# 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



## **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



## General Research Problem

Extant literature has documented as potential negative consequences of increasing inequality:

- Unemployment, increasing fiscal expenses, indebtedness and political instability (Berg & Ostry, 2011).
- Crime rates, health and education (Atkinson, 2015).
- Social and economic mobility and trust.
- Slow down **economic growth** by making it less inclusive and sustainable.

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

However, inequality still occupies a **secondary role** in the design of economic policy

## Essay 1:

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

## Research so far

#### **Sources (causes) of income inequality** include:

- **Globalization** (Milanovic, 2016),
- **Skill-biased technological change** (Tinbergen, 1975),
- Investment in **physical and human capital** (Murphy & Topel, 2016; Gylfason & Zoega, 2003),
- Institutions, redistributive policy and country-specific characteristics (Acemoglu, 1995, 2002; Acemoglu et al., 2001a, 2001c)
- Endowment of natural resources (Engerman & Sokoloff, 1994, 1997; Engerman, Sokoloff, Urquiola, & Acemoglu, 2002; Leamer, Maul, Rodriguez, & Schott, 1999)

#### Evidence for the Chilean economy has documented

• **High and persistent** levels of **income inequality** with **significant geographical differences** (Aroca & Bosch, 2000; Paredes, Iturra, & Lufin, 2016)

## Research Question

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

## Research Hypothesis

"A higher degree of dependence on natural resources is associated with higher levels of income inequality"

## **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
- In total 1944 observations (324 counties in 6 years)

#### Dep. Variable (*gini*)

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

#### Indep. Variable (*pss\_casen*)

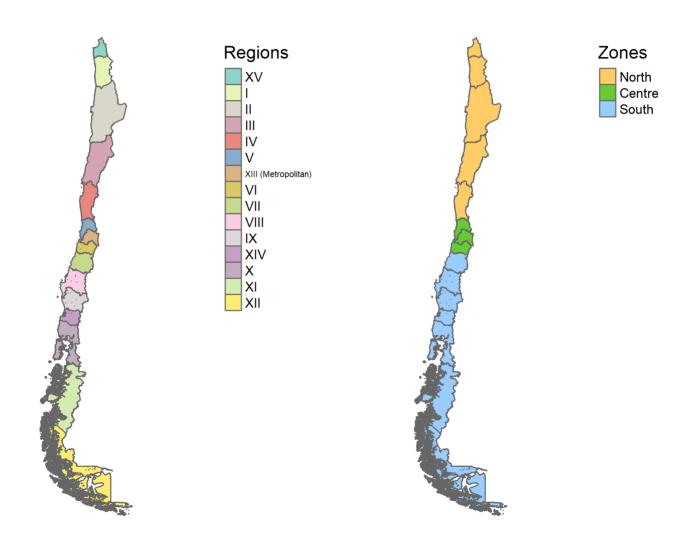
Measure of natural resource dependence: Percentage of employment in the primary sector (mining, fishing, forestry and agriculture) in each county

## Methodology (Spatial Approach) and Results

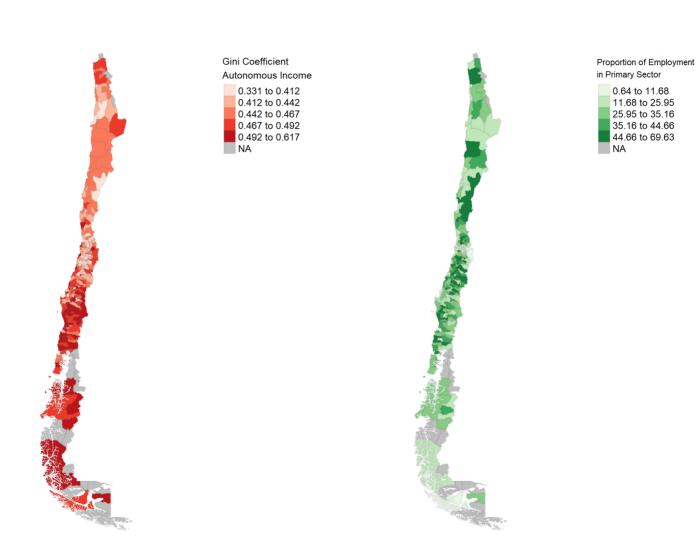
## Where (What) is Chile?



