# Achieving Peace and the SDGs in Colombia:

## Municipal Convergence, Crime, and the Role of Conditional Cash Transfers

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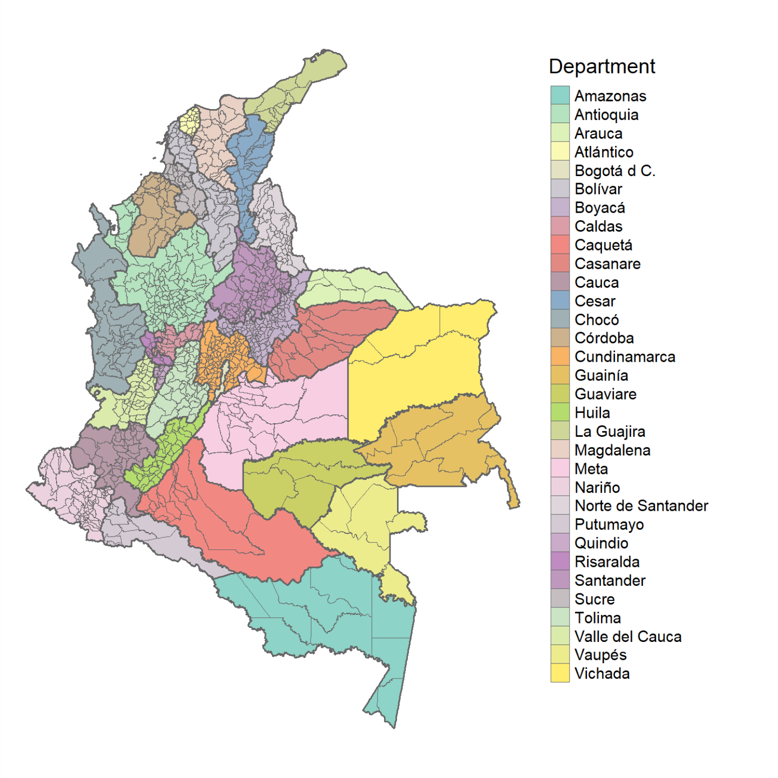
slides available at: https://masters-felipe-santos.netlify.app/

