# Meta- Granger Causality

16th IWH-CIREQ Macroeconometric Workshop
*Challenges for Forecasting – Structural Breaks, Revisions and Measurement Errors*

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# Motivation

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Energy Consumption

Growth →

← Conservation

↔ Bicausality

Neutrality

Economic Growth


- Important implications for climate policy, energy security, and the effect of energy price shocks on the economy (Hamilton, 2009; Stern, 2011)
- Large empirical literature using Granger causality tests
  - → Inconclusive and heterogenous results (Ozturk, 2010; Payne, 2010)
  - → Publication selection for statistically significant results? (Bruns *et al.*, 2014)

# Agenda

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(1) *p*-Hacking

(2) Meta-Regression Models

(3) Simulations

(4) Energy-Growth Literature

# *p*-Hacking

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- Search for statistically significant estimates within each study

  (Simonsohn *et al.*, 2014)

  - Sampling error (Rosenthal, 1979)
  - Omitted-variable bias (Leamer, 1983)
  - Overfitting bias (in small samples)
    - Overfitting (Ozcicek and McMillin, 2010; Nickelsburg, 1985; Lütkepohl, 1985)
    - Overrejection (Zapata and Rambaldi, 1997)

→ Significant Granger causality tests due to overfitting bias?

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# Meta-Regression Models

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- Basic meta-regression model
  - $z_i = \alpha + \beta_B \sqrt{df_i} + \epsilon_i$ with $z_i = \Phi^{-1}(1 - \pi_i)$

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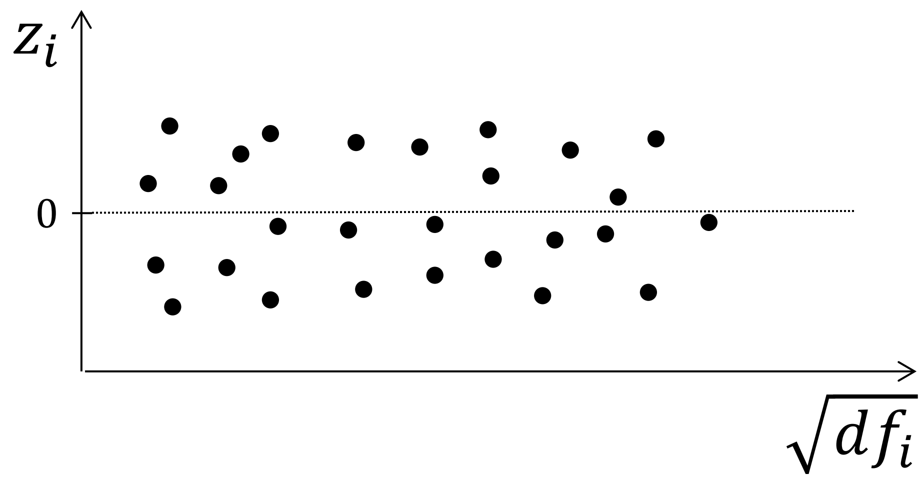
(1) No genuine Granger causality
$\rightarrow \beta_B = 0$



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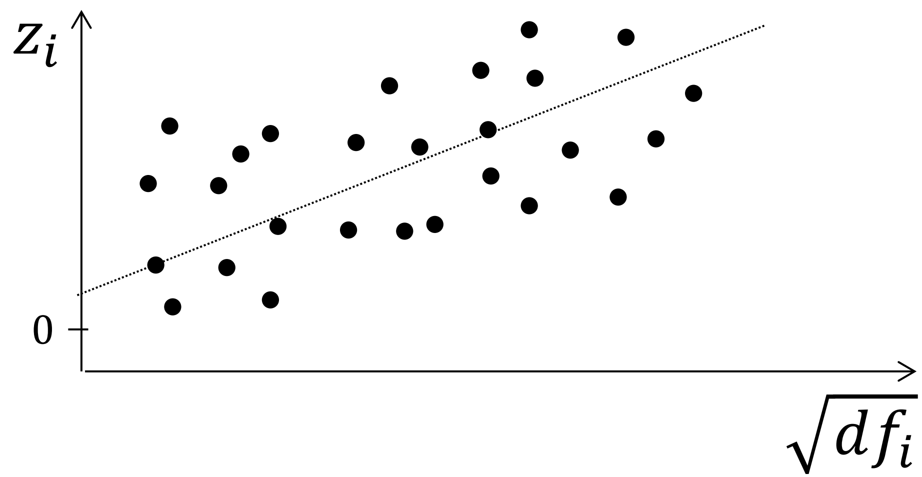

