`itsCausal`: Interrupted Time Series in real world data

The User's Guide

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The “no control group” setting

- **Problem:** In many real-world scenarios, finding a credible control group to evaluate a policy is not feasible.
- **Example:** Health care policies often affect all providers simultaneously, like changes in physician compensation or changes in guidelines.



- **Solution:** interrupted time series (ITS)
- **Challenge:** Standard interrupted time series (ITS) may produce biased estimates because of poor prediction, poor forecasting, and simplification assumptions with panel data.

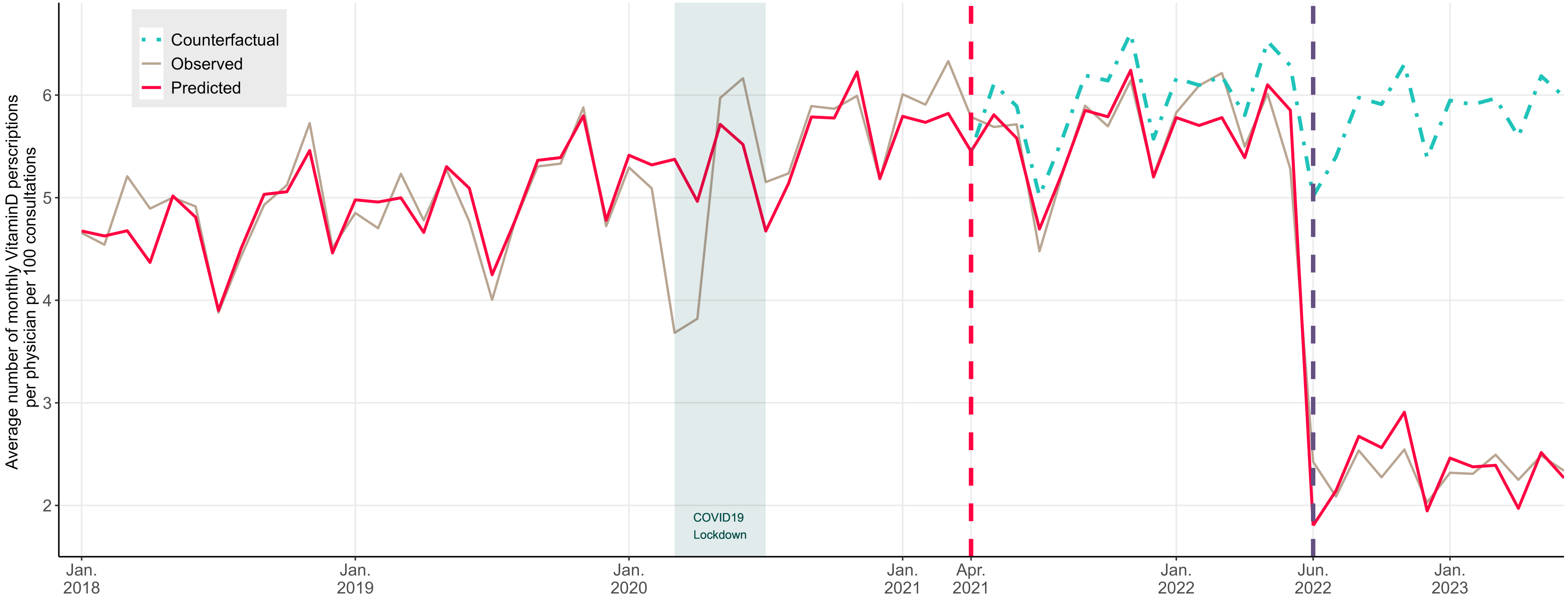
The use of ITS in the evaluation of health system interventions has increased considerably

"The risk of bias for ITS studies was high for 53.3% and very high for 19.2%". (Hategeka et al. (2020), N = 120, 1990-2020)

- The intervention was dependent of other changes.
- Time series techniques were not propertly used.
- Trends and time-dependent covariates were not correctly specified.
- ...

`itsCausal` was born from the practical need for effective healthcare monitoring

- Example: **two population-level interventions against low-value care (Vit. D testing) in Switzerland**.