# Colombian administrative levels

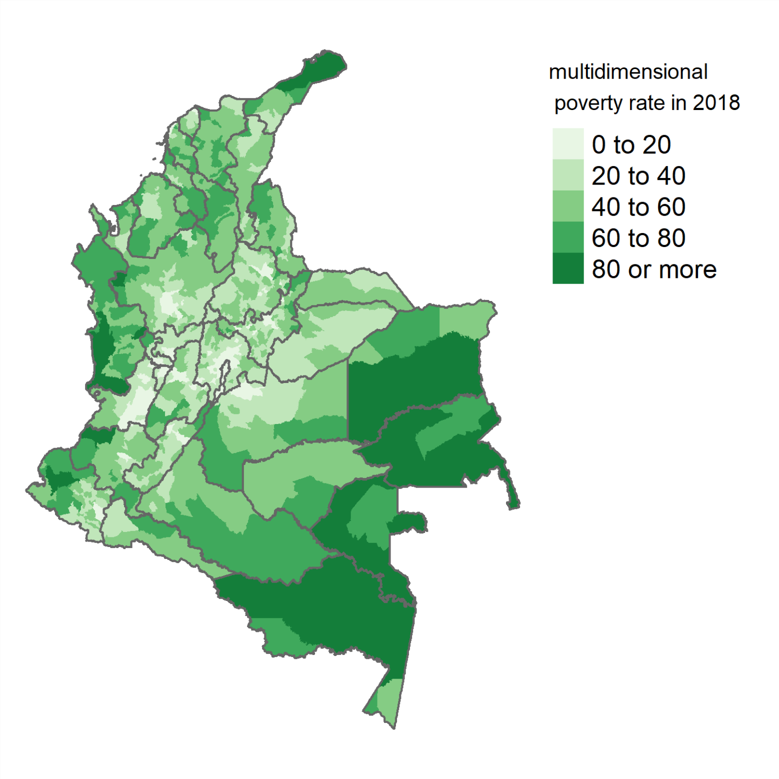
## States and Municipalities



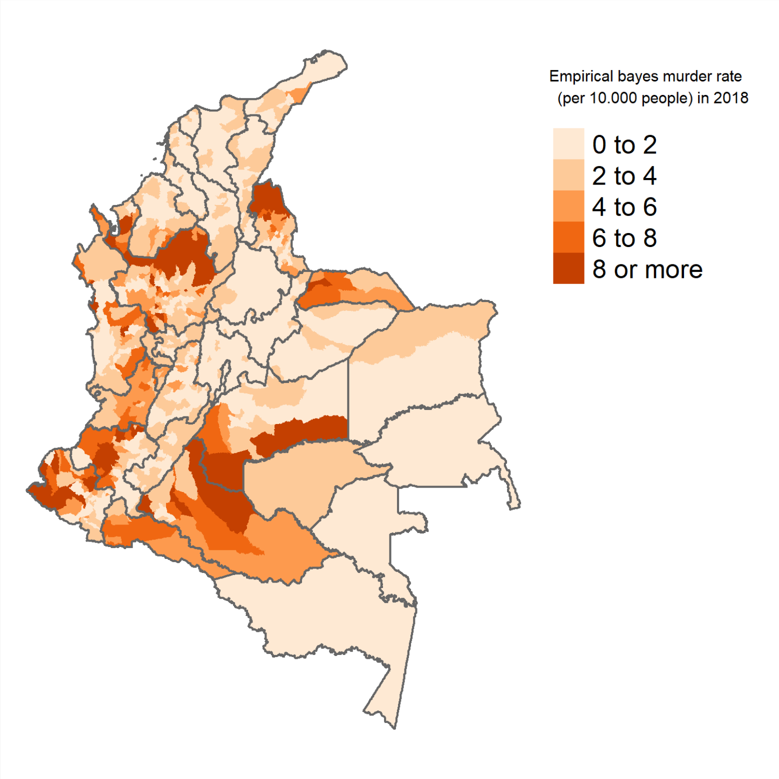

## Natural Regions

# Large regional disparities in Colombia

## Well-being

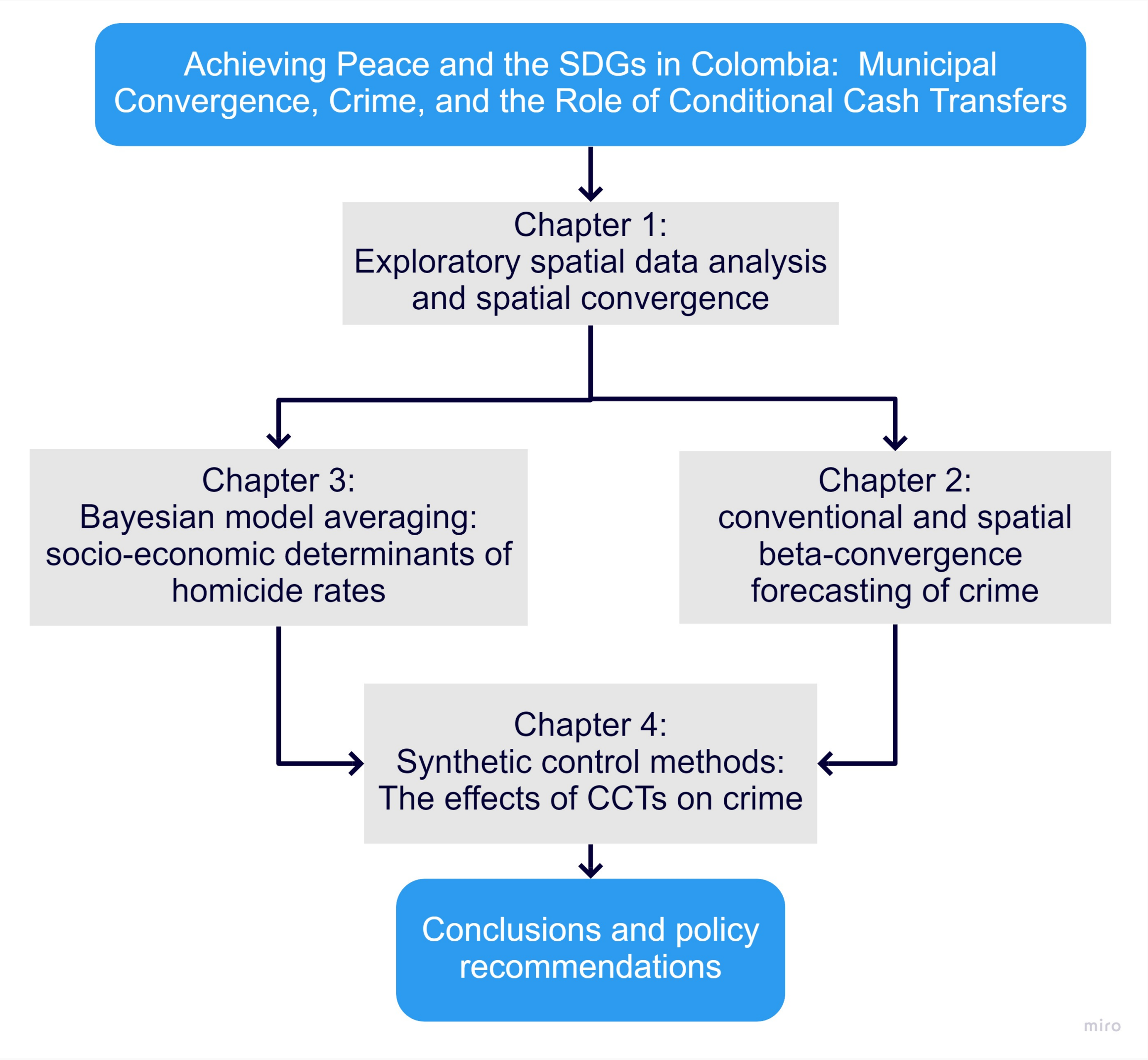



## Crime




**(In Germany = about 0.1 per 10.000 people,**
**In Japan = about 0.02 per 10.000 people)**

# Structure of the Dissertation



# Chapter 1: Exploration and convergence

**Methods: Classical beta convergence**

$$(1/T) \cdot \log \frac{y_{iT}}{y_{i0}} = \alpha - [1 - e^{-\beta T}] \cdot \log(y_{i0}) + w_{i,0T}$$

**The spatial lag model:**

$$\log \frac{y_{iT}}{y_{i0}} = \alpha + \beta \cdot \log(y_{i0}) + \rho W \cdot \log \frac{y_{iT}}{y_{i0}} + \epsilon_t$$

**The Spatial error model:**

$$\log \frac{y_{iT}}{y_{i0}} = \alpha + \beta \cdot \log(y_{i0}) + \lambda W \epsilon_t + u_t$$

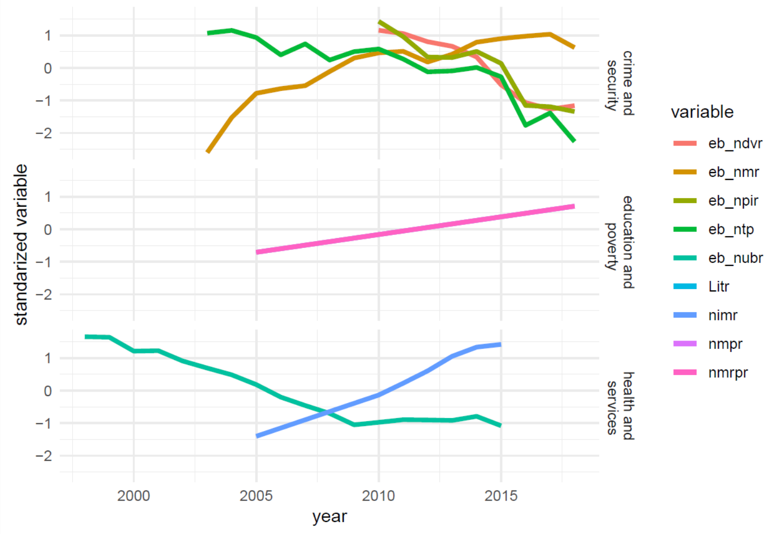
**Global Spatial Autocorrelation: Global Moran's I**

$$I_t = \frac{N}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \left[ \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n} (X_i - \bar{X})^2} \right]$$

