Essays on Causes and Consequences of Income Inequality in Natural Resource-Rich Countries:

Empirical Evidence from the Chilean Economy

Javier Beltran

Queensland University of Technology

QUT Business School

Motivation

"If income gaps are not reduced, the next crisis will happen as surely as autumn follows summer"

An interview with Michael Kumhof by Mikael Feldbaum,
https://www.eurozine.com, 2012

"If income gaps are not reduced, the next crisis will happen as surely as autumn follows summer"

General Research problem

Income inequality could have a significant effect on social cohesion and instability, spreading its influence like a *disease*

(Brunori, Ferreira, & Peragine, 2013; R. Kanbur, 2005; S. M. R. Kanbur & Venables, 2005; Milanovic, 2016; Ocampo, 2004)

The issue of inequality has taken a secondary place in the design of economic policy compared to efficiency measures such as Economic Growth

Essay 1:

Natural Resources: Curse or Blessing? Evidence on the Spatial Dimension of Income Inequality at the County Level in Chile

Research so far

- **Causes of income inequality** include **Globalization** (Milanovic, 2016), **Skill-biased technological change** (Tinbergen, 1975), investment in **human capital** (Murphy & Topel, 2016), **Institutions**, **redistributive policy** and **country-specific characteristics** (Acemoglu, 1995, 2002; Acemoglu et al., 2001a, 2001c)

The endowment of natural resources can influence inequality by:

- Determining its **initial levels** (Engerman & Sokoloff, 1994, 1997; Engerman, Sokoloff, Urquiola, & Acemoglu, 2002),

- Shaping the evolution of **institutions** (Acemoglu, 2002),

- Dumbing the **educational system** and moulding the **structure of economic activity** (Leamer, Maul, Rodriguez, & Schott, 1999)

- **Rent-seeking**, **delays in manufacturing and technology adoption** and **lower incentives for investment in physical and human capital** (Gylfason & Zoega, 2003).

- Impact on economic growth **("Natural Resource Curse Hypothesis")**

Research so far

Evidence for the Chilean economy has documented

- High and persistent levels of income inequality
- Significant spatial dimension (Aroca & Bosch, 2000; Paredes, Iturra, & Lufin, 2016)

About the relevance of the spatial dimension

- **Decomposing general indicators of inequality**. Evidence from countries including the US (Doran & Jordan, 2016), China (Akita, 2003; Gustafsson & Shi, 2002; Ye, Ma,Ye, Chen, & Xie, 2017; Yue, Zhang, Ye, Cheng, & Leipnik, 2014), Japan (Ohtake, 2008), South Africa (Leibbrandt, Finn, & Woolard, 2012) and Chile (Paredes et al., 2016).

- Using **spatial methods** to analyse the nature of the spatial effects:

  - **Spatial heterogeneity** (different relationships in distinct locations)
  - **Spatial dependence** (cross-sectional interactions such as spillover effects among units from distinct locations)

Research Questions

How does the natural resource endowment influence the paths and structure of income inequality in natural resource-rich countries?

Can the endowment of natural resources help to explain the persitently high levels of income inequality?

What type of process describes the spatial dimension shown by income inequality?

Research Hypoteses

The Role of Natural Resources

> *H1:* A higher degree of dependence on natural resources is associated with higher levels of income inequality.

Nature and Relevance of the spatial dimension

> *H2:* Income inequality shows a significant process of spatial dependence, that is, a process of interaction among units from distinct locations

Data and Variables

- Merging of the following datasets:

  - Six waves of CASEN Survey for household data (years 2006-2009-2011-2013-2015-2017)
  - SINIM for information about municipalities
  - INE for population data
  - SII for data on employment and number of firms

- In total 1944 obsevations (324 municipalities in 6 years)
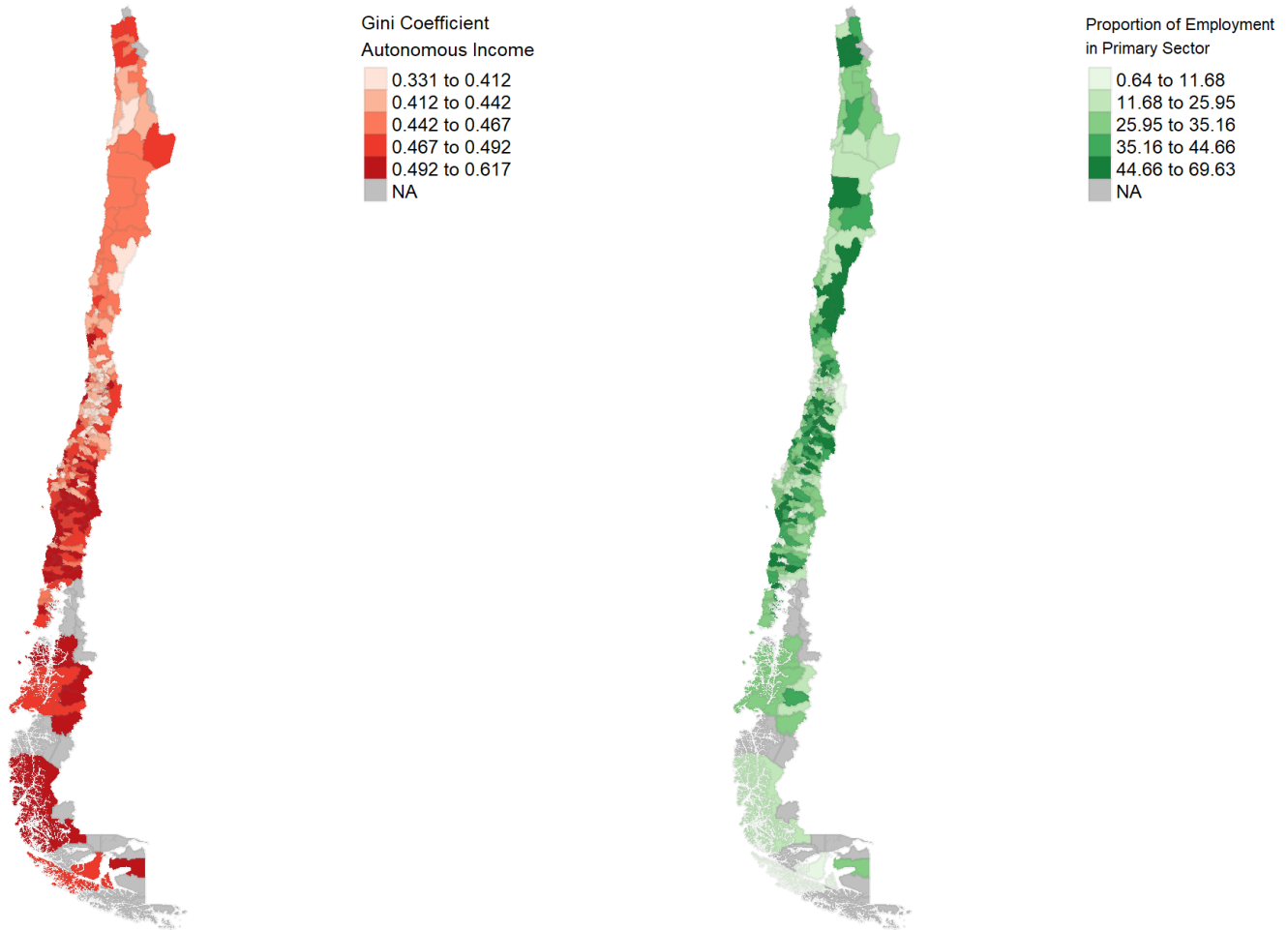
Dependent Variable

Gini coefficient of outonomous income (the sum of labour income and non-labour income such as rents, interests and pensions) for each county.