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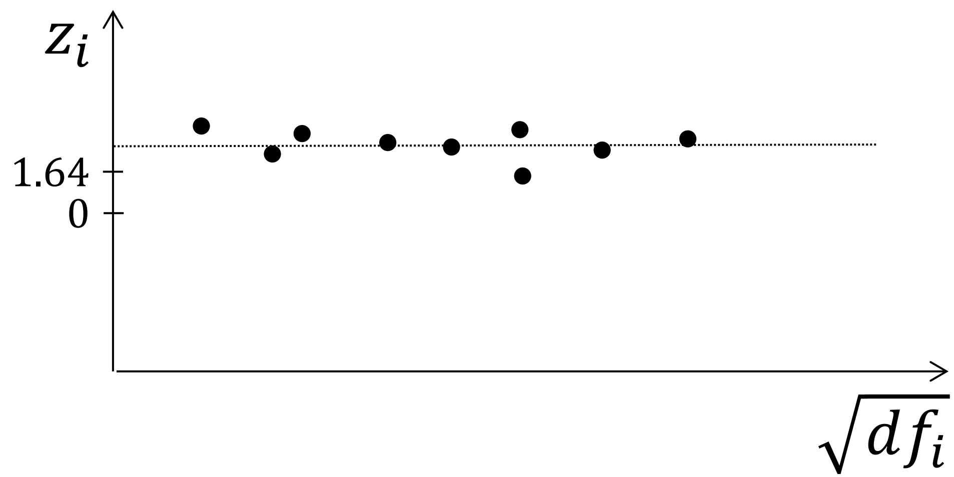

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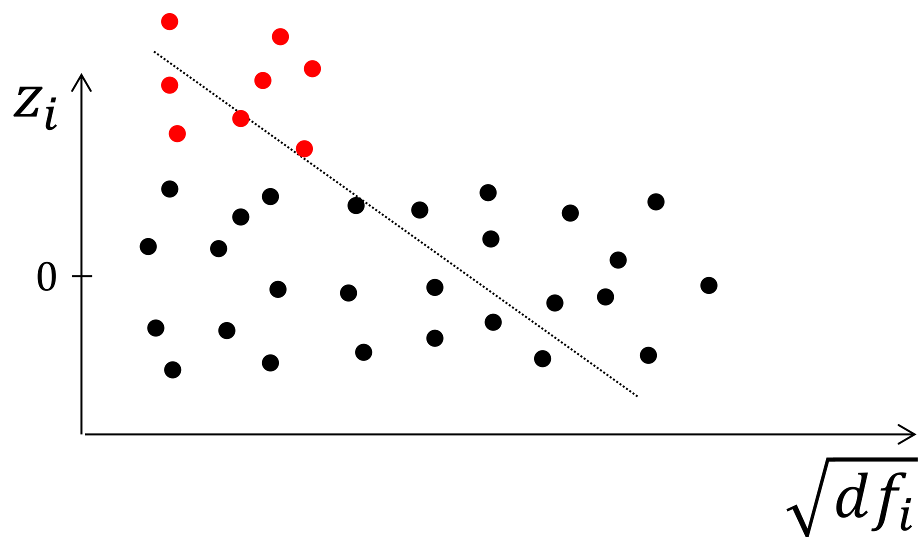

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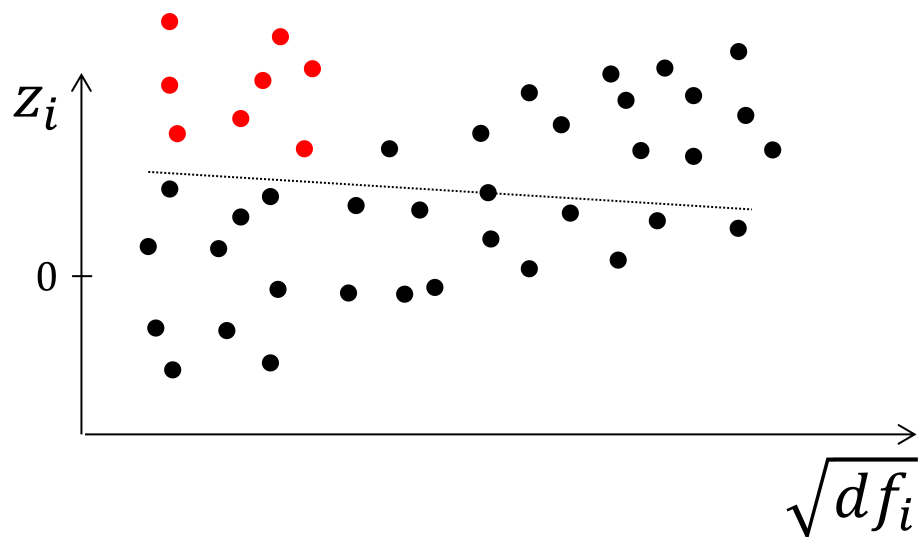

# Meta-Regression Models

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- Basic meta-regression model
  - $z_i = \alpha + \beta_B \sqrt{df_i} + \epsilon_i$ with $z_i = \Phi^{-1}(1 - \pi_i)$
- Extended meta-regression model
  - $z_i = \alpha + \beta_E \sqrt{df_i} + \gamma \, \#lags + \epsilon_i$

# Agenda



(1) *p*-Hacking

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(3) Simulations

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# Simulations

- **Design (No *p*-hacking)**
  - DGPs: $Y \nrightarrow X$, but $\mathrm{X} \longrightarrow Y$

