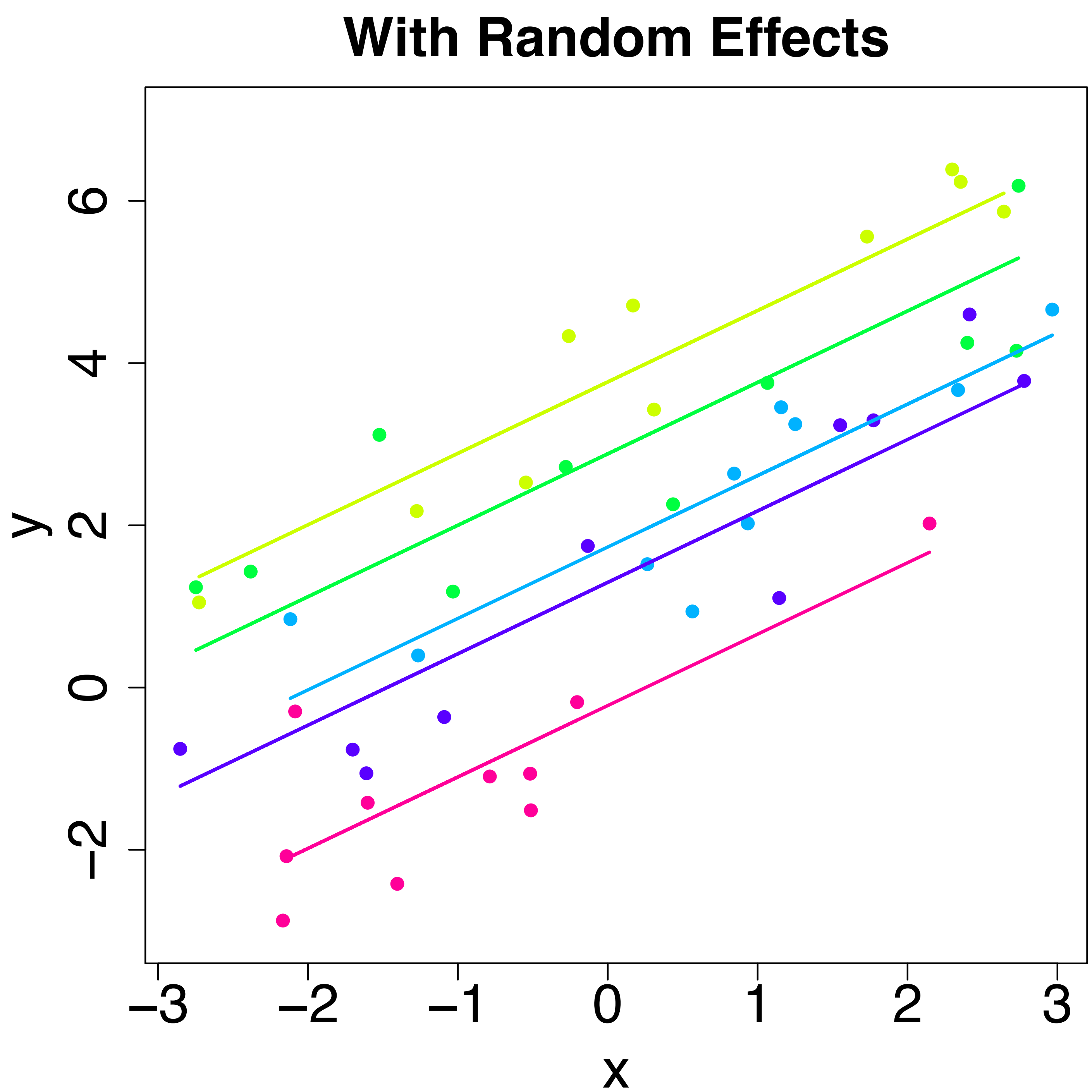
Random Effects and Fixed Effects Models

- coefficient on x (RE model, with SE):

    0.88051 (0.06565)

- coefficient on x (FE model, with SE):

    0.87558 (0.06574)


With Random Effects
y
x
6
4
2
0
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−3
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−1
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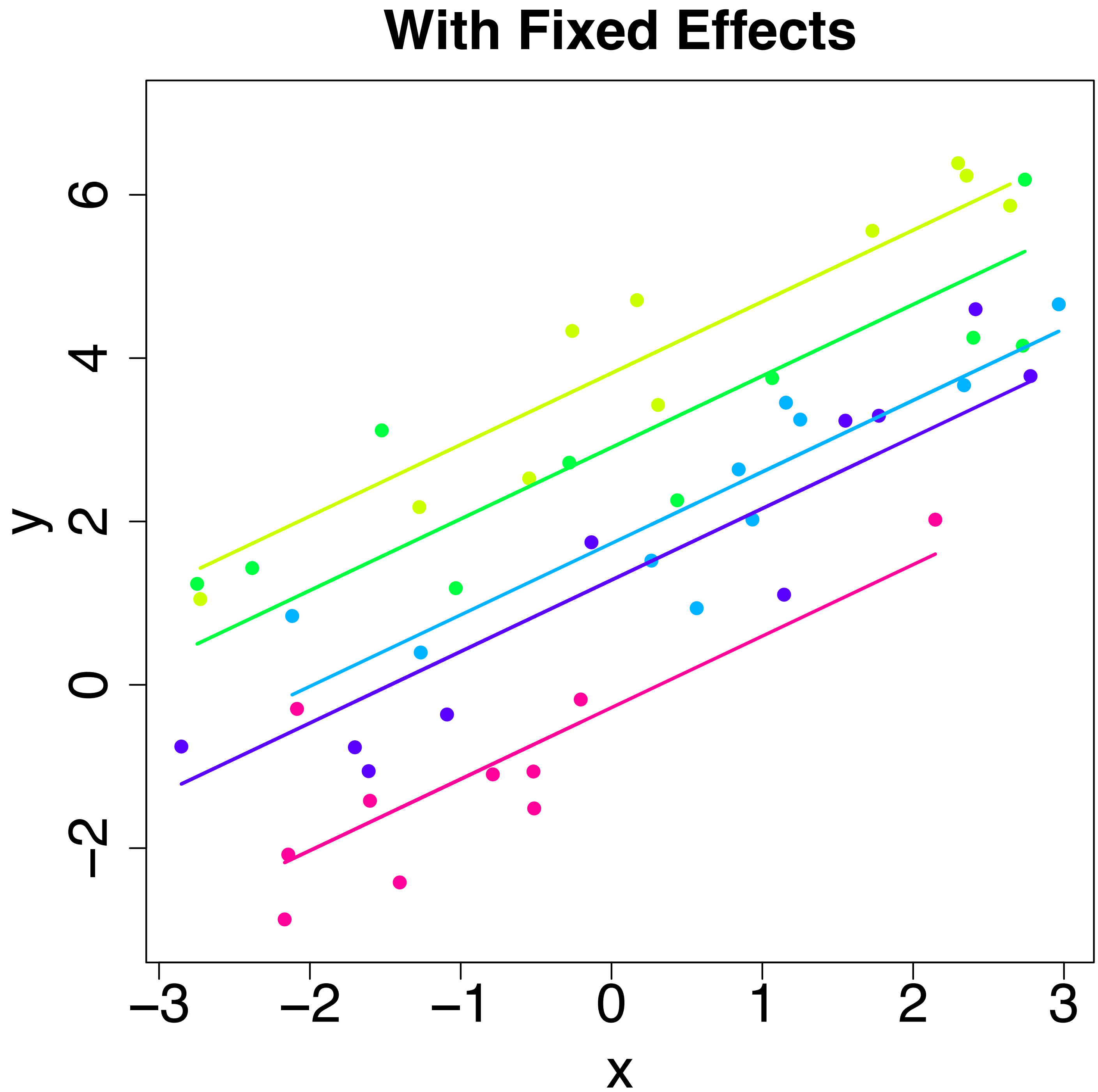
1
2
3


With Fixed Effects
y
x
−3
−2
−1
0
1
2
3
−2
0
2
4
6

Random Effects and Fixed Effects Models

- coefficient on *x* (RE model, with SE):

  0.88051 (0.06565)

- coefficient on *x* (FE model, with SE):

  0.87558 (0.06574)

Random Effects and Fixed Effects Models

- coefficient on *x* (RE model, with SE):

  0.88051 (0.06565)

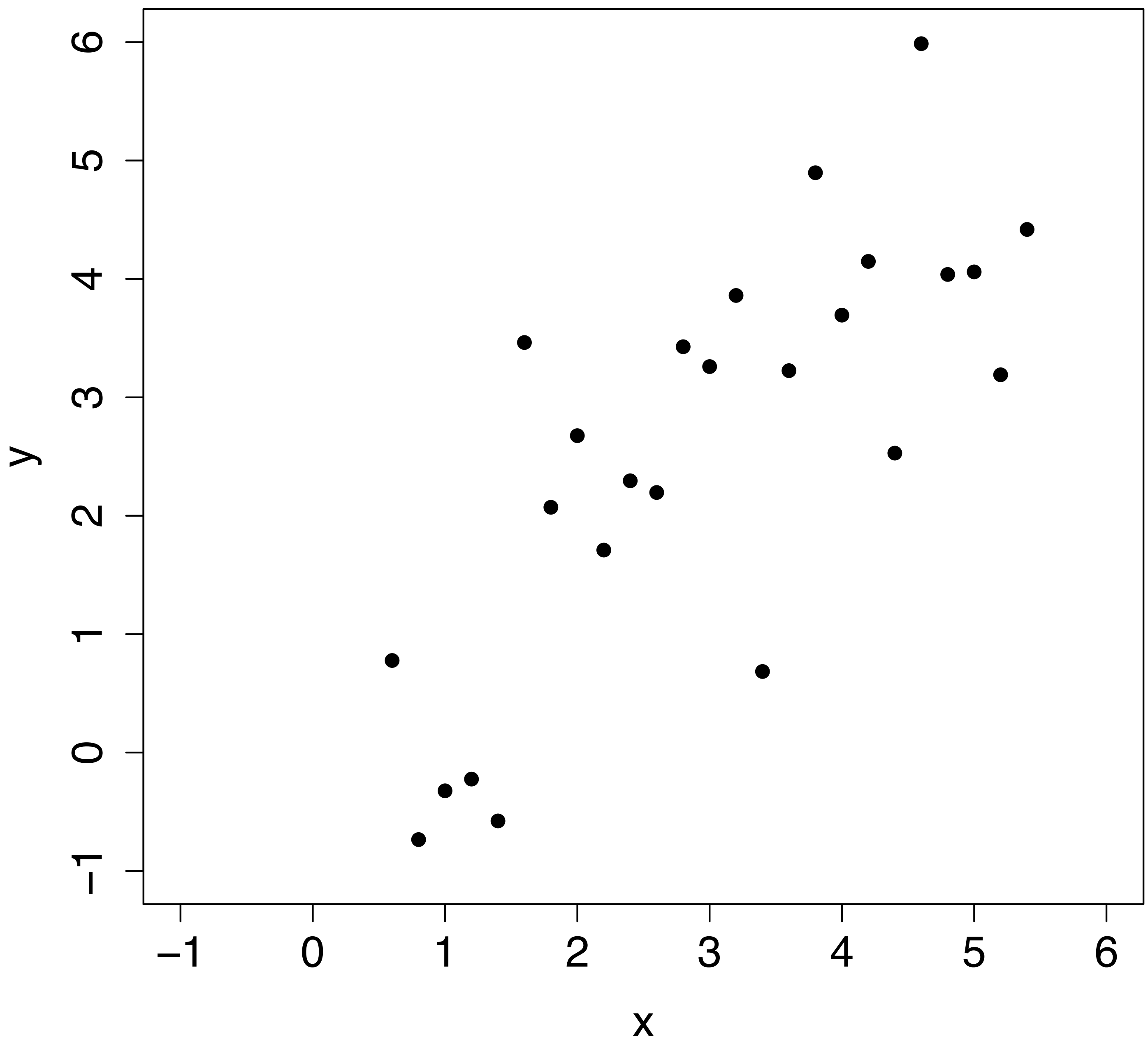
- coefficient on *x* (FE model, with SE):

  0.87558 (0.06574)

- coefficient on *x* (“REWB” model, with SE):

  0.87558 (0.06574) “within”

  2.67648 (1.01047) “between”



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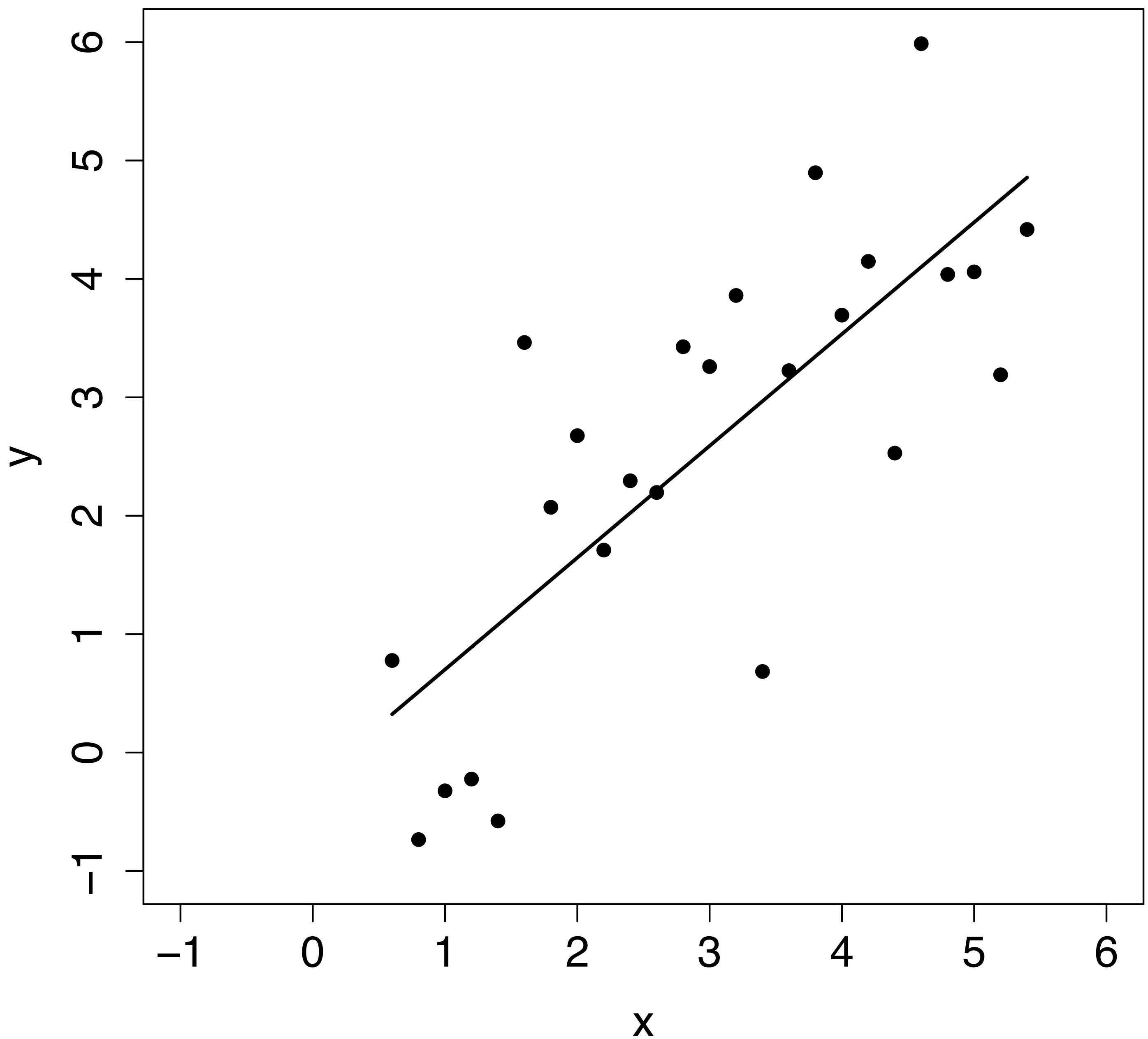

