Spatial Models for Targeting and Evaluating Public Health Interventions

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Prevention and public health

What conditions are needed in society to create good and equal health for the entire population? Which interventions have the best effect and how should they be designed and implemented? Forte is conducting a initiative on research on prevention and public health.

In 2020, Forte was commissioned by the Swedish government to initiate a long-term investment in research on prevention and public health. The initiative is linked to the overall direction of public health policy adopted by the Swedish parliament. The political goal is to create societal conditions for good and equal health in the entire population, and to close the health gaps within a generation. The initiative was extended in 2025 and will last until 2028.

Goals and direction

Forte's vision with the initiative on prevention and public health is to increase knowledge about

- how health equity can be promoted
- how ill health can be prevented
- how effective interventions to improve public health can be designed and implemented
- how effective interventions can be designed and implemented to improve public health.

Program grants:

- 6-years
- 11 programs funded
- 2024-2029
- High flexibility

Our program:

- Methods-focused
- Intervention targeting
- Evaluation
- ”Precision public health”
- Area-level

Worksteams

Targeting

- Identify areas in need of intervention
- Develop epidemiologic measures
- Register data
- Surveillance
- Disease mapping
- Local decision-making

Evaluation

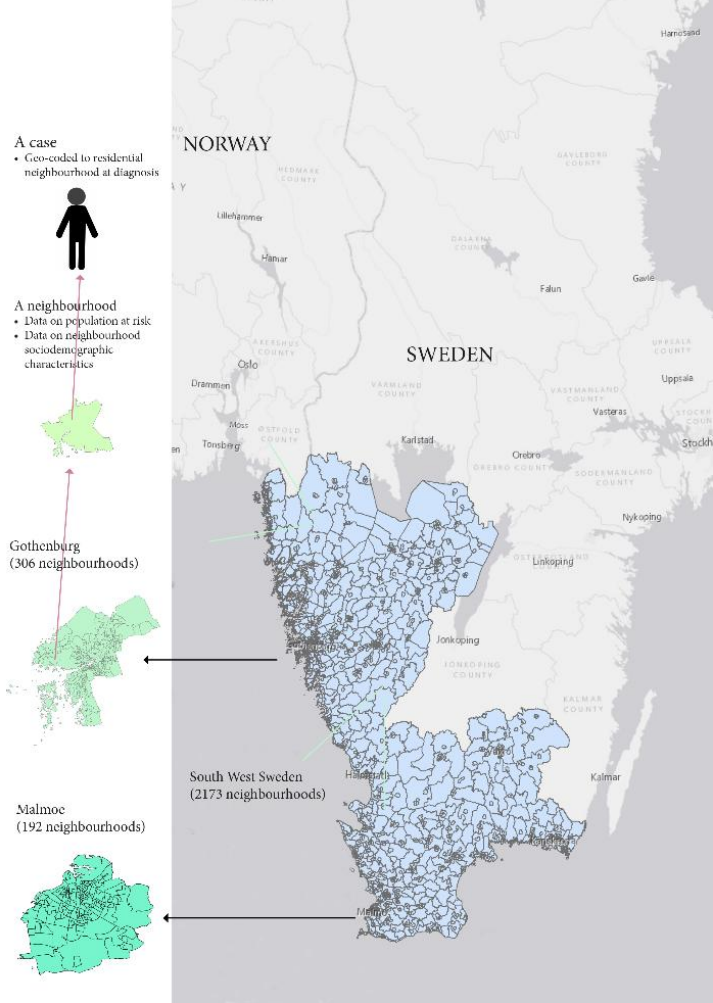
- Estimate intervention effects
- Small area interventions
- Local effects
- Effects that vary in space and time
- Causal methods + disease mapping
- Counterfactual imputation

Small area data for targeting

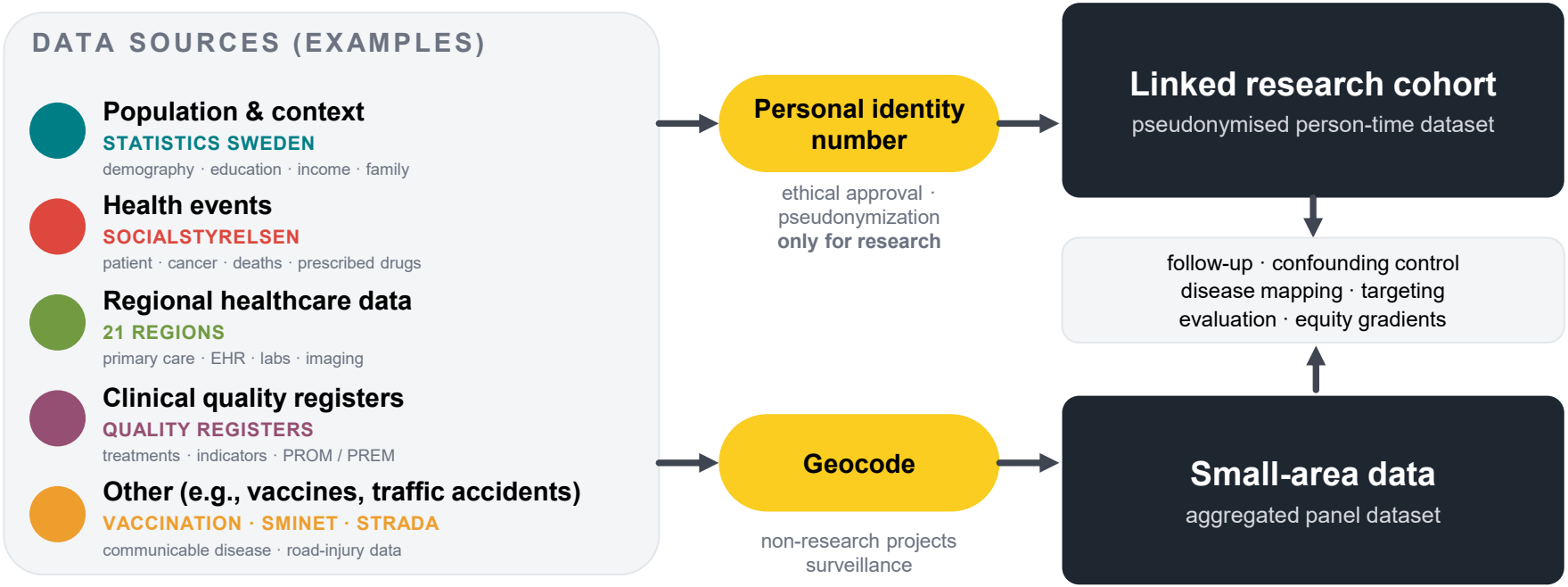
- National register infrastructure
  - Individual linkage
  - But only for research purposes