# Simulations

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- **Design (No *p*-hacking)**
  - DGPs: $Y \nrightarrow X$, but $X \longrightarrow Y$

| Name | VAR model |
|---|---|
| DGP1a | $\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} 1.5 & 0.4 \\ 0 & 1.5 \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} -0.25 & -0.2 \\ 0 & -0.25 \end{bmatrix} \begin{bmatrix} Y_{t-2} \\ X_{t-2} \end{bmatrix} + \begin{bmatrix} -0.25 & -0.2 \\ 0 & -0.25 \end{bmatrix} \begin{bmatrix} Y_{t-3} \\ X_{t-3} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$ |
| DGP1b | $\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} 1.5 & 0.8 \\ 0 & 1.5 \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} -0.25 & -0.4 \\ 0 & -0.25 \end{bmatrix} \begin{bmatrix} Y_{t-2} \\ X_{t-2} \end{bmatrix} + \begin{bmatrix} -0.25 & -0.4 \\ 0 & -0.25 \end{bmatrix} \begin{bmatrix} Y_{t-3} \\ X_{t-3} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$ |
| DGP2a | $\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} 1.5 & 0.4 \\ 0 & 1.5 \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} -0.5 & 0.2 \\ 0 & -0.25 \end{bmatrix} \begin{bmatrix} Y_{t-2} \\ X_{t-2} \end{bmatrix} + \begin{bmatrix} -0.25 & -0.2 \\ 0 & -0.25 \end{bmatrix} \begin{bmatrix} Y_{t-3} \\ X_{t-3} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$ |
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# Simulations



- **Design (No *p*-hacking)**
  - DGPs: $Y \nrightarrow X$, but $\mathrm{X} \longrightarrow Y$
  - Meta-sample size: $s = 10, 20, 40, 80$
  - Primary sample sizes: $n_i = \mathrm{round}\left(\Gamma\left(\frac{(\mu-30)^2}{\sigma^2}, \frac{\sigma^2}{(\mu-30)}\right) + 30\right)$
    - $\mu = 35, 40, 50, 60$
    - $\sigma^2 = 25, 100, 225$

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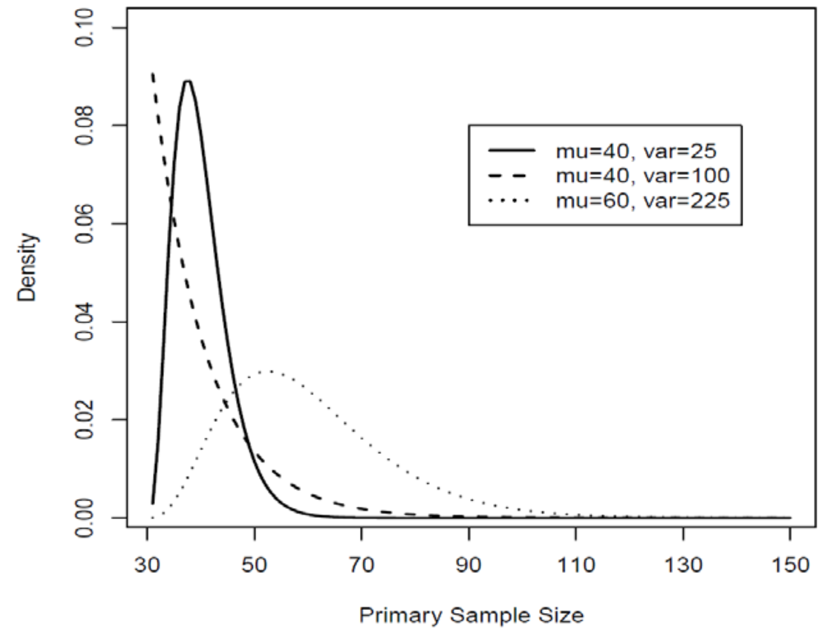