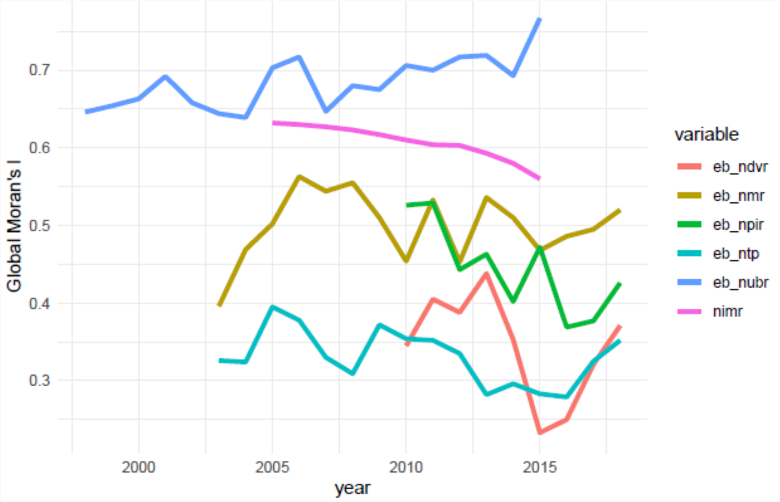
# Chapter 1: Data and Results

| Variable | Measurement | 2018 baseline | 2022 target | SDG | Other SDGs |
|---|---|---|---|---|---|
| Infant mortality | per 1000 | 16,5(2016) | 14.0 | 3 | 1,2 and 4 |
| Underweight birth | per 1000 | 9.1 | 8.0 | 3 | 1 |
| Literacy | % | 5.2 | 4.2 | 4 | 8 |
| Domestic violence | per 100.000 | 157.5 | 132.0 | 16 | - |
| Personal injuries | per 100.000 | 246.2 | 233.4 | 16 | - |
| Theft to people | per 100.000 | 594.7 | 485.5 | 16 | 11 |
| Homicide | per 100.000 | 25.8 | 23.2 | 16 | 11 |
| Multi. poverty | % | 17 | 11.9 | 1 | 3,4,6,7,8,9,10 |
| Rural multi. poverty | % | 36.6 | 33.0 | 1 | 3,4,6,7,8,9,10 |

## Global trend




## Spatial autocorrelation trend



# Spatial regression and OLS results

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | eb_ntpr | | | eb_nmr | | | eb_ndvr | | |
| | no spatial effects | spatial error | spatial lag | no spatial effects | spatial error | spatial lag | no spatial effects | spatial error | spatial lag |
| $\alpha$ | $-5.20^{***}$ | $-4.18^{***}$ | $-3.74^{***}$ | $8.74^{***}$ | $9.08^{***}$ | $8.03^{***}$ | $4.11^{***}$ | $5.72^{***}$ | $4.07^{***}$ |
| | (0.67) | (0.69) | (0.61) | (0.13) | (0.11) | (0.15) | (0.39) | (0.40) | (0.37) |
| $Y_{T0}$ | $0.57^{***}$ | $0.45^{***}$ | $0.41^{***}$ | $-0.95^{***}$ | $-0.99^{***}$ | $-0.87^{***}$ | $-0.45^{***}$ | $-0.62^{***}$ | $-0.44^{***}$ |
| | (0.07) | (0.07) | (0.07) | (0.01) | (0.01) | (0.02) | (0.04) | (0.04) | (0.04) |
| speed of convergence | -0.03 | -0.025 | -0.023 | 0.199 | 0.283 | 0.137 | 0.074 | 0.121 | 0.073 |
| half life | -23.21 | -27.8 | -30.49 | 3.49 | 2.45 | 5.07 | 9.39 | 5.72 | 9.49 |
| $\lambda$ | | $0.492^{***}$ | | | $0.766^{***}$ | | | $0.516^{***}$ | |
| $\rho$ | | | $0.482^{***}$ | | | $0.218^{***}$ | | | $0.43^{***}$ |
| Adjusted $R^2$ | 0.05 | 0.194 | 0.195 | 0.809 | 0.888 | 0.826 | 0.09 | 0.231 | 0.188 |
| Akaike Inf. Crit. | -11892.7 | -12074.2 | -12075.2 | -14794.3 | -15387.5 | -14895.3 | -12643.8 | -12828.8 | -12769.2 |
| LM test SEM | $274.83^{***}$ | | | $807.67^{***}$ | | | $251.12^{***}$ | | |
| LM test SAR | $281.81^{***}$ | | | $112.69^{***}$ | | | $170.95^{***}$ | | |
| Robust LM test SEM | 0.33 | | | $705.64^{***}$ | | | $138.46^{***}$ | | |
| Robust LM test SAR | $7.31^{***}$ | | | $10.66^{***}$ | | | $58.29^{***}$ | | |
| Observations | 1,120 | 1,120 | 1,120 | 1,120 | 1,120 | 1,120 | 1,120 | 1,120 | 1,120 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

**Exponential smoothing methods**

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha)y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \cdots$$

**ARIMA models**

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots \theta_q \varepsilon_{t-q} + \varepsilon_t$$

**Space time Autoregressive models (STAR)**

$$y_{it} = \sum_{k=1}^{p} \sum_{l=0}^{\lambda_k} \phi_{kl} \sum_{j=1}^{N} w_{ij}^{(l)} y_{jt-k} + a_{it}$$