- Demographic statistical areas (Deso)
  - Geocode addresses
  - Statistics Sweden can handle linkage

- Work with register holders to add Deso
  - Enables disease mapping
  - Linkage to area-level demographics/SES



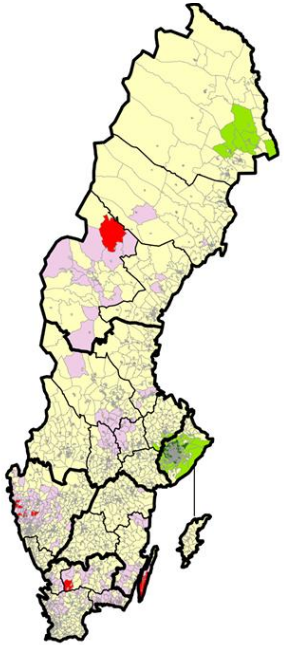
Swedish register data infrastructure



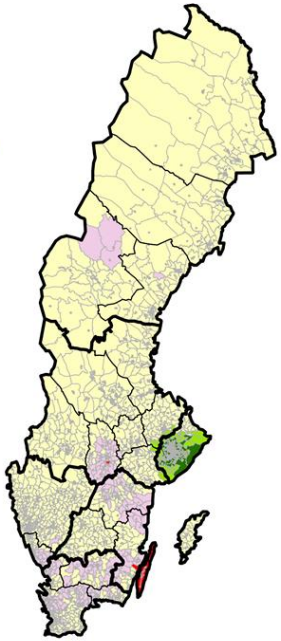
Stage-specific cancer incidence

Colorectal cancer

Any stage

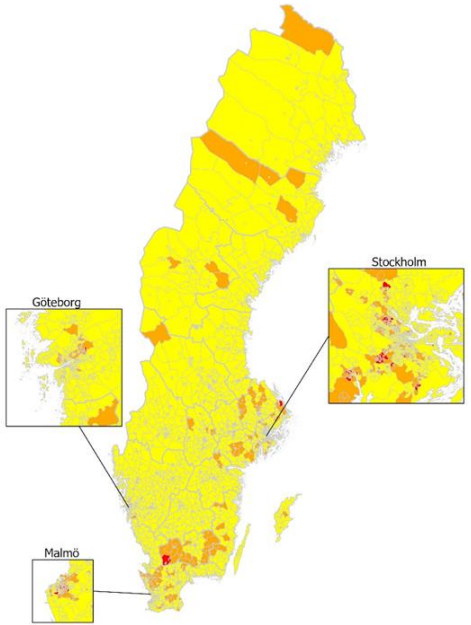


Stage II-IV



Screening non-attendance

10-year, cervical cancer



Red: worse than national average
Green: better than national average

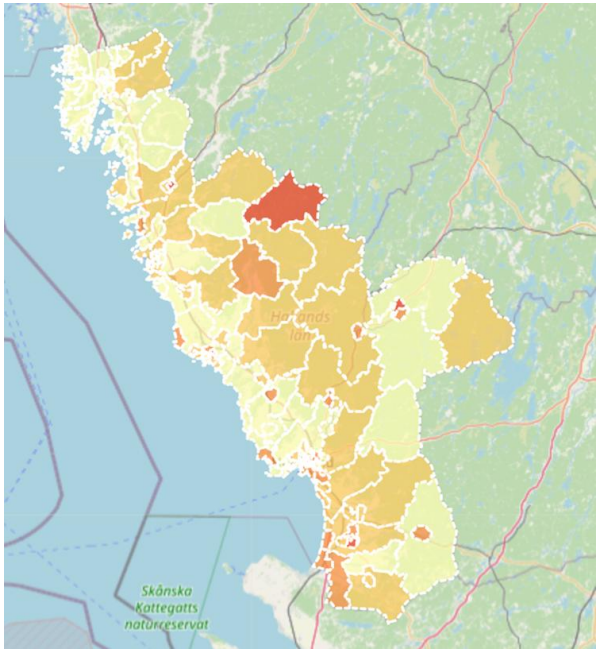
Targeted area-level dental care reimbursement in Halland

- Dental care reimbursement model
  - Children and young adults aged 3–23 years
  - Implemented in Halland from 2023

- 50% of the annual reimbursement per individual is adjusted based on area-level need

- Adjustment is based on estimated caries prevalence by Deso

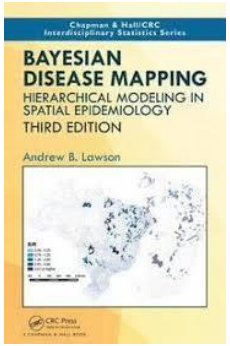
Caries prevalence in children
(*Region Halland*)