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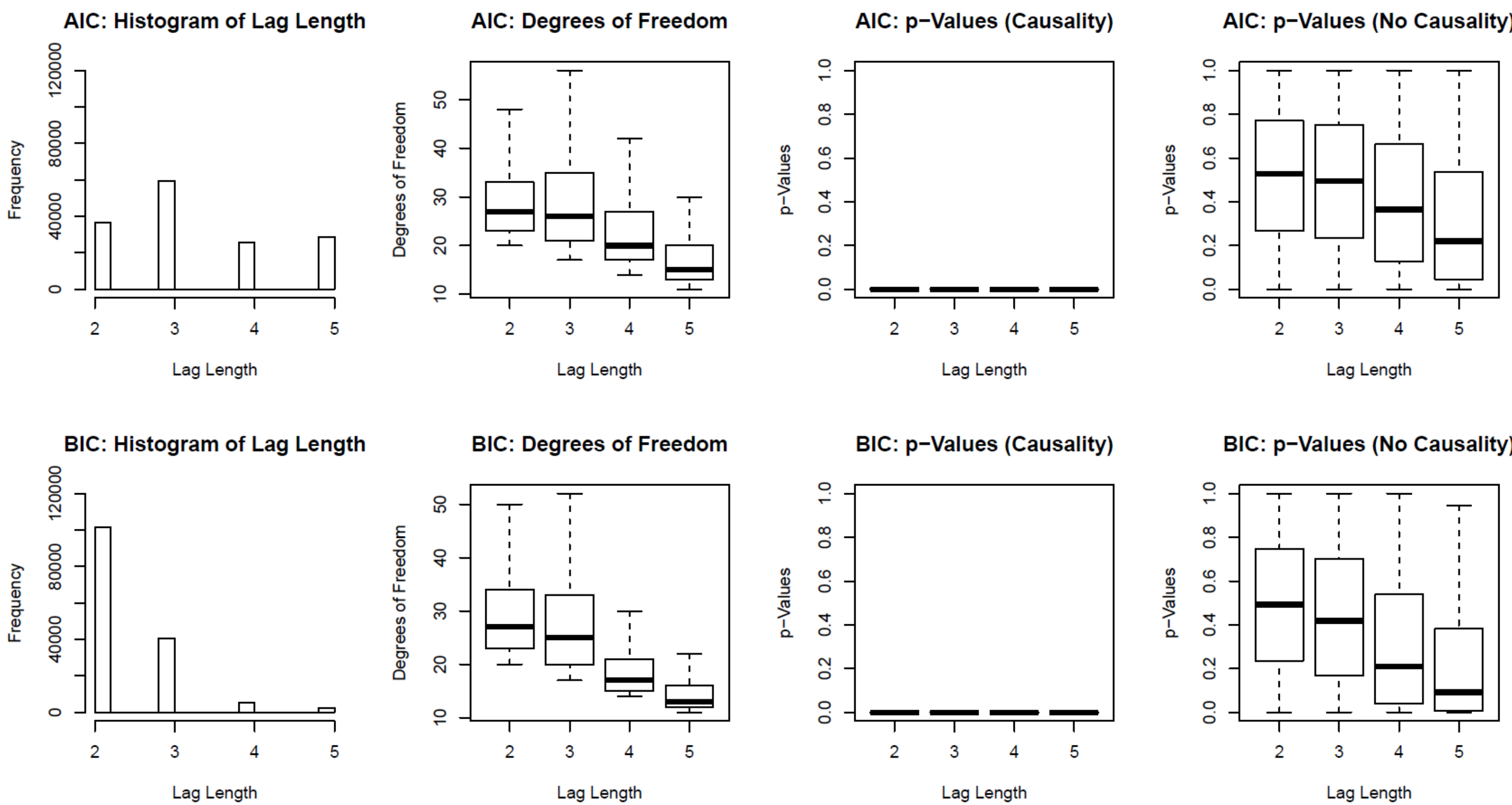
    - $\mu = 35, 40, 50, 60$
    - $\sigma^2 = 25, 100, 225$
  - Primary authors use AIC or BIC (max lag length = 5)
  - Primary authors estimate the VAR and test for Granger causality using the approach of Toda-Yamamoto
  - Application of meta-regression models to $s$ primary studies