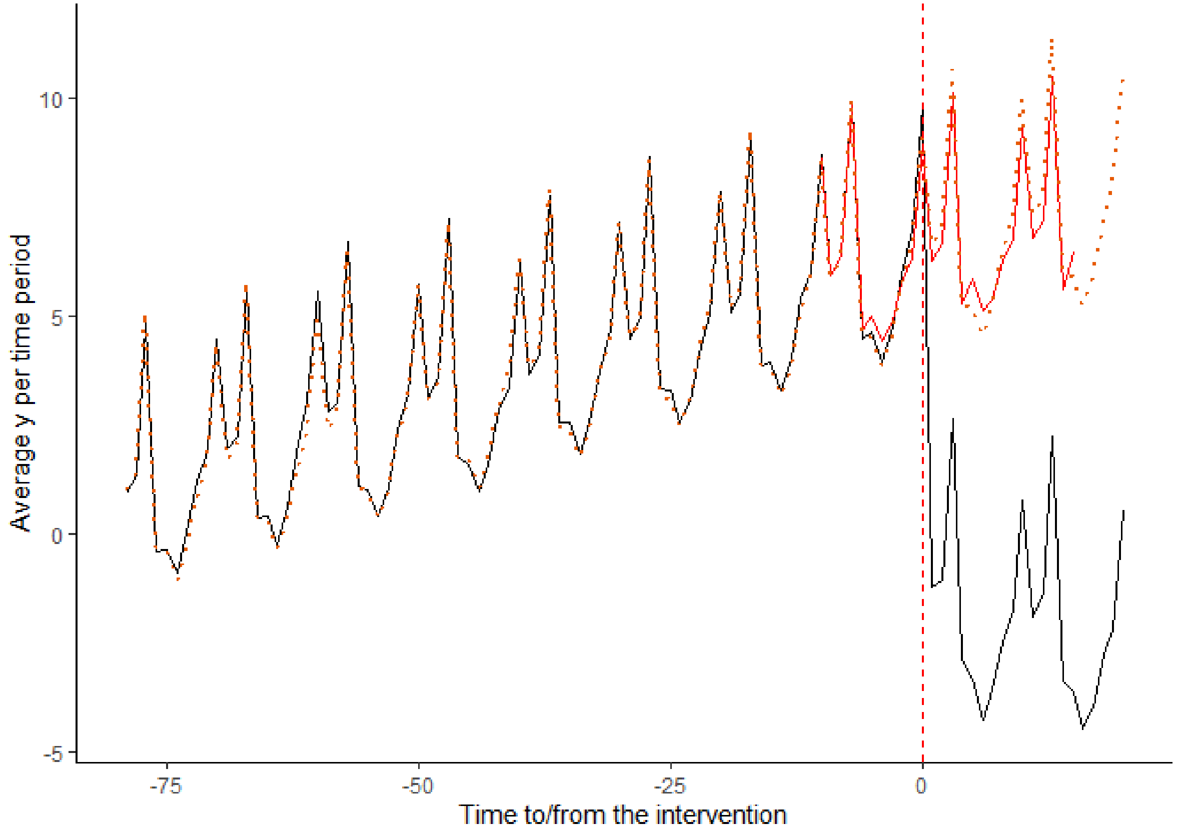
With "`itsCausal`", we aim to deliver a set of recommendations for practitioners

- **Key Idea: create an R-package "`itsCausal`", which**
  - Provides guidance on the application of Interrupted Time Series
  - Enhances the traditional model with a machine learning-based method to address the "no control group" scenario and improve counterfactual forecasting.
  - Tailors the method to panel data where the number of units exceeds the number of time periods.

Development of a user's guide for `itsCausal`

R Package

- **ML learners** (random forest, gradient boosting, neural networks, catboost, lstm) with hyperparameters tuning.
- **Rolling-window approach** for post-intervention forecasts with time-variant and invariant predictors.
- Effect computed as the difference between the observed and the forecasted values.
- **Simulations** of different data-generating processes show good performance.