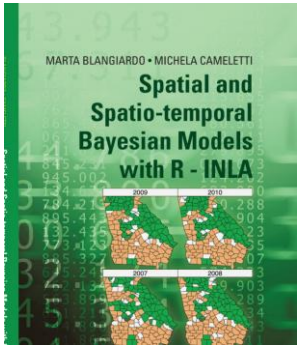


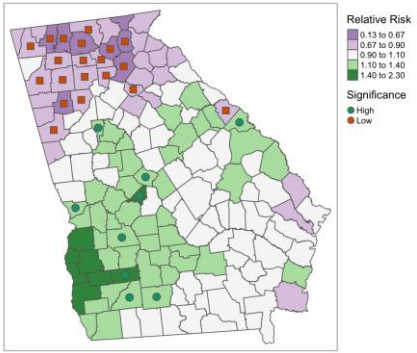
Challenges

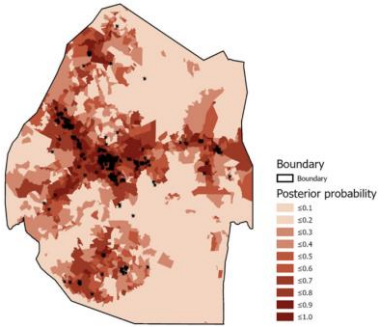
- Small area data is typically noisy
  - Obscures true patterns
  - Small populations, rare diseaes
  - Need to rely on spatial smoothing
  - Borrow information from nearby areas

- What epidemiologic measures are useful?
  - Depends on problem/intervention(s)
  - Decision-relevant
  - Available









Combining measures

- Jointly analyze stage-specific cancer incidence

- Prostate cancer incidence, treating:
  - *Late-stage* as proxy for disease burden
  - *Late – early* as proxy for diagnostic activity
  - Highest need when high values on both

- Idea can easily be extended to syndemics
  - Two or more diseases cluster

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A Bayesian bivariate spatial modeling framework for stage-specific cancer incidence and targeting of screening efforts

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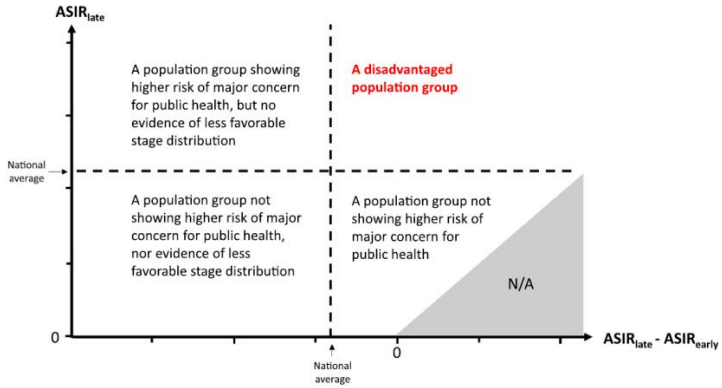
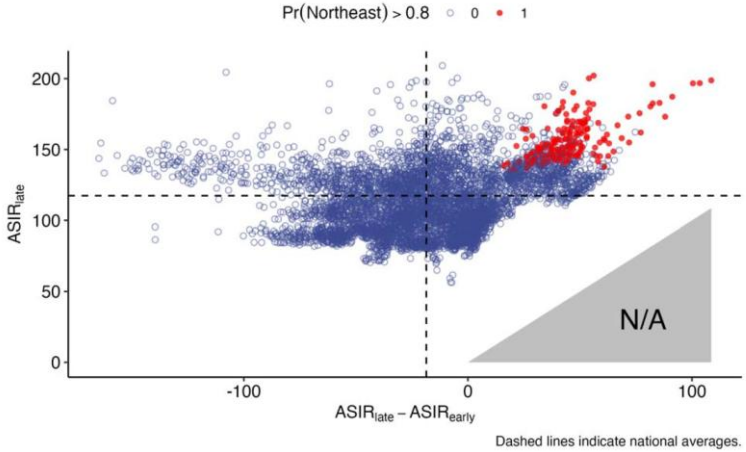
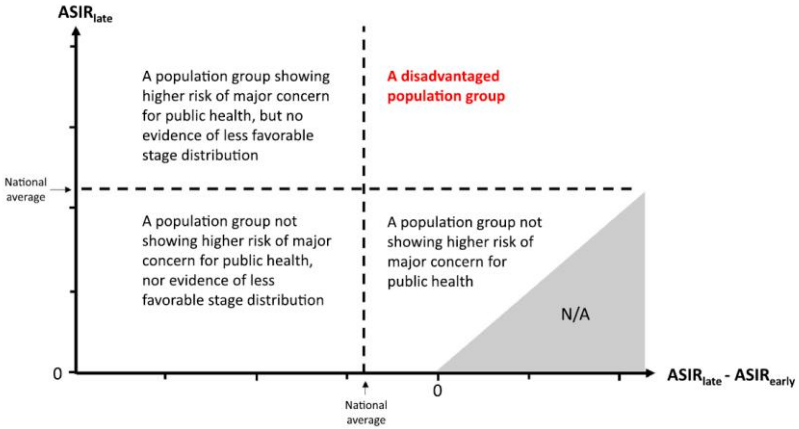
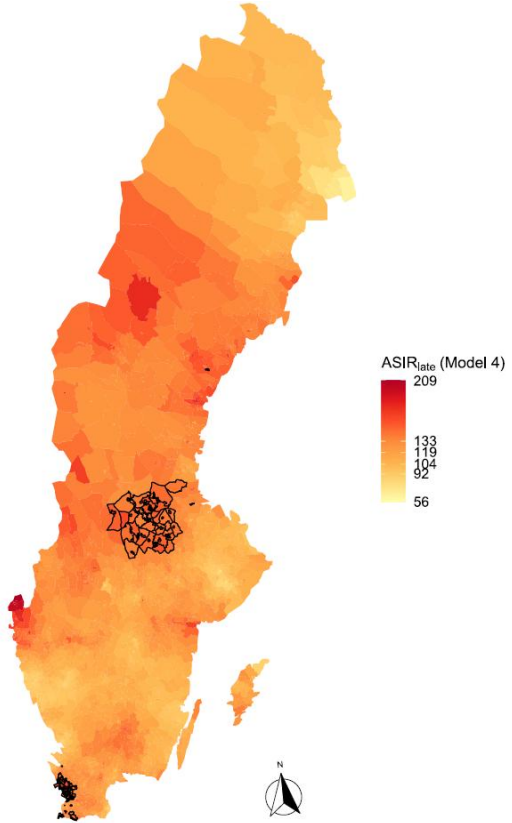




Dashed lines indicate national averages.