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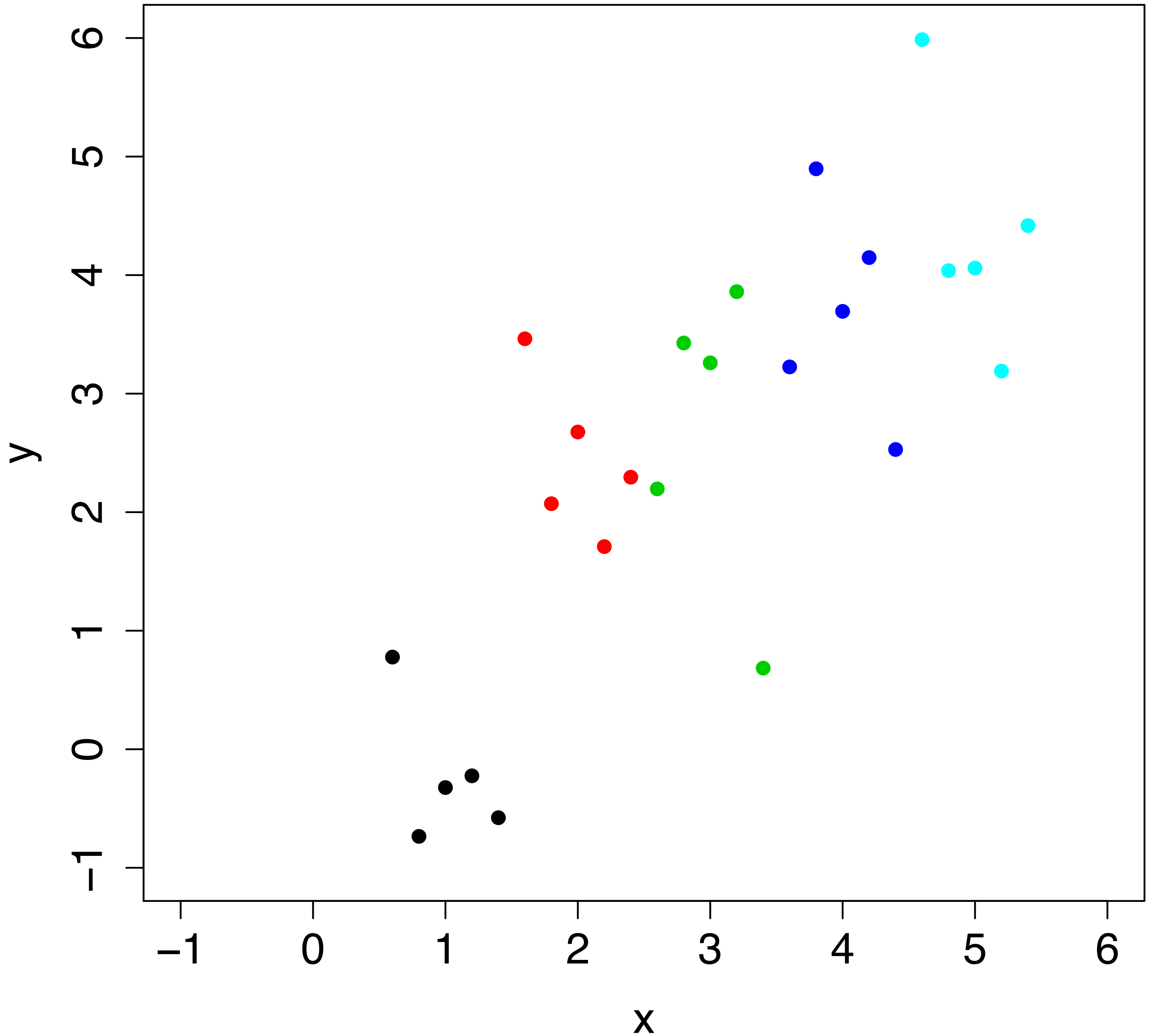

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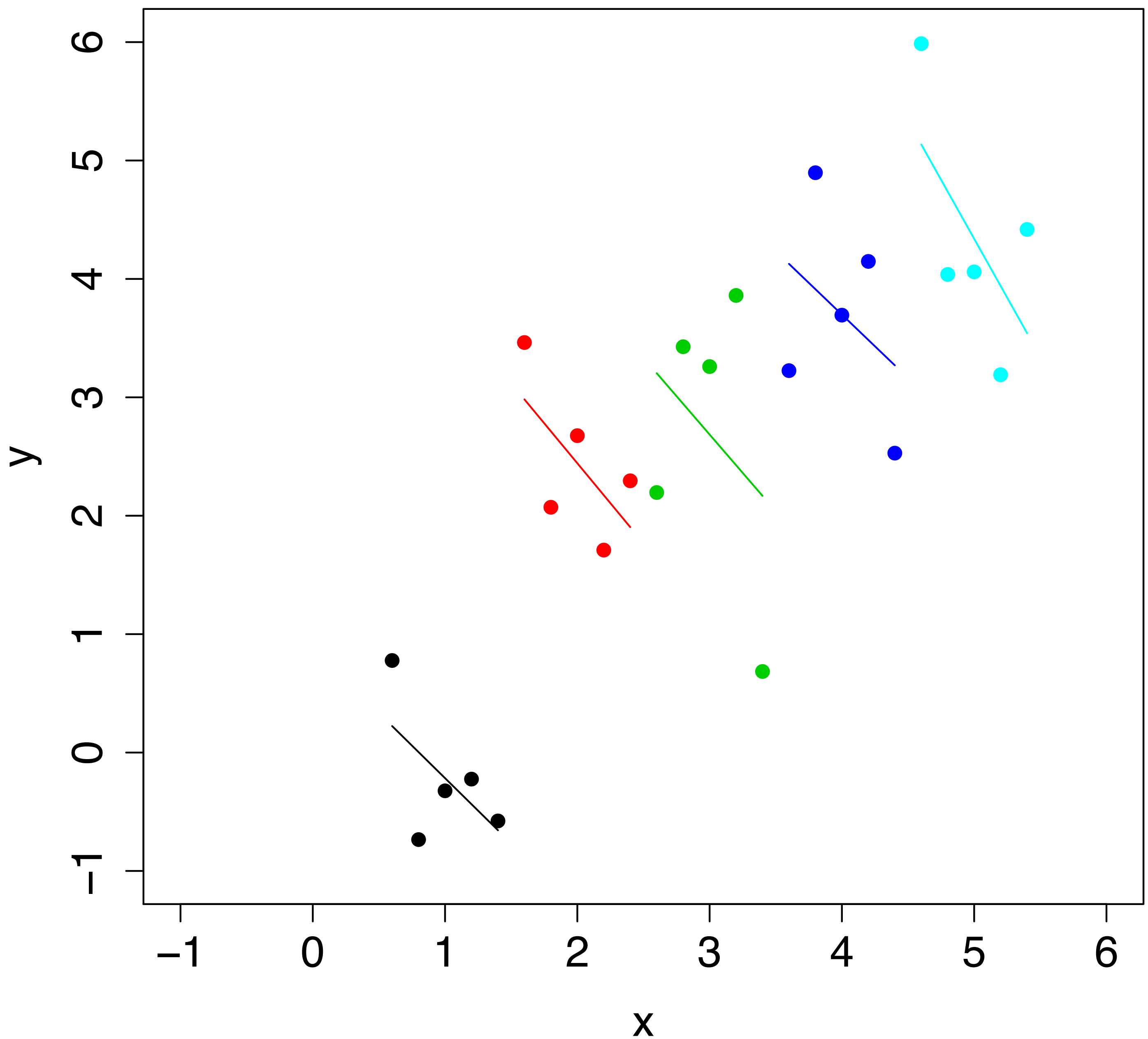

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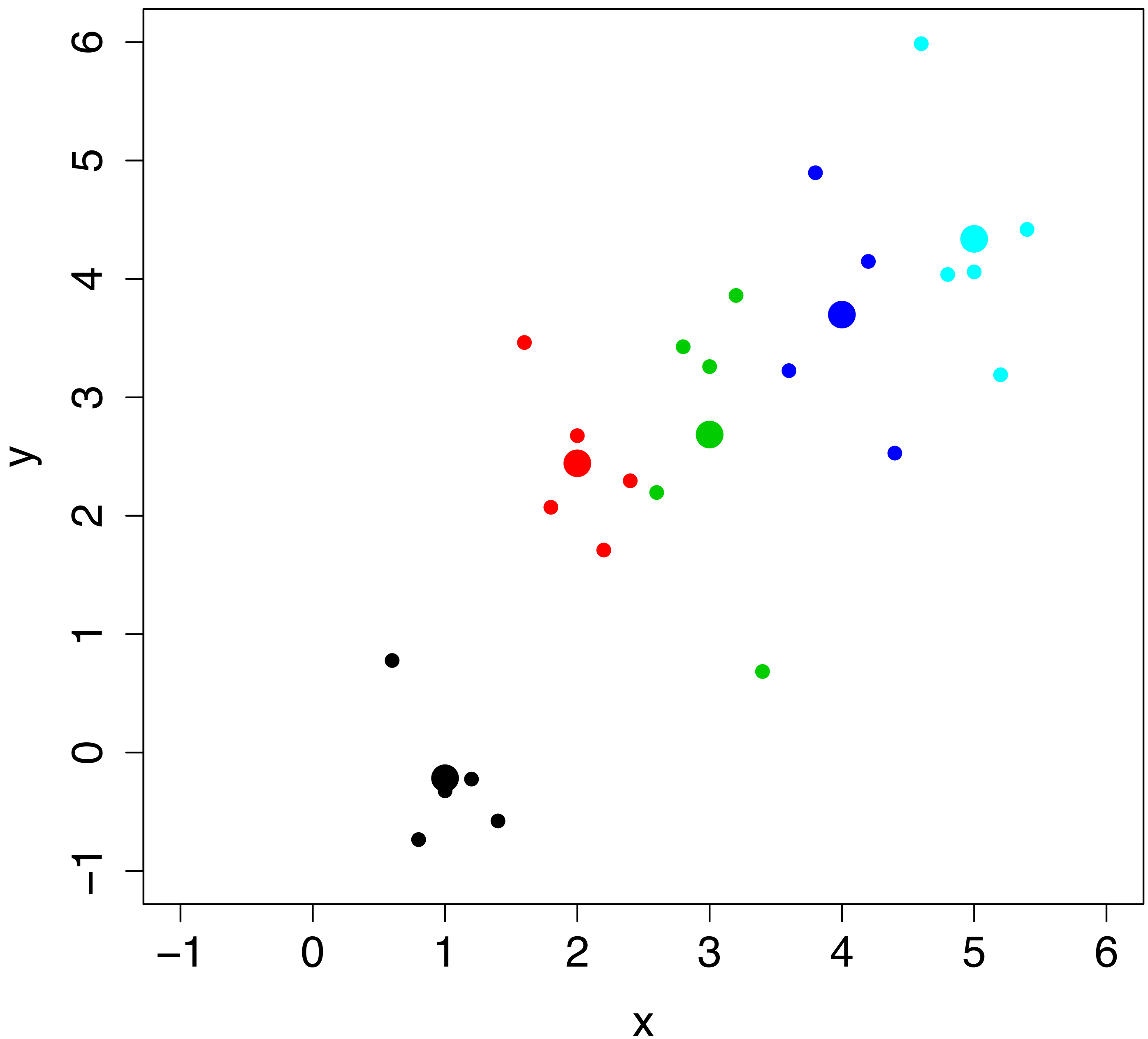

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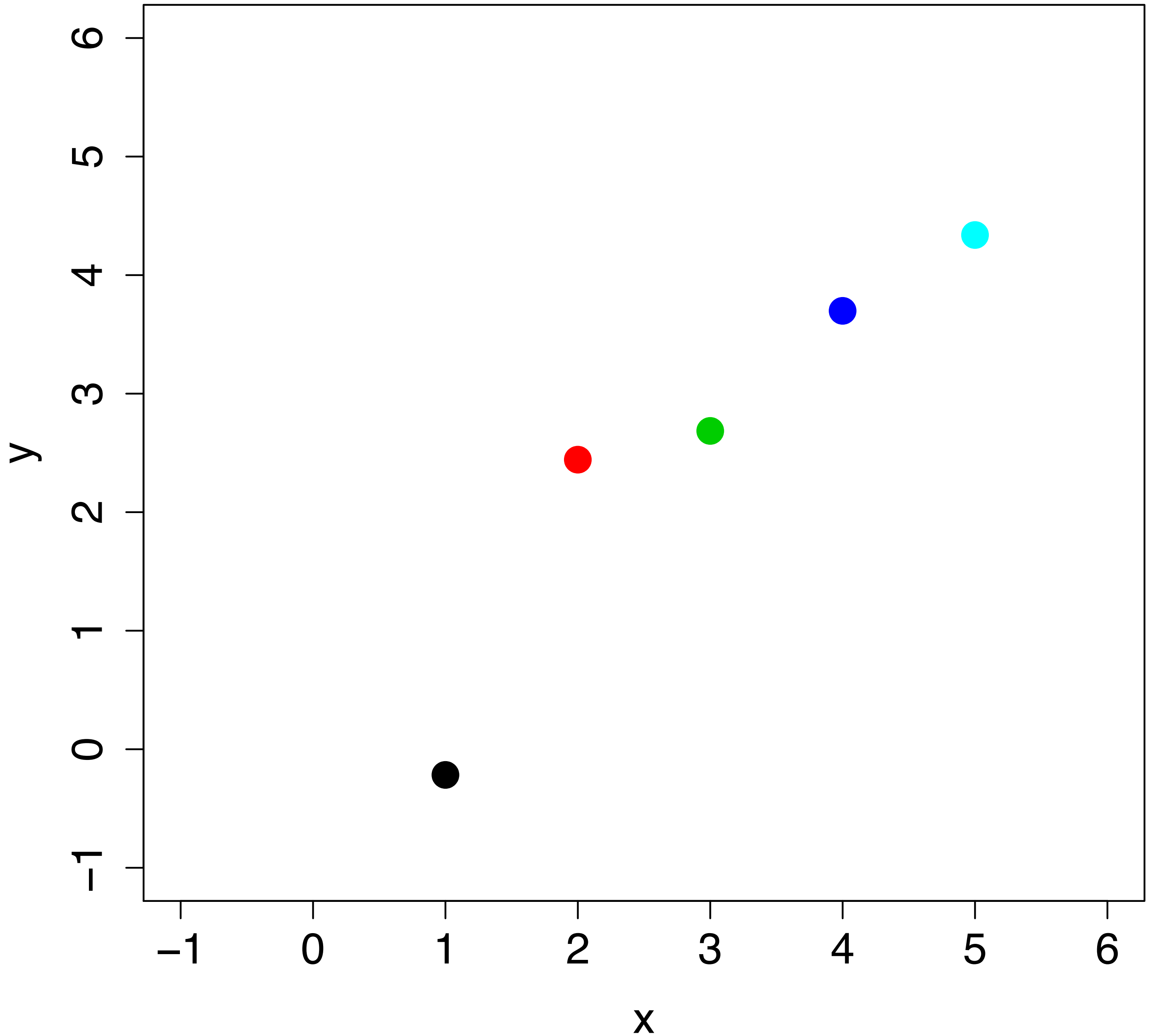

