Modeling Without Conditional Independence: Gaussian Process Regression for Time-Series Cross-Sectional Analyses

David Carlson

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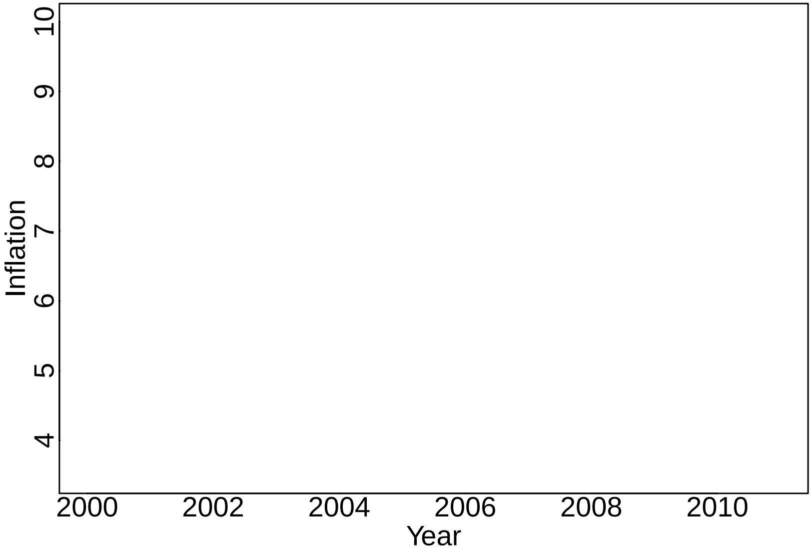
- Variables in political science violate modeling assumptions
- Observations not conditionally independent
- Example: How does inflation explain anti-Americanism?

Inflation and Anti-Americanism in Mexico



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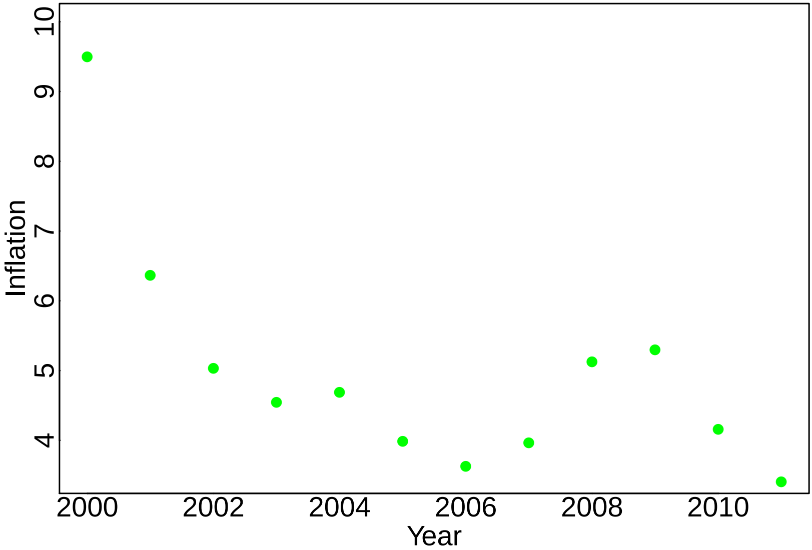

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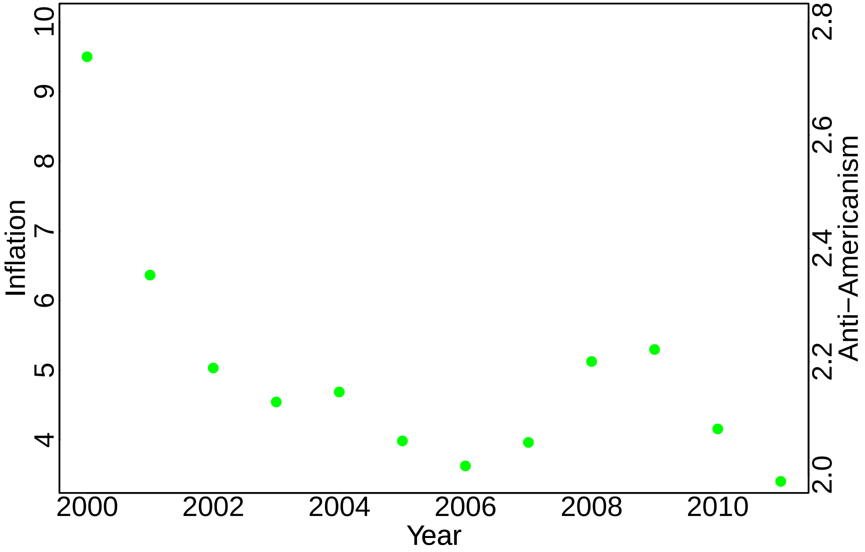

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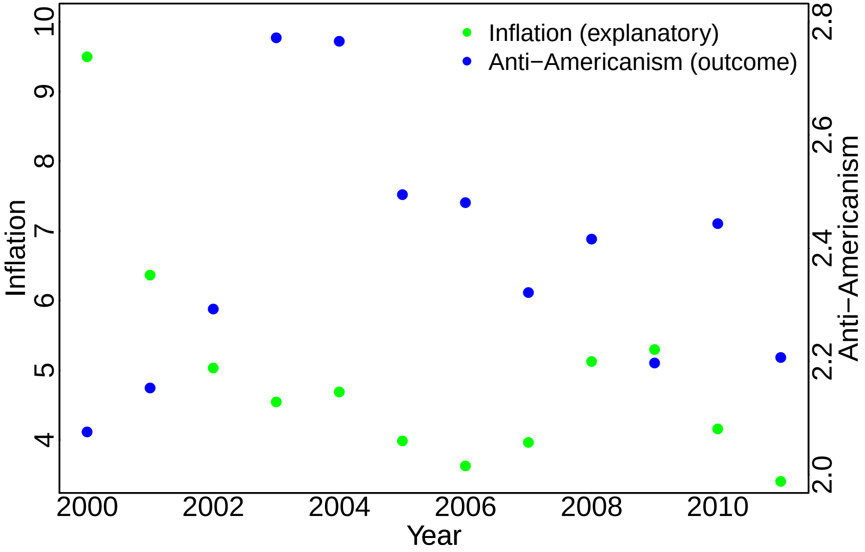

