

# Consistent and equivariant estimation in errors-in-variables models with dependent errors

Michal Pešta

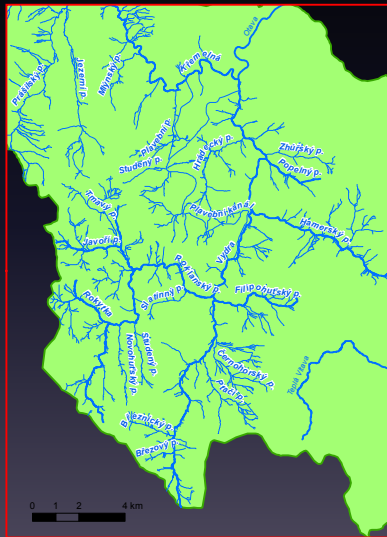
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*Salmo trutta* morpha *fario*; L., 1758



# Šumava



# Vydra (Javoří potok)



# Pitfalls, problems, and our approach

- length and weight

# Pitfalls, problems, and our approach

- covariate or response

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- covariate or response
- least squares or least absolute distance or ... ML

# Pitfalls, problems, and our approach

- covariate or response
- invariant penalization



# Pitfalls, problems, and our approach

- covariate or response
- invariant penalization
- water depth and changing conditions

# Pitfalls, problems, and our approach

- covariate or response
- invariant penalization
- data dependence

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- covariate or response
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- data dependence
- measurement units

# Pitfalls, problems, and our approach

- covariate or response
- invariant penalization
- data dependence
- equivariant estimate (consistency, asymptotic normality)

# Pitfalls, problems, and our approach

- covariate or response
- invariant penalization
- data dependence
- equivariant estimate (consistency, asymptotic normality)
- unknown quantities

# Pitfalls, problems, and our approach

- covariate or response
- invariant penalization
- data dependence
- equivariant estimate (consistency, asymptotic normality)
- computational feasibility

# Outline

Errors-in-variables estimation

EIV Model

Equivariant estimate

Inference

Assumptions of the EIV model

Asymptotic properties of the estimate

Bootstrapping

Moving block bootstrap

Conclusions

# Errors-in-Variables (EIV) Model

$$\mathbf{Y} = \mathbf{Z} \boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

$n \times 1$        $n \times p$   $p \times 1$        $n \times 1$

$$\mathbf{X} = \mathbf{Z} + \boldsymbol{\Theta}$$

$n \times p$        $n \times p$        $n \times p$



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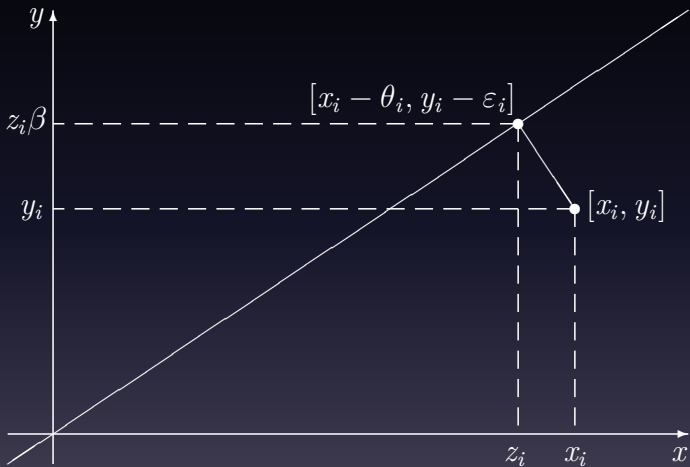
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- $\boldsymbol{\varepsilon}$  and  $\boldsymbol{\Theta}$  ... random errors
- $\boldsymbol{\beta}$  ... regression parameters (to be estimated)

# Illustration



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scale, rotation, and **coordinate change**

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- for a unitary invariant matrix norm

$$\min \|[\Theta, \epsilon]\| \quad \text{s.t.} \quad \mathbf{Y} - \epsilon = (\mathbf{X} - \Theta)\beta$$

# Class of the Ul matrix norms

- Schatten norms

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operator norm ( $k = 1$ ), Schatten norms ( $k = \text{last}$ )

# Estimate

- solution with desired properties for any UI MN

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$\lambda$  is the  $(p + 1)$ -st largest eigenvalue of  $[\mathbf{X}, \mathbf{Y}]^T [\mathbf{X}, \mathbf{Y}]$

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# Weak dependence

- strong mixing ( $\alpha$ -mixing)

$$\alpha(\mathcal{A}, \mathcal{B}) = \sup_{A \in \mathcal{A}, B \in \mathcal{B}} |\mathbb{P}(AB) - \mathbb{P}(A)\mathbb{P}(B)|$$

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- uniformly strong mixing  $\Rightarrow$  strong mixing

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- rows  $[\Theta_{i,\bullet}, \varepsilon_i]$  with zero mean and non-singular covariance matrix  $\sigma^2 \mathbf{I}$ , where  $\sigma^2$  is unknown (for simplicity)
- exists a **positive definite** matrix

$$\Delta := \lim_{n \rightarrow \infty} n^{-1} \mathbf{Z}^\top \mathbf{Z}$$

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- asymptotic normality under stationary strong mixing and finite  $(4 + \delta)$ -th moment of errors

$$\sqrt{n} (\hat{\beta} - \beta) \xrightarrow{\mathcal{D}} \mathcal{N}(\mathbf{0}, \cdot), \quad n \rightarrow \infty$$

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- approaching (each other) in distribution almost surely along  $[\mathbf{X}, \mathbf{Y}]$

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- ex.:  $H_0 : \beta = 2$  vs  $H_1 : \beta \neq 2$

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- consistency and asymptotic normality

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- EIV with weakly dependent errors
- equivariant estimate
- consistency and asymptotic normality
- MBB correctness

# Bibliography

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