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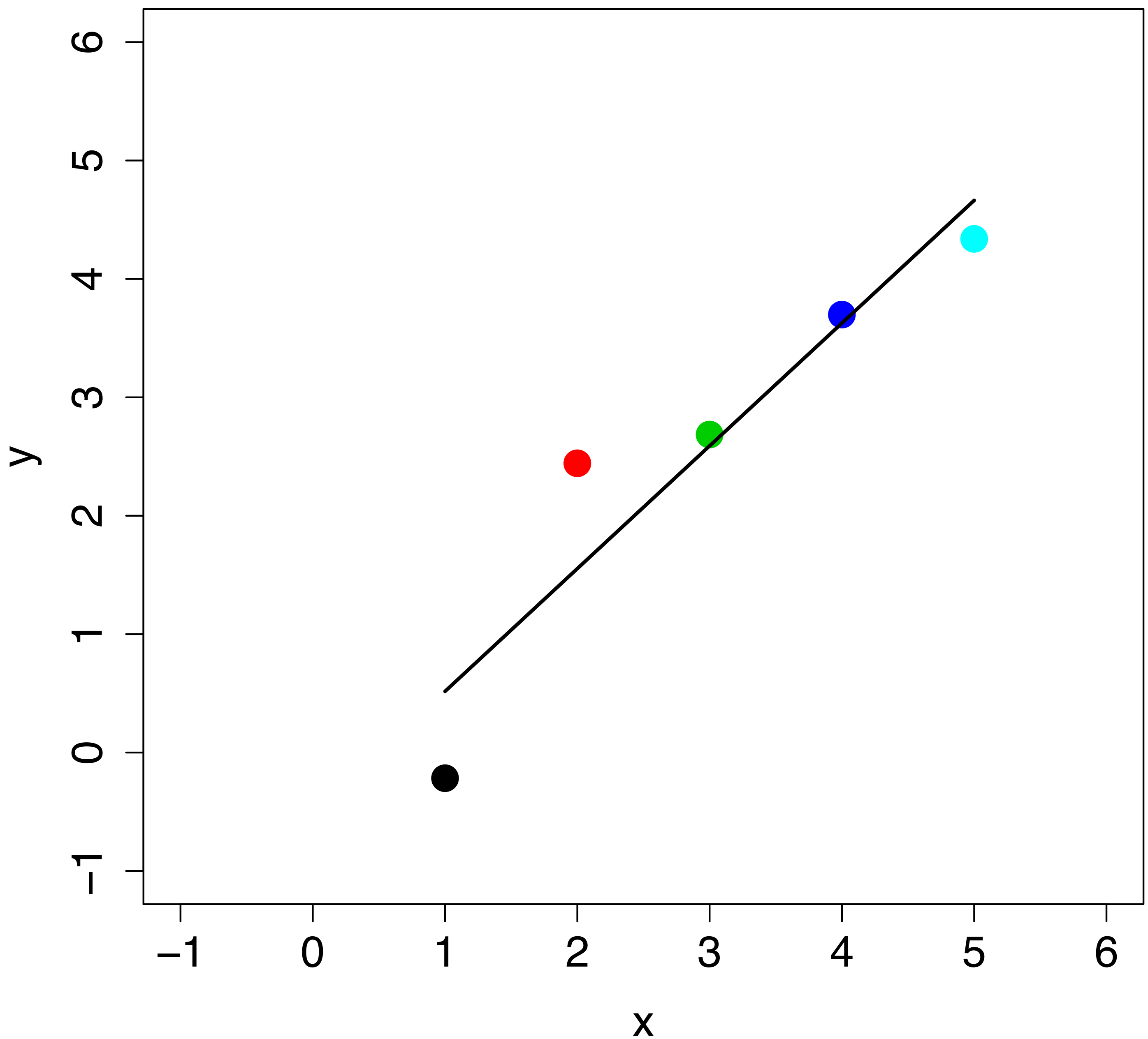

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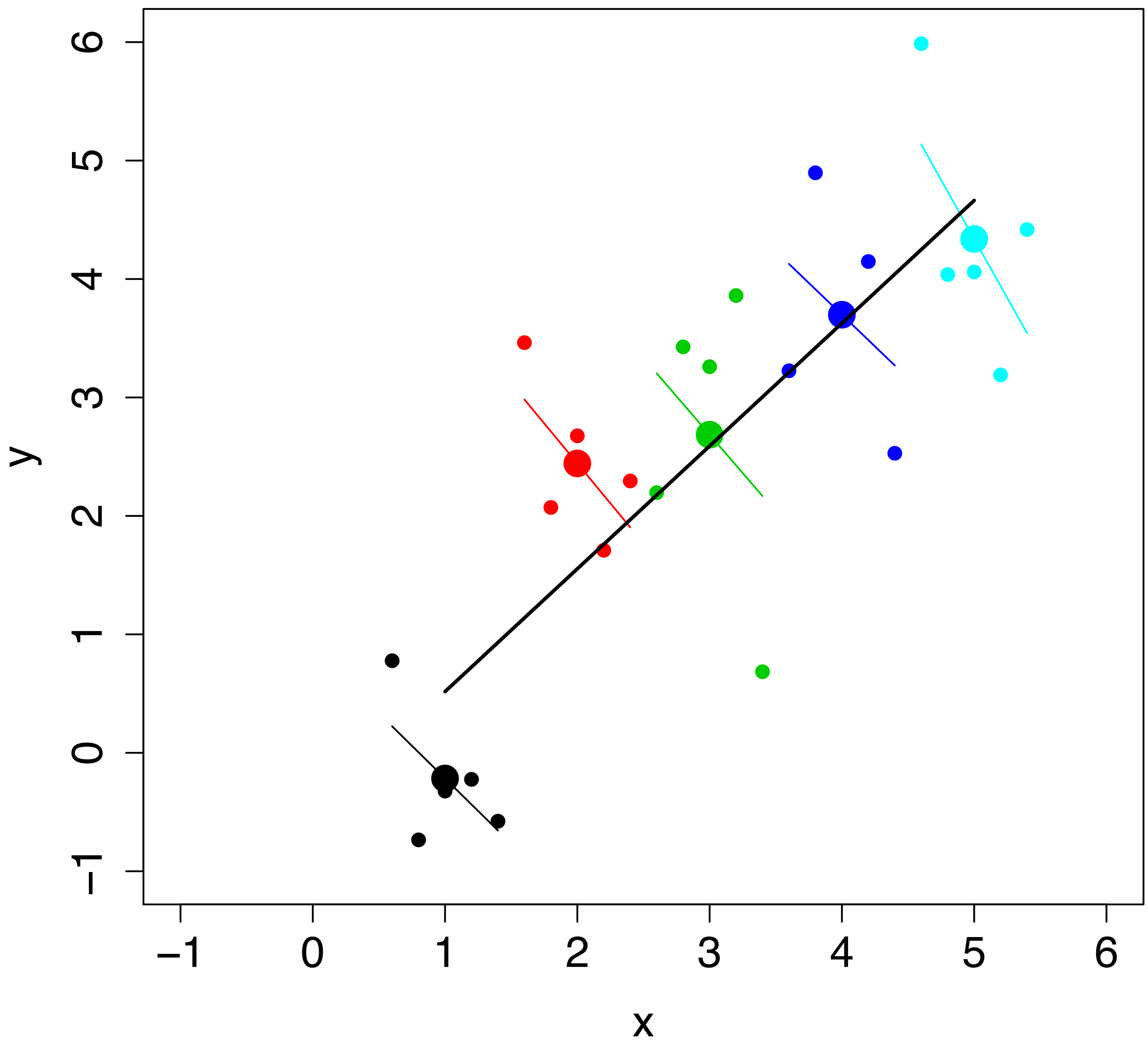

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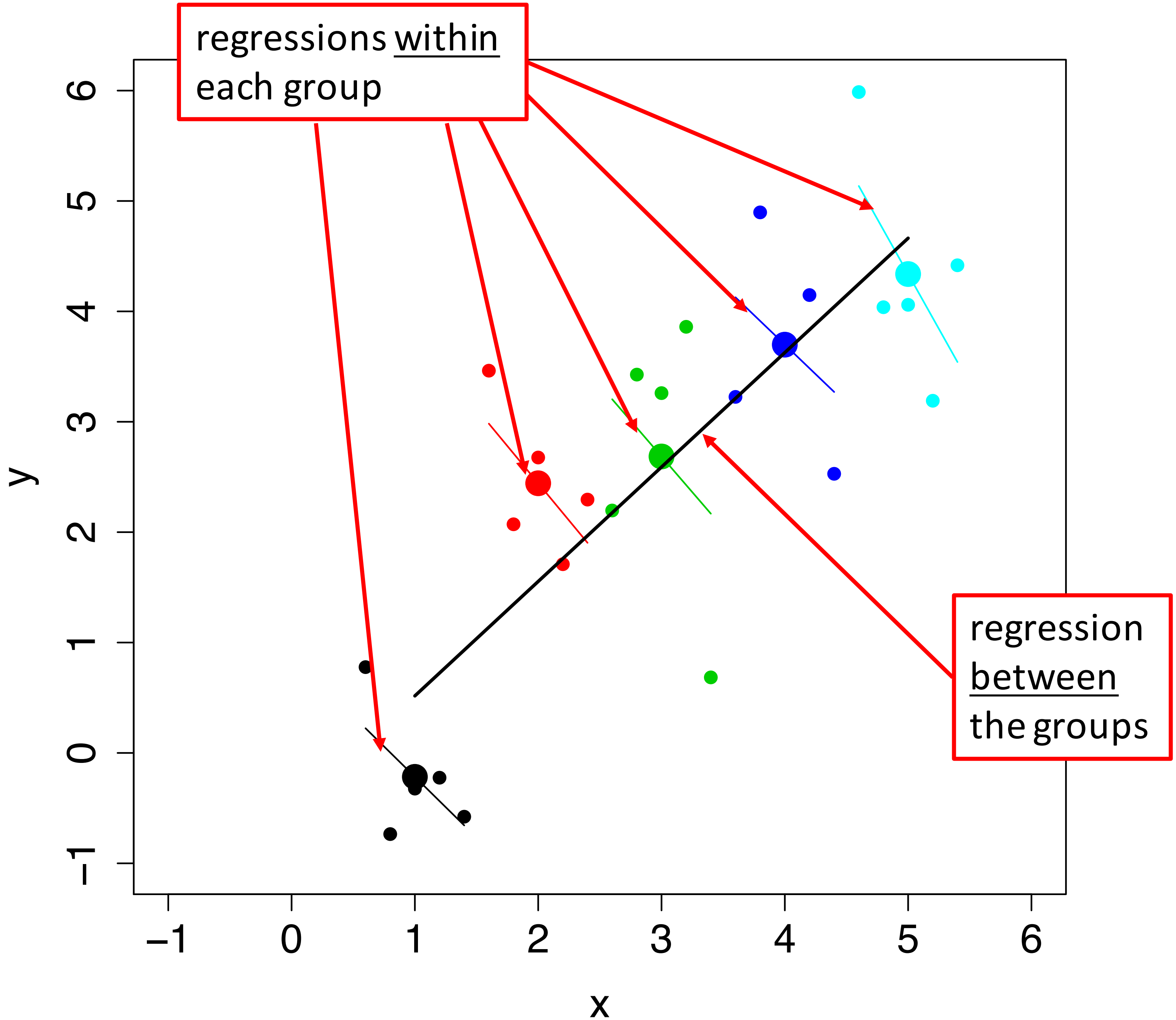
regressions within each group
regression between the groups
x
y
−1
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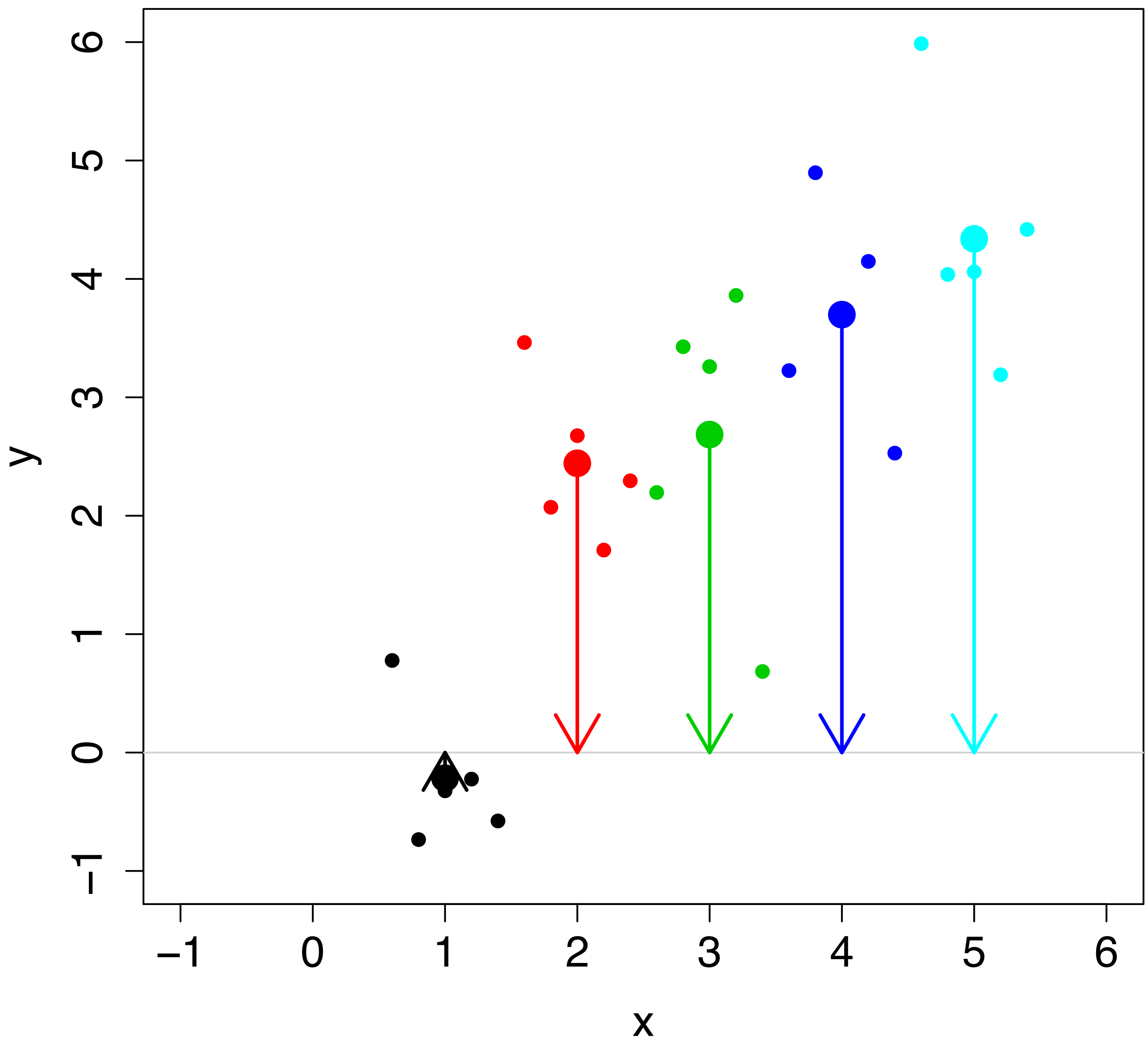