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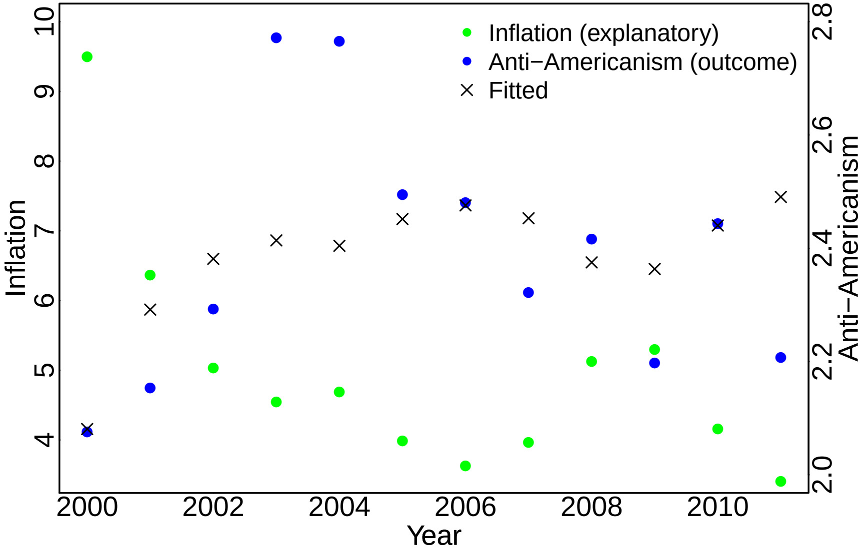

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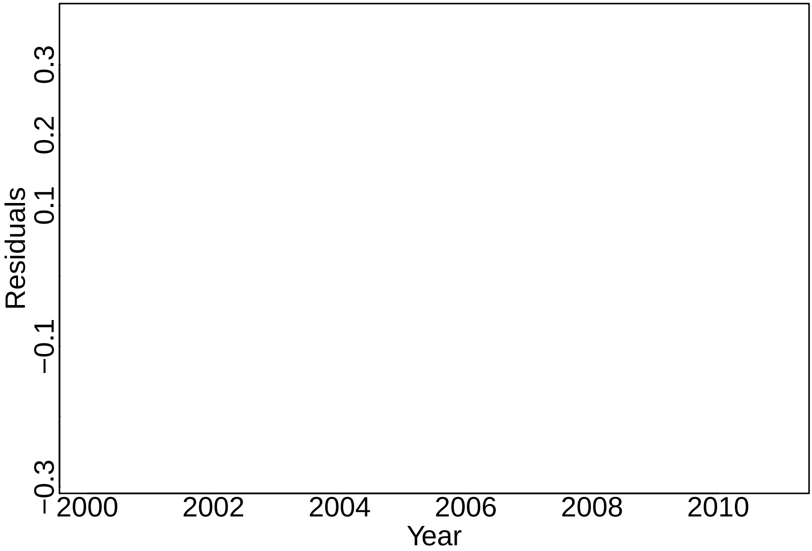

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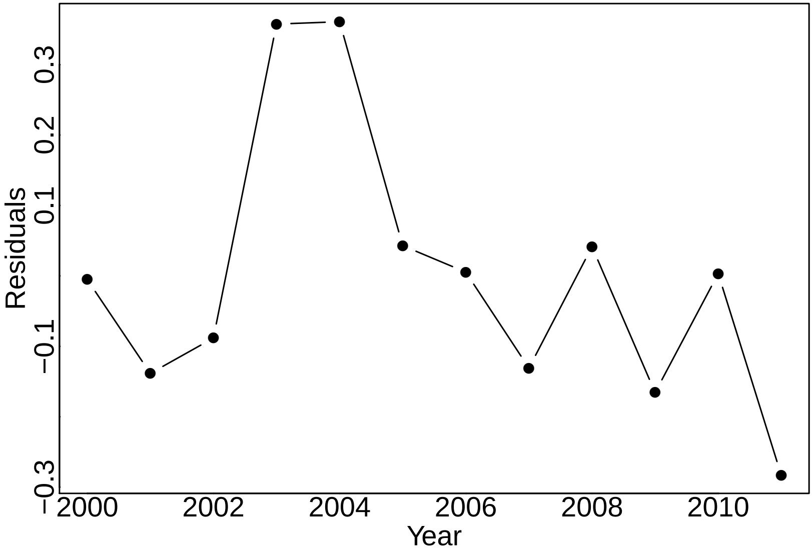

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- Machine learning algorithm models outcomes jointly as a process

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- Very flexible, still interpretable

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- Data in mean and $\boldsymbol{\Omega}$ do not have to be the same

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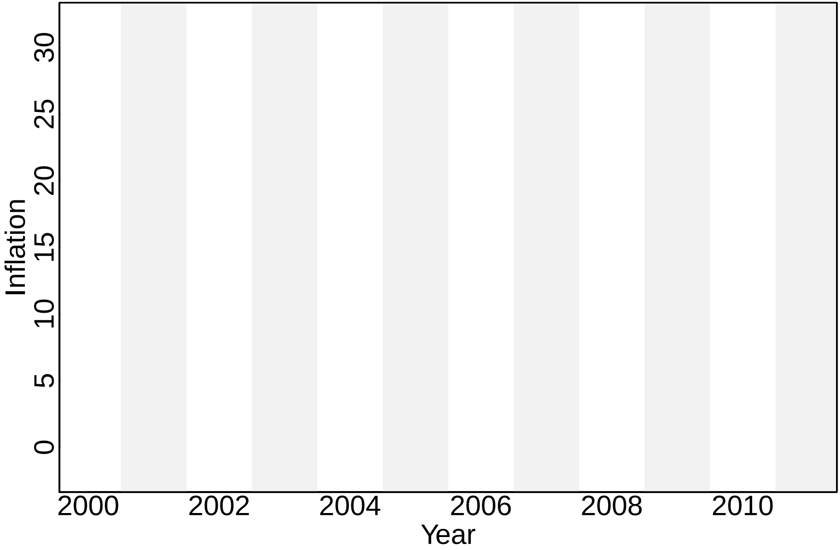

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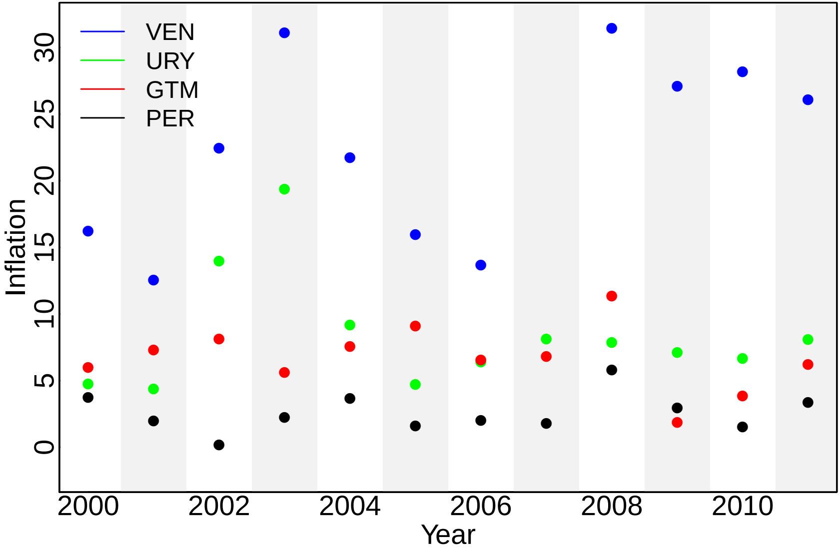