Independent Variable

Measure of natural resource dependence: Employment in the primary sector (mining, fishing, forestry and agriculture) as a percentage of the total employment in each county

Gini and NRD: Spatial distribution (average 2006-17)

Gini Coefficient
Autonomous Income

- 0.331 to 0.412
- 0.412 to 0.442
- 0.442 to 0.467
- 0.467 to 0.492
- 0.492 to 0.617
- NA

Proportion of Employment
in Primary Sector

- 0.64 to 11.68
- 11.68 to 25.95
- 25.95 to 35.16
- 35.16 to 44.66
- 44.66 to 69.63
- NA

Methods: "Spatial Approach"

What do we mean by "spatial approach"?

- Mapping the spatial distribution of the variable

- Defining the relevant neighborhood for each county (matrix **W**).

- Testing the significance of the spatial patterns (Spatial Autocorrelation)

- Checking whether the clustering pattern in inequality is the result of a process of spatial dependence in the variable itself or it can be explained by other variables:

  - Run an OLS regression of Gini against NRD and controls

  - Test for spatial autocorrelation in the OLS residuals

- Using spatial models to find the spatial structure that best fits the clustering process of income inequality after controlling for other variables

  - Spatial cross-sectional models
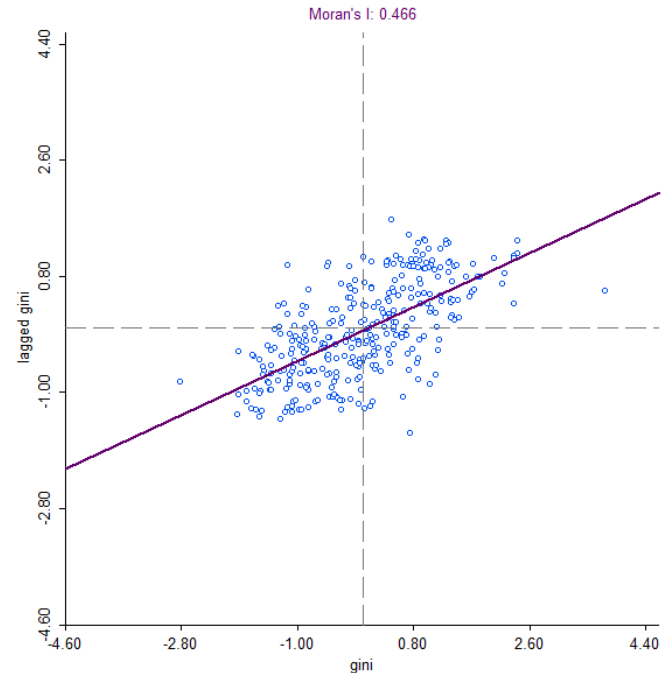 - Spatial static panel models

Results

Testing spatial correlation (Moran's I)

- H_0: Spatial randomness (I = 0)
- H_1: Spatial autocorrelation:
  - Positive (I > 0)
  - Netagive (I < 0)

Positive Spatial Autocorrelation:

Counties with similar levels of inequality tend to be close each other

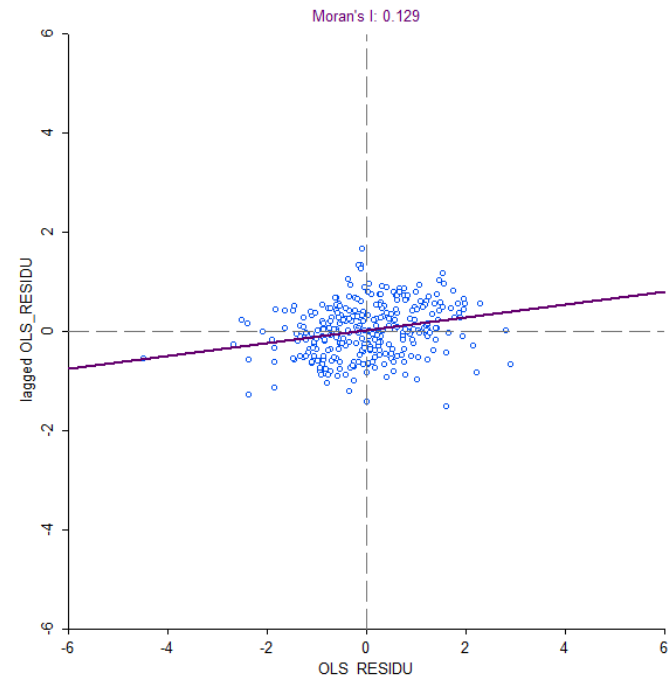# Analysis of OLS residuals

- We run the model:

$$gini_i = \beta_0 + \beta_1 pss\_casen + \beta_2 lnincome + \beta_3 poverty + \beta_4 unemployment +$$
$$\beta_5 labour\_force + \beta_6 education + \beta_7 lndensity + \beta_8 rural +$$
$$\beta_9 lnmuni\_expenditure + \beta_{10} north + \beta_{11} south$$

- We get the OLS residuals
- We test for spatial autocorrelation in OLS residuals

Spatial Model Specification (Cross-Sectional)

The model could be expressed as:

$$y = \lambda W y + X \beta + W X \gamma + u$$

where

$$u = \rho W u + \varepsilon$$

- W is our weight matrix that works as a NxN spatial lag operator (**Spatial Lag**: Weighted sum of the values observed at neighboring locations)

- Thus, the parameter:

  - λ capture the influence of the spatial lag for the dependent variable, $W y$,
  - γ capture the influence of the spatial lag for the explanatory variables, $W X$,
  - ρ capture the influence of the spatial lag for the errors, $W u$,
  - ϵ is a vector of idiosyncratic errors.