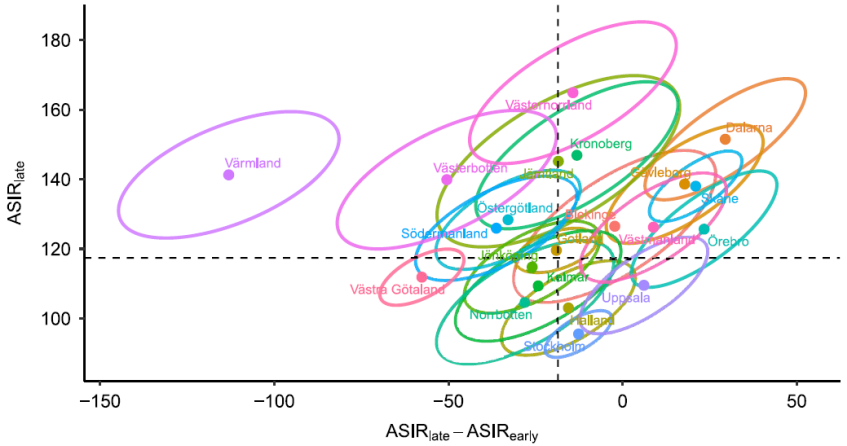


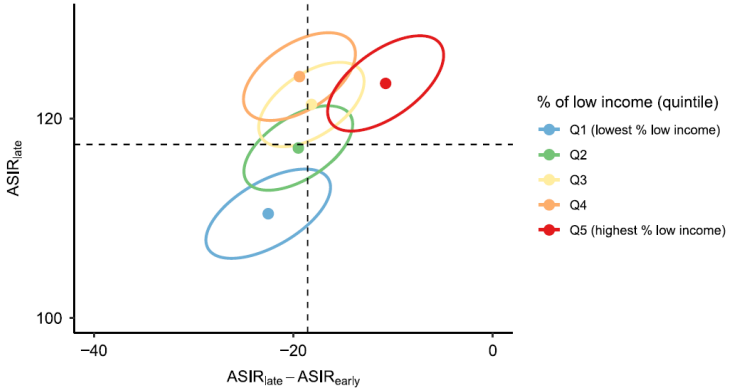
AI Overview

Region Värmland was the pioneer of organized prostate cancer testing (OPT) in Sweden, operating the program since 2015. It continuously invites men aged 50–75 to participate. The program integrates regular PSA sampling with the Stockholm3 test to accurately detect aggressive cancers while reducing unnecessary biopsies. www.a3p.com +4

How the Screening Works in Värmland

- **Age Group:** Men between the ages of 50 and 75 are regularly contacted by letter with an offer to test. 1177 +1



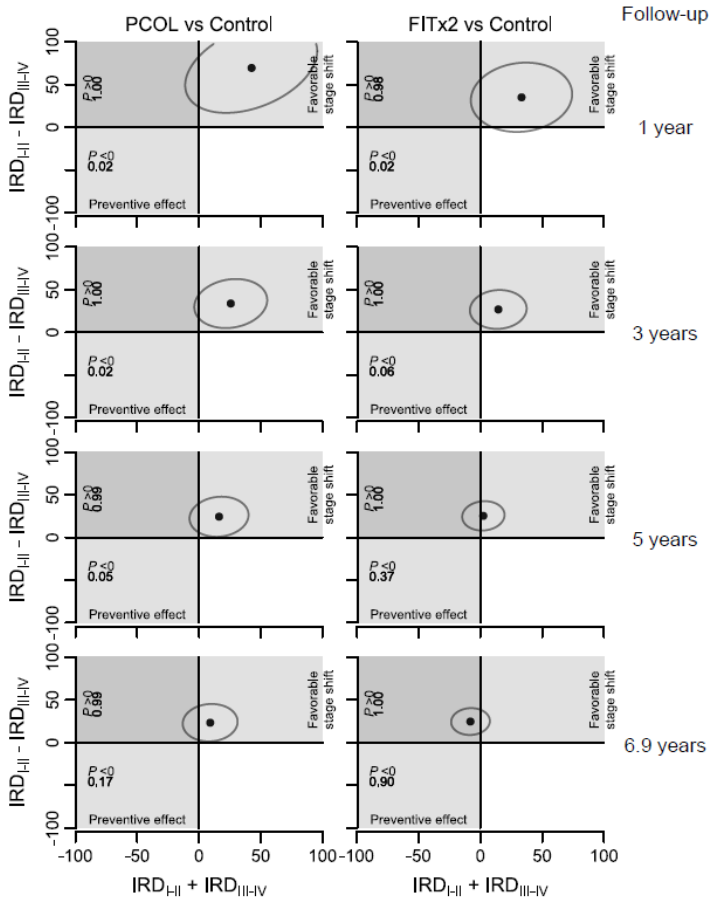


Clear socioeconomic inequality aspect

Experimental follow-up

- Colorectal cancer screening experiment
  - Randomized trial
  - Register-based follow-up
  - *n* ~ 270,000
  - Direct colonoscopy, FIT, vs. unaware controls