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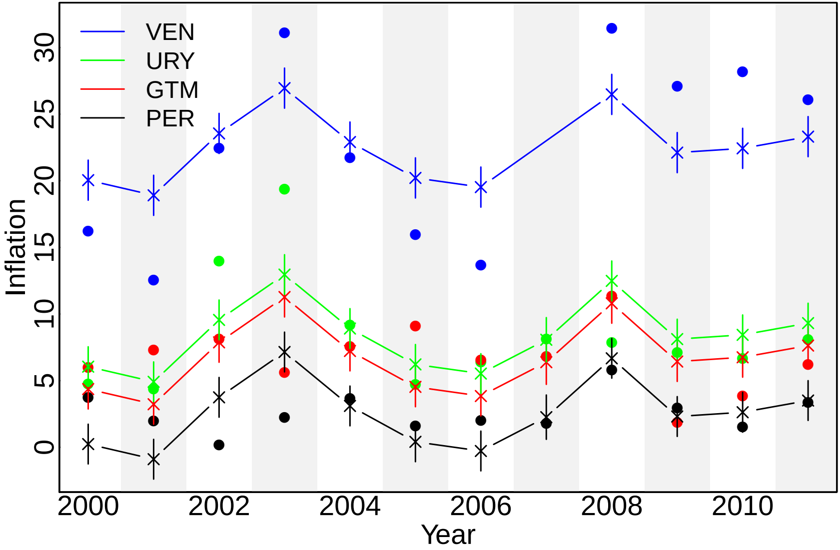

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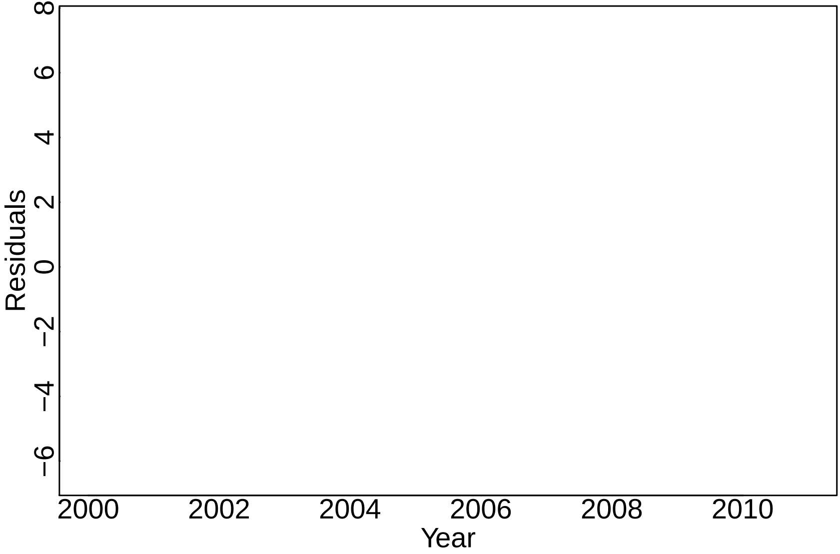

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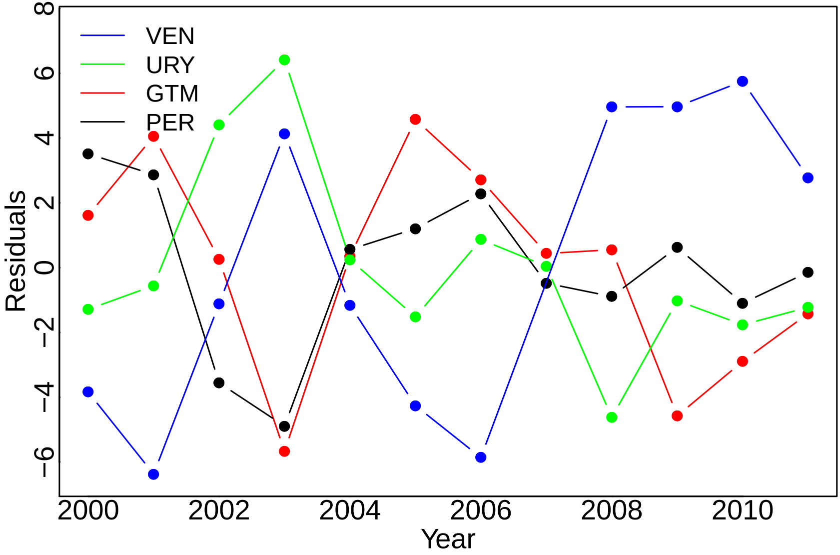

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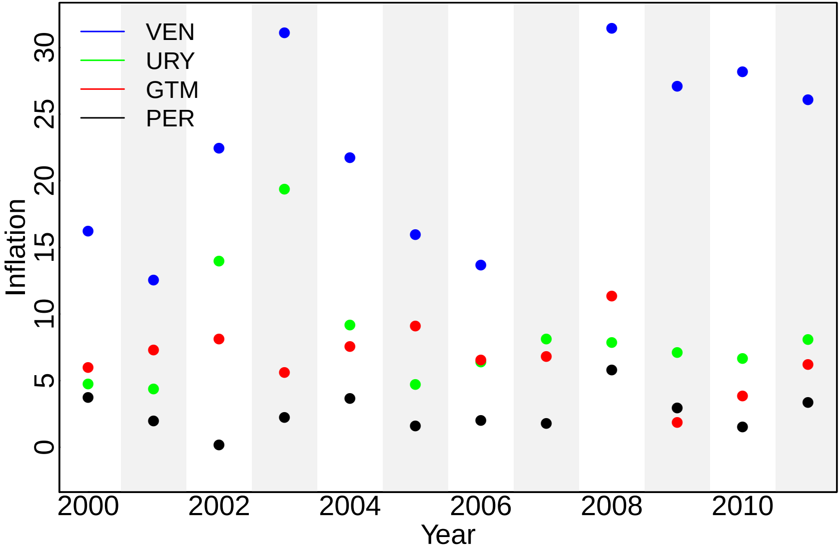

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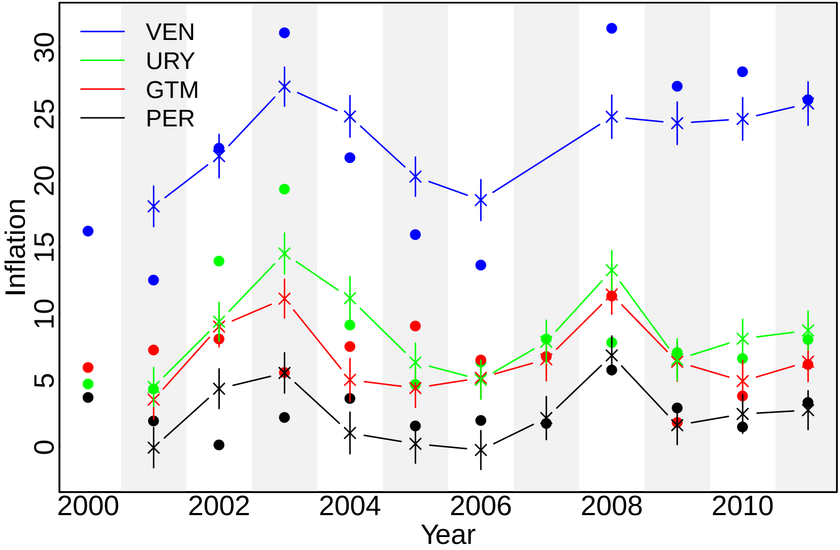