Cross-sectional Model Comparison (six-year average data)

	OLS	SLX	SAR	SEM	SARAR	SDM	SDEM	SARARX
pss_casen	−0.001***	−0.002***	−0.001***	−0.001***	−0.002***	−0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnincome	0.163***	0.171***	0.154***	0.171***	0.172***	0.176***	0.177***	0.177***
	(0.014)	(0.016)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)
poverty	0.005***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
unemployment	−0.000	−0.000	−0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
labour_force	−0.002*	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
education	−0.017***	−0.021***	−0.017***	−0.020***	−0.020***	−0.023***	−0.022***	−0.023***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
lndensity	−0.005***	−0.004*	−0.005***	−0.005***	−0.005***	−0.004*	−0.004*	−0.004*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
rural	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnmuni_expenditure	−0.019***	−0.017***	−0.018***	−0.017***	−0.017***	−0.017***	−0.018***	−0.017***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
north	0.012*	0.026	0.010	0.015	0.015	0.030	0.033	0.030
	(0.006)	(0.027)	(0.006)	(0.008)	(0.008)	(0.025)	(0.024)	(0.025)
south	0.021***	0.005	0.013**	0.023***	0.024**	0.002	0.001	0.001
	(0.005)	(0.019)	(0.005)	(0.006)	(0.008)	(0.018)	(0.018)	(0.018)
lambda			0.200**		−0.030	0.273***		0.228
			(0.064)		(0.112)	(0.078)		(0.422)
rho				0.345***	0.372***		0.280***	0.059
				(0.075)	(0.112)		(0.079)	(0.473)
Adj. R^2	0.630	0.652						
Num. obs.	324	324	324	324	324	324	324	324
Parameters			14	14	15	25	25	26
Log Likelihood			728.017	730.916	730.949	744.840	744.408	744.868

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Panel Data Regressions (non-spatial)

	Dependent variable: Gini Coefficient Autonomous Income			
	Pooled	Pooled	Fixed Effects	Random Effects
pss_casen	−0.001***	−0.001***	−0.0003*	−0.001***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
lnincome		0.158***	0.184***	0.161***
		(0.007)	(0.008)	(0.007)
poverty		0.002***	0.0002	0.001***
		(0.0002)	(0.0002)	(0.0002)
unemployment		0.003***	0.003***	0.003***
		(0.0004)	(0.0004)	(0.0003)
labour_force		−0.002***	−0.006*	−0.003***
		(0.0005)	(0.003)	(0.001)
education		−0.022***	−0.022***	−0.023***
		(0.002)	(0.003)	(0.002)
lndensity		−0.003***	0.011	−0.002**
		(0.001)	(0.026)	(0.001)
rural		0.0004***	−0.00004	0.0003***
		(0.0001)	(0.0002)	(0.0001)
lnmuni_expenditure		−0.014***	0.005	−0.013***
		(0.003)	(0.007)	(0.004)
north	0.026***	0.015***		0.016**
	(0.004)	(0.005)		(0.006)
south	0.054***	0.035***		0.041***
	(0.003)	(0.003)		(0.004)
Constant	0.468***	0.037		0.052
	(0.004)	(0.042)		(0.051)
Year Dummies?	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,944	1,944	1,944	1,944
Adjusted R^2	0.230	0.443	0.272	0.410

Note: *p<0.1; **p<0.05; ***p<0.01

Panel Data Regressions (Spatial)

ML Spatial SAR Models

Coefficients	Pooled	Pr(>|t|)	FE	Pr(>|t|)	RE	Pr(>|t|)
lambda	0.007	0.875	-0.002	0.949	0.001	0.700
pss_casen	-0.001	0.000	0.000	0.056	-0.001	0.000
lnincome	0.157	0.000	0.184	0.000	0.163	0.000
poverty	0.002	0.000	0.000	0.236	0.001	0.000
unemployment	0.003	0.000	0.003	0.000	0.003	0.000
labour_force	-0.002	0.000	-0.006	0.063	-0.003	0.000
education	-0.022	0.000	-0.022	0.000	-0.024	0.000
lndensity	-0.003	0.000	0.011	0.627	-0.002	0.079
rural	0.000	0.000	0.000	0.870	0.000	0.001
lnmuni_expenditure	-0.014	0.000	0.005	0.442	-0.012	0.002

ML Spatial SEM Models

Coefficients	Pooled	Pr(>|t|)	FE	Pr(>|t|)	RE	Pr(>|t|)
rho	0.097	0.009	0.061	0.098	0.076	0.047
pss_casen	-0.001	0.000	0.000	0.065	-0.001	0.000
lnincome	0.159	0.000	0.186	0.000	0.164	0.000
poverty	0.002	0.000	0.000	0.249	0.001	0.000
unemployment	0.003	0.000	0.003	0.000	0.003	0.000
labour_force	-0.002	0.000	-0.005	0.074	-0.003	0.000
education	-0.022	0.000	-0.022	0.000	-0.024	0.000
lndensity	-0.003	0.000	0.013	0.584	-0.002	0.085
rural	0.000	0.000	0.000	0.840	0.000	0.001
lnmuni_expenditure	-0.014	0.000	0.006	0.417	-0.012	0.002

GM Spatial Models

Coefficients	SAR				SEM			
	FE	Pr(>|t|)	RE	Pr(>|t|)	FE	Pr(>|t|)	RE	Pr(>|t|)
pss_casen	0.000	0.052	-0.001	0.000	0.000	0.065	-0.001	0.000
lnincome	0.183	0.000	0.161	0.000	0.185	0.000	0.163	0.000
poverty	0.000	0.270	0.001	0.000	0.000	0.250	0.001	0.000
unemployment	0.003	0.000	0.003	0.000	0.003	0.000	0.003	0.000
labour_force	-0.006	0.086	-0.003	0.000	-0.006	0.074	-0.003	0.000
education	-0.022	0.000	-0.024	0.000	-0.022	0.000	-0.024	0.000
lndensity	0.010	0.694	-0.002	0.063	0.013	0.588	-0.002	0.047
rural	0.000	0.900	0.000	0.000	0.000	0.843	0.000	0.000
lnmuni_expenditure	0.005	0.493	-0.013	0.000	0.005	0.421	-0.012	0.001

Discussion and Recomendations

- Contrary to our main hypothesis, NRD shows a significant and negative association with income inequality.

- This result is robust to the type of analysis (cross-sectional vs panel data), the approach (spatial vs nonspatial) and the inclusion of different controls.

- Implication: The downward trend in the participation of the primary sector in terms of employment in the Chilean economy could be one of the main reasons explaining the high persistence in the levels of income inequality.

- Policies oriented to transform the structure of local economies to less dependent ones on natural resources will generate additional challenges for local and central governments in their attemps to reduce inequality

- Education and municipal expenditure seem to be effective policy tools aiming to reduce inequality in Chile.

Limitations and Future Research

Limitations

- Data availability at the county level
- Results do not allow us to make causal inferences about the effect of NRD on income inequality
- Results are sensitive to the specification of the spatial weights

Future Research

- "Innovative" ways to define "distance" and W.
- Incorporate measures of commuting and migration between counties.
- Using measures of NRD as instrument for income inequality in studies about its consequences.

Essay 2:

Assessing and Explaining
Local Government Efficiency
in Natural Resource-Rich Countries:
The case of Chilean Municipalities

Research so far

- **Trade-off between efficiency and equity**:

    - Pursuing equality can reduce efficiency (see Okun 1975; Browning & Johnson 1984; Andersen & Maibom 2016)

    - But, equality could also be an important ingredient in promoting and sustaining growth (see Berg & Ostry 2011; kumhof, Rancière & Winant 2015)

- **Local Government Efficiency (LGE)** studies focus on:

Measuring LGE

- Provision of single services vs overall efficiency
- Parametric (SFA) vs non-parametric (DEA) measurement techniques
- Input oriented vs output oriented approach and selection of inputs and outputs

Explaining differences in LGE

- Discretionary factors (associated with the measurement process)

- Non-discretionary (contextual) factors including economic, financial, social, demographic, geographic, political and institutional characteristics.