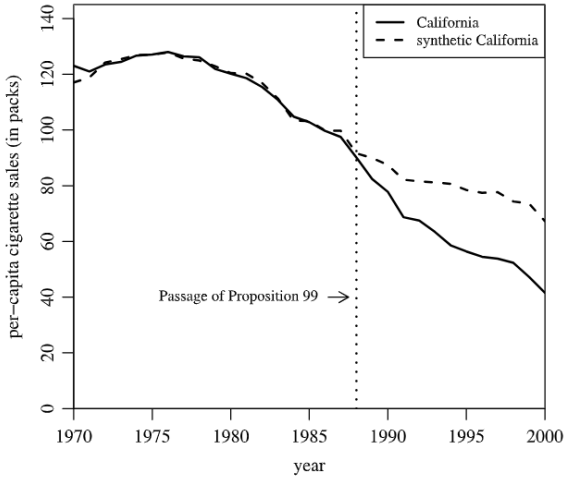
- Stage shift (y-axis), total incidence (x-axis)
  - Short-term: expect increased total
  - Long-term: preventive effect?



Westerberg et al. Early indicators of inequality from initiation of colorectal cancer screening: the SCREESCO randomized trial. *Unpublished manuscript.*

Quasi-experimental methods

- Many (most?) interventions are not randomized
- Quasi-experimental methods for policy evaluation
  - Difference-in-differences
  - Synthetic controls
  - Matrix completion
- Not developed for small area analyses



Policy evaluation with disease mappnig models

- Can we combine modern causal policy evaluation methods with disease mapping techniques?

- Potential benefits:
  - Robust and credible causal inference (or, at least, clear assumptions)
  - Borrow strength → more precise estimates
  - Bayesian inference for honest uncertainty quantification

- Some challenges:
  - Ensuring causal assumptions/identification are properly transferred
  - Computational efficiency
  - Ease of use

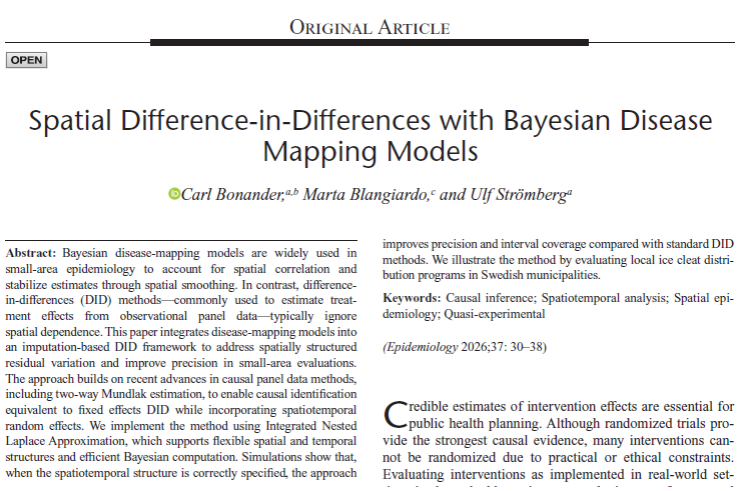
Core philosophy

- After an intervention is implemented, we can observe what *happened*
- Key challenge is estimating what would have happened without the intervention
- This is a missing data problem, we can use:
  - Untreated areas (controls)
  - Pre-intervention time periods

Difference-in-differences

- Compare before-after, treatment vs. control group
  - Valid assuming parallell trends
  - Typically using two-way fixed effects

- How can we incorporate spatial smoothing?
  - Disease mapping models use random effects
  - Well-known that random effects are insufficient for causal robustness



ORIGINAL ARTICLE

OPEN

Spatial Difference-in-Differences with Bayesian Disease Mapping Models

Carl Bonander,[a,b] Marta Blangiardo,[c] and Ulf Strömberg[a]

Abstract: Bayesian disease-mapping models are widely used in small-area epidemiology to account for spatial correlation and stabilize estimates through spatial smoothing. In contrast, difference-in-differences (DID) methods—commonly used to estimate treatment effects from observational panel data—typically ignore spatial dependence. This paper integrates disease-mapping models into an imputation-based DID framework to address spatially structured residual variation and improve precision in small-area evaluations. The approach builds on recent advances in causal panel data methods, including two-way Mundlak estimation, to enable causal identification equivalent to fixed effects DID while incorporating spatiotemporal random effects. We implement the method using Integrated Nested Laplace Approximation, which supports flexible spatial and temporal structures and efficient Bayesian computation. Simulations show that, when the spatiotemporal structure is correctly specified, the approach improves precision and interval coverage compared with standard DID methods. We illustrate the method by evaluating local ice cleat distribution programs in Swedish municipalities.

Keywords: Causal inference; Spatiotemporal analysis; Spatial epidemiology; Quasi-experimental

(*Epidemiology* 2026;37: 30–38)

Credible estimates of intervention effects are essential for public health planning. Although randomized trials provide the strongest causal evidence, many interventions cannot be randomized due to practical or ethical constraints. Evaluating interventions as implemented in real-world set-

Difference-in-differences

- We combine:
  - Correlated random effects (”two-way Mundlak”; Woolridge, 2025)
  - Imputation-based DID (Borusyak et al., 2024)

- What this buys:
  - Same causal identification as regular DID
  - But can use spatial/temporal random effects
  - Simulation evidence → improved precision (noisy data/with local dependence)
  - Staggered adoption designs/flexible local heterogeneity

TABLE. Estimated Average Effects of Ice Cleat Distribution Programs in 73 Swedish Municipalities on Ice-related Fall Injury Rates (per 1,000 person-winters) Among Older Adults, Using Unstructured Frequentist and Bayesian Spatial Imputation-Difference-in-Differences (DID) Models