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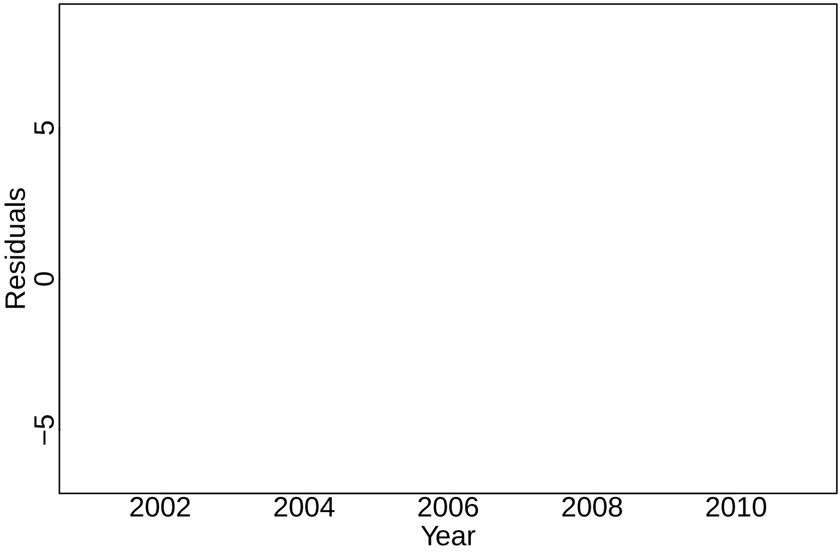

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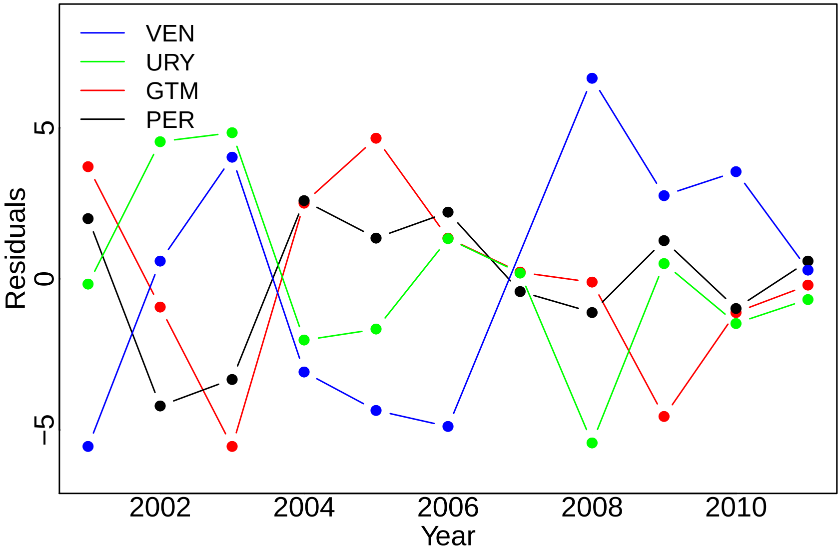

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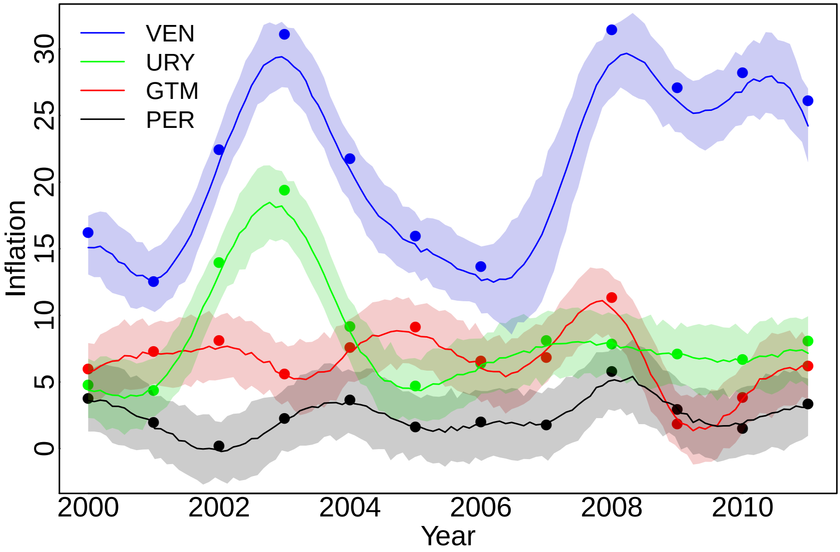
GPR allows correlated but different time trends



Overview

- Current practices
- GPR discussion
- Specification
- **Simulations**
- Application: Inflation and anti-Americanism in Latin America
- Future work

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- GPR best on coverage probability and mean squared error

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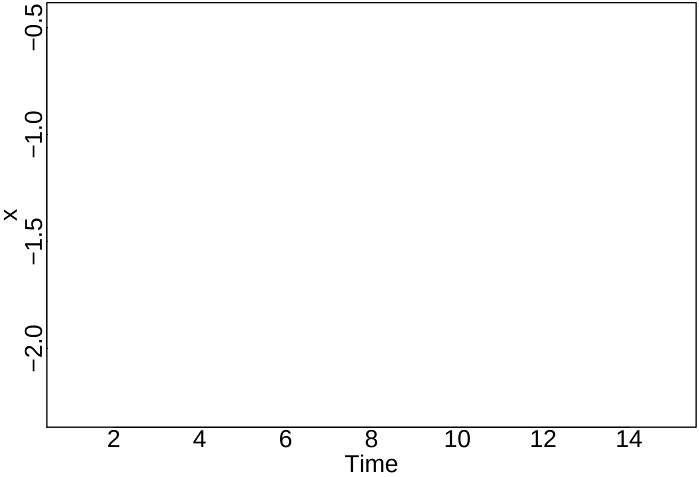