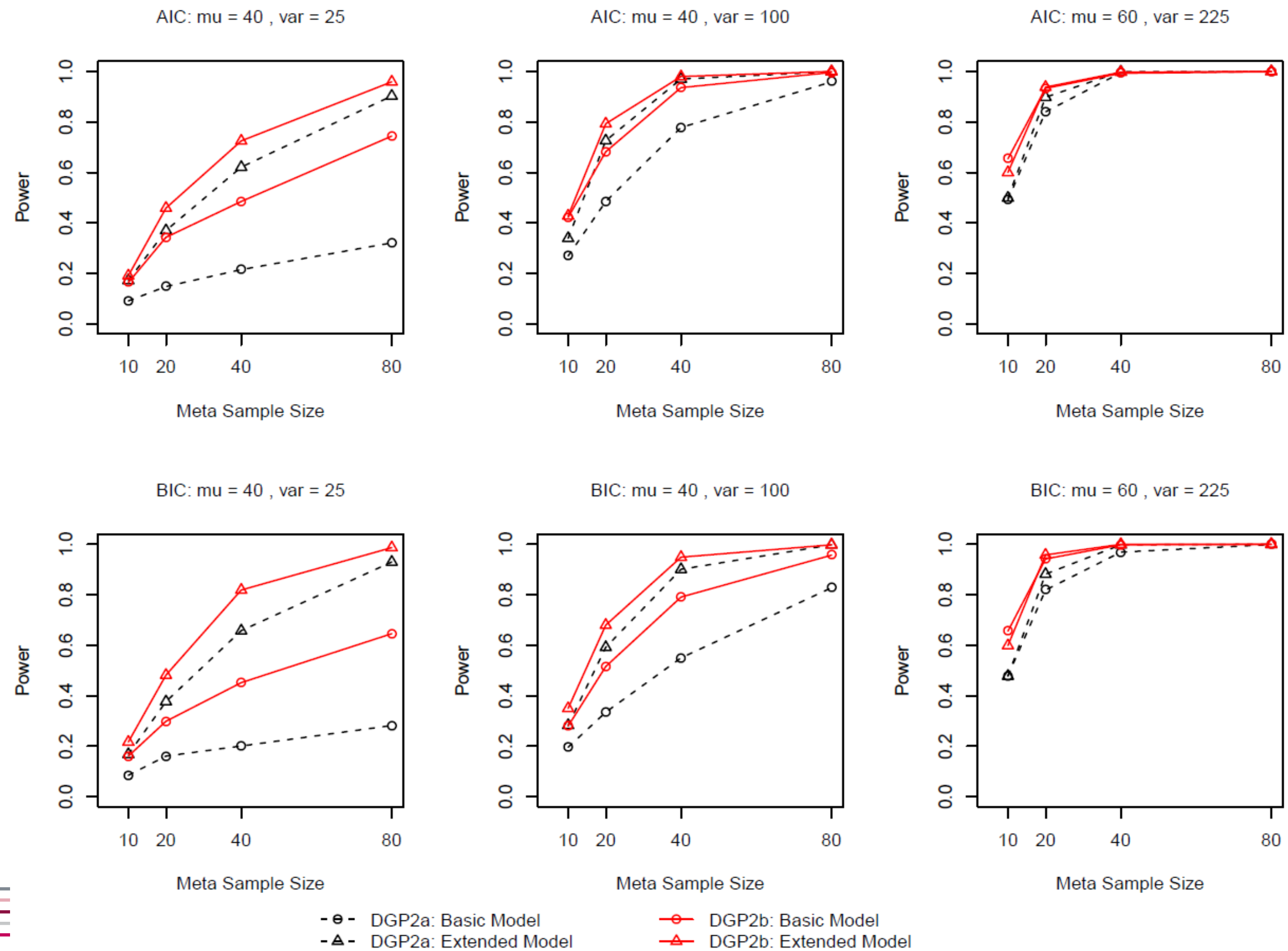
# Simulations

- **Results (No *p*-hacking)**
  - Prevalence of Overfitting Bias (DGP2a)



# Simulations

- **Results (No *p*-hacking)**
  - Power (DGP2)



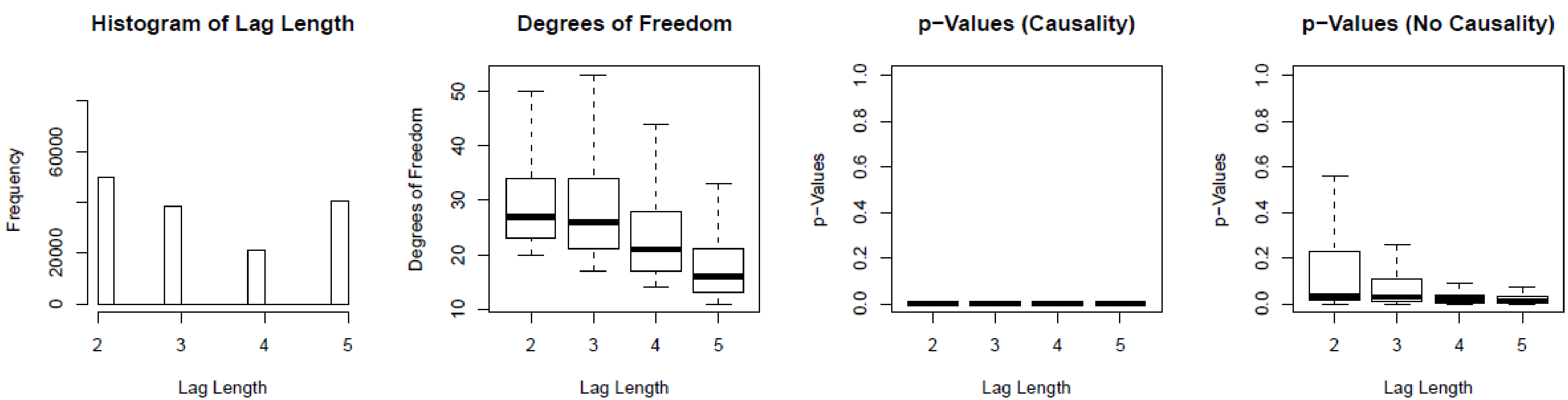
# Simulations



- **Design (Theory-Confirmation Bias)**
  - Remember: $Y \nrightarrow X$, but $\mathrm{X} \longrightarrow Y$
  - Primary authors *p*-hack Granger causality tests for $Y \nrightarrow X$
    - $(100 - h)\%$
      - Estimation of VAR model with AIC and BIC and selection of most significant Granger causality test for $Y \nrightarrow X$
    - $h\%$
      - If the most significant Granger causality test for $Y \nrightarrow X$ is not significant, DGP is resampled until a significant result is obtained

