Achieving Peace and the SDGs in Colombia:

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

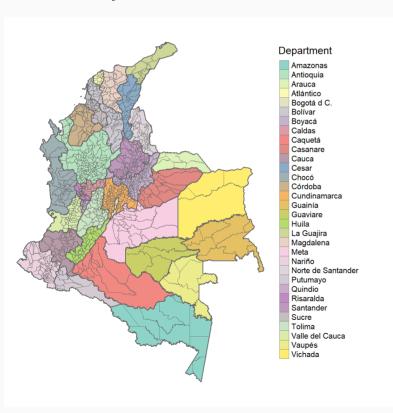
Felipe Santos-Marquez

GSID, Nagoya University, JAPAN Prepared for the TUD (Prof. Lessmann) meeting on November 13th 2020

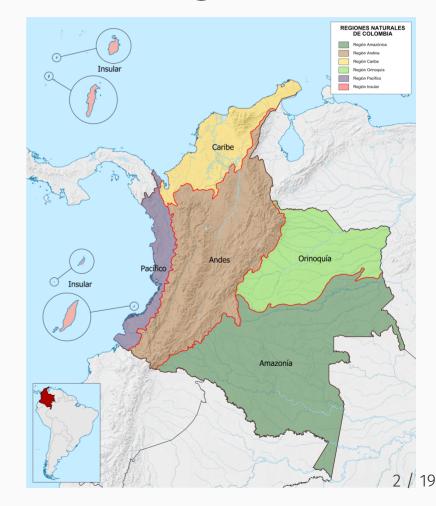
slides available at: https://masters-felipe-santos.netlify.app/

Colombian administrative levels

States and Municipalities

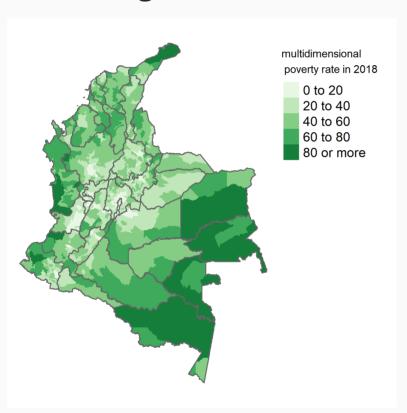


Natural Regions

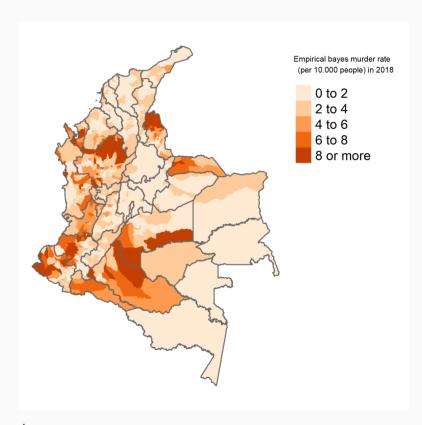


Large regional disparities in Colombia

Well-being

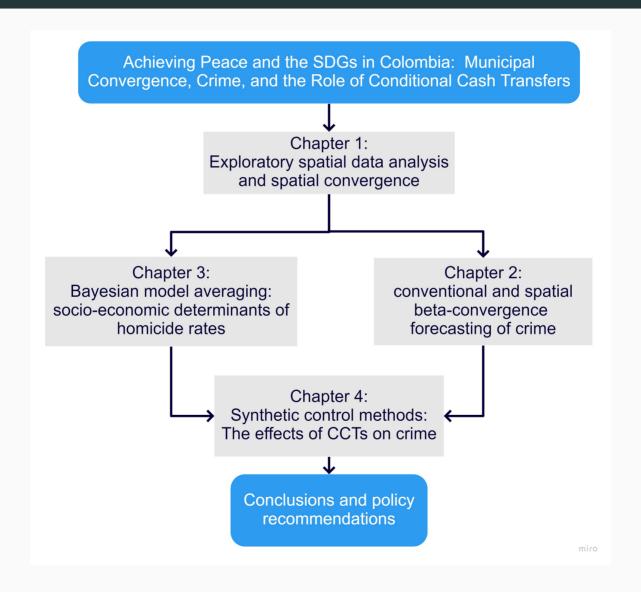


Crime



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

Structure of the Dissertation



Chapter 1: Exploration and convergence

Methods: Classical beta convergence

$$(1/T)\cdot\lograc{y_{iT}}{y_{i0}}=lpha-\left[1-e^{-eta T}
ight]\cdot\log(y_{i0})+w_{i,0T}$$

The spatial lag model:

$$\log rac{y_{iT}}{y_{i0}} = lpha + eta \cdot \log(y_{i0}) +
ho W \cdot \log rac{y_{iT}}{y_{i0}} + \epsilon_t$$