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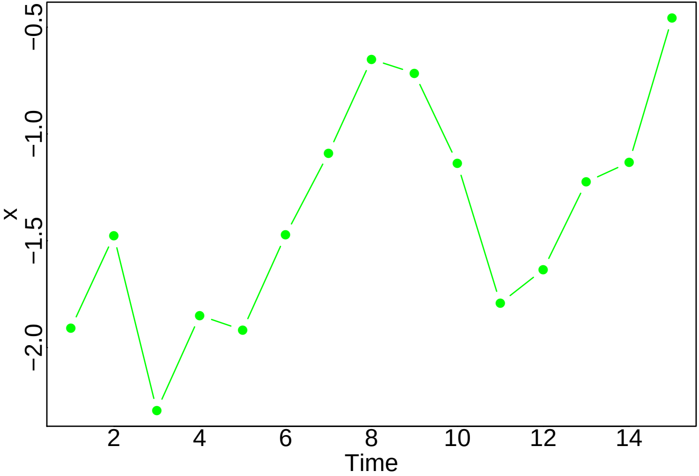

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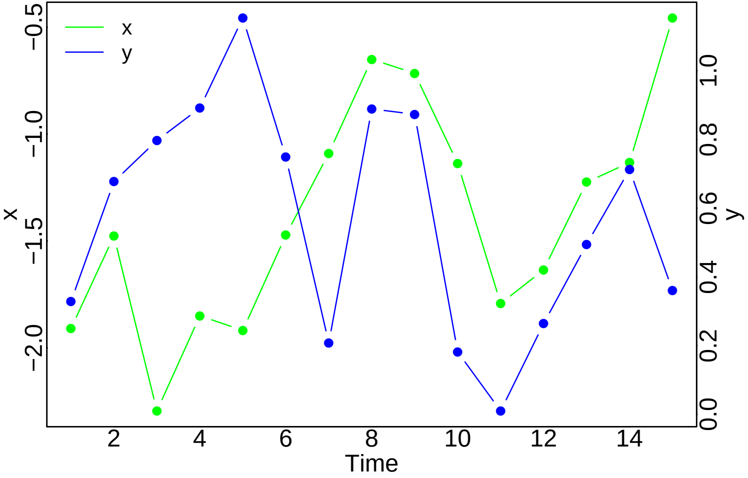
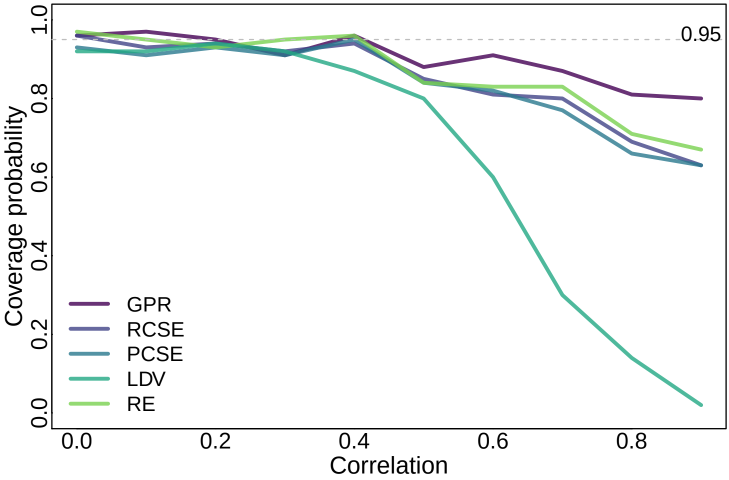


Serial Correlation Results

Coverage probability



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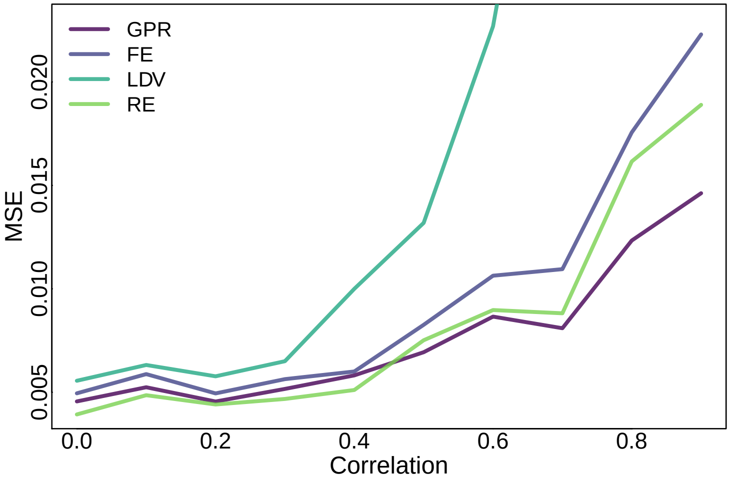

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- RE very bad at false positives

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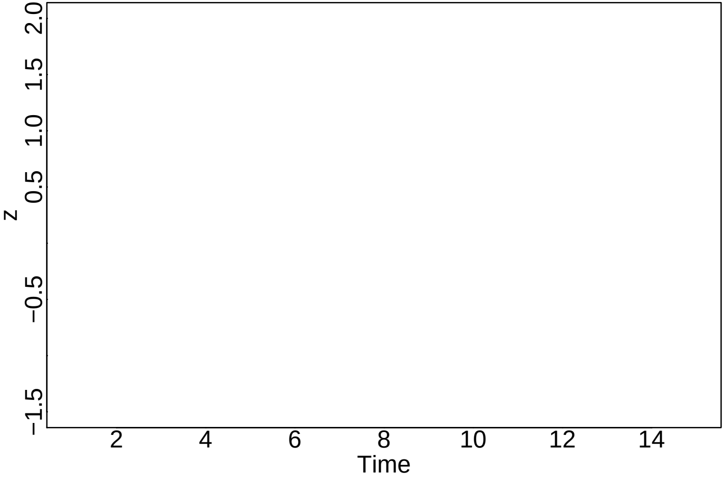
Example when $\rho = 0.9$, $\gamma_{1:3} = [-1, 0, 1]$



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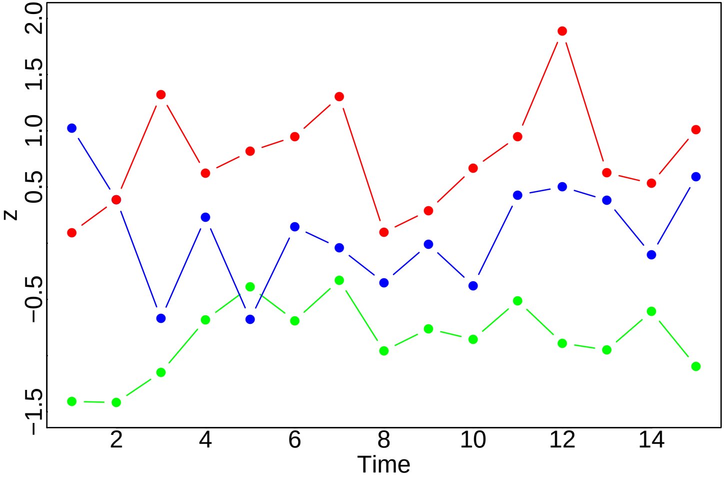
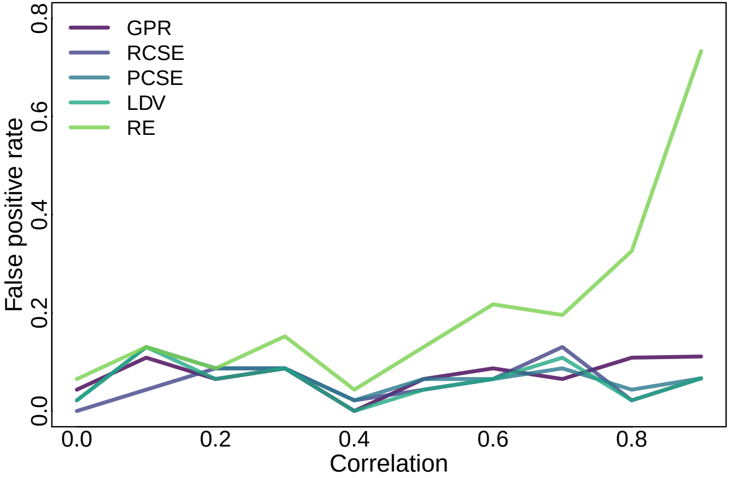