# Simulations

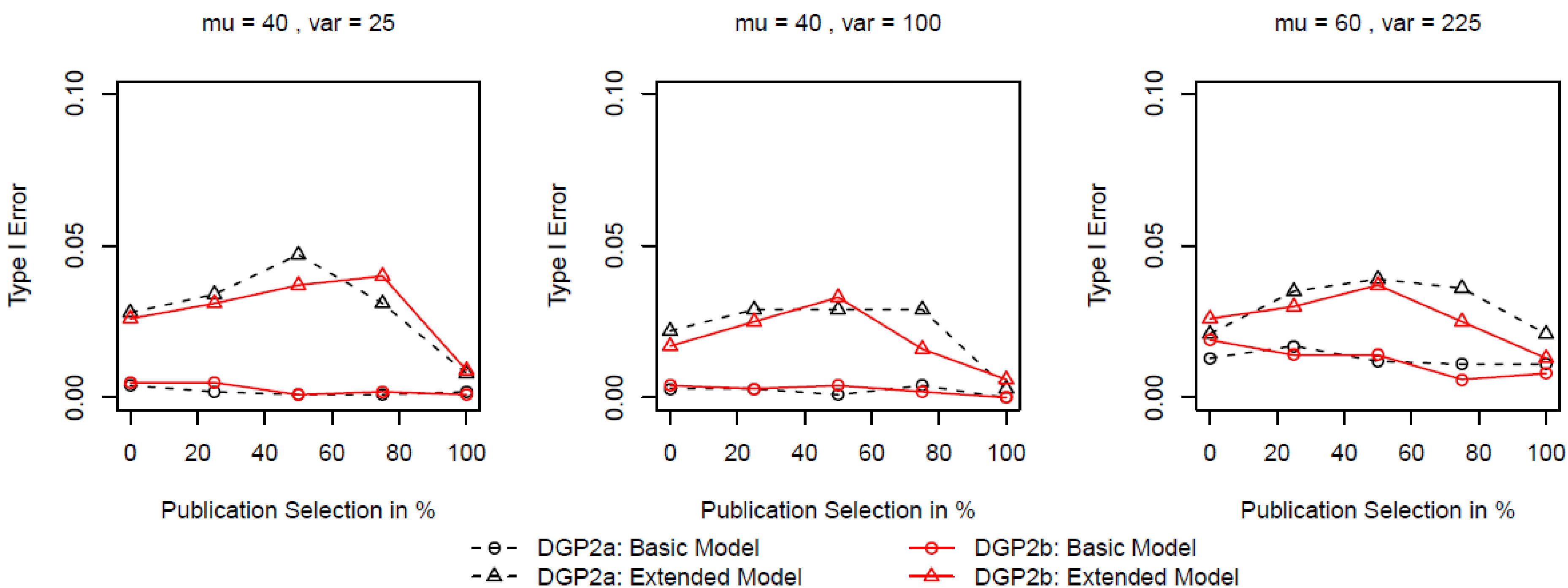
- **Results**
  - Prevalence of Overfitting Bias in the Presence of Theory Confirmation Bias (h=75, DGP2a)



# Simulations



- **Results**
  - Type I Errors in the Presence of Theory-Confirmation Bias (DGP2)



# Simulations

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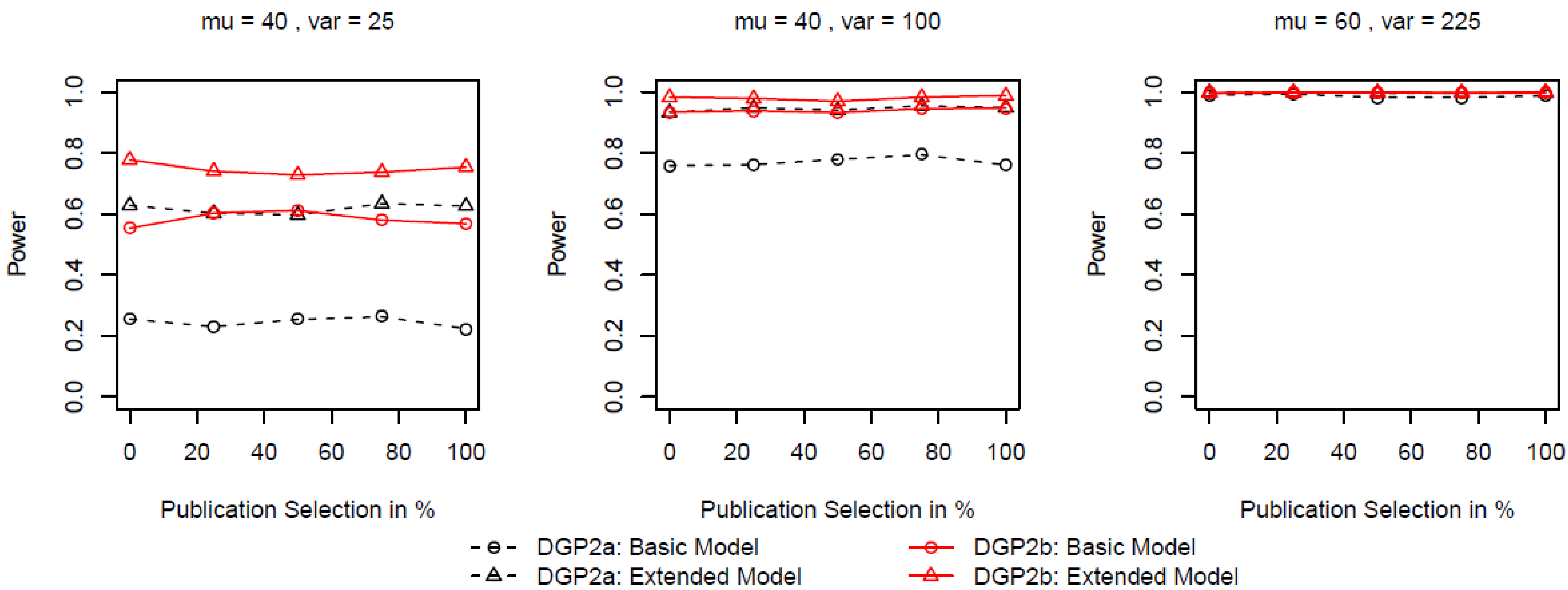
- **Results**
  - Power in the Presence of Theory-Confirmation Bias (DGP2)