x
y
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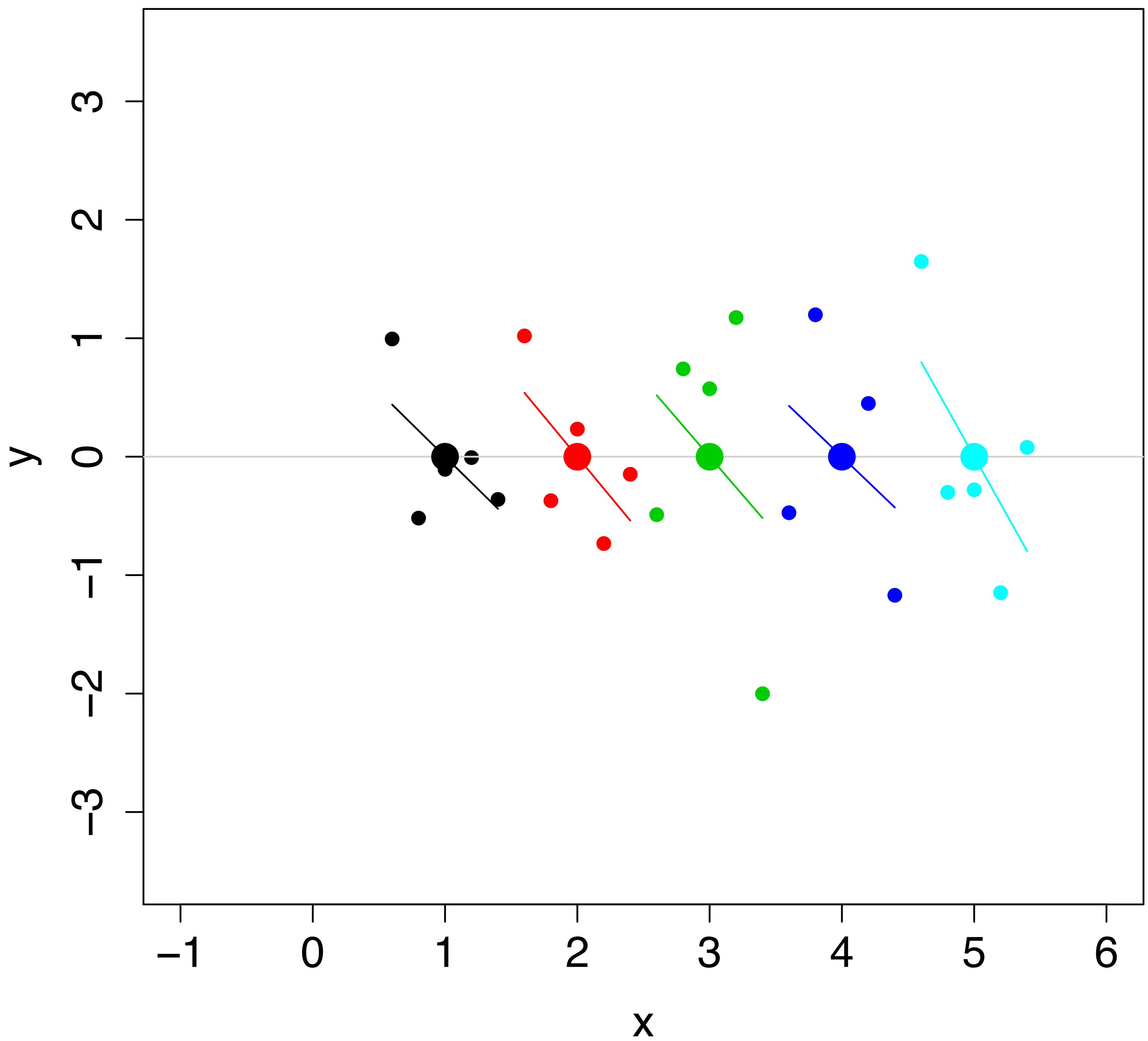

y
3
2
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0
−1
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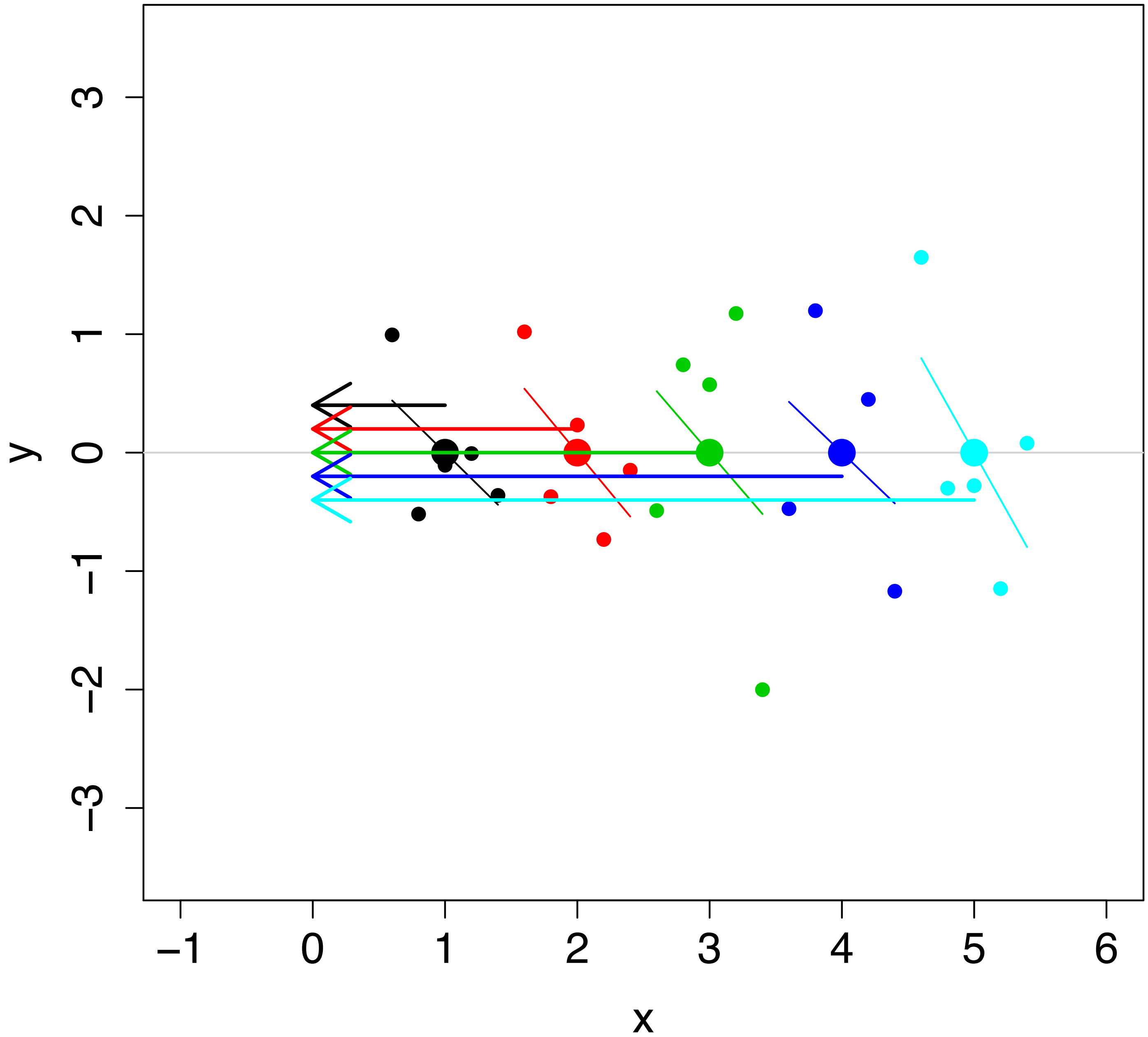
−3
−1
0
1
2
3
4
5
6
x



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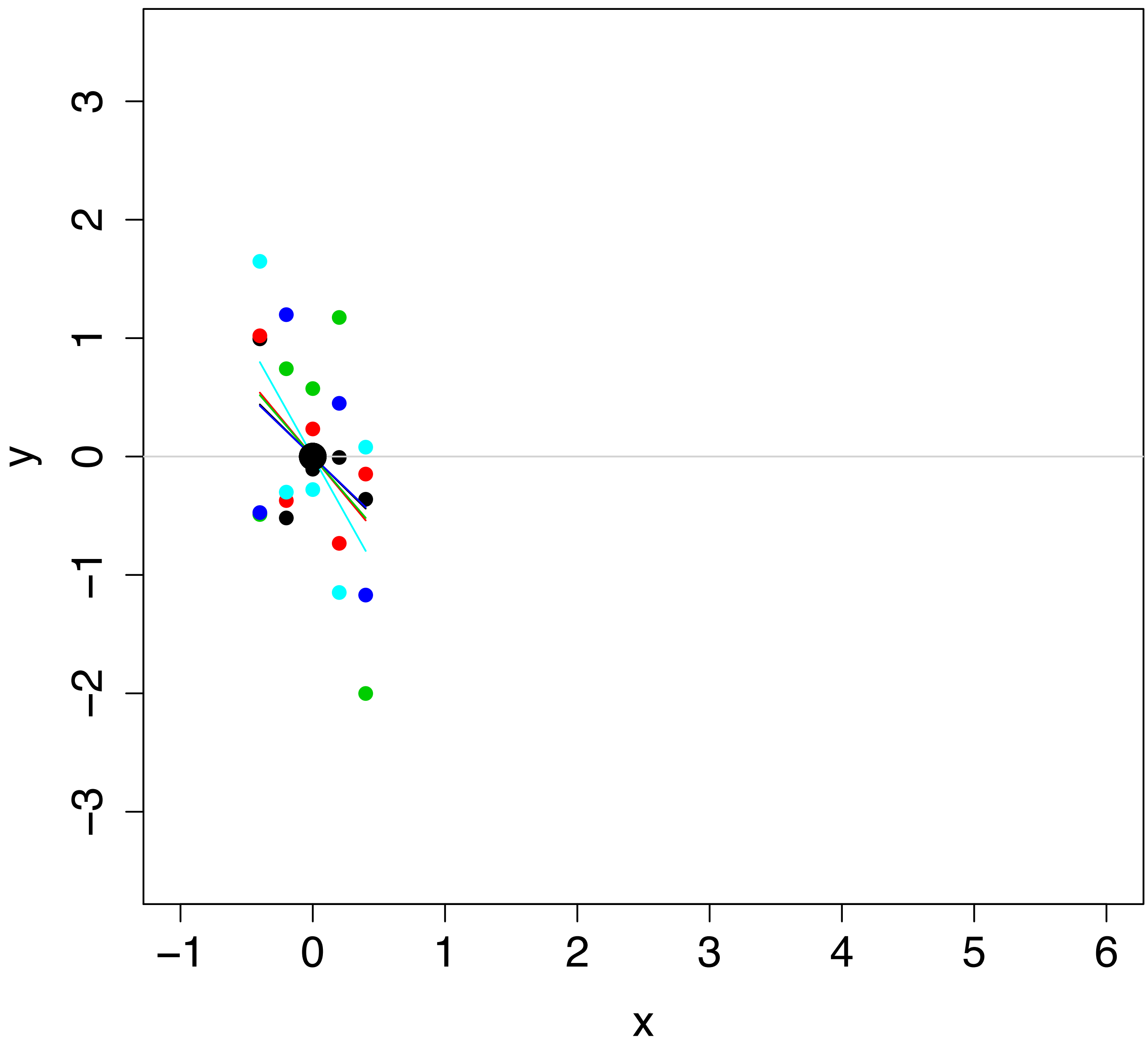