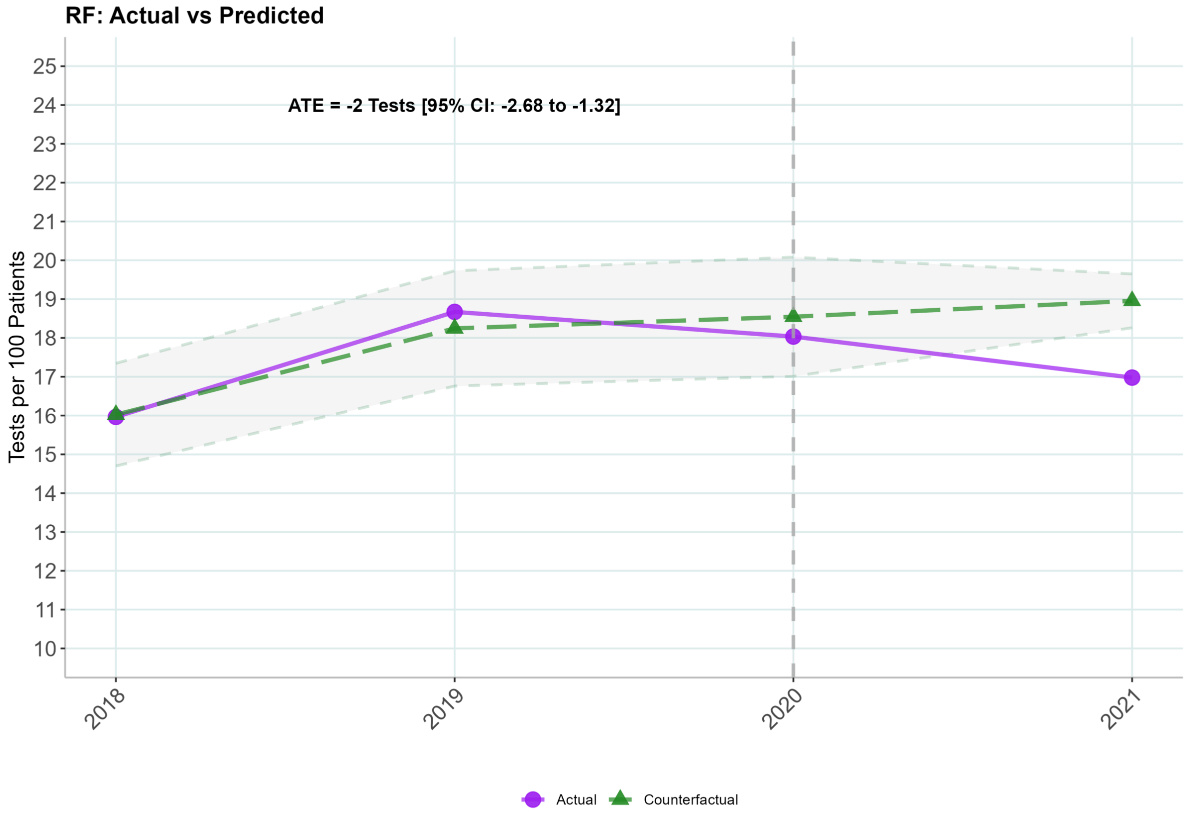


Simulation of an ARMA Process

Development of a user's guide for `itsCausal`

Benchmarking

- We benchmark our method with **experimental evidence**
  - Randomized controlled trial: Primary Care Physicians in Switzerland were sent an information letter combining professional norms and peer comparison feedback about vitamin D testing (Müller, Van Gestel, and Gerfin (2023))
  - ATE from `itsCausal` is within the 95% CI of the ATE from the RCT



Development of a user's guide for `itsCausal`

User's guide

- Offer researchers and industry analysts recommendations for the implementation of interrupted time series.
- Tests for the assumption of causal effects, especially for the "no-confounding" assumption.
- Provide guidance on how to implement ML learners.

Conclusion

- `itsCausal`**:** A powerful tool for estimating causal effects without a control group.
- **Benchmarking** of the method with published research and experimental evidence.
- **User's guide** for sound implementation of ITS in real-world evidence, public health, health services research, and health economics.

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`itsCausal` on GitHub

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Identifying assumptions for the causal effect in its

The following assumptions must hold (see Cerqua, Letta, and Menchetti (2024)):

1. There are no hidden forms of treatment leading to different potential outcomes (**weak SUTVA**).
2. **Additivity**
3. **No anticipation and no confounding** - Absence of anticipatory effects of the intervention on the covariates and the potential outcomes - Future covariates do not affect current potential outcomes - Covariates remain unaffected by the policy in the post-intervention period (post-treatment exogeneity of the covariates)
4. **Dynamic potential outcomes model**: the potential outcomes absent the policy (the "counterfactual") can be predicted using lagged values of the outcome and of the covariates.
5. **Post-intervention non-linear multi-step-ahead model**: the counterfactual can be predicted for multiple periods ahead using lagged values of the outcomes until the intervention, conditional expectations of the outcome after the intervention, and the covariates.

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