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# Energy-Growth Literature

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- Overview of the sample
  - 23 studies using the Granger causality test of Toda and Yamamoto
  - 126 estimates of Granger causality in each direction

| Control Variables | Obs. | Number of Studies | Energy- Growth ($p$- value < 0.05 and 0.1) | | Growth- Energy ($p$- value < 0.05 and 0.1) | | Percentiles of $df$ | | | Number of Lag Lengths | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 0.05 | 0.1 | 0.05 | 0.1 | 25 | 50 | 75 | 1 | 2 | 3 |
| **None** | 66 | 6 | 19.70% | 22.73% | 27.27% | 37.88% | 28 | 35 | 38 | 47 | 18 | 1 |
| **Capital and Labor** | 41 | 7 | 48.78% | 51.22% | 46.34% | 56.10% | 12 | 14 | 21 | 7 | 5 | 29 |
| **Other** | 19 | 10 | 10.53% | 21.05% | 36.84% | 42.11% | 17 | 21 | 28.5 | 12 | 3 | 4 |

# Energy-Growth Literature

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- Empirical Strategy
  - Omitted-variable biases may generate positive relation between $z_i$ and $\sqrt{DF_i}$
  - Estimated model:

$$
\begin{aligned}
z_i = \alpha_1 + \beta_1 \sqrt{DF_i} \\
&+ D_{KL}\left(\alpha_2 + \beta_2 \sqrt{DF_i}\right) \\
&+ D_{Ot}\left(\alpha_3 + \beta_3 \sqrt{DF_i}\right) \\
&+ \gamma\, p_i + \varepsilon_i
\end{aligned}
$$

  - $D_{KL} = 1$ if capital and labor are used and zero otherwise
  - $D_{Ot} = 1$ if other control variables are used and zero otherwise