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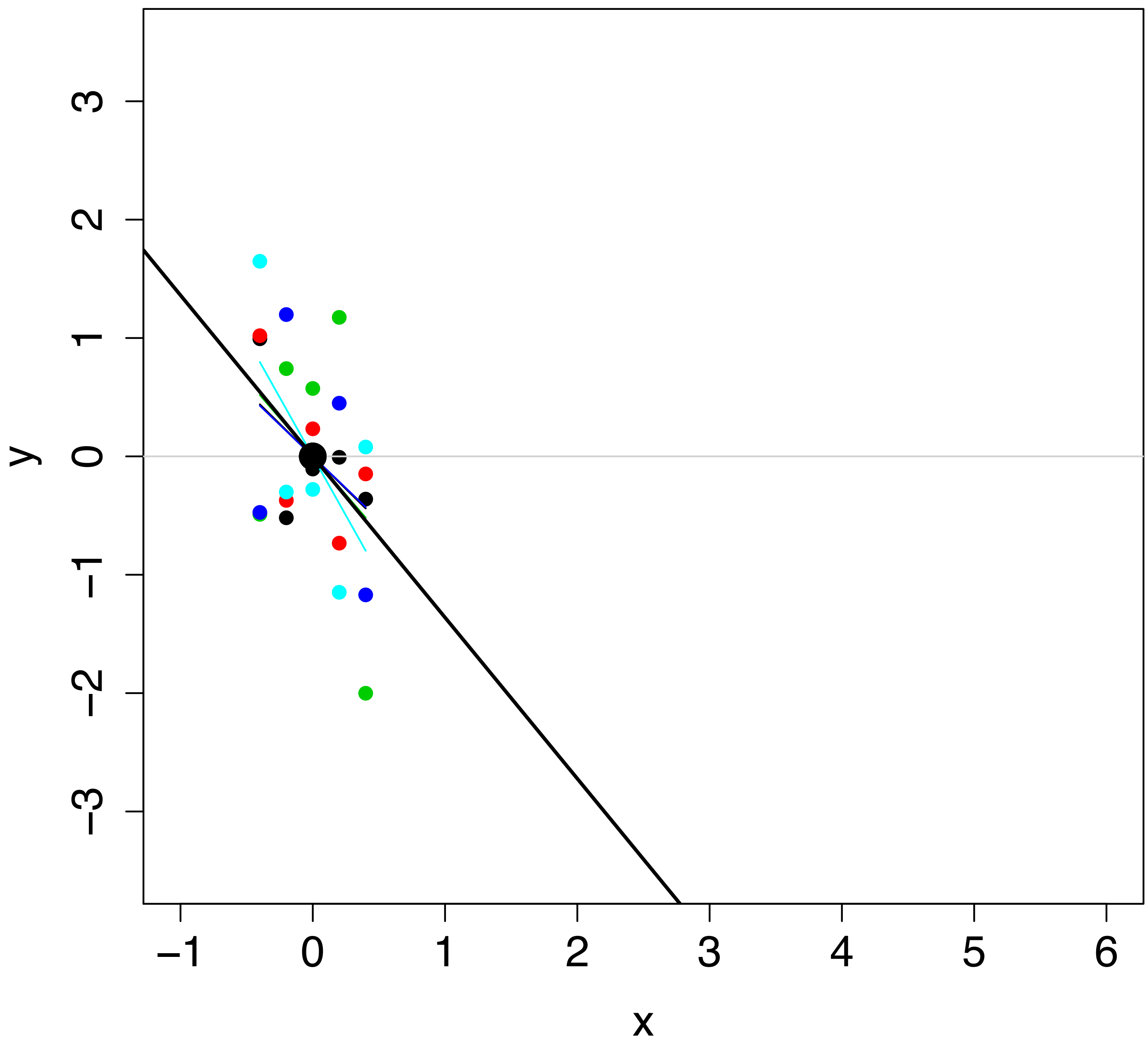
6
x



y
x
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0
−1
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−3
−1
0
1
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3
4
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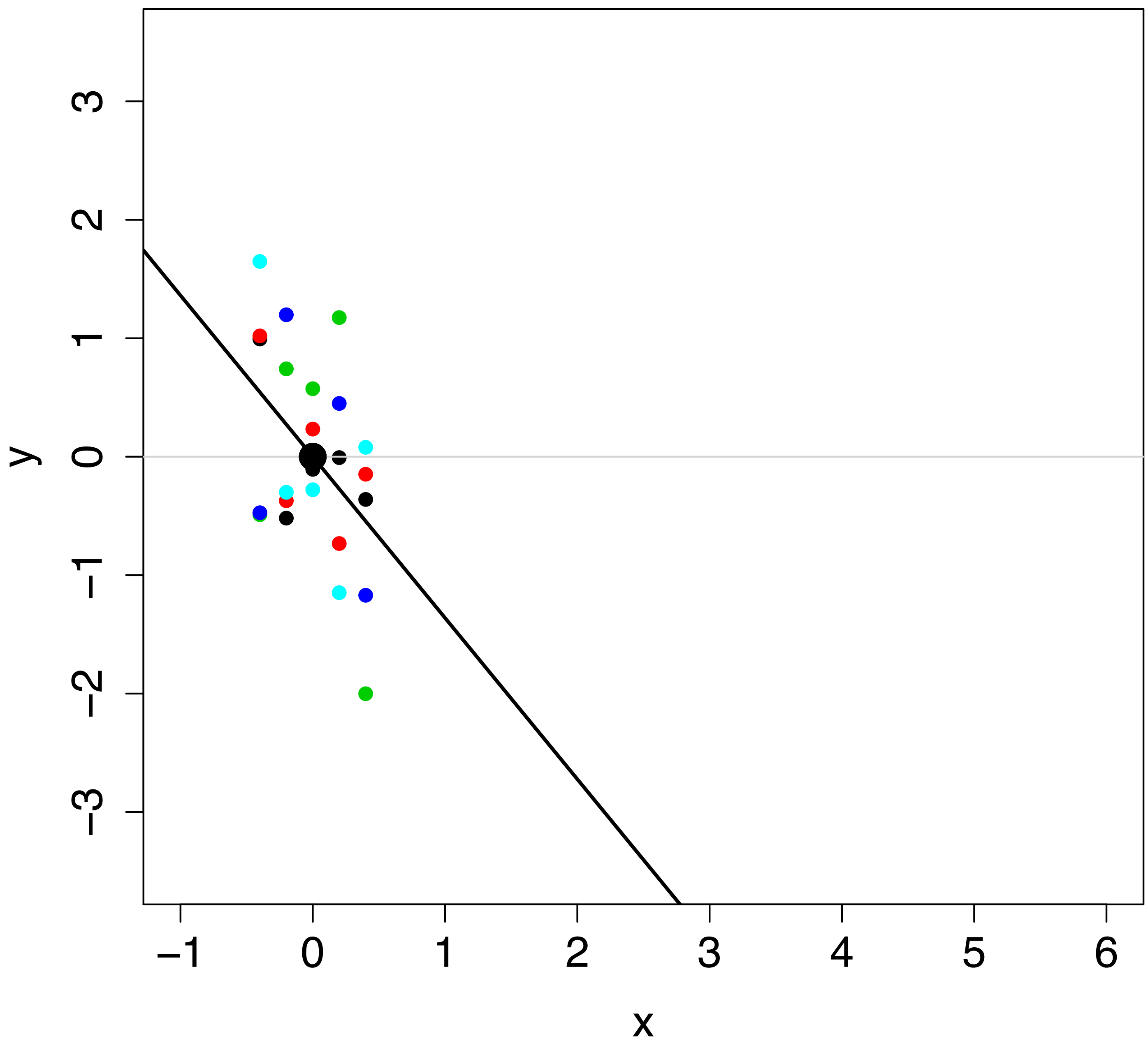
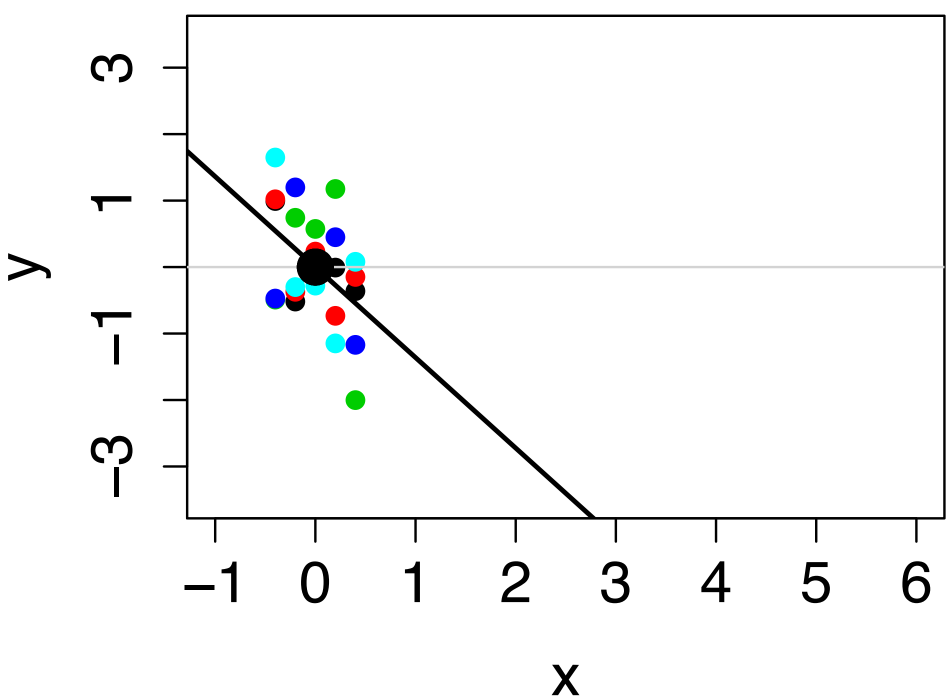
6