	Frequentist DID	Bayesian spatial DID		
	Original	Model 1	Model 2	Model 3
Estimate (95% CI)	−0.24 (−0.49, 0.02)	−0.23 (−0.51,0.03)	−0.17 (−0.40, 0.06)	−0.21 (−0.45, 0.01)
95% CI width	0.51	0.54	0.47	0.46
Ineligible age controls	Yes	No	Yes	Yes
Spatiotemporal interactions	No	No	No	Yes
Deviance information criterion		10197.7	8781.2	8457.3
Spatial variance contribution (ϕ)		0.61	0.91	0.99

Notes: Estimates represent sample average treatment effects on ice-related injury rates per 1,000 person-winters across all treated municipalities and post-intervention periods. 95% confidence or credible intervals (CI) are shown in parentheses. Models with ineligible age controls use injury rates from age groups 1–15 years below the eligibility threshold as controls. All Bayesian spatial DID models are estimated using a Gaussian likelihood and include two-way Mundlak terms, first-order autoregressive global temporal random effects, and Besag–York-Mollié spatial effects (parameterized following Riebler et al.[35]). Model 2 includes injury rates among ineligible age groups as a time-varying covariate with both fixed and spatially varying coefficients. Model 3 further includes a spatiotemporal interaction between a first-order autoregressive temporal effect and an intrinsic conditional autoregressive spatial effect. Penalized complexity priors (with R-INLA default values) are applied to the precision of all random effects, and each random effect is constrained to sum to zero to improve model identifiability. Credible intervals are based on 1,000 posterior predictive draws. The spatial variance contribution refers to the mixing parameter in Riebler et al.'s re-parameterized Besag–York-Mollié model. The frequentist DID model is a triple differences specification with ineligible age controls from Eklund et al.,[44] estimated using the imputation-based DID approach by Borusyak et al.[18]

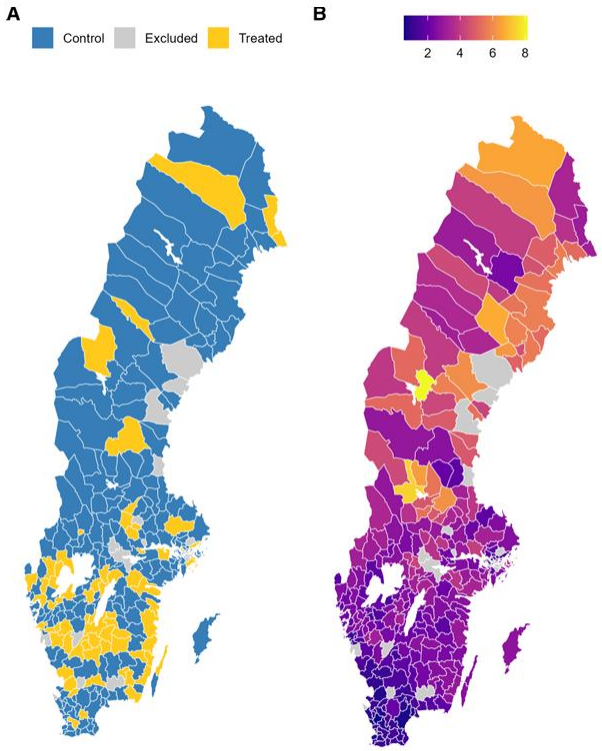


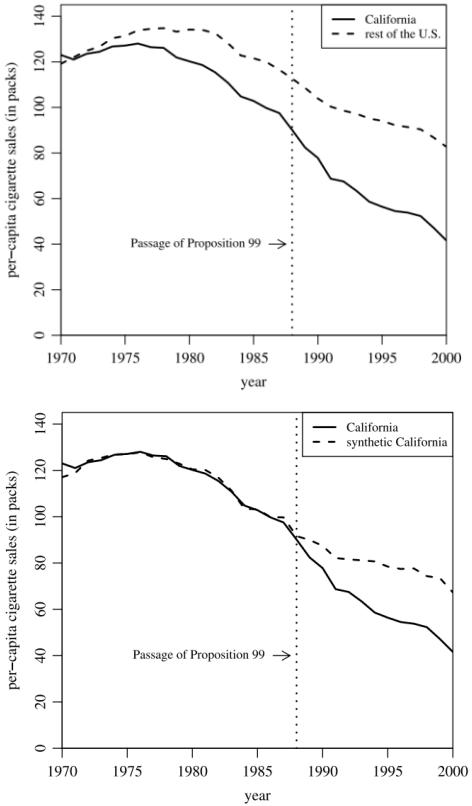
FIGURE 2. Panel A, Swedish municipalities with (n = 73) and without (n = 200) ice cleat distribution programs (per survey data collected in 2019; n = 17 municipalities with known programs but lacking survey data on intervention start date and/or clear age thresholds excluded). Panel B, Average number of patients treated for injuries after falls on snow or ice in specialized outpatient or inpatient care per 1,000 person-winters from the winter 2001/2002 to 2018/2019, according to data from the National Patient Register.

Non-parallell trends?