**Proposed models: Beta convergence -> Forecasting**

$$\log(\hat{y}_{i(t+4)|t}) = \hat{\alpha}_{t+4|t} + \hat{\beta}_{t+4|t} \cdot \log(y_{it}) + w_{i,t}$$

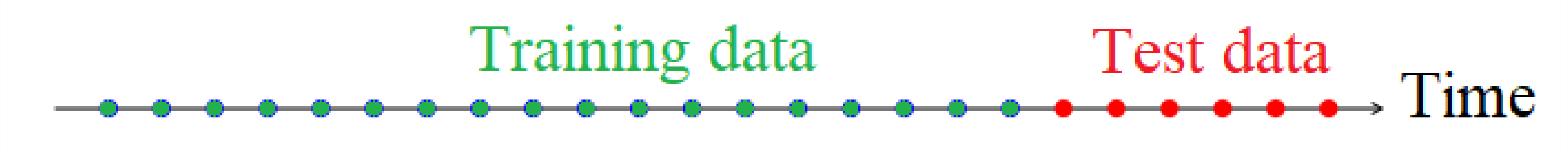
$$\log(\hat{y}_{i(t+4)|t}) = \hat{\alpha}_{t+4|t} + \hat{\beta}_{t+4|t} \cdot \log(y_{it}) + \hat{\theta}_{t+4|t} W \cdot \log(y_{it}) + \epsilon_{i,t}$$

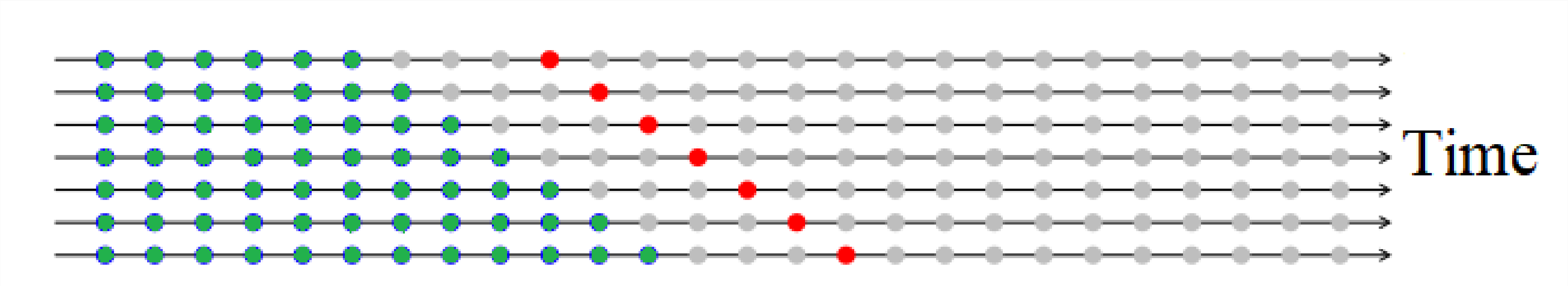
# Cross validating forecasting models

## How can the best forecasting model be chosen?

$$\text{Mean absolute error: MAE} = \text{mean}(|e_t|)$$
$$\text{Root mean squared error: RMSE} = \sqrt{\text{mean}(e_t^2)}$$