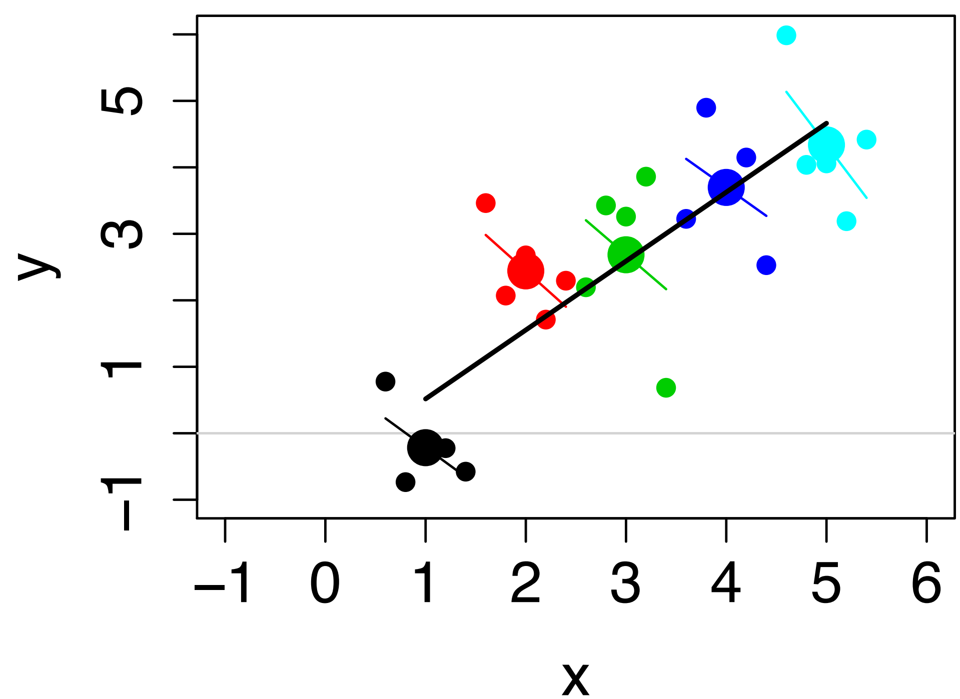


y
x
3
2
1
0
−1
−2
−3
−1
0
1
2
3
4
5
6

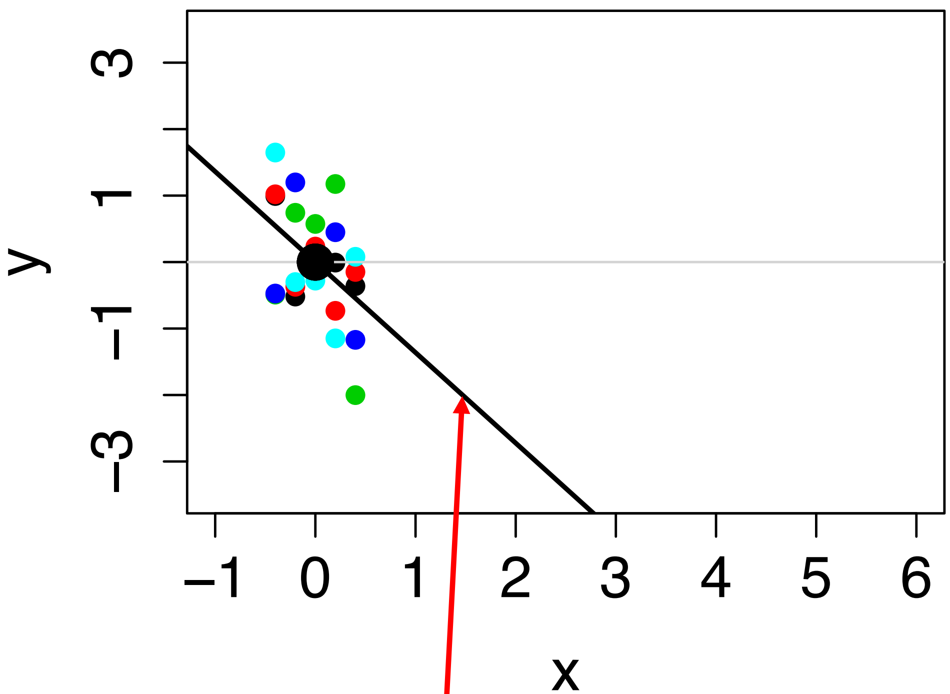
Fixed Effects



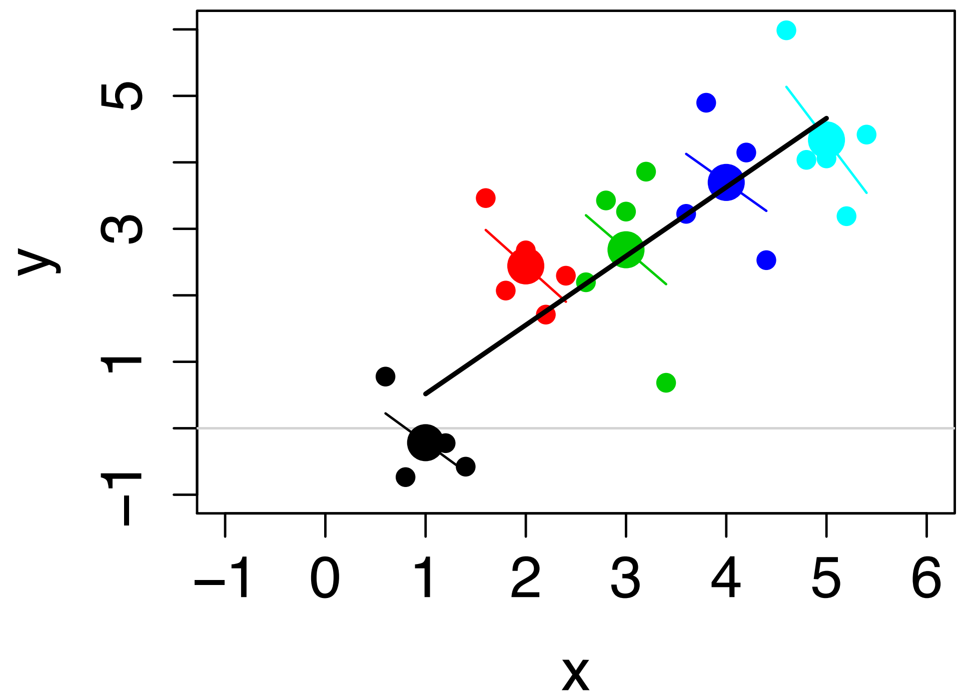
Random Effects



Fixed Effects



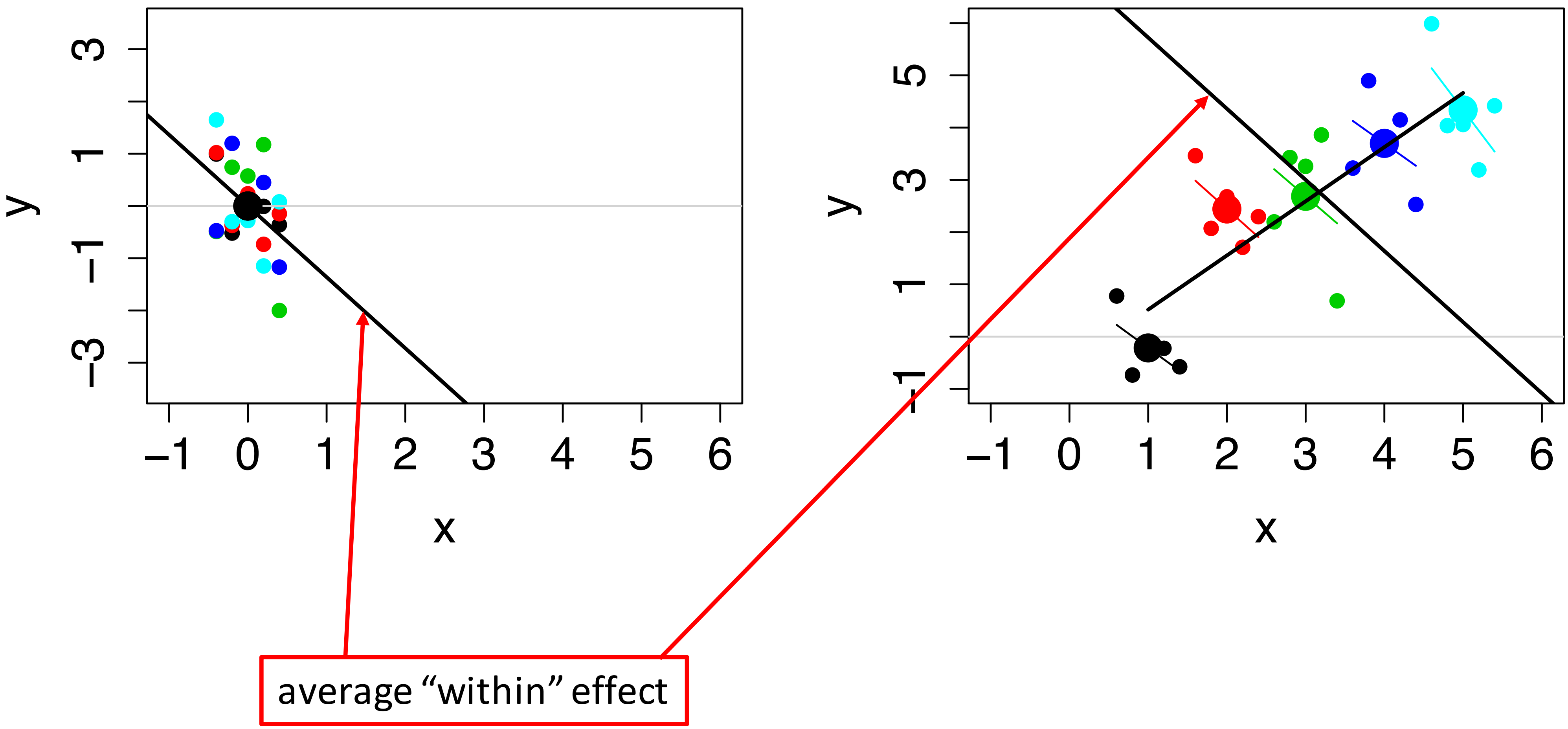
Random Effects



average “within” effect

Fixed Effects

Random Effects



“Random Effects” and “Fixed Effects” Models

- in “random effects models” the variance of the group effects is estimated (rather than assumed to be either zero or infinity):

$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2j} + u_j + e_{ij}$

$u_j \sim N(0,\sigma_u^2)$

$e_{ij} \sim N(0,\sigma_e^2)$

- “fixed effects models” are slightly different, in treating that variance as infinite (not from a distribution):

$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2j} + u_j + e_{ij}$

$e_{ij} \sim N(0,\sigma_e^2)$

* here u_j is a series of dummy variables (one for each higher-level unit, other than one reference unit)

“Random Effects” and “Fixed Effects”

"When we treat an effect as fixed we believe that the only information regarding its value comes from data associated with that particular level. If we treat an effect as random we also use this information, but we weight it by what other data tell us about the likely values that the effects could take. …

The degree to which this additional information is important depends on the variability of the effects, as measured by the estimated variance component, and the degree of replication within a particular level. ... The estimates are shrunk towards zero.” (Hadfield, MCMCglmm Course Notes)

- remember the distinction between levels/classifications and variables?

-> “random effects” models treat group as a <u>classification</u>, while “fixed effects” models treat group as a <u>variable</u>

“Random Effects” and “Fixed Effects”

- in FE models, the u_j’s are parameters (generally considered a nuisance)
- in RE models, the u_j’s are <u>not</u> parameters… they’re like the e_{ij}’s (residuals)
  - the only parameter that is estimated is their <u>variance</u>
- there are consequences: fixed effects models require the estimation of many more parameters, and use up all the degrees of freedom at the higher level, such that between effects <u>cannot</u> be estimated

* note that (confusingly) “random effects” models also <u>include</u> “fixed effects” (the β coefficients)…

“Random Effects” and “Fixed Effects”

- summary: fixed effects models remove (and ignore) the “between” relationship, and only illuminate the “within” effect
    - in a longitudinal context, “within” means “over time”

- by implication, fixed effects models “trust” within/longitudinal relationships more

Why Trust "Within" Effects More?

- in classical (single-level, linear) regression, any correlation between x_{1i} and e_i leads to <u>bias</u> in our estimate of β_1 ("endogeneity")
  - such as because of spuriousness, reverse causality, etc.

- that holds true in clustered data also: any correlation between an x_j and the u_j's will lead to <u>bias</u> in our estimate of the β on that variable x_j
  - in that sense, the "between" effects seem less trustworthy

- fixed effects models purge the "within" effects of any endogeneity at the group level (in the "between" relationship), by <u>averaging</u> x and y
  - so the model only uses variation in x and y <u>relative</u> to the group mean

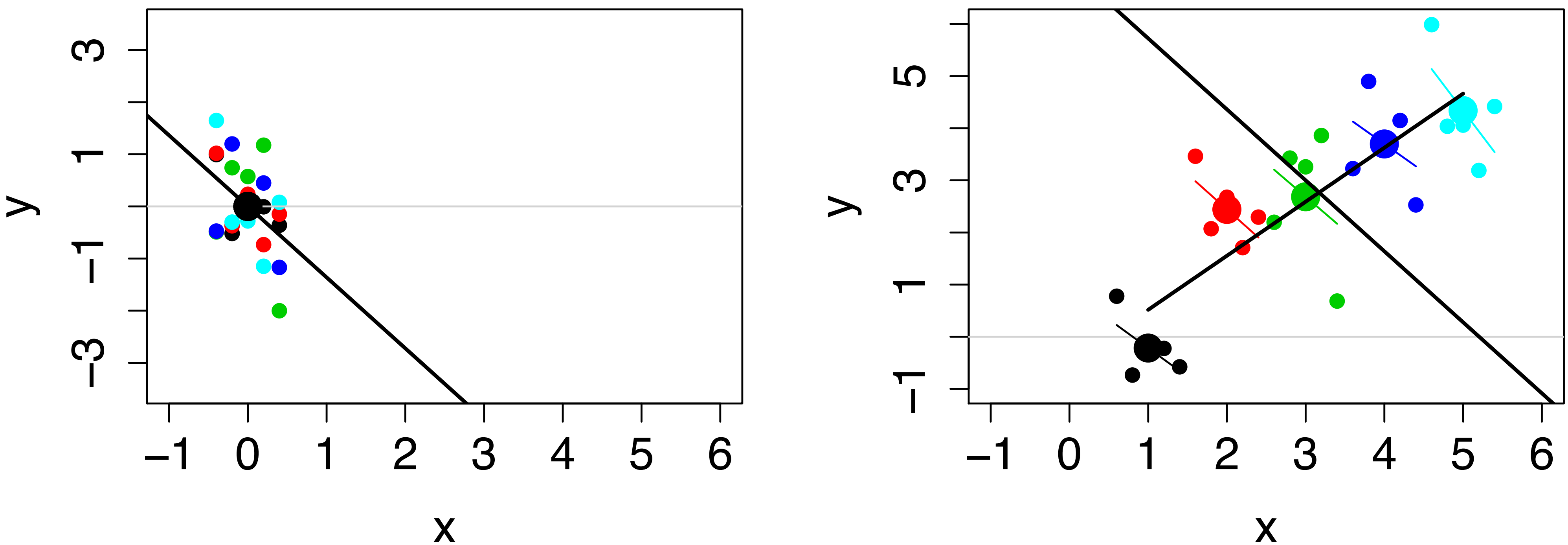
Why Trust "Within" Effects More?

- panel data models are sometimes taken as more powerful evidence of a causal relationship
- intuition: with panel data, we can control for enduring (and unobserved or unobservable) characteristics of units observed on multiple occasions
- and thereby exploit change over time: $\Delta y \sim \Delta x$
- the argument is often made that exploiting variation "within" groups, such as with panel data, is less vulnerable to endogeneity

- but why would change over time not also be vulnerable to spuriousness?
  - the same dangers hold for the "within" effects

Group Mean Centering

- “fixed effects” models work, effectively, by centering covariates at their group means
  - dummy variables remove differences across groups by subtracting their means
- but there is no reason not to do the same with in a “random effects” (multilevel) context…

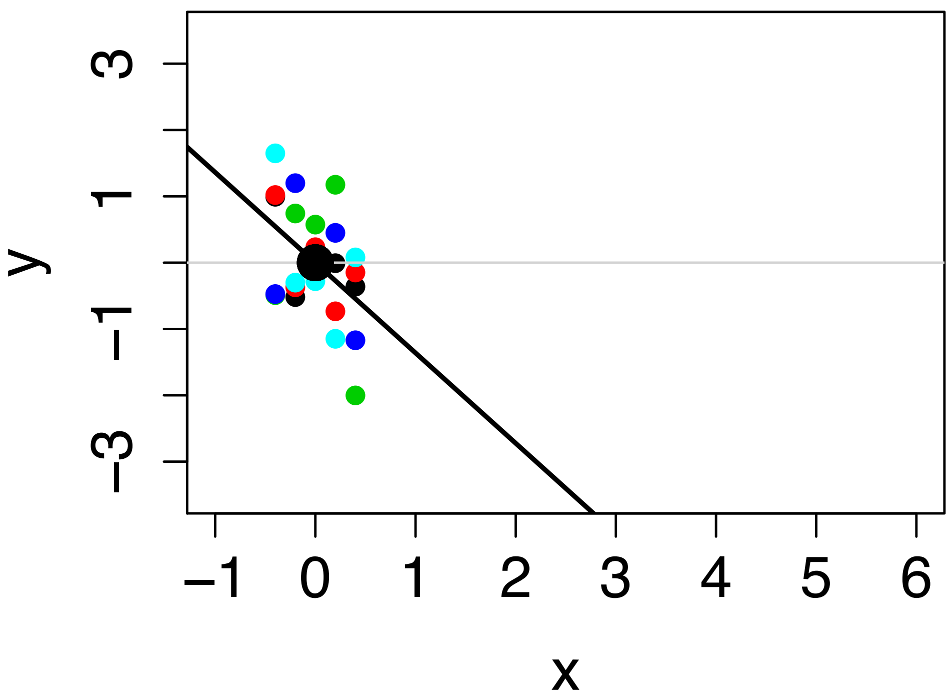


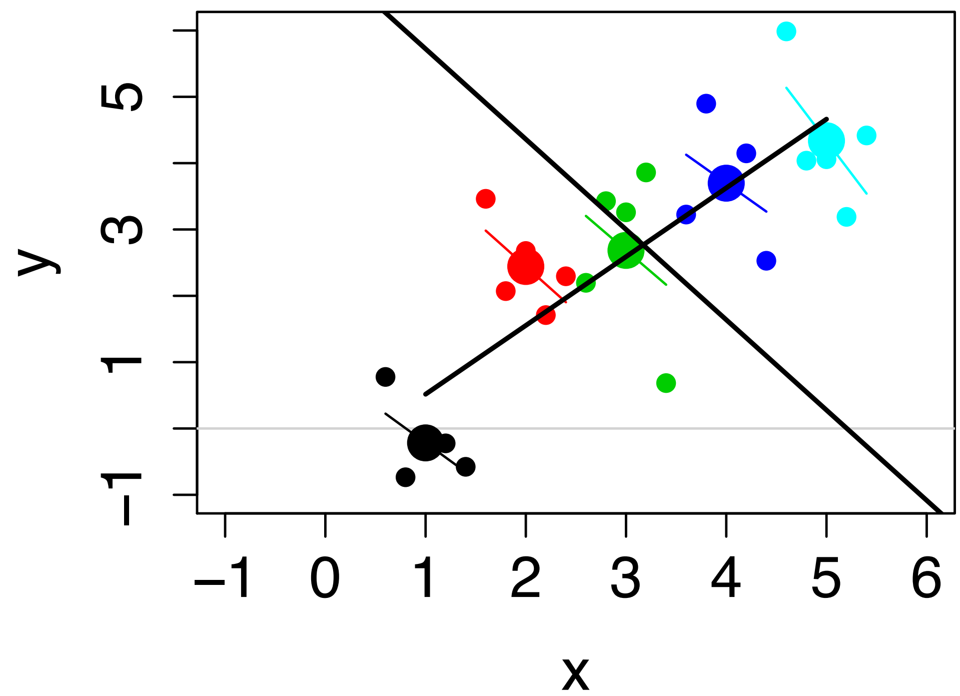
The "Random Effects Within and Between" (REWB) Specification

$$y_{ij} = \beta_0 + \beta_1(x_{ij} - \bar{x}_j) + \beta_2\bar{x}_j + u_j + e_{ij}$$

$\bar{x}_j$ is the mean of x_i for group j

$x_{ij} - \bar{x}_j$ is a "de-meaned" version of x_{ij}





Uncentered Random Effects Models

- if we do <u>not</u> center covariates by their group means, with a random effects model we effectively model the between and within effects using a single parameter

- if those effects are identical (or close to identical), we get the advantage of “extra” statistical power (ability to detect a relationship) compared to modelling either the between or within effects alone (“efficiency”)

- but if the effects are different, we will end up with a meaningless estimate (an uninterpretable weighted average of the between and within relationships, possibly unlike either one)

The Hausman (1978) Test: Myths and Facts

"The hypotheses on parameters and error terms (and hence the choice of the most appropriate estimator) are usually tested by means of:

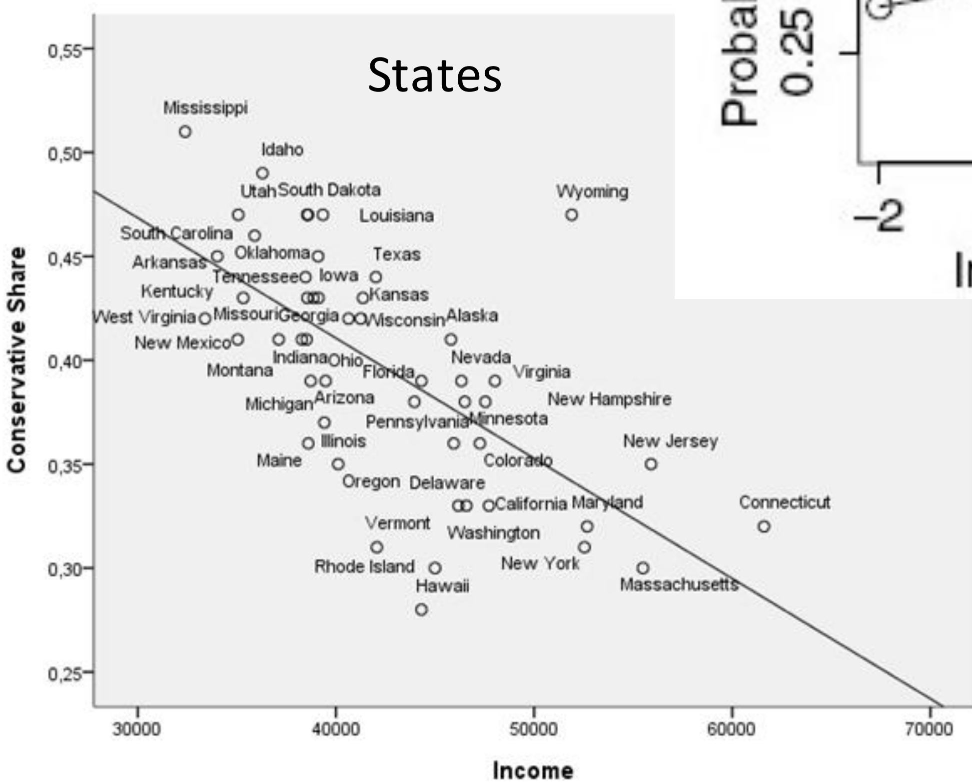
…

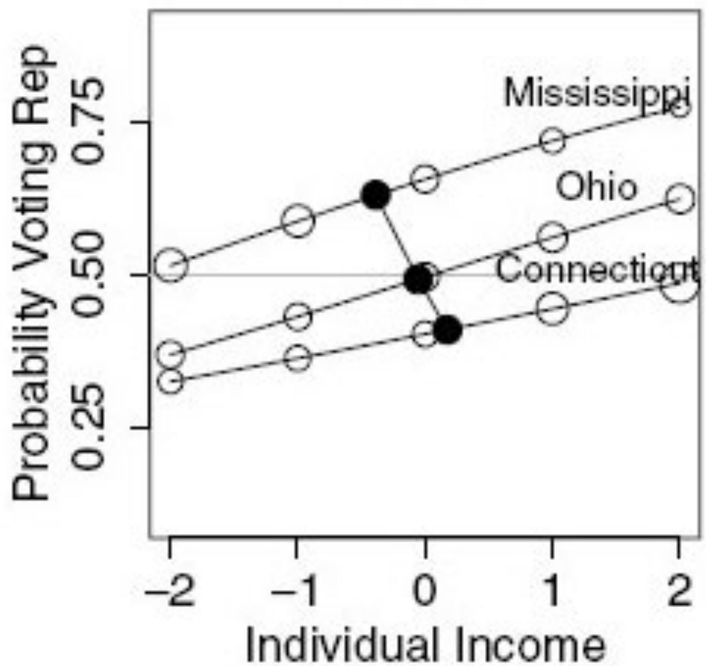
the choice between fixed and random effects specifications is based on Hausman-type tests, comparing the two estimators under the null of no significant difference: if this is not rejected, the more efficient random effects estimator is chosen." (Croissant and Millo 2008)

- but all the Hausman test does is check whether the "between" and "within" relationships are <u>different</u>

Croissant, Yves, and Giovanni Millo. 2008. "Panel Data Econometrics in R: The plm Package." *Journal of Statistical Software* 27[2].

Gelman et al. on Income and Voting in USA: Patterns for States Versus Individuals





Basic Theory

$$y_i = \beta_0 + \beta_1 x_{1i} + e_i$$
$$e_i \sim N(0,\sigma_e^2)$$

$$y_{ij} = \beta_0 + \beta_1(x_{ij} - \bar{x}_j) + \beta_2 \bar{x}_j + u_j + e_{ij}$$
$$u_j \sim N(0,\sigma_u^2)$$
$$e_{ij} \sim N(0,\sigma_e^2)$$

- the random errors u_j are assumed to be uncorrelated with covariates

The "Random Effects Within and Between" Specification Applied to Comparative Longitudinal Survey Data

- split any time-varying, country-level X variable of interest (e.g., GDP per capital, Gini coefficient) into two components…

- calculate the group (country) mean of X, pooling all relevant years
  - this variable captures the cross-sectional (between) relationship
  - Q: do countries have higher levels of X do they also tend to have higher (or lower) levels of Y?

- then, subtract that mean from country-year observations on X, leaving a *differenced* X
  - this component captures the longitudinal (within) relationship

The “Random Effects Between and Within” Specification Applied to Comparative Longitudinal Survey Data

- the longitudinal (within) component captures only the effect of change over time in X:
    - is an increase in X over time associated with an increase (or decrease) in Y over time?

- so this technique yields both the “fixed effects” results (the within relationship) and the between relationships
    - more to come tomorrow…

- estimation can be frequentist/(RE)ML or Bayesian/MCMC

Social Science Research 42 (2013) 347–360

Contents lists available at SciVerse ScienceDirect

Social Science Research

journal homepage: www.elsevier.com/locate/ssresearch

Does inequality erode social trust? Results from multilevel models of US states and counties

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ARTICLE INFO

Article history:
Received 28 March 2011
Revised 22 June 2012
Accepted 11 September 2012
Available online 27 September 2012

Keywords:
Trust
Inequality
Multilevel modeling
Longitudinal effects
General Social Survey

ABSTRACT

Previous research has argued that income inequality reduces people's trust in other people, and that declining social trust in the United States in recent decades has been due to rising levels of income inequality. Using multilevel models fitted to data from the General Social Survey, this paper substantially qualifies these arguments. We show that while people are less trusting in US states with higher income inequality, this association holds only cross-sectionally, not longitudinally; since the 1970s, states experiencing larger increases in inequality have not suffered systematically larger declines in trust. For counties, there is no statistically significant relationship either cross-sectionally or longitudinally. There is therefore only limited empirical support for the argument that inequality influences generalized social trust; and the declining trust of recent decades certainly cannot be attributed to rising inequality.

1. Introduction

A growing scholarly literature substantiates the belief that economic inequality has important consequences for social life. Studies have found correlations between inequality and social ills such as violence, poor health, political polarization

Survey, this paper substantially qualifies these arguments. We show that while people are less trusting in US states with higher income inequality, this association holds only cross-sectionally, not longitudinally; since the 1970s, states experiencing larger increases in inequality have not suffered systematically larger declines in trust. For counties, there is

makes many forms of social exchange and interaction possible (as classically formulated by Durkheim (1893); see Beckert (2009) for a discussion). In the absence of trust, many arms-length transactions are prevented. Evidence suggests that nations with more trust therefore experience faster economic growth (Knack and Keefer, 1997; La Porta et al., 1997), while residents of more trusting neighborhoods are better able to achieve collectively desirable ends, such as personal safety (Sampson et al., 2002).

Previous studies seeking to explain variations in trust have found negative correlations with inequality both across nations (Bjørnskov, 2006, 2008; Freitag and Bühlmann, 2009; Knack and Keefer, 1997; Rothstein and Uslaner, 2005; Uslaner,

Socio-Economic Review Advance Access published October 3, 2014

Socio-Economic Review (2014) 1–27 doi:10.1093/ser/mwu030

Economic inequality and public demand for redistribution: combining cross-sectional and longitudinal evidence

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One proposition of the popular median-voter hypothesis is a positive relationship between demand for redistribution and levels of inequality. However, empirical evidence of this relationship is scarce. A major shortcoming of previous research is that it is either cross-sectional, which casts general doubt on the causal nature of the estimates, or it is longitudinal and based on aggregated data, which makes it difficult to control for compositional effects or to analyze the individual-level implications of the hypothesis. This article estimates cross-sectional and longitudinal effects of inequality, while simultaneously controlling for the composition of data at the individual level. The article finds a positive within-country effect of inequality on demand for redistribution but no such relationship between countries. This finding points to an unobserved variable at the country level. Following the literature, the article considers welfare regimes as a possible factor capturing these unobserved country differences. However, none of the existing welfare regime typologies performs well in terms of capturing unobserved heterogeneity or in general explanatory power. All in all, the article finds robust support for the proposition that demand for redistribution is positively related to inequality, but it casts doubt on the utility of cross-sectional analysis and the welfare regime approach.

Keywords: political economy, inequality, redistribution, income distribution, new growth theory, Europe
JEL Classification: D31, D63, O15

the hypothesis. This article estimates cross-sectional and longitudinal effects of inequality, while simultaneously controlling for the composition of data at the individual level. The article finds a positive within-country effect of inequality on demand for redistribution but no such relationship between countries. This

1. Introduction

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European Sociological Review, 2015, Vol. 31, No. 5, 643–654
doi: 10.1093/esr/jcv069
Advance Access Publication Date: 29 July 2015
Original Article

OXFORD

The between and within Effects of Social Security on Church Attendance in Europe 1980–1998: The Danger of Testing Hypotheses Cross-Nationally

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Submitted February 2014; revised May 2015; accepted June 2015

Abstract

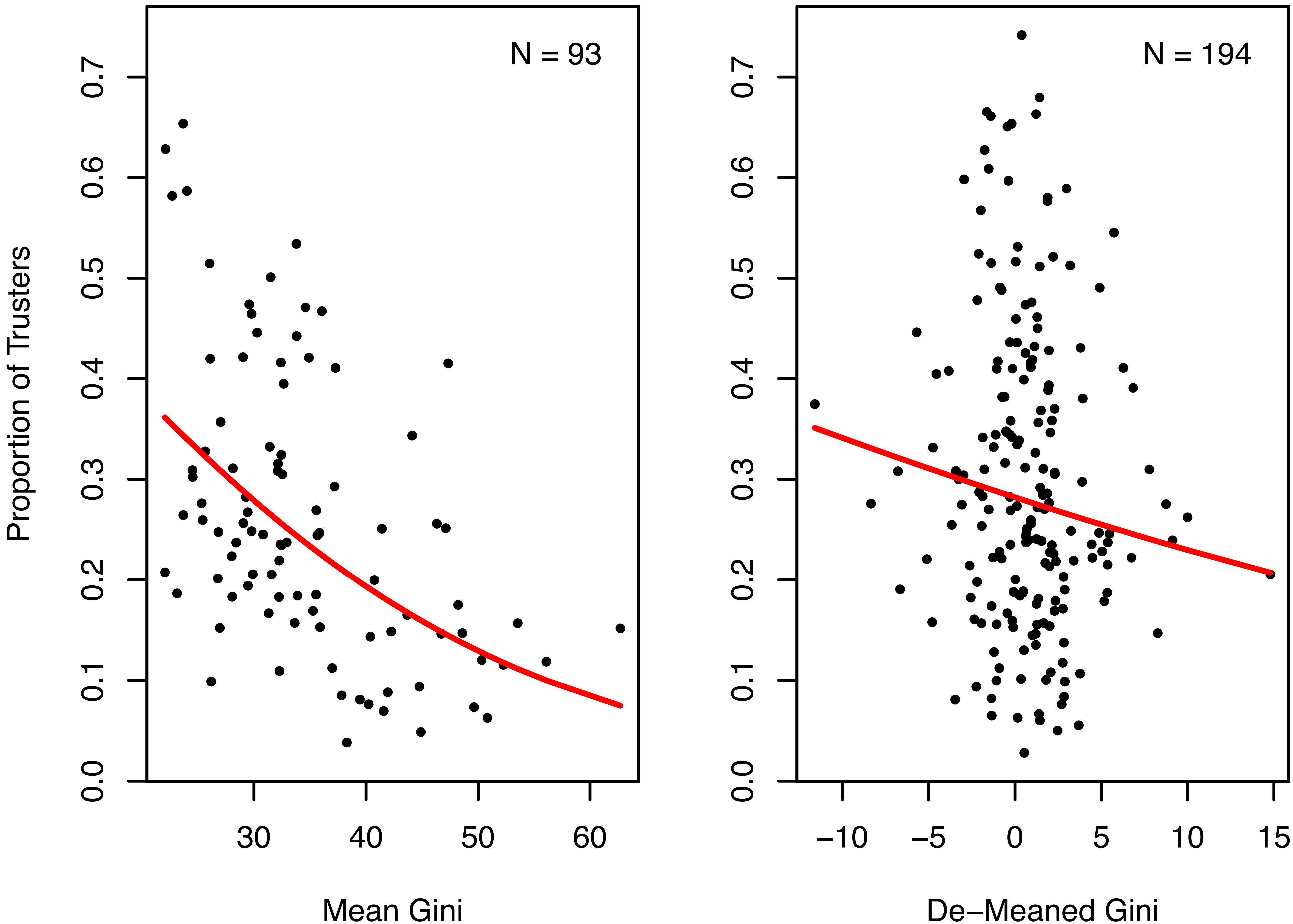
Tests of hypotheses explaining the variation in church attendance are dominated by the use of international comparative survey data covering many countries with only a limited number of samples within these countries. As a result, the main research focus is on between country effects and hardly on within country effects. The latter, however, comprises a more convincing test, because fewer assumptions about unobserved country-specific variables are required. Elaborating on various analytical models, we show that results from a between country research design may lead to inaccurate conclusions. To illustrate this point, we selected the Mannheim Eurobarometer Trend File, which includes as many European countries on as many points in time as possible. Step by step we disentangle the well-known strong negative overall between country correlation of social security with church attendance. We show that this correlation most likely is owing to unspecified country characteristics, as within countries, social security is sometimes positively related to church attendance and sometimes negatively, whereas on average there is no effect at all. Rather than increases in social security spending, rising gross domestic product seems to reduce church attendance. Our cautionary tale about the use of between country research designs applies to other fields of research as well.