The Spatial error model:

$$\log rac{y_{iT}}{y_{i0}} = lpha + eta \cdot \log(y_{i0}) + \lambda W \epsilon_t + u_t$$

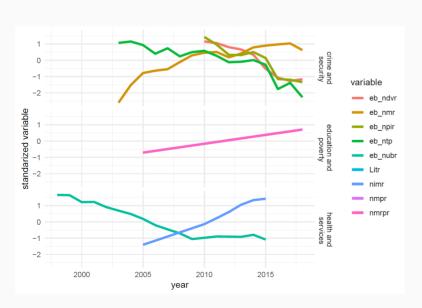
Global Spatial Autocorrelation: Global Moran's I

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

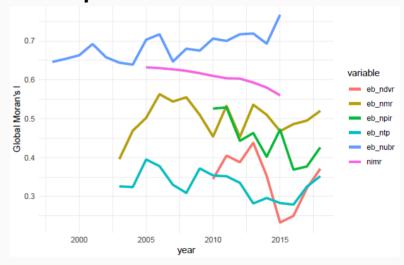
Chapter 1: Data and Results

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



Regression results

				Depe	ndent varie	able:			
	no spatial effects	eb_ntpr spatial error	spatial lag	no spatial effects	eb_nmr spatial error	spatial lag	no spatial effects	eb_ndvr spatial error	spatial lag
α	-5.20^{***} (0.67)	-4.18^{***} (0.69)	-3.74^{***} (0.61)	8.74*** (0.13)	9.08*** (0.11)	8.03*** (0.15)	4.11*** (0.39)	5.72*** (0.40)	4.07*** (0.37)
Y_{T0}	0.57*** (0.07)	0.45*** (0.07)	0.41*** (0.07)	-0.95^{***} (0.01)	-0.99*** (0.01)	-0.87^{***} (0.02)	-0.45^{***} (0.04)	-0.62^{***} (0.04)	-0.44*** (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
λ		0.492^{***}			0.766***			0.516***	
ρ			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:

Chapter 2: Convergence and Forecasting

Exponential smoothing methods

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

ARIMA models

$$y_t' = c + \phi_1 y_{t-1}' + \dots + \phi_p y_{t-p}' + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

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

$$\log\Bigl(\hat{y}_{i(t+4)|t}\Bigr) = \hat{lpha}_{t+4|t} + \hat{eta}_{t+4|t} \cdot \log(y_{it}) + w_{i,t}$$

$$\log\Bigl(\hat{y}_{i(t+4)|t}\Bigr) = \hat{lpha}_{t+4|t} + \hat{eta}_{t+4|t} \cdot \log(y_{it}) + \hat{ heta}_{t+4|t}W \cdot \log(y_{it}) + \epsilon_{i,t}$$

Cross validating forecasting models

How can the best forecasting model be chosen?

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

Cross-validation of forecasts



Results (Beta and spatial Beta)

Table 1 Forecast accuracy cross validation

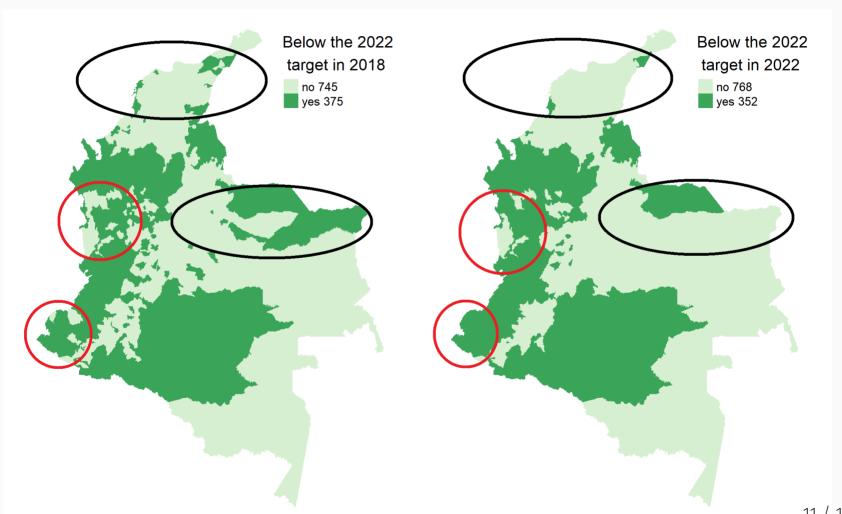
method	2011	2012	2013	2014	2015	2016	2017	2018
ETS (MAE)	2.83	2.31	1.49	1.46	1.43	1.38	1.37	1.42
ETS (RMSE)	5.74	4.66	2.40	2.36	2.33	2.44	2.14	2.66
ARIMA (MAE)	2.34	1.94	1.54	1.57	1.60	1.51	1.53	1.50
ARIMA (RMSE)	3.68	3.43	2.45	2.49	2.66	2.56	3.09	2.79
BETA (MAE)	1.83	2.36	2.21	1.84	1.51	1.19	1.02	1.31
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