## Cross-validation of forecasts



# Results (Beta and spatial Beta)

**Table 1** Forecast accuracy cross validation

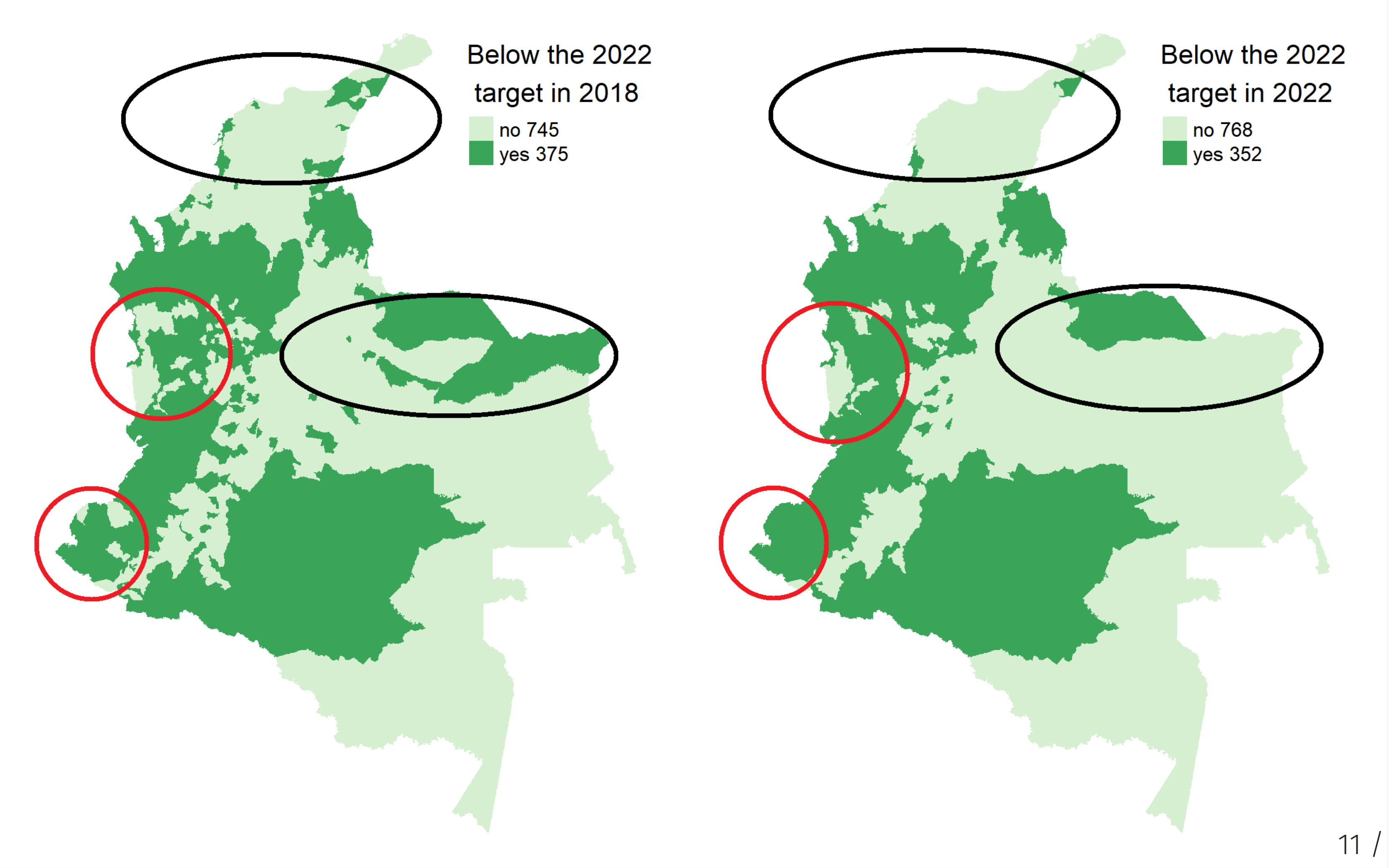
| method | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|
| ETS (MAE) | 2.83 | 2.31 | 1.49 | 1.46 | 1.43 | 1.38 | 1.37 | 1.42 |
| ETS (RMSE) | 5.74 | 4.66 | 2.40 | 2.36 | 2.33 | 2.44 | 2.14 | 2.66 |
| ARIMA (MAE) | 2.34 | 1.94 | 1.54 | 1.57 | 1.60 | 1.51 | 1.53 | 1.50 |
| ARIMA (RMSE) | 3.68 | 3.43 | 2.45 | 2.49 | 2.66 | 2.56 | 3.09 | 2.79 |
| BETA (MAE) | 1.83 | 2.36 | 2.21 | 1.84 | 1.51 | 1.19 | 1.02 | 1.31 |
| BETA (RMSE) | 2.29 | 3.42 | 2.66 | 2.32 | 2.14 | 2.18 | 1.72 | 2.80 |
| Spatial B (MAE) | 1.63 | 2.53 | 1.94 | 1.56 | 1.31 | 1.15 | 1.03 | 1.23 |
| Spatial B (RMSE) | 2.14 | 3.50 | 2.39 | 2.05 | 1.97 | 1.97 | 1.67 | 2.65 |
| STAR (MAE) | 2.49 | 2.46 | 2.19 | 2.23 | 2.37 | 2.32 | 2.37 | 2.59 |
| STAR (RMSE) | 2.80 | 3.31 | 2.55 | 2.53 | 2.76 | 2.71 | 2.79 | 3.54 |

**Table 2** Forecasts yearly cross validation

| method | MAE | RMSE |
|---|---|---|
| ETS | 1.71 | 3.34 |
| ARIMA | 1.69 | 2.93 |
| Beta | 1.66 | 2.49 |
| Beta Spatial | 1.55 | 2.35 |
| STAR | 2.38 | 2.89 |

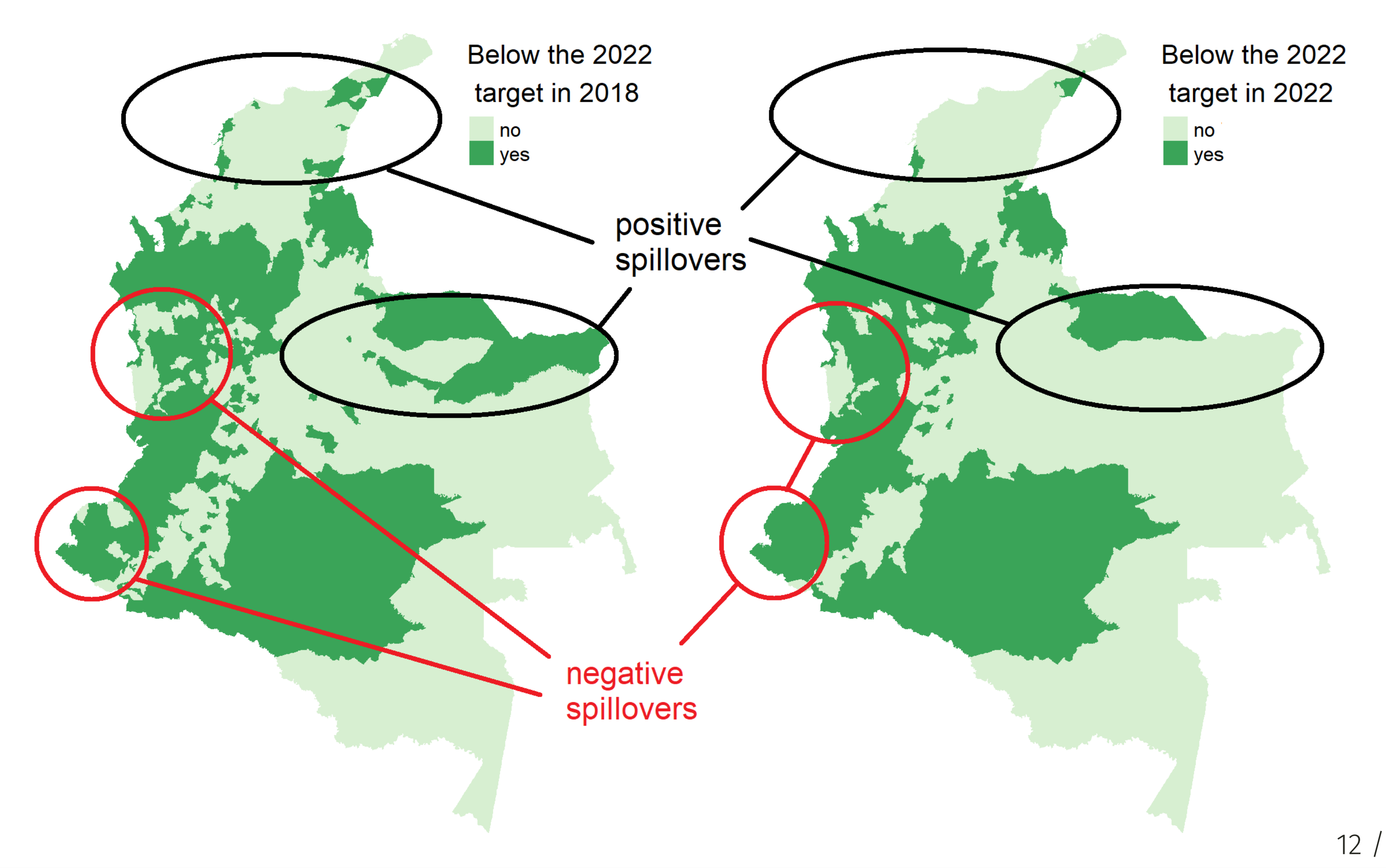
# Spatial distribution of forecasted crime