- Settings with non-parallell trends
  - DID not valid

- Modern solutions:
  - Synthetic controls (augmented, generalized)
  - Synthetic difference-in-differences
  - Matrix completion

- Not impossible but tricky to implement in a fully Bayesian model with spatiotemporal smoothing



Proposed solution

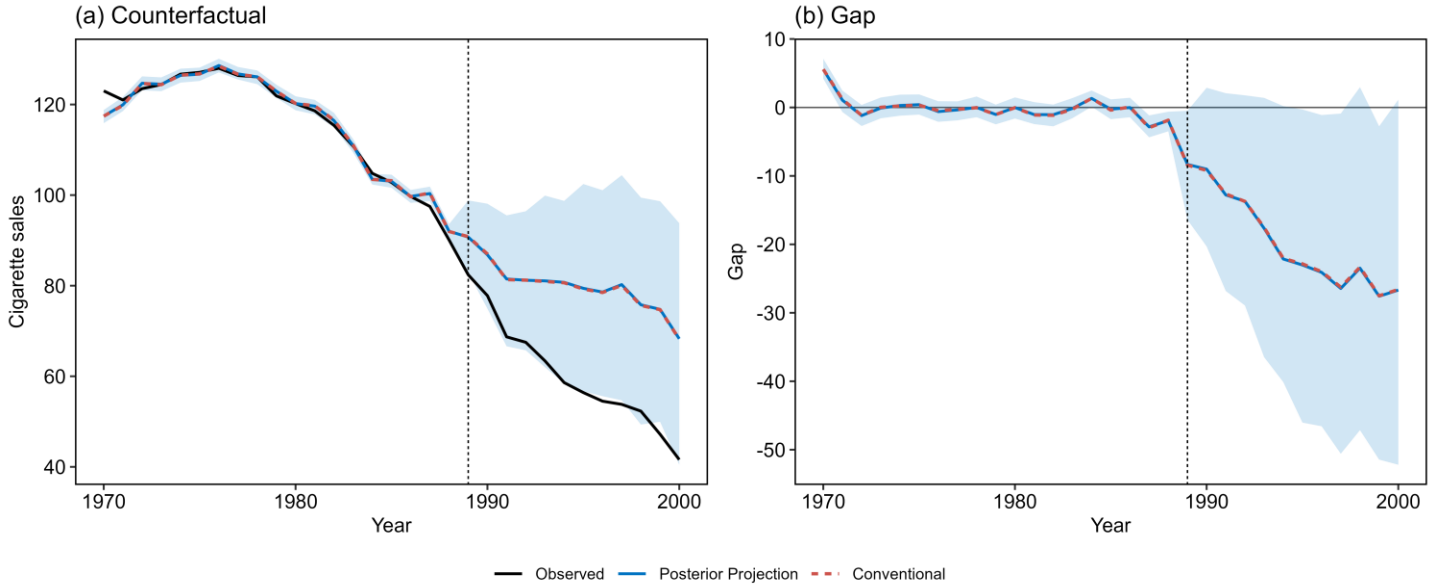
- Spatiotemporal model to smooth the observed parts of the data
  - Fast Bayesian inference (INLA)
  - Easy to use, well-established in the disease mapping community
  - Cannot fit latent factor models directly
  - But can learn outcome dependence structures well

- Apply causal panel data methods repeatedly to posterior draws of the latent predictor
  - Yields smoothed versions of *any* causal panel data estimator
  - Model-based uncertainty quantification
  - Works with generalized linear models
  - Smoothing improves accuracy in noisy data/small area evaluations

Bonander, C., Lin, Q., Strömberg, U., & Blangiardo, M. Posterior Projection for Spatiotemporal Causal Panel Models. *Unpublished manuscript*.

Synthetic controls

California's Proposition 99 on cigarette sales per capita (Abadie et al., 2010)

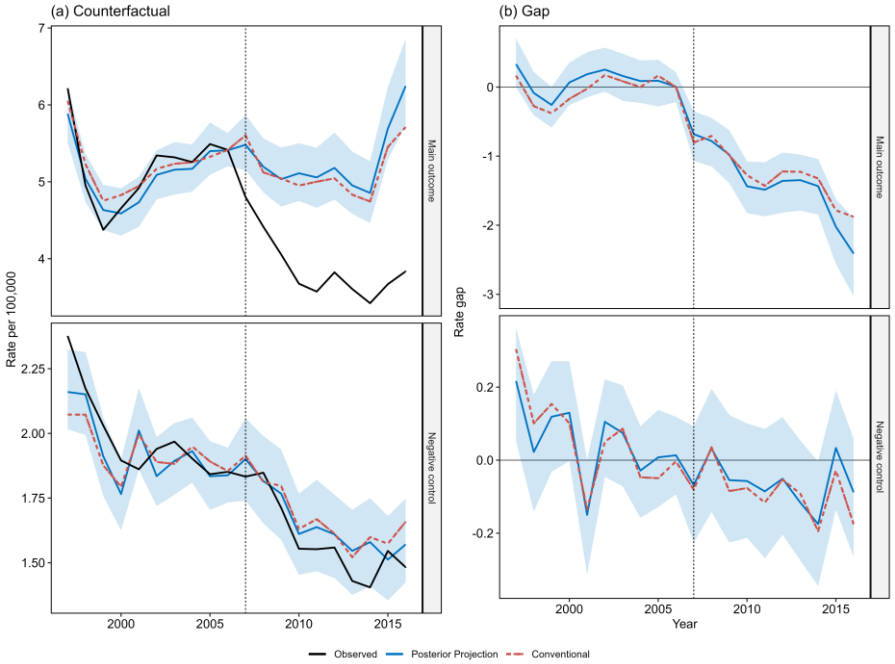


Synthetic difference-in-differences

California's Armed and Prohibited Persons System on firearm homicides (Ben-Michael et al., 2023)