## How is the country geographically (spatially) divided?



## How are our main variables spatially distributed?



## Testing for spatial correlation (Moran's I)

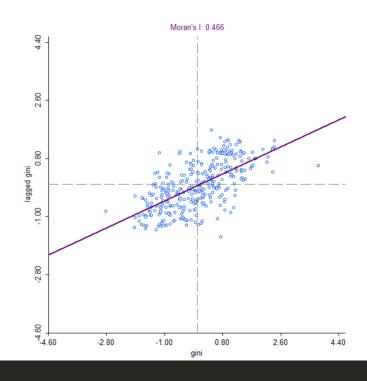
### Define "Neighbourhood" (W): 5-nearest neighbours

So, we will be analysing how "similar" is the level of inequality in one county compared to the weighted average level of inequality in the 5-nearest neighbouring counties (this is know as the **Spatial Lag**)

- $H_0$ : Spatial randomness (I = 0)
- $H_1$ : Spatial autocorrelation:
  - $\circ$  Positive (I > 0)
  - Negative (I < 0)

#### **Positive Spatial Autocorrelation:**

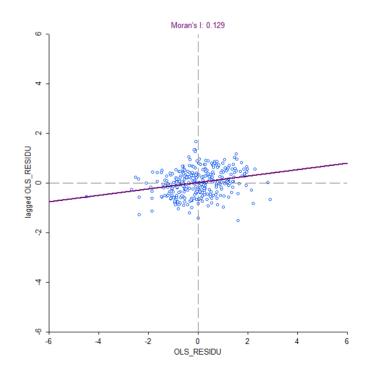
Counties with similar levels of inequality tend to be close each other



## Run an **OLS regression** of Gini against NRD (+ controls) and test for **spatial autocorrelation** in the **OLS residuals**

$$gini_i = eta_0 + eta_1 pss\_casen + eta_2 lnincome + eta_3 poverty + eta_4 unemployment + eta_5 labour\_force + eta_6 education + eta_7 lndensity + eta_8 rural + eta_9 lnmuni\_expenditure + eta_{10} north + eta_{11} south$$

- We get the OLS residuals
- We test for spatial autocorrelation in OLS residuals
- If OLS residuals show significant spatial autocorrelation,
- How should we include the spatial autocorrelation (Spatial Dependence)



## Spatial Model Specification (Cross-Sectional)

The model could be expressed as:

$$y = \lambda Wy + X\beta + WX\gamma + u$$

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 neighbouring locations)
- Thus, the parameter:
  - $\circ$   $\lambda$  capture the influence of the spatial lag for the dependent variable, Wy (Spatial Autoregressive Model, **SAR**)
  - $\circ \ \gamma$  capture the influence of the spatial lag for the explanatory variables, WX (SLX model)
  - $\circ$  ho capture the influence of the spatial lag for the errors, Wu (Spatial Error Model, **SEM**)

 $\circ$   $\epsilon$  is a vector of idiosyncratic errors.

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

	OLS	SLX	SAR	$_{\mathrm{SEM}}$	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)
Indensity	-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 <sup>2</sup>	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

 $<sup>^{***}</sup>p < 0.001,\ ^{**}p < 0.01,\ ^*p < 0.05$ 

## Panel Data Regressions (non-spatial)

_	Pooled	variable: Gini Co Pooled	Fixed Effects	Random Effects
pss_casen	-0.001***	-0.001***	<del>-0.0003*</del>	-0.001***
pss_casen	(0.0001)	(0.0001)	(0.0003)	(0.0001)
lnincome	(0.0001)	0.158***	0.184***	0.161***
mineome		(0.007)	(0.008)	(0.007)
poverty		0.002***	0.0002	0.001***
poverty		(0.002)	(0.0002)	(0.0002)
unemployment		0.003***	0.003***	0.003***
unemployment		(0.0004)	(0.0004)	(0.0003)
labour_force		$-0.002^{***}$	$-0.006^*$	$-0.003^{***}$
labout_lorce		(0.0005)	(0.003)	(0.001)
education		$-0.022^{***}$	$\frac{(0.003)}{-0.022^{***}}$	-0.023***
education		(0.002)	(0.003)	(0.002)
Indensity		$-0.003^{***}$	0.011	-0.002**
indensity		(0.001)	(0.026)	(0.001)
rural		0.0004***	-0.00004	0.0003***
lulai		(0.0004)	(0.0004)	(0.0003)
Inmuni_expenditure		-0.014***	$\frac{(0.0002)}{0.005}$	-0.013***
mmum_expenditure		(0.003)	(0.007)	(0.004)
north	0.026***	0.015***	(0.007)	0.016**
1101 011	(0.004)	(0.005)		(0.006)
south	$0.054^{***}$	0.035***		0.041***
SOUTH	(0.003)	(0.003)		(0.004)
Constant	0.468***	0.037		0.052
Constant	(0.004)	(0.037)		(0.051)
	(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**

#### **ML Spatial SEM Models**

Coefficients	Pooled	$\Pr(> \mid \! t \mid)$	FE	$\Pr(> \mid \! t \mid)$	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
Indensity	-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

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
Indensity	-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**

		SA	AR			SE	EM	
Coefficients	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
Indensity	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 Recommendations

- 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 non-spatial) 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 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 attempts 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.
- In studies about causal effects of income inequality over other variables, we could use a measure of NRD as instrument for income inequality.