**municipalities in dark green are lagging behind**



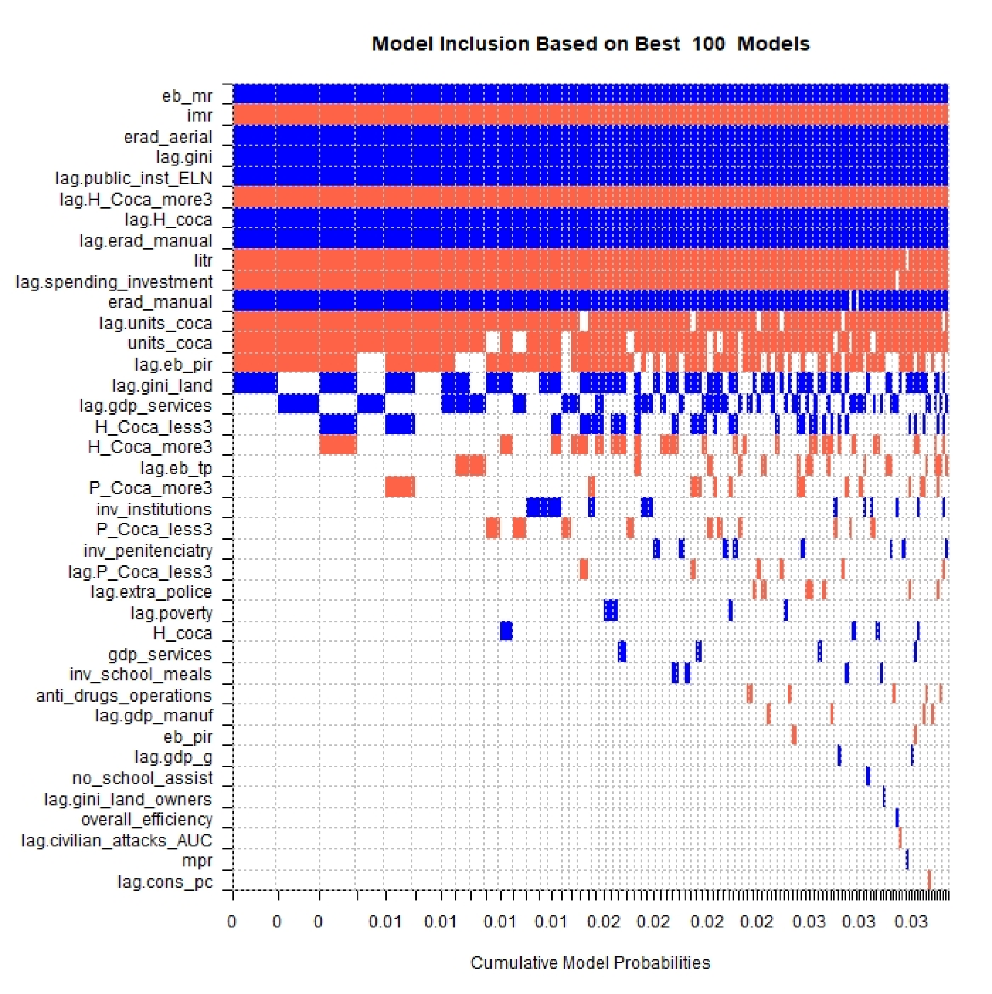
# Spatial distribution of forecasted crime

**municipalities in dark green are lagging behind**



# Chapter 3: BMA - crime determinants

212 variables (original and spatially lagged). **some significant determinants of homicides are**



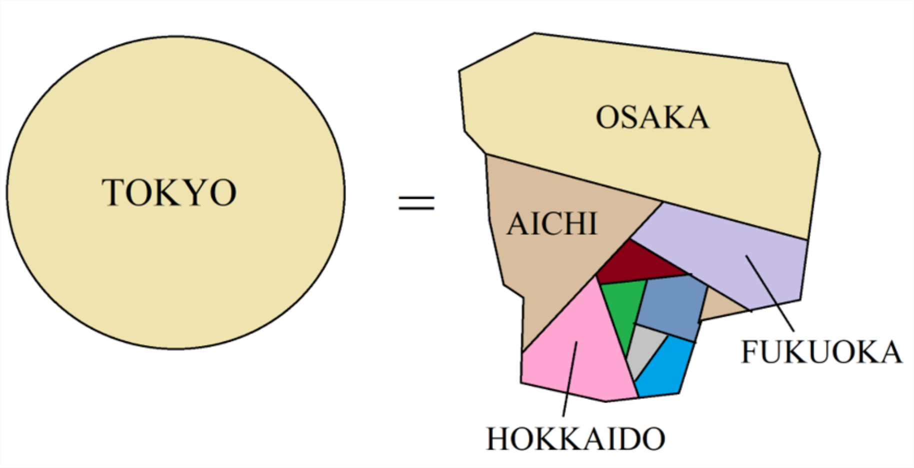
# Significant determinants of homicides:

## After running 2 million regressions...

| description | variable | PIP all variables | Post mean all |
|---|---|---|---|
| murder rate | eb_mr | 1.000 | 0.356 (0.031) |
| infant mortality rate | imr | 1.000 | -0.058 (0.011) |
| Coca H aerial eradication | erad_aerial | 1.000 | 0.001 (0) |
| Lag. Coca crops with more than 3 H | lag.H_Coca_more3 | 1.000 | -0.041 (0.006) |
| Lag. Coca hectares | lag.H_coca | 1.000 | 0.023 (0.003) |
| Lag Attacks against public institutions by rebels | lag.public_inst_ELN | 1.000 | 36.062 (7.46) |
| Lag. H manual eradication | lag.erad_manual | 1.000 | 0.004 (0.001) |
| Lag. Income Gini | lag.gini | 1.000 | 0.25 (0.041) |
| H manual eradication | erad_manual | 0.990 | 0.002 (0.001) |
| Lag. Spending on investment local government | lag.spending_investment | 0.986 | -0.095 (0.025) |
| Literacy rate | litr | 0.984 | -0.051 (0.013) |
| Number of land units with coca crops | units_coca | 0.961 | -0.004 (0.003) |
| Lag. Number of land units with coca crops | lag.units_coca | 0.943 | -0.015 (0.004) |
| Lag. Personal injury rates | lag.eb_pir | 0.681 | -0.034 (0.025) |
| Lag. Land Gini | lag.gini_land | 0.564 | 0.022 (0.021) |

## Synthetic control methods: visual intuition

### In terms of GDP per capita




$$TOKYO = 0.4 * OSAKA + 0.2 * AICHI + 0.1 * FUKUOKA + \ldots$$

### In terms of crime

The weights are found so that the synthetic municipality has a similar crime trend compared to the treatment region (2003-2011) and similar determinants from the BMA chapter.

# Results: Pacific region

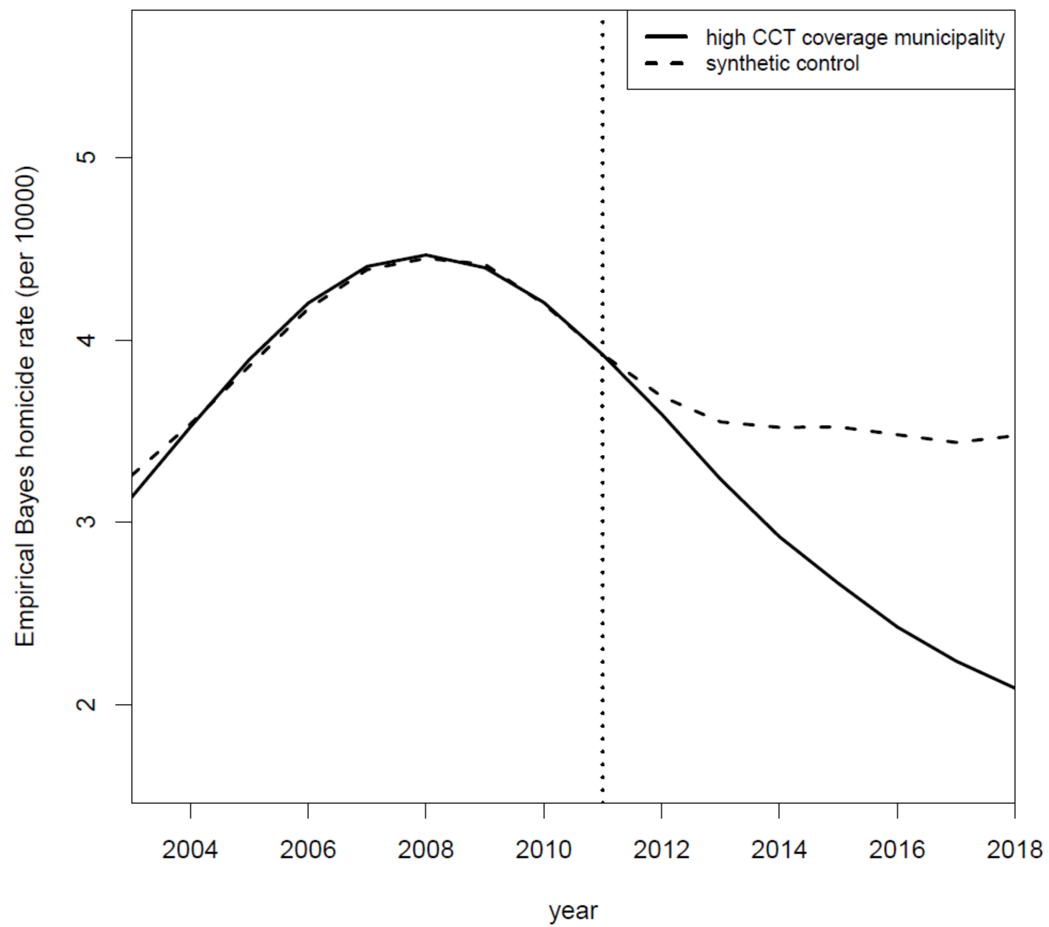
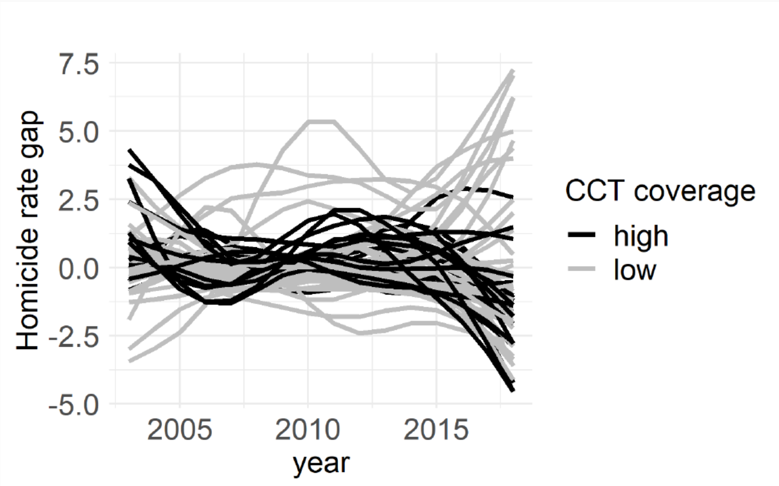