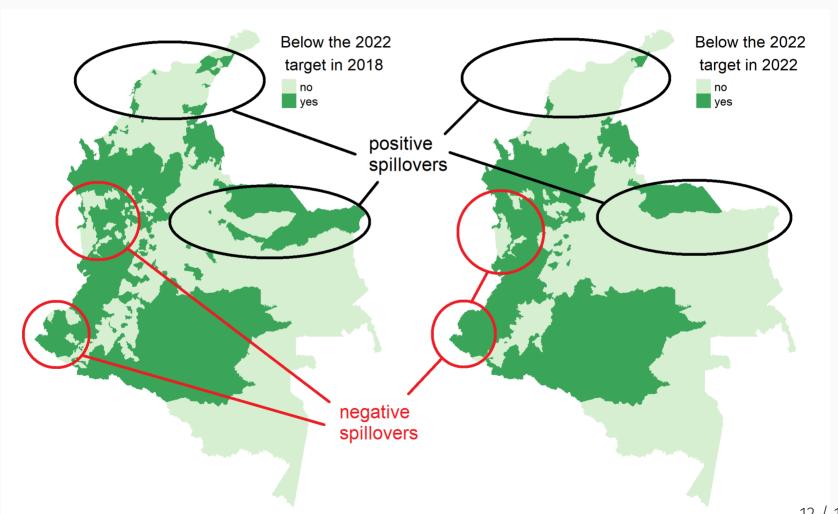
Spatial distribution of forecasted crime

municipalities in dark green are lagging behind



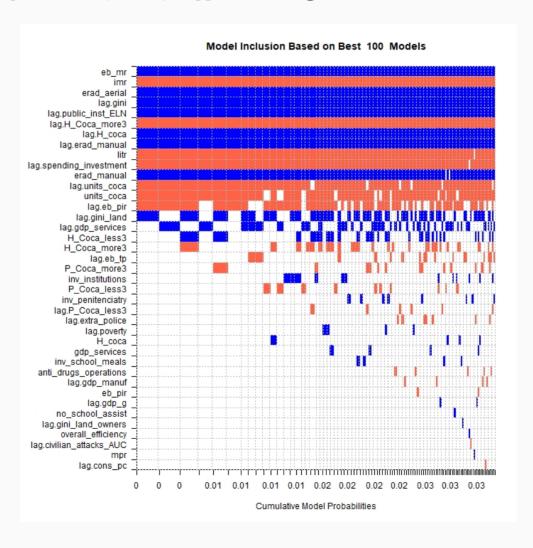
Spatial distribution of forecasted crime

municipalities in dark green are lagging behind



Chapter 3: BMA - crime determinants

212 variables (original and spatially lagged). The significant determinants of homicides are:



Significant determinants of homicides:

After running 2 million regressions...

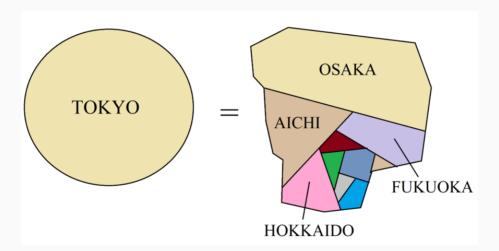
murder rate infant mortality rate Coca H aerial eradication Lag. Coca crops with more than 3 H Lag. Coca hectares Lag Attacks against public institutions by rebels Lag. H manual eradication Lag. Income Gini H manual eradication				
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Lag. H manual eradication Lag. Income Gini				
Lag. Income Gini				
H manual eradication				
Lag. Spending on investment local government				
Literacy rate				
Number of land units with coca crops				
Lag. Number of land units with coca crops				
Lag. Personal injury rates				
Lag. Land Gini				

variable	PIP all variables	Post mean all	
eb_mr	1.000	$0.356 \ (0.031)$	
imr	1.000	-0.058 (0.011)	
erad_aerial	1.000	0.001 (0)	
lag.H_Coca_more3	1.000	-0.041 (0.006)	
lag.H_coca	1.000	$0.023 \ (0.003)$	
$lag.public_inst_ELN$	1.000	36.062 (7.46)	
lag.erad_manual	1.000	$0.004 \ (0.001)$	
lag.gini	1.000	$0.25 \ (0.041)$	
erad_manual	0.990	0.002 (0.001)	
lag.spending_investment	0.986	-0.095 (0.025)	
litr	0.984	-0.051 (0.013)	
units_coca	0.961	-0.004 (0.003)	
lag.units_coca	0.943	-0.015 (0.004)	
$lag.eb_pir$	0.681	-0.034 (0.025)	
lag.gini_land	0.564	$0.022 \ (0.021)$	
	•	•	