Research Question

What role does income inequality play in explaining differences in municipal efficiency?

Research Hypoteses

About the relationship between LGE and income inequality

H_1: Income inequality has a negative effect on municipal efficiency.

See Tandon ,2005; Jottier, Ashworth, & Heyndels, 2012; Ortega, Sanjuán, & Casquero, 2017

Why?; How?

About the level of inefficiency of Chilean municipalities

H_2: Chilean municipalities show an average level of inefficiency of 30%.

See Pacheco, Sanchez & Villena, 2013

Data

First Stage (DEA): Inputs - Output used to measure LGE

- National System of Municipal Information, SINIM (2006-2017)
- Sample of 324 municipalities (3888 observations)

County-Level Data on Contextual Factors

- National Socioeconomic Characterization Survey, CASEN (2006 - 2009 - 2011 - 2013 - 2015 - 2017)
- SINIM
- "Servicio de Impuestos Internos", SII
- National Institute of statistics, INE
- in total 1944 observations

Methodology: Two Stage Approach

First Stage: DEA analysis

- Input oriented assuming variable returns to scale
- Result: A vector of **efficiency scores (ES)** for each municipality

Second Stage: Regression Analysis

- **Dependent variable**: DEA efficiency scores

- **Independent variables**:

  - Measure of Income inequality + Remaining contextual factors
  - County (zone) specific + time effects

- **Estimation method**: Censored regression + Instrumental Variable (IV)

- **Proposed Instrument**: $pss\_firms = \dfrac{\text{Number of firms in primary sector}}{\text{Total number of firms}}$

First Stage: DEA Results

Evolution Efficiency Scores by Zone (Full Period)
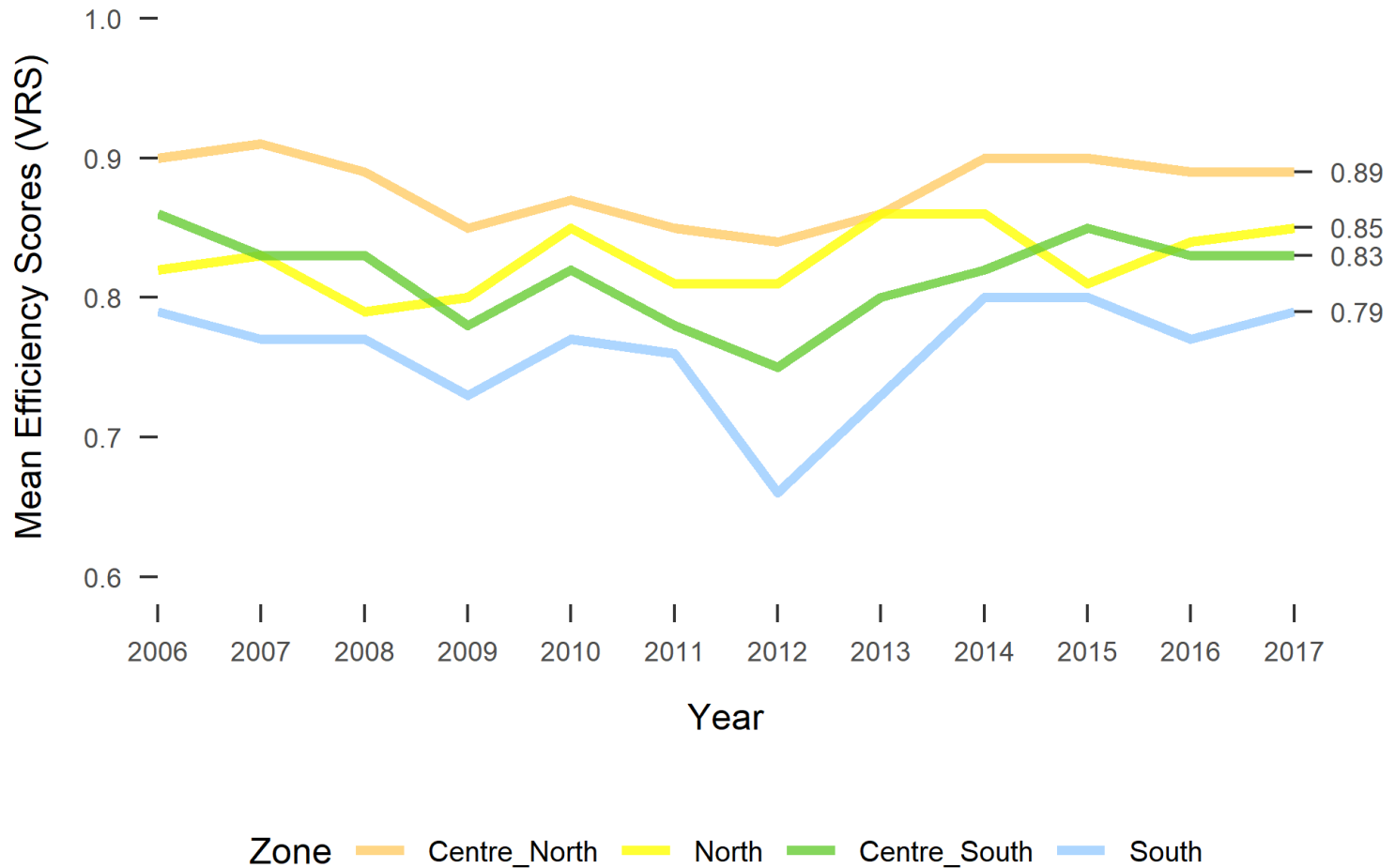
Efficiency Scores by Zone and Region

Unit	n_counties	mean	median	sd	min	max
North	41	0.83	0.86	0.19	0.26	1
XV	3	0.88	1.00	0.22	0.27	1
I	6	0.73	0.80	0.28	0.26	1
II	8	0.98	1.00	0.07	0.70	1
III	9	0.79	0.79	0.14	0.53	1
IV	15	0.80	0.81	0.16	0.49	1
Centre_North	121	0.88	0.94	0.14	0.32	1
V	36	0.82	0.84	0.15	0.39	1
XIII	52	0.95	1.00	0.09	0.47	1
VI	33	0.81	0.82	0.15	0.32	1
Centre_South	116	0.82	0.83	0.15	0.34	1
VII	30	0.81	0.82	0.15	0.40	1
VIII	54	0.84	0.88	0.15	0.34	1
IX	32	0.77	0.77	0.16	0.40	1
South	46	0.77	0.77	0.18	0.31	1
XIV	12	0.74	0.74	0.13	0.46	1
X	25	0.74	0.75	0.19	0.31	1
XI	6	0.89	0.98	0.15	0.44	1
XII	3	0.85	0.91	0.17	0.52	1
Country	324	0.83	0.86	0.16	0.26	1