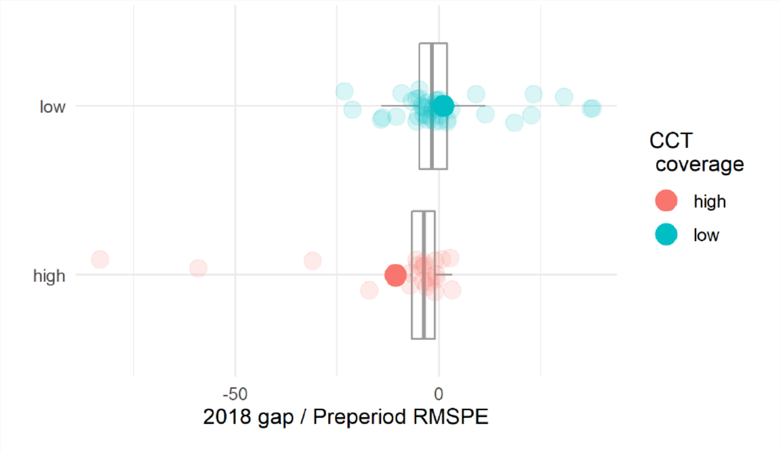

**Figure 5.3:** Trends in homicide rates: treated municipality (Popayan, Cauca) vs. synthetic control unit.

# The effect on crime of CCTS

**Crime gaps for treatment municipalities and low CCT coverage placebos**

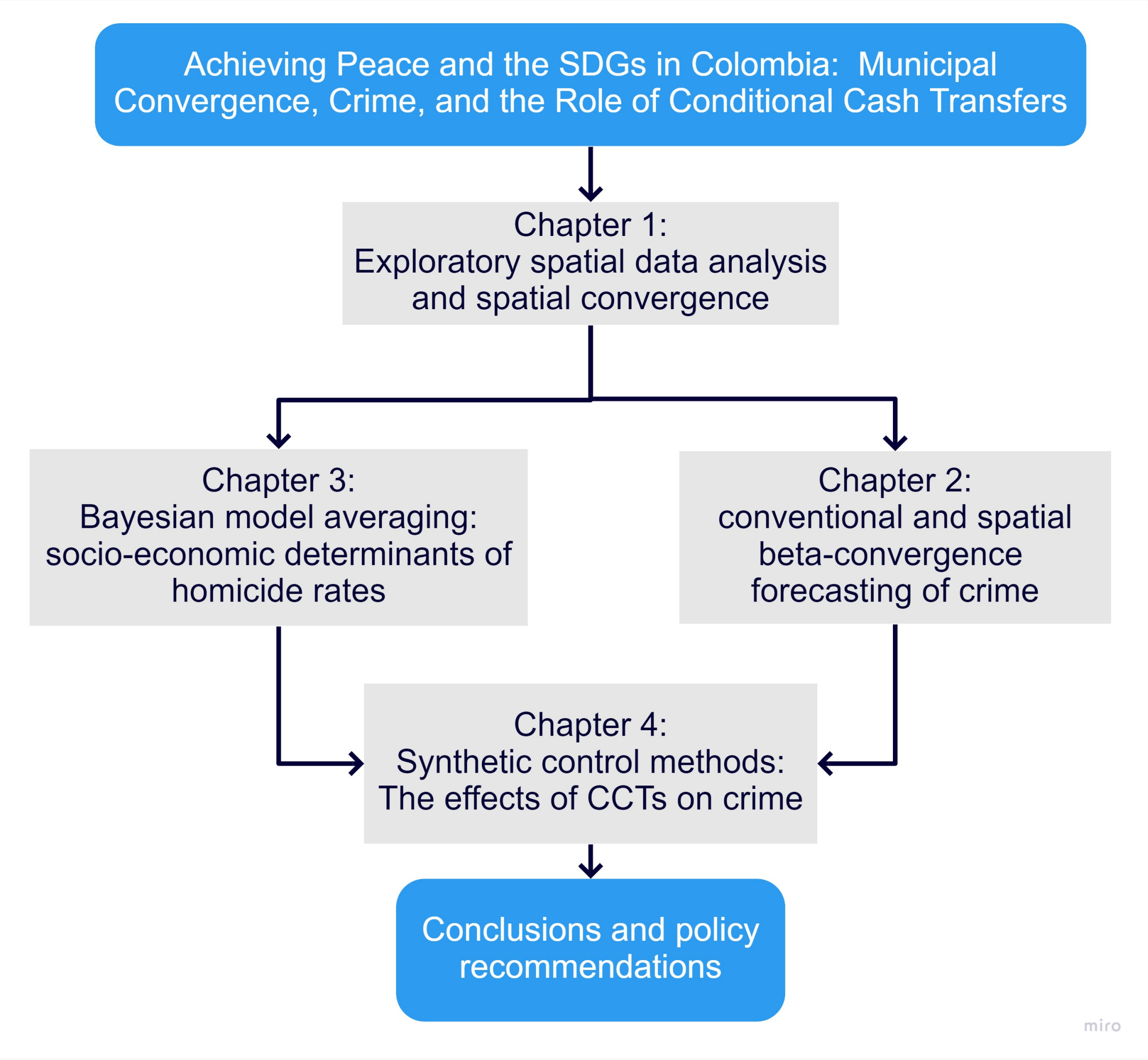



**Overall effects = the gap in 2018 / Root mean sqaured predicted error**




A t-test shows that the mean effect is statistically lower for the treatment group.

# In just 15 minutes:



# Thanks!

**Thank you very much for your attention**

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