The Relationship between Social Security and Religious Involvement

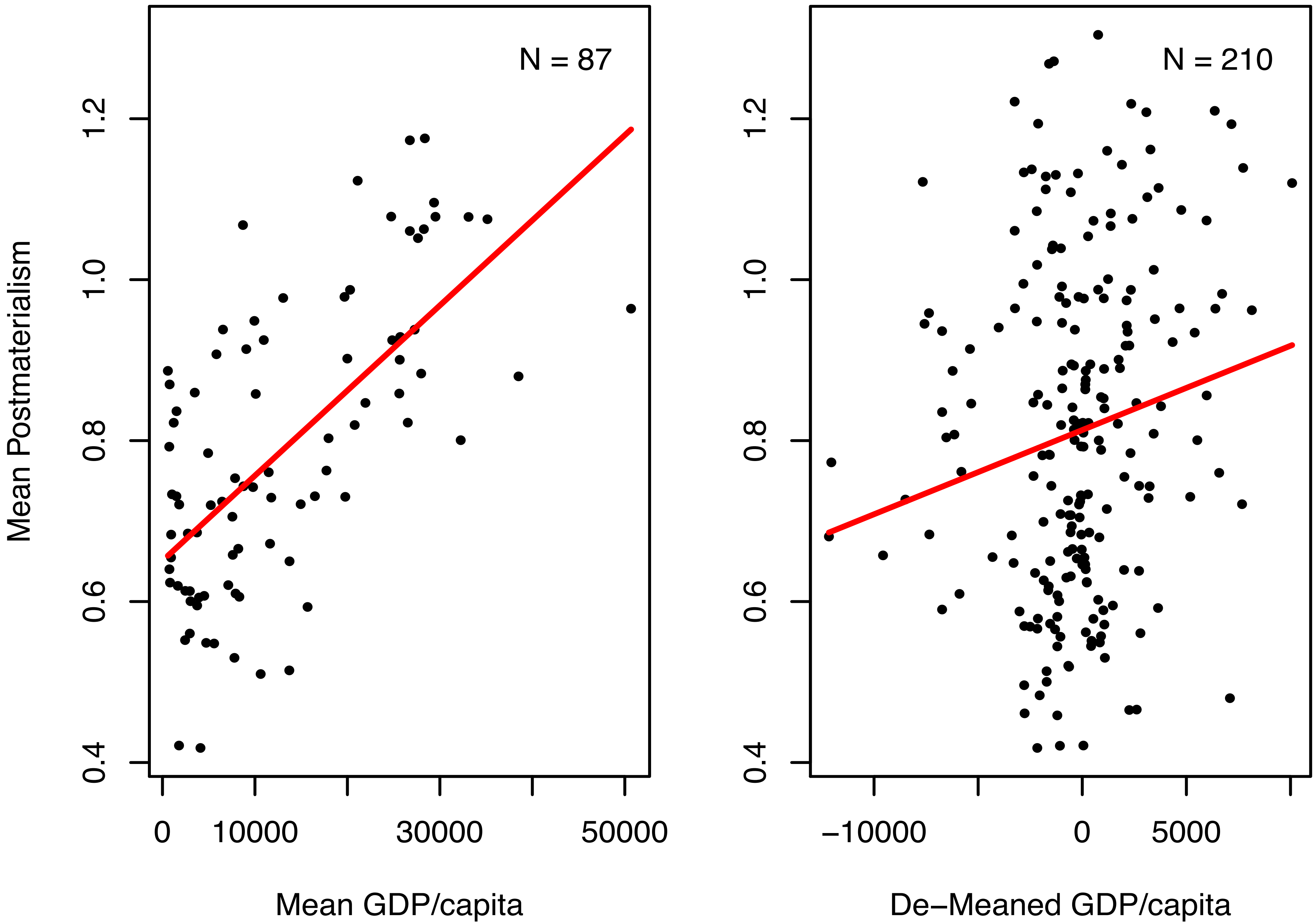
The explanation of religious behaviour, like church attendance, has been a subject of research within the exact mechanism remains part of the debate among scholars, the basic idea is that increasing modernity has undermined the social significance of religion (Wilson, 1966). Peter Berger, one of the founders of

includes as many European countries on as many points in time as possible. Step by step we disentangle the well-known strong negative overall between country correlation of social security with church attendance. We show that this correlation most likely is owing to unspecified country characteristics, as within countries, social security is sometimes positively related to church attendance and sometimes negatively, whereas on average there is no effect at all. Rather than increases in social secur-

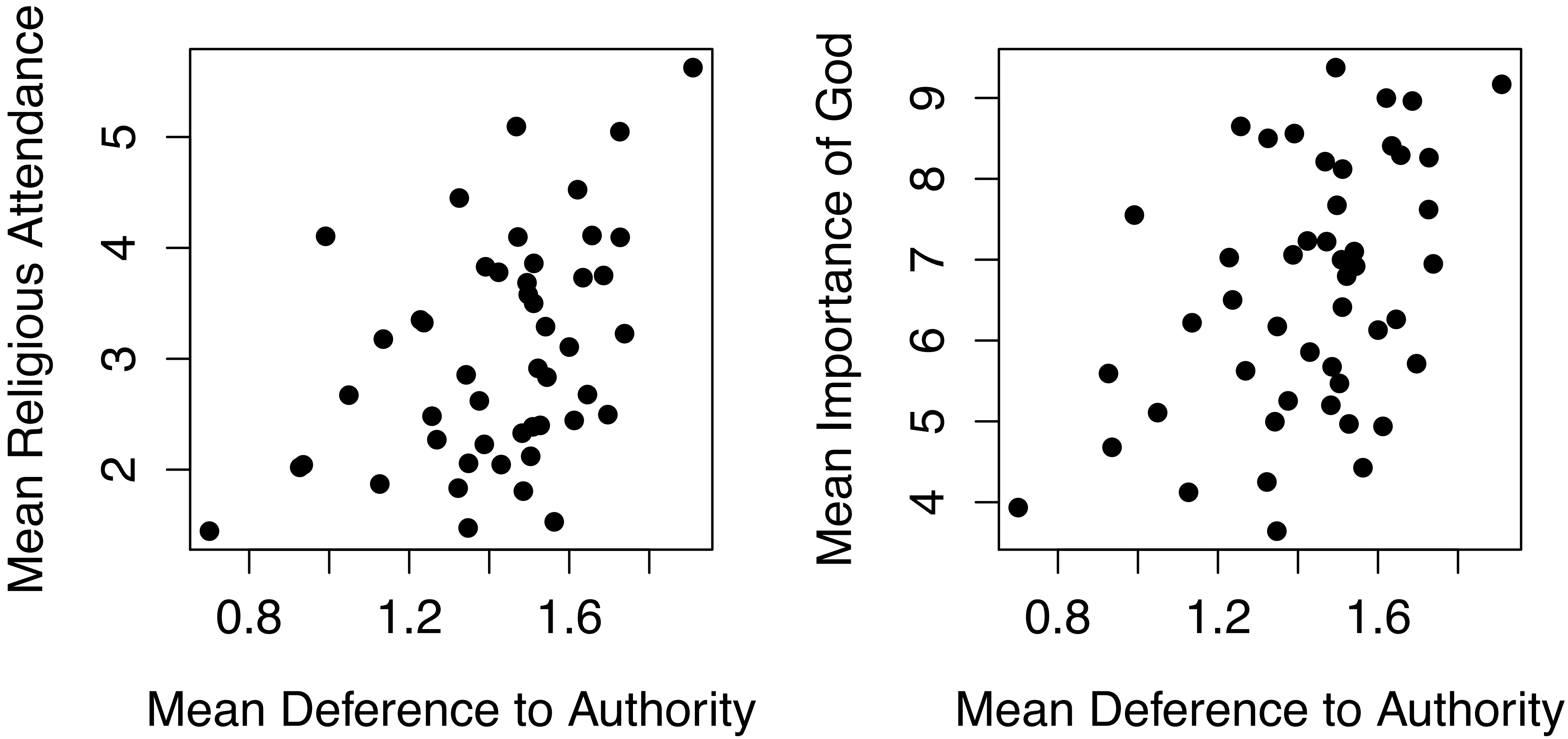
Income Inequality and Social Trust



GDP/capita and Post-Materialist Values



Mean National Religiosity versus Deference to Authority



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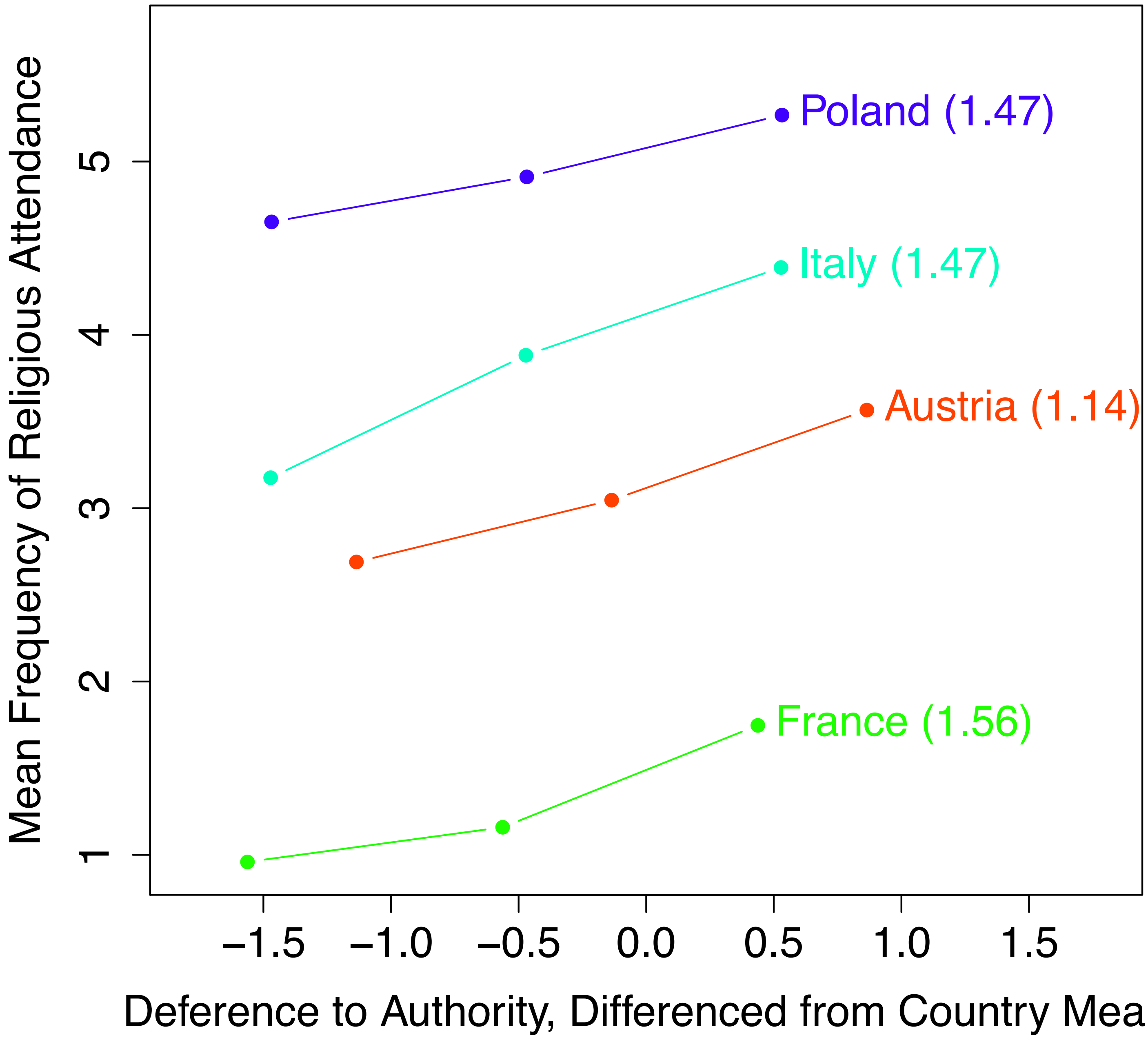
Religious Attendance versus Deference to Authority, Within Nations



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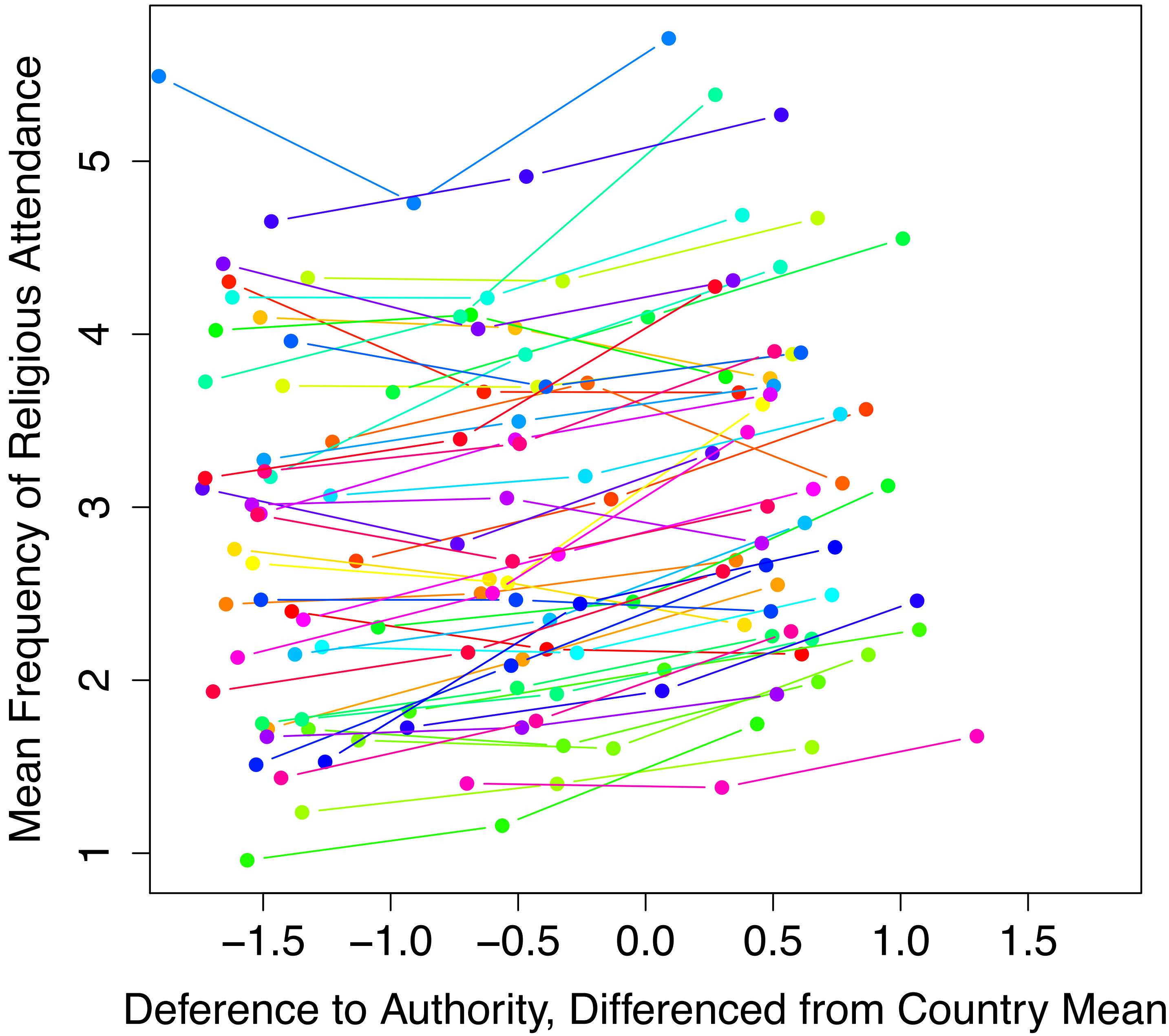

A Toy Dataset: US States Production ("Produc" in the "plm" package)

- a panel of 48 observations per year for 17 years (1970 to 1986)
- used in an influential econometrics textbook by Baltagi
- total *N*=816

- variables:

  state

  year

  gsp = gross state product (y)

  pcap = private capital stock

  pc = public capital

  emp = labor input measured by the employment in non–agricultural payrolls

  unemp = state unemployment rate

Lab 1

`http://bit.ly/29qBHX2`