2006

Status
Efficient (es = 1)
Inefficient (es < 1)
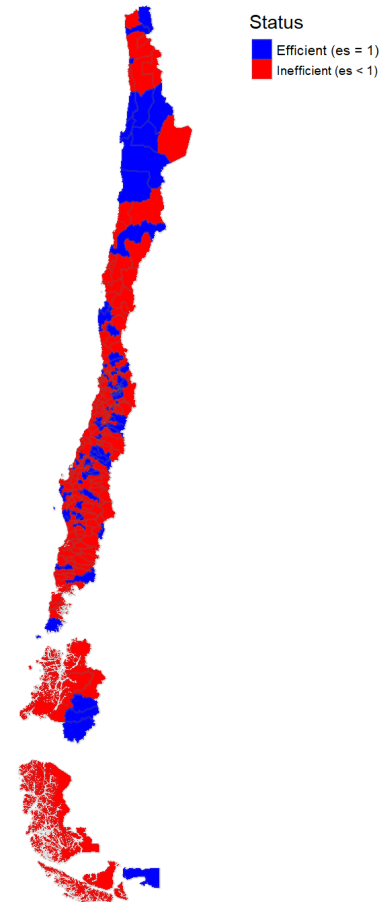
Second Stage

The model

To test our hypothesis, the empirical model is defined as:

$$\theta_{it} = \beta_1 gini_{it} + Z_{it}\beta + \delta_t + \alpha_i + \epsilon_{it}$$

- θ_{it} is the vector of efficiency scores from the DEA analysis,

- $gini_{it}$ is the Gini coefficient of each county,

- Z is a vector of controls.

- δ_t are year-specific effects,

- α_i are municipality-specific constants,

- ϵ_{it} is a vector of error terms and

Model Comparisons - Cross-sectional Censored Regressions

	Dependent variable: Efficiency Score (VRS)					
	2006	2009	2011	2013	2015	2017
gini	−0.228	−0.447**	−0.393*	−0.242	−0.189	−0.371*
log(income)	0.119*	0.249***	0.208***	0.164**	0.221***	0.257***
agroland	−0.002***	−0.003***	−0.003***	−0.001	−0.002***	−0.001
log(density)	0.019**	0.032***	0.021***	0.034***	0.017**	0.005
own	−0.002*	−0.002	−0.003**	−0.004***	0.002*	−0.002
education	−0.018	−0.038*	−0.046**	−0.026	−0.009	−0.020
IDD	−0.005**	−0.006***	−0.004*	−0.001	−0.004*	−0.006***
professional	0.001	−0.0001	−0.0002	0.003**	0.002	0.0003
mcf	0.002*	0.002**	0.002**	0.0003	0.0004	0.0004
LEFT mayor	−0.016	0.012	0.008	0.003	0.020	−0.022
RIGHT mayor	0.007	−0.002	0.032	0.013	0.038	0.002
reg_cap	−0.039	−0.061	−0.043	−0.106*	0.0004	−0.012
Centre South	0.068**	0.126***	0.050	0.028	0.054*	0.040
North	−0.019	0.099**	0.056	0.135***	0.006	0.034
South	−0.051	0.044	0.015	−0.025	−0.019	−0.065*
Observations	324	324	324	324	324	324
Log Likelihood	-14.778	12.330	-15.924	-24.773	-1.200	6.937
Akaike Inf. Crit.	63.555	9.339	65.848	83.546	36.400	20.127

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

	Panel Data Regressions : Dependent variable - Efficiency Score (VRS)					
			censored regression		instrumental variable	
	Pooled	RE	Pooled	RE	OLS IV	Tobit IV
	(1)	(2)	(3)	(4)	(5)	(6)
gini	−0.033	−0.049	−0.282***	−0.189***	−1.434***	−1.196*
	(0.082)	(0.068)	(0.081)	(0.073)	(0.432)	(0.538)
log(income)			0.184***	0.106***	0.258***	0.292***
			(0.026)	(0.025)	(0.054)	(0.069)
agroland			−0.002***	−0.002***	−0.002***	−0.002***
			(0.0003)	(0.0004)	(0.0003)	(0.0003)
log(density)			0.022***	0.020***	0.012***	0.021***
			(0.003)	(0.005)	(0.003)	(0.003)
own			−0.002***	−0.001**	−0.001***	−0.001***
			(0.001)	(0.001)	(0.0004)	(0.0005)
education			−0.022***	−0.005	−0.034***	−0.033**
			(0.008)	(0.008)	(0.008)	(0.010)
IDD			−0.004***	−0.005***	−0.002**	−0.003**
			(0.001)	(0.001)	(0.001)	(0.001)
professional			0.001*	−0.00004	0.0004	0.0008
			(0.0005)	(0.0005)	(0.0004)	(0.0005)
mcf			0.001***	0.002***	0.001***	0.001**
			(0.0003)	(0.0004)	(0.0003)	(0.0004)
LEFT mayor			−0.001	0.006	−0.007	−0.005
			(0.011)	(0.010)	(0.009)	(0.011)
RIGHT mayor			0.017	0.005	0.003	0.013
			(0.012)	(0.011)	(0.010)	(0.012)
reg_cap			−0.047**	−0.069**	0.024	−0.021
			(0.023)	(0.034)	(0.022)	(0.028)
Centre South	−0.089***	−0.086***	0.058***	0.022	0.123***	0.113**
	(0.012)	(0.019)	(0.014)	(0.022)	(0.028)	(0.035)
North	−0.054***	−0.045	0.050***	0.059*	0.030*	0.061**
	(0.016)	(0.033)	(0.019)	(0.032)	(0.016)	(0.020)
South	−0.142***	−0.124***	−0.019	−0.033	0.036	0.021
	(0.016)	(0.044)	(0.016)	(0.026)	(0.023)	(0.029)
Year Dummies?	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01

Discussion and Recomendations

Main results

- **DEA**

  - The "production function" of municipalities shows variable returns to scale.

  - The average level of inefficiency is 17%, with higher levels in the South area of the country.

  - Efficiency shows a ciclical behaviour and, on average, has remained stable in the period 2006 - 2017.

- **Regression analysis**

  - Empirical **evidence of a negative relationship between inequality and efficiency**, that is, a reduction of income inequality (or an increase in equality) could have positive effects on economic efficiency, at least at the level of local governments.

Limitations and Future Research

Limitations

- Results sensitive to the selection and number of inputs and outputs

- Associated with observational data and the interpretation of results as causal relationships.

Future research

- Include some output capturing the quality in the provision of public services

- Alternatives IV´s (?)

- Program evaluation in Chilean municipalities

- Modelling spatial dependence-heterogeneity in LGE.

- Given the current situation of the country: What about the issue of **reverse causality?**

Essay 3:

Does economic disadvantage diminish social cohesion?
A study of the relationship between incivilities and income inequality at the municipal level in Chile

What are "Incivilities"?

> Incivilities are those visible disorders in the public space that violate respectful social norms and tend not to be treated as crimes by the criminal justice system

There two types of incivilities:

- **Social incivilities** include antisocial behaviours such as public drinking, noisy neighbours, fighting in public places and street drug sales.
- **Physical incivilities** include, among others, vandalism, graffiti, abandoned cars and garbage on the streets.

What is the problem?