Chapter 4: Synthetic control - CCT

Synthetic control methods: visual intuition

In terms of GDP per capita



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

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

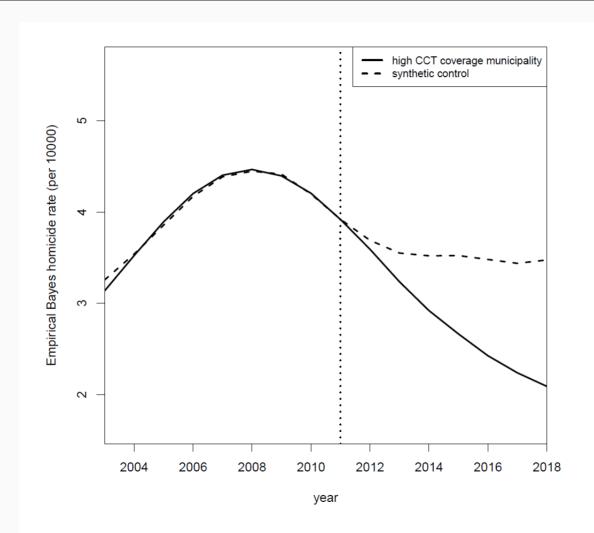
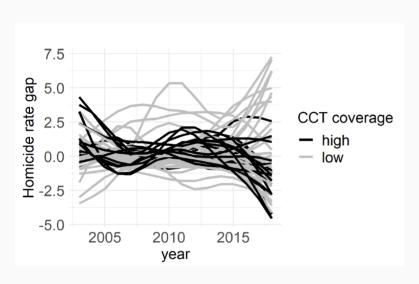


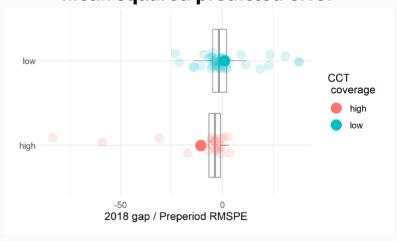
Figure 5.3: Trends in homicide rates: treated municipality (Popayan, Cauca) vs. synthetic control unit.

The effect on crime of CCTS

Crime gaps for treatment municipalities and low CCT coverage placebos

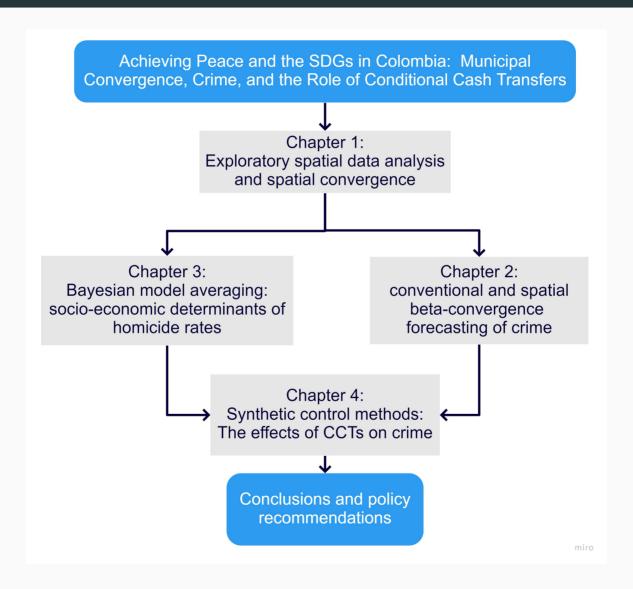


Overall effects = the gap in 2018 / Root mean sqaured predicted error



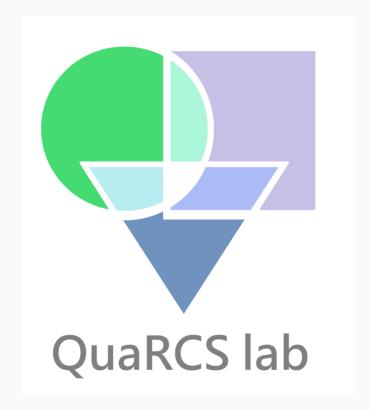
A t-test shows that the mean effect is statistically lower for the treatment group.

In just 15 minutes:



Thanks!

Thank you very much for your attention



Quantitative Regional and Computational Science Lab

https://quarcs-lab.org/