Intercept Unrelated Correlate Results

False positive rates



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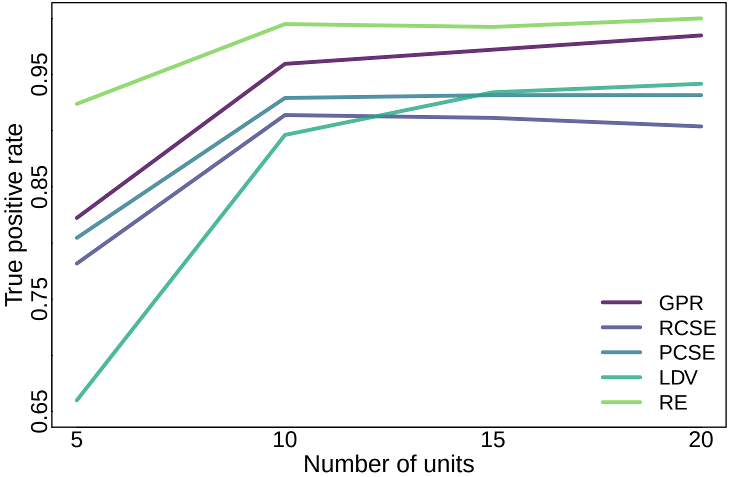
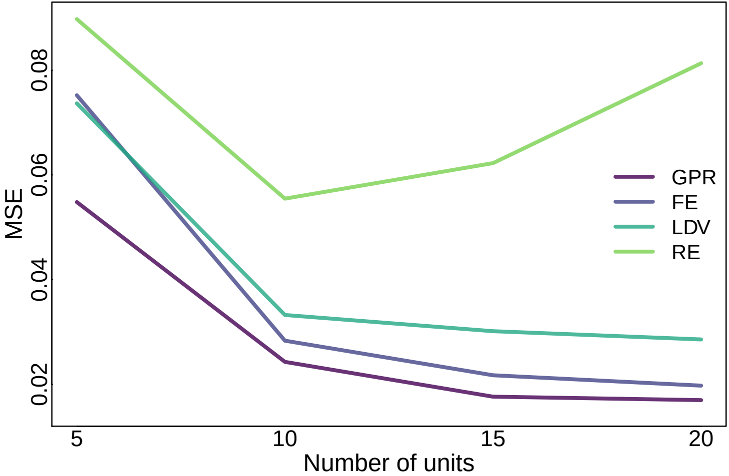
Varying N Results

True positive rates as units increase



Varying N Results

Mean squared of estimates as units increase



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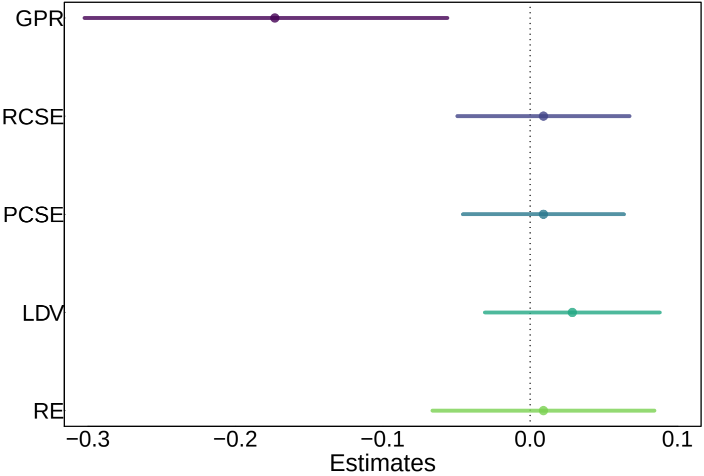
Effect of inflation on anti-Americanism



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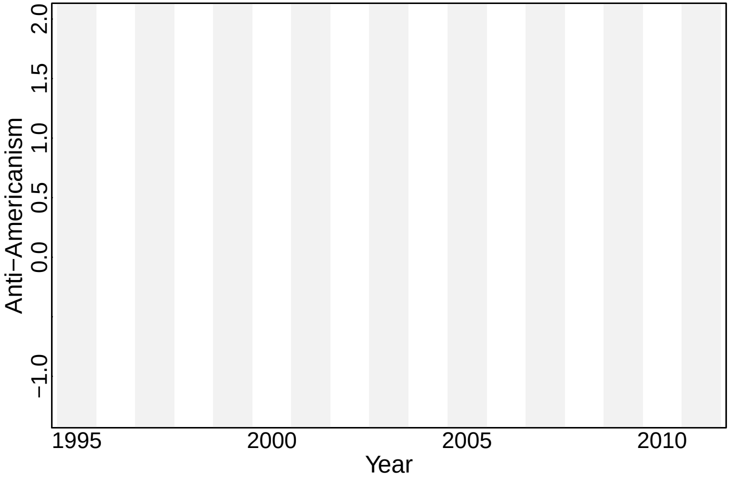
Model fit in Mexico



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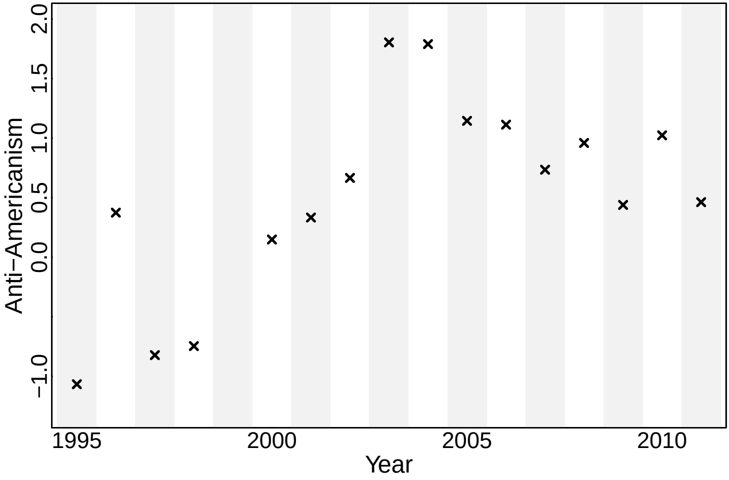