Broken Window Theory

> Higher rates of incivilities are a signal of social disorganization which result in higher crime rates (Wilson & Kelling, 1982)

Research so far

> The negative impact of incivilities is not merely reflected in its **association with crime rates** (Skogan, 2015)

Incivilities have been associated with:

- **Health problems** (Branas et al., 2011; Cohenet al., 2000; Hill & Angel, 2005; Ross, 2011; Ross & Mirowsky, 2001)

- **Greater victimization** and **fear of crime** (Brunton-Smith, Jackson, & Sutherland, 2014; Mijanovich & Weitzman, 2003)

- Multiple negative **economic effects**:

  - Reduction in commercial activity, lower investment in real state and reduction in house prices (Skogan, 2015)
  - Population instability (Hipp, 2010).

Research so far

The "Incivilities Thesis"

> Incivilities are caused by inequality and the lack of informal mechanisms of social control. The patterns of incivilities should mirror the patterns of inequality (Taylor, 1999)

Chilean evidence:

- Focussed on crime and showing weak and ambiguous results

  - **Indicators of socio-economic disadvantage** would only have significant effects on property crime (Beyer & Vergara, 2006; Nuñez, Rivera, Villavicencio, & Molina, 2003; Rivera, Gutiérrez, & Núñez,2009).

  - **Crime deterrence variables**: The probability of being caught or the number of police resources (Beyer & Vergara, 2006; Rivera et al., 2009; Vergara, 2012).

Research Question

Do differences in the rate of incivilities mirror differences in income inequality between counties?

Research Hypoteses

H_1: Incivilities will be higher in counties with high levels of inequality.

H_2: Incivilities will be higher in counties with a high proportion of the young population.

H_3: Incivilities will be higher in counties with a high proportion of foreign inhabitants.

H_4: Incivilities will be lower in counties managed by municipalities more autonomous from central government transfers.
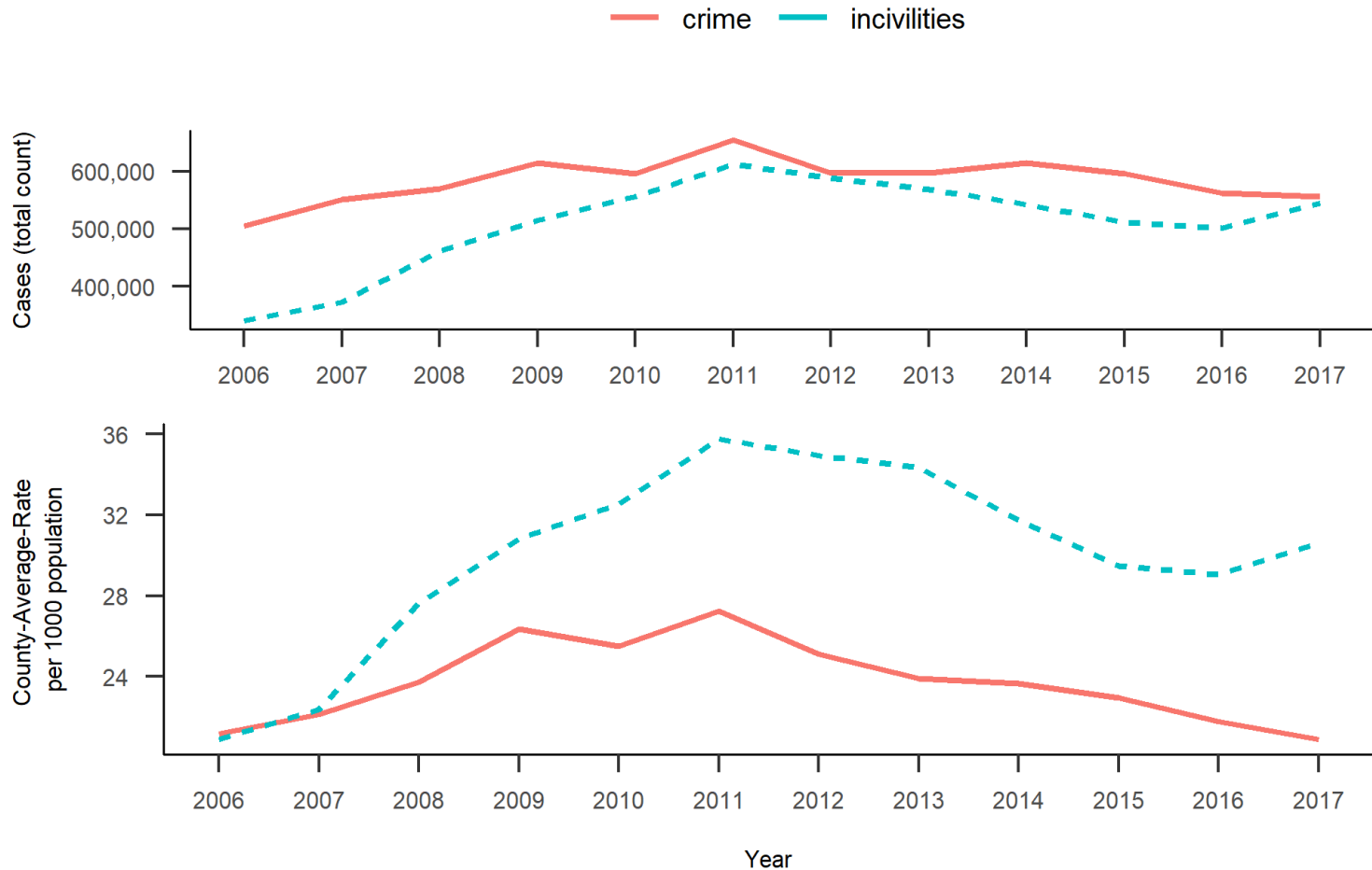
Data

- Data on the number of **incivilities** were obtained from the **"Centre of Studies and Analysis of Crime"** (Chilean government)

- Dependent variable:

$$inciv\_rate = \frac{incivilities_{it}}{n_{it}} * 1000;$$

- Where $inciv\_rate$ is the incivilities rate, t is the year, i the county and n is the population of the county per year.

- Independent variable:

  - The **Gini coefficient** is calculated for each county and included through the variable $gini$.
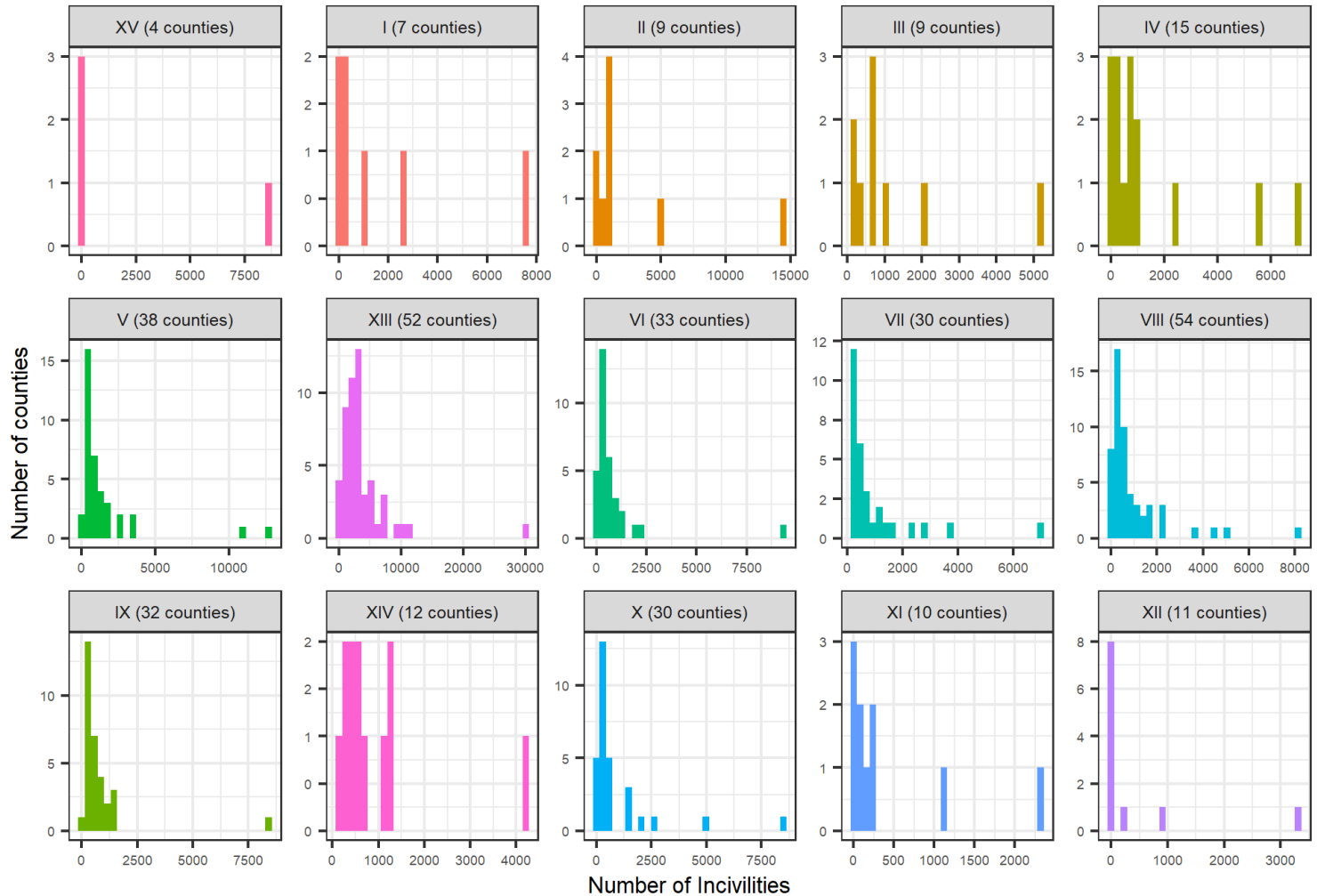
Evolution Average County Rate of Incivilities per 1000 inhabitants

Evolution Total Number of Incivilities by Category
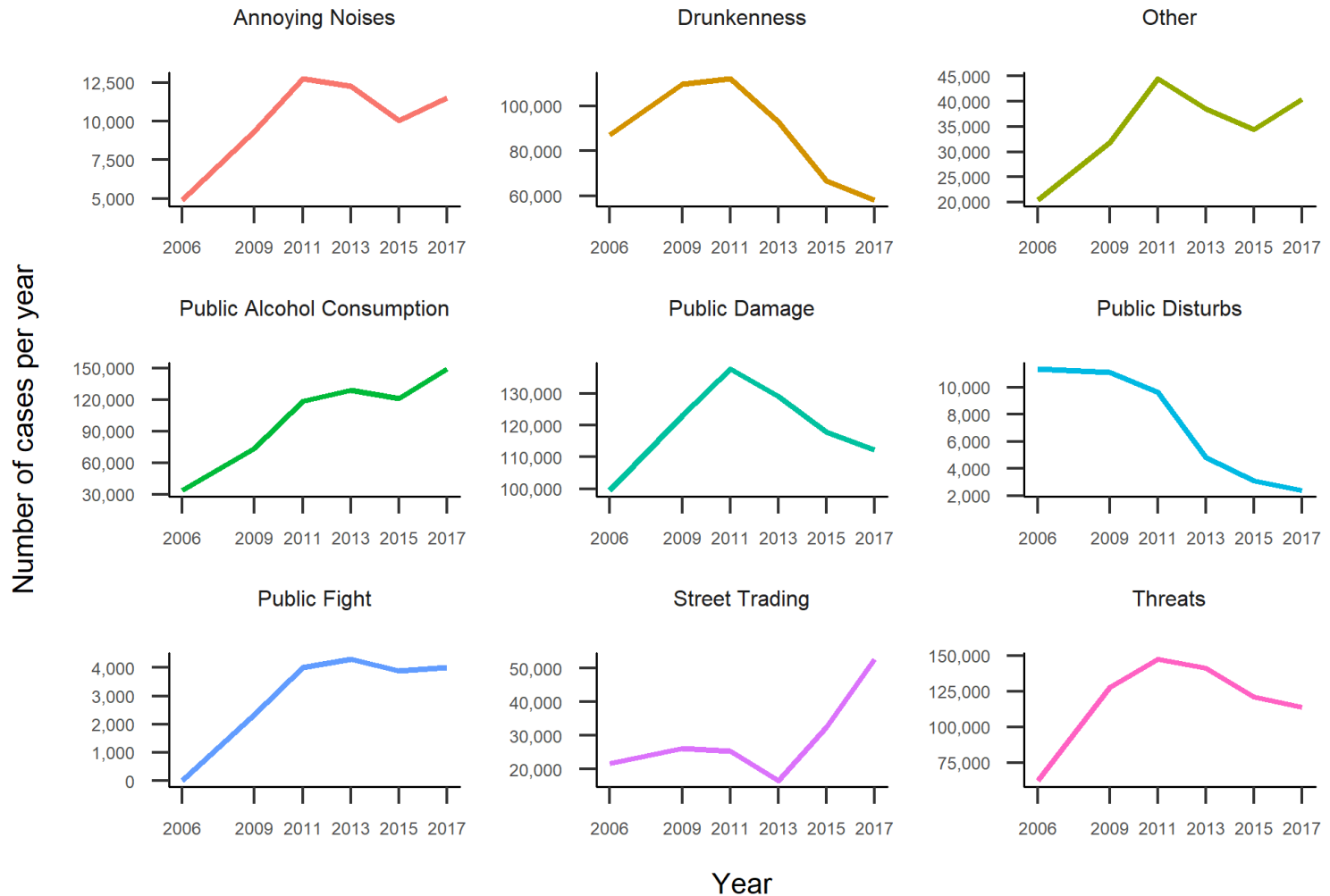
Annual Average Number of Incivilities per County

Method: Panel Count Data models

- Considering as the response variable the count of incivilities:

$$\lambda_{it} = exp(\beta_0 + \beta_1 gini_{it} + X\gamma + \alpha_i + \theta_t)$$

- where

  - λ is the rate of incivilities,
  - X is our vector of controls,
  - $\alpha's$ are county-specific constants and
  - $\theta's$ are time-specific constants.