# Energy-Growth Literature

- Results

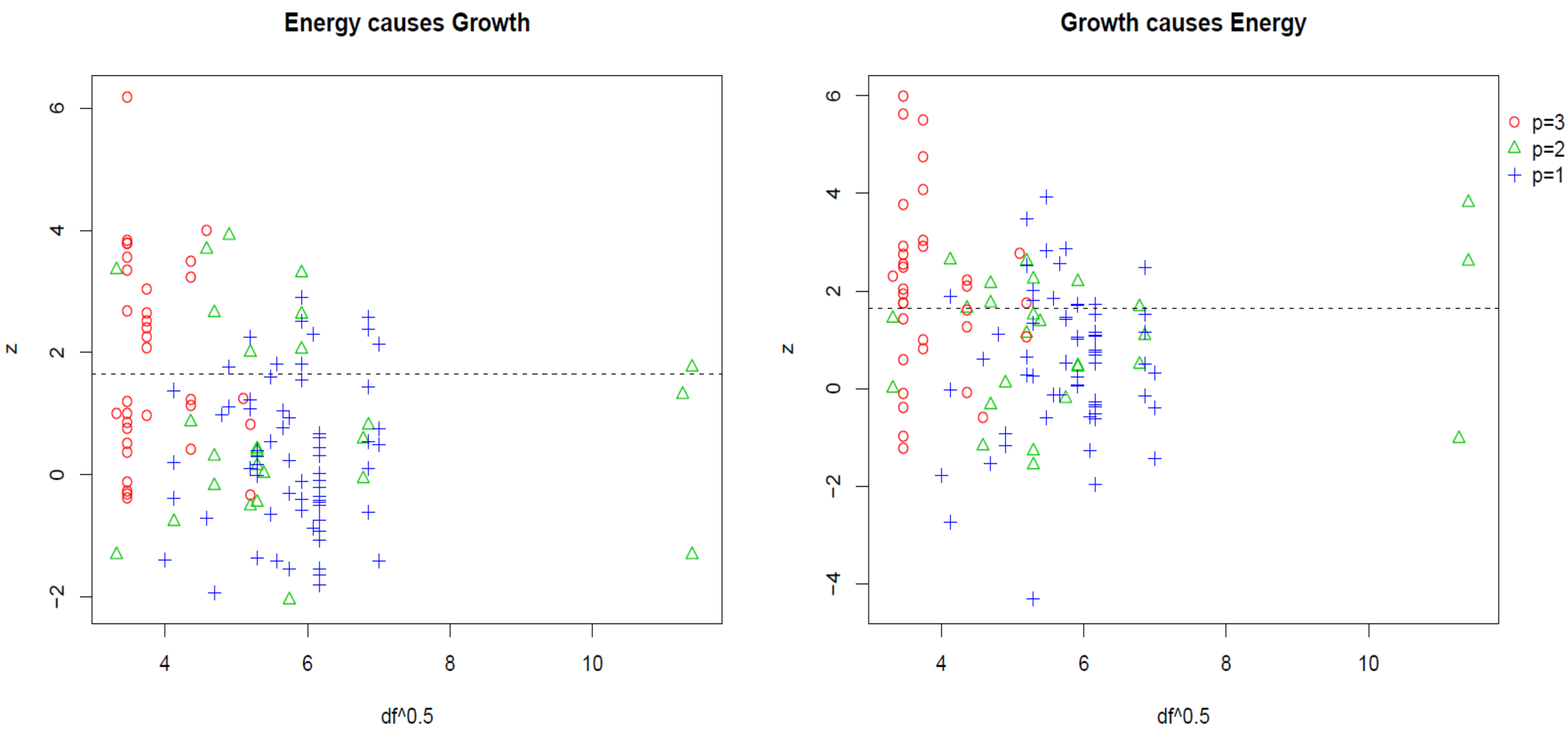
| | Energy causes Growth | | | Growth causes Energy | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) |
| Constant | 2.32** | -0.16 | 0.04 | 2.09† | -0.55 | -0.35 |
| | (0.86) | (0.86) | (3.67) | (1.11) | (1.09) | (16.51) |
| Df | -0.28† | -0.05 | -0.06 | -0.2 | 0.04 | 0.02 |
| | (0.16) | (0.12) | (0.47) | (0.21) | (0.15) | (1.53) |
| Lags | | 0.73*** | 0.52 | | 0.77** | 0.70* |
| | | (0.2) | (0.34) | | (0.26) | (0.29) |
| KL | | | 0.47 | | | 0.44 |
| | | | (4.89) | | | (16.79) |
| KL*Df | | | 0.04 | | | -0.07 |
| | | | (0.82) | | | (1.63) |
| Other | | | -1.18 | | | -2.97 |
| | | | (4.52) | | | (16.86) |
| Other*Df | | | 0.22 | | | 0.63 |
| | | | (0.7) | | | (1.7) |
| Obs. | 126 | 126 | 126 | 126 | 126 | 126 |
| Adj. R^2 | 0.06 | 0.17 | 0.18 | 0.02 | 0.13 | 0.12 |

Signif. codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘†’ 0.1

Notes: Bootstrapped standard errors in parentheses. We bootstrap primary studies rather than single Granger causality tests to account for the dependence of multiple Granger causality tests per primary study. Significance codes represent a two-sided t-test.

# Energy-Growth Literature

- Results



# Conclusions



- *p*-hacking based on overfitting bias may be a threat to the validity of inferences in Granger causality testing
- Meta-regression models can adjust for the loss of power that is introduced by overfitting bias

- Excess significance in the energy-growth literature
  - No evidence for genuine Granger causality in our sample
  - Evidence for the presence of overfitting bias
  - *p*-hacking for statistically significant results?

Thank you!

Stephan Bruns

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# Overfitting Bias



- Toda-Yamamoto (1995) test for Granger causality
  - $\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} \delta_{10} \\ \delta_{20} \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} \delta_{11,i} & \delta_{12,i} \\ \delta_{21,i} & \delta_{22,i} \end{bmatrix} \begin{bmatrix} Y_{t-i} \\ X_{t-i} \end{bmatrix} + \sum_{j=1}^{d_{max}} \begin{bmatrix} \delta_{11,p+j} & \delta_{12,p+j} \\ \delta_{21,p+j} & \delta_{22,p+j} \end{bmatrix} \begin{bmatrix} Y_{t-p-j} \\ X_{t-p-j} \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \end{bmatrix}$
  - Granger causality test for $X \longrightarrow Y$
    - $H_0^X: \delta_{12,1} = \delta_{12,2} = \cdots = \delta_{12,p} = 0$

# Simulations

- **Results (No Publication Bias)**
  - Type I Errors (DGP2a and DGP2b)