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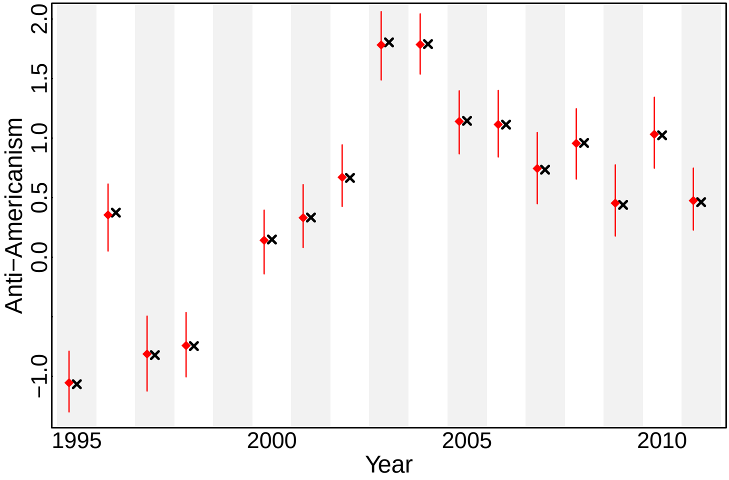

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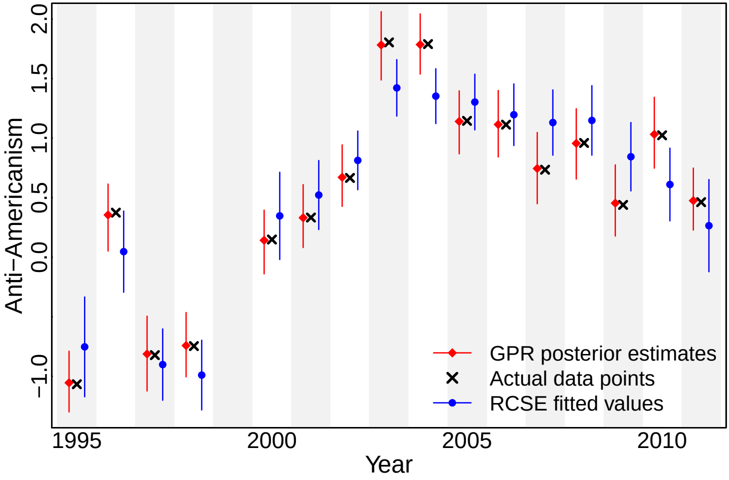

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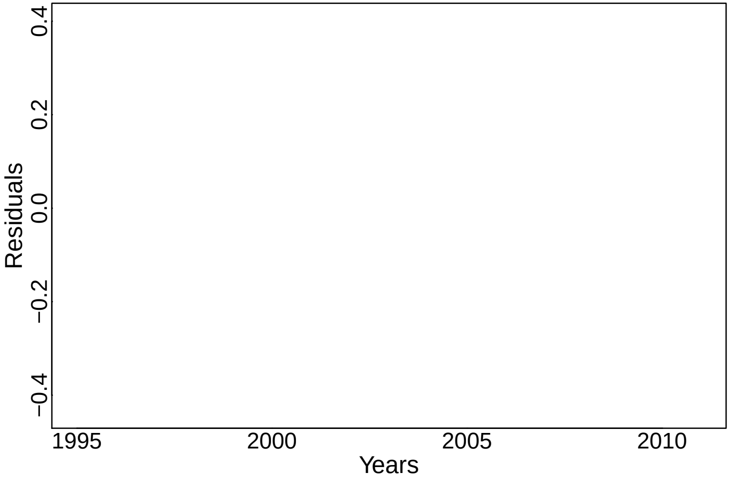

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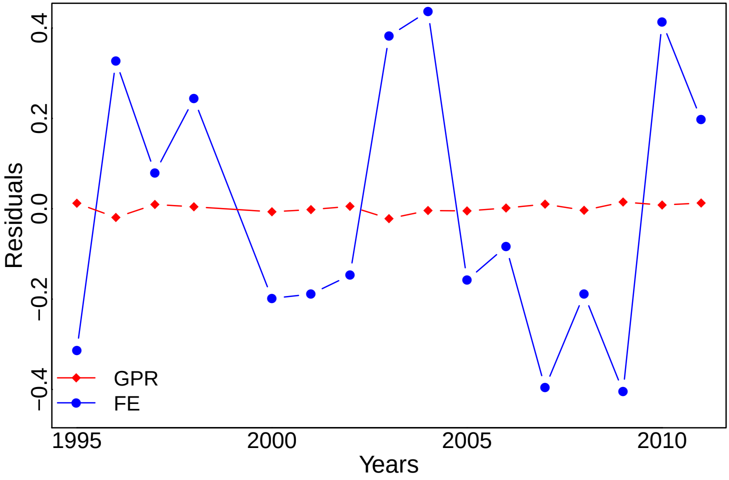

Concluding Remarks

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- Code available: `https://github.com/carlson9/GPRPanel`

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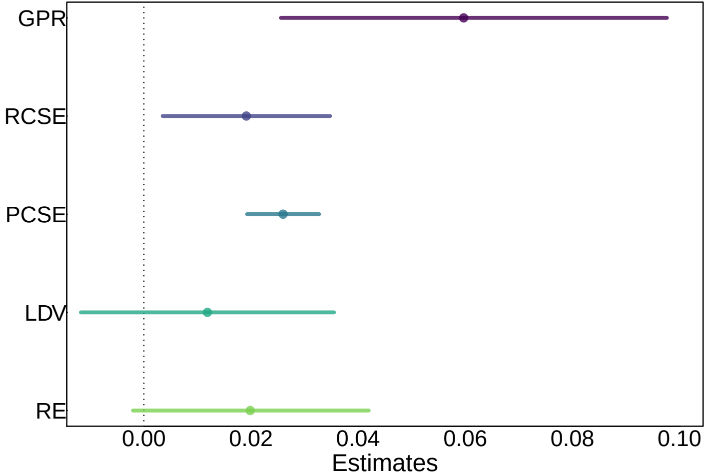
Replication: Results

Effect of rocket range on right vote



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- Including inflation in example significantly outperforms null with both measures