- To account for differences in county population, we have:

$$\frac{\lambda_{it}}{\left(\frac{population_{it}}{1000}\right)} = exp(\beta_0 + \beta_1 gini_{it} + X\gamma + \alpha_i + \theta_t)$$

- The model estimated using Maximum Likelihood Estimation (MLE) is:

$$log(\lambda_{it}) = \beta_0 + \beta_1 gini_{it} + X\gamma + \alpha_i + \theta_t + log(\frac{population_{it}}{1000})$$

Results: Poisson Regression

	Pooled			Fixed Effects			Random Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
gini	0.042***	−0.010***	−0.003**	0.039***	0.021***	0.022**	0.039***	0.021***	0.020***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
log(income)	0.395***	−0.317***	−0.186***	0.275***	0.100***	0.125***	0.277***	0.101***	0.112***
	(0.011)	(0.012)	(0.013)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)
poverty	−0.0004***	0.0003**	0.0001	−0.0003***	0.003***	0.001***	0.003***	0.003***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
unemployment	−0.006***	0.003***	0.005***	0.006***	0.007***	0.008***	0.006***	0.007***	0.008***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
youth		−0.059***	−0.050***		−0.032***	−0.002		−0.031***	−0.010***
		(0.0004)	(0.0004)		(0.003)	(0.003)		(0.003)	(0.003)
foreign		0.119***	0.083***		0.028***	0.044***		0.028***	0.041***
		(0.0004)	(0.0005)		(0.0006)	(0.0007)		(0.0006)	(0.0007)
autonomy		0.004***	0.003***		−0.003***	−0.001***		−0.003***	−0.002***
		(0.00004)	(0.00004)		(0.0001)	(0.0001)		(0.0001)	(0.0001)
housing			−0.010***			−0.0003			−0.0002
			(0.0001)			(0.0002)			(0.0001)
log(density)			−0.009***			−0.469***			−0.268***
			(0.001)			(0.017)			(0.017)
women			−0.026***			0.033***			0.033***
			(0.0003)			(0.001)			(0.001)
community_org			0.002***			0.002***			0.002***
			(0.0001)			(0.0001)			(0.0001)
deterrence			0.007***			0.004***			0.005***
			(0.0001)			(0.00007)			(0.00007)
capitalYes			0.101***						0.409***
			(0.001)						(0.080)
mayorLEFT			0.010***			0.044***			0.041***
			(0.002)			(0.002)			(0.002)
mayorRIGHT			0.021***			0.034***			0.031***
			(0.002)			(0.002)			(0.002)
gini:log(income)	−0.006***	0.003***	0.001***	−0.007***	−0.004***	−0.004***	−0.007***	−0.004***	−0.004***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Constant	0.380***	5.521***	6.737***				1.409***	3.208***	2.802***
	(0.062)	(0.067)	(0.071)				(0.105)	(0.127)	(0.185)
Year Dummies?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies?	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	1,944	1,944	1,944	1,944	1,944	1,944	1,944	1,944	1,944
Log Likelihood	-285,168.100	-189,792.700	-167,855.800	-73,068.100	-71,772.252	-68,801.188	-75,895.29	-74,599.891	-71,802.581

Dependent variable: Number of Incivilities

Note: *p<0.1; **p<0.05; ***p<0.01

Results: Negative Binomial

	Dependent variable: Number of Incivilities								
	Pooled			Fixed Effects			Random Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
gini	0.064***	0.037*	0.039*	0.005	0.002	0.006	0.017	0.008	0.011
	(0.021)	(0.020)	(0.020)	(0.016)	(0.017)	(0.014)	(0.016)	(0.016)	(0.014)
log(income)	0.733***	0.339*	0.450**	−0.275*	−0.289*	0.017	0.073	−0.002	0.115
	(0.191)	(0.186)	(0.187)	(0.157)	(0.159)	(0.145)	(0.148)	(0.147)	(0.139)
poverty	−0.003	−0.001	−0.001	0.005***	0.005***	0.001	0.003*	0.003*	−0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
unemployment	0.001	0.002	0.004	0.000	0.002	0.002	0.001	0.002	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
youth		−0.015***	−0.015***		−0.077***	−0.009		−0.038***	−0.011
		(0.005)	(0.005)		(0.016)	(0.017)		(0.009)	(0.009)
foreign		0.128***	0.136***		0.026***	0.049***		0.036***	0.049***
		(0.012)	(0.013)		(0.008)	(0.011)		(0.007)	(0.008)
autonomy		0.002***	0.002***		−0.008***	−0.002*		−0.002**	0.000
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
housing			0.002			0.002			0.001
			(0.002)			(0.001)			(0.001)
log(density)			−0.032***			−0.275***			−0.106***
			(0.007)			(0.017)			(0.016)
women			−0.007*			0.014**			−0.006
			(0.004)			(0.007)			(0.006)
community_org			−0.001			0.002**			−0.002
			(0.001)			(0.001)			(0.001)
deterrence			0.003***			0.001			0.003***
			(0.001)			(0.001)			(0.001)
capitalYes			0.077***			−1.168***			−0.279***
			(0.029)			(0.104)			(0.071)
mayorLEFT			0.045**			0.048**			0.032*
			(0.022)			(0.019)			(0.018)
mayorRIGHT			−0.001			0.038*			−0.017
			(0.025)			(0.022)			(0.020)
gini:log(income)	−0.012***	−0.007*	−0.008**	−0.000	0.001	−0.001	−0.003	−0.001	−0.002
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Constant	−0.929	1.331	1.114	−0.192	2.115**	−0.533	−2.068	−0.632	−1.509*
	(1.012)	(0.999)	(1.029)	(0.832)	(0.924)	(0.931)	(1.012)	(0.819)	(0.852)
Year Dummies?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region Dummies?	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	1,944	1,944	1,944	1,944	1,944	1,944	1,944	1,944	1,944
Log Likelihood	-13,789.950	-13,712.540	-13,688.350	-10,761.609	-10,719.727	-10,493.015	-13,550.774	-13,529.049	-13,469.624

Note: *p<0.1; **p<0.05; ***p<0.01

Discussion and Recomendations

- We found strong evidence of a **significant and positive association between the rate of incivilities and income inequality**.

- Policies aimed at controlling the behaviour of **young people** do not have strong empirical support.

- The significant increase in the **foreign population** seems to be associated with a significant increase in the problem of incivilities.

- Efforts managed from the municipalities can be an important complement to those from the central government.

- Mayors supported by "LEFT" oriented political parties face higher challenges in terms of incivilities than those independent or RIGHT supported mayors.

Conclusions and Future Research

- Increasing income inequality or persistently high levels might be associated with the rise of antisocial behaviours in the form of incivilities.

- Future research should go further on the role of local authorities analysing the impact of specific programs in counties with similar characteristics.

- Program evaluation could help to elucidate the question of whether local interventions from the local governments have a causal effect on incivilities and crime rates.

- A deeper analysis of the impact that foreign migration is having on social cohesion in the Chilean society is an interesting avenue for future studies

Thanks

Thanks for Listening!

Questions?