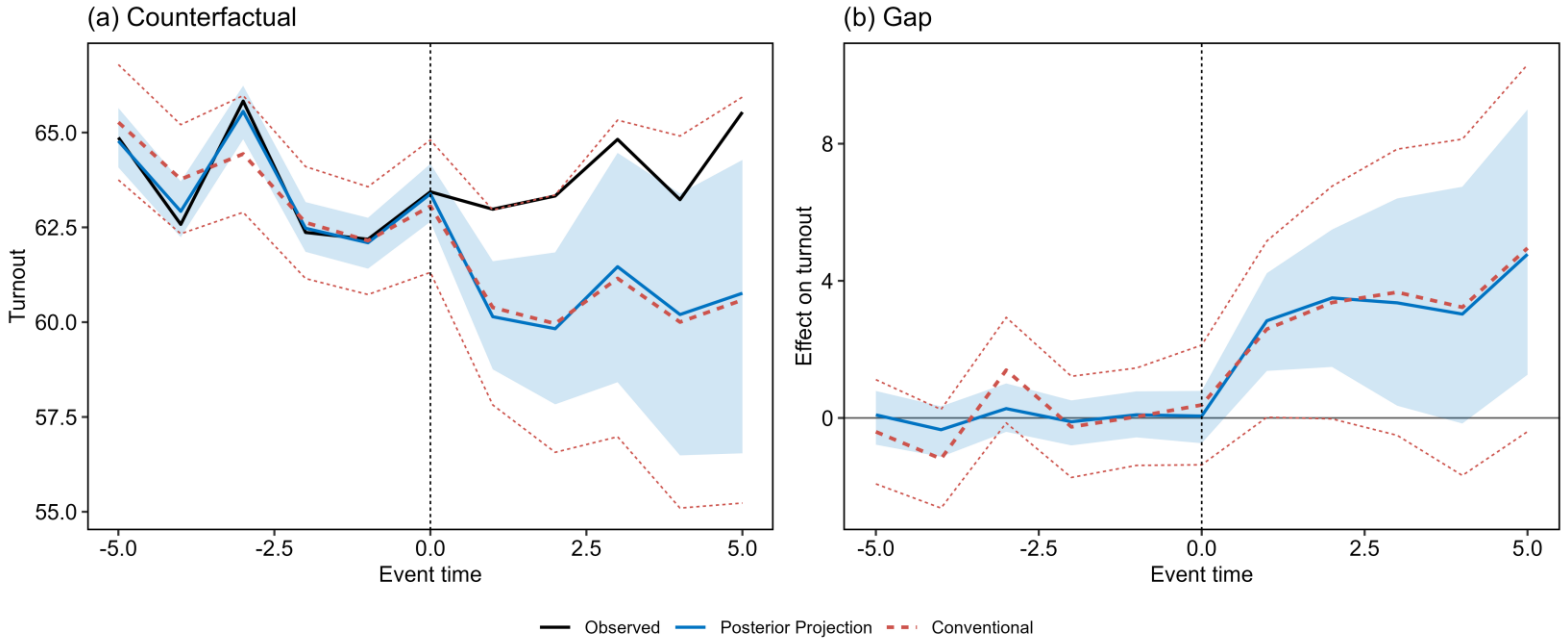
Firearm homicide rates:

Non-firearm homicide rates:



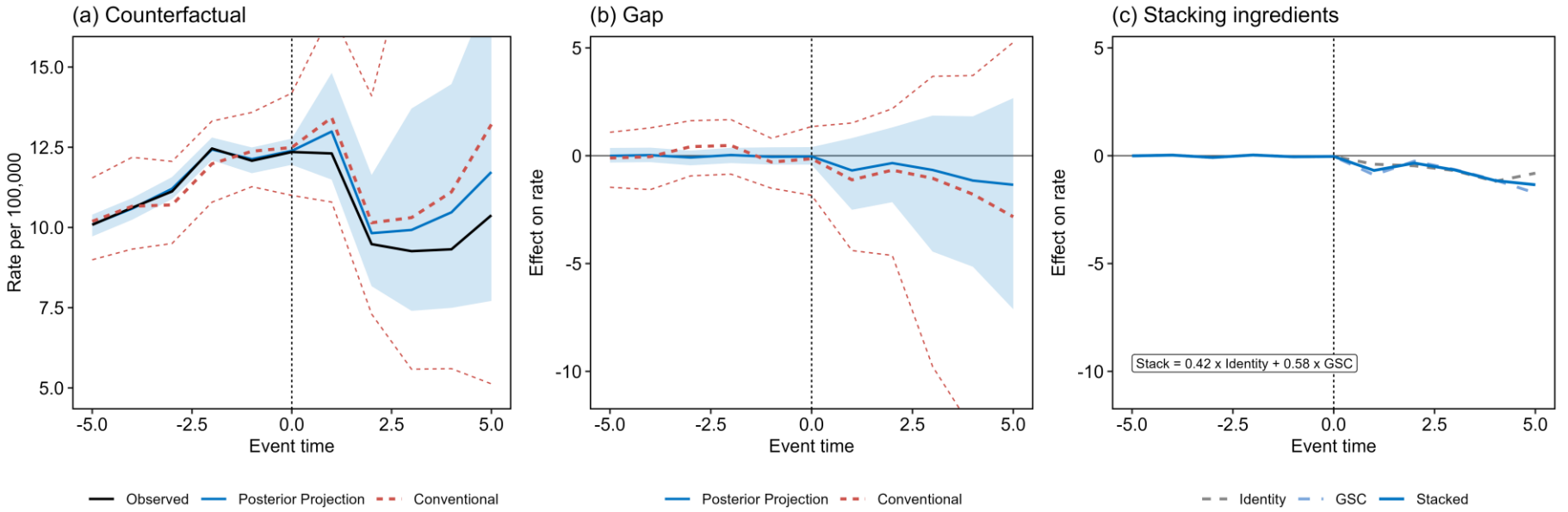
Generalized synthetic controls

Election day voter registration laws on voter turnout (Xu, 2017)



Model selection with stacking weights

Recreational cannabis laws on opioid-related mortality (count data example)



Summing up

Targeting

- Identify areas in need of intervention
- **Develop epidemiologic measures**
- **Register data**
- Surveillance
- **Disease mapping**
- Local decision-making

Evaluation

- Estimate intervention effects
- Small area interventions
- Local effects
- Effects that vary in space and time
- **Causal methods + disease mapping**
- **Counterfactual imputation**

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