Priors

$$\mathbf{y} \sim \mathcal{MVN}(\tilde{\mathbf{X}}\beta, \sigma^2\mathbf{\Omega}),$$

$$\mathbf{\Omega}^*(\mathbf{x}_j^*, \mathbf{x}_i^* | \zeta) = \exp\left\{ -\sum_{p=1}^{m} \frac{|x_{pj}^* - x_{pi}^*|^2}{\zeta_p} \right\},$$

$$\mathbf{\Omega}(\mathbf{x}_j^*, \mathbf{x}_i^*) = \mathbf{\Omega}^*(\mathbf{x}_j^*, \mathbf{x}_i^*) + \delta g_{j,i},$$

$$g_{j,i} = \begin{cases} 1 & \text{if } j = i, \\ 0 & \text{otherwise.} \end{cases}$$

$$\delta \sim Exp(1)$$

$$\zeta_p = \frac{\zeta_{p1} + \zeta_{p2}}{2}$$

$$\zeta_{p1} \sim G(1, 20)$$

$$\zeta_{p2} \sim G(10, 10)$$

$$\sigma^2 \sim IG(1, 1)$$

$$\beta \sim \mathcal{N}(0, 3)$$

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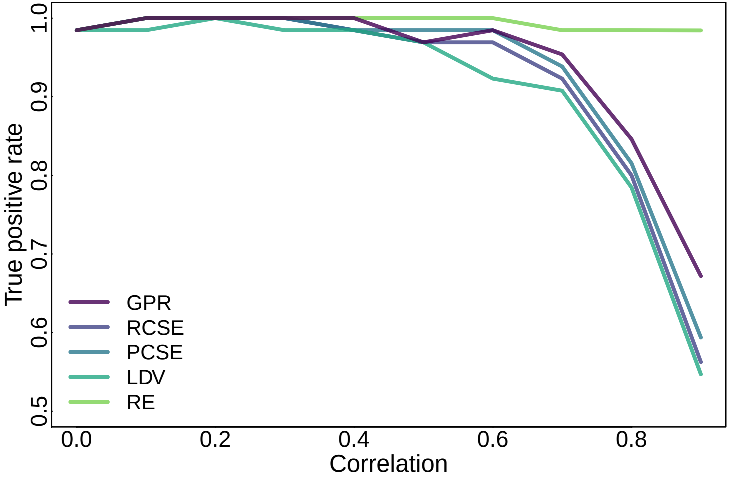
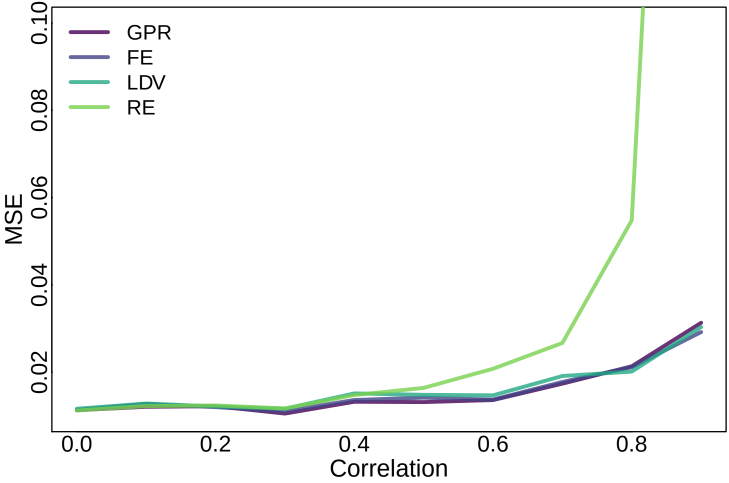
True positive rates



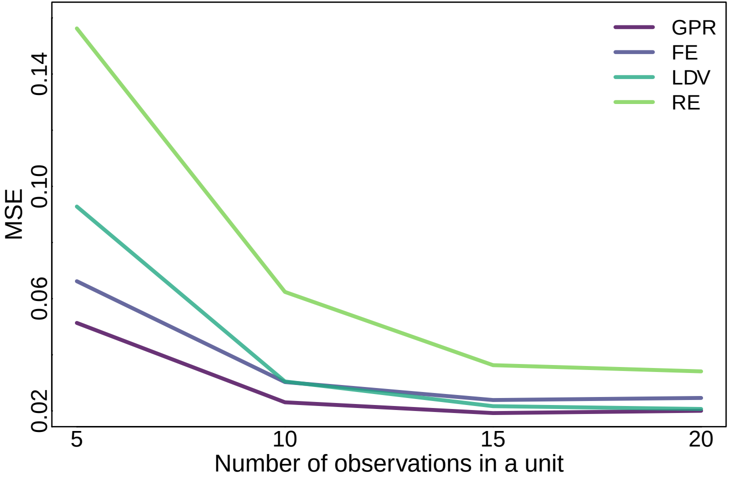
Intercept Correlation Results

Mean squared error of estimates



Varying N Results

Mean squared of estimates as observations increase



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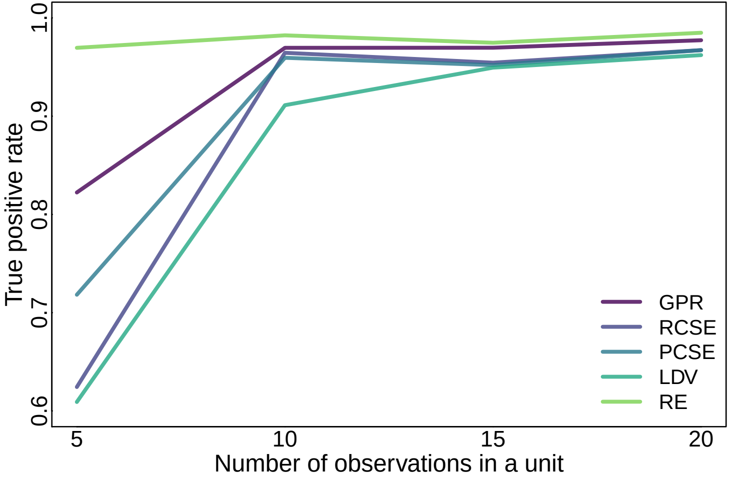
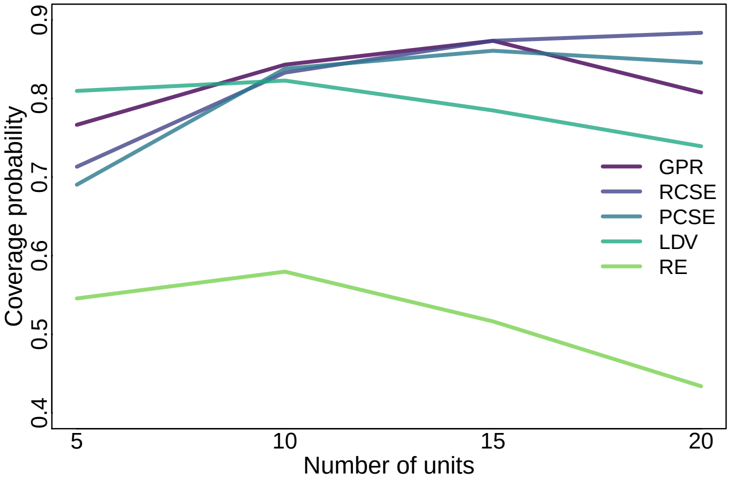


Varying N Results

Coverage probabilities as units increase



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