## Essay 2:

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

## Research so far

- Evidence on the **Trade-off** between **efficiency and equity** is not conclusive
  - 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 have been focus on:

#### **Measuring LGE**

- Single service vs overall efficiency
- Parametric (SFA) vs nonparametric (DEA) techniques
- Input oriented vs output oriented
- Selection of inputs and outputs

#### **Explaining differences in LGE**

- Discretionary factors (inputs and outputs)
- Non-discretionary (contextual) factors: Socioeconomic, demographic, geographic, political, institutional, etc.

## Research Question

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

## Research Hypotheses

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

## Data

#### Inputs - Outputs used to measure LGE

- National System of Municipal Information, SINIM (2006-2017)
- Sample of 324 municipalities in 12 years (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

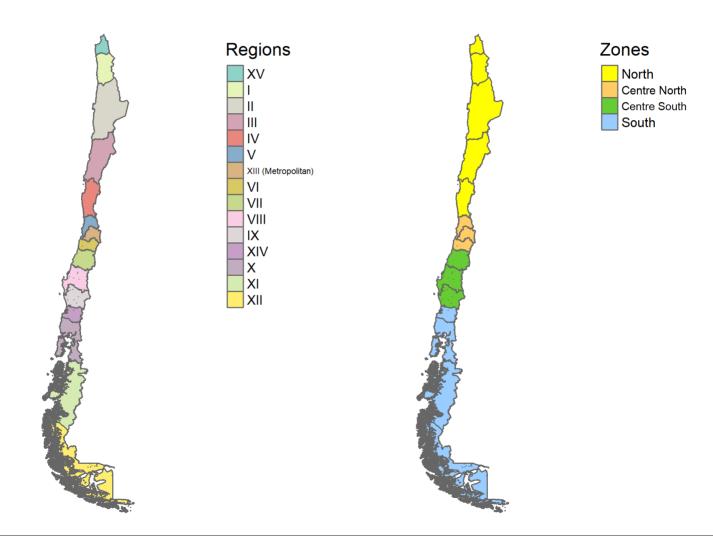
#### First Stage: DEA analysis

- Input oriented assuming variable returns to scale
- Five inputs and four outputs.
- Result: A vector of **efficiency scores (ES)** for each municipality

#### Second Stage: Regression Analysis

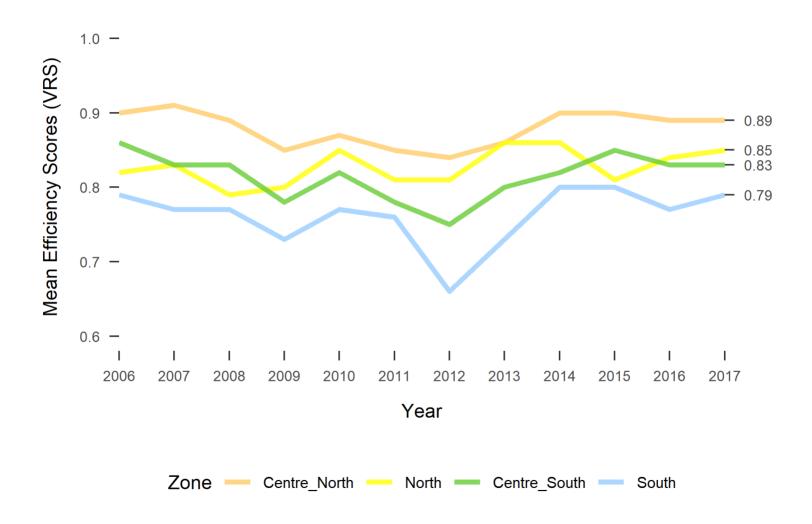
- **Dependent variable**: DEA efficiency scores
- **Independent variables**: Measure of Income inequality + remaining contextual factors including county (zone) specific and time fixed effects
- Estimation method: Censored regression + Instrumental Variable (IV)
- ullet Proposed Instrument:  $pss\_firms = rac{ ext{Number of firms in primary sector}}{ ext{Total number of firms}}$

## How do we capture geographical differences in LGE?



## First Stage: DEA Results

#### Evolution Efficiency Scores by Zone (Full Period)

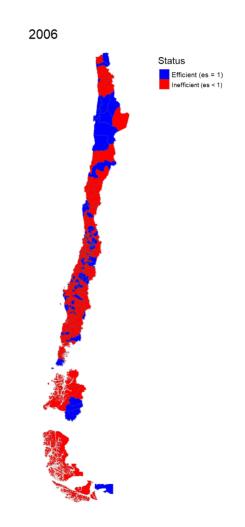


#### Efficiency Scores by Zone and Region

Unit	$n\_counties$	mean	median	$\operatorname{sd}$	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

The **mean efficiency** score for the country and the full period is **0.83**.

This means, municipalities could, on average, reduce the use of inputs in 17% to get the same level of outputs



## Second Stage

## The model

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

$$heta_{it} = eta_1 gini_{it} + Z_{it}eta + \delta_t + lpha_i + \epsilon_{it}$$

#### Where:

- $heta_{it}$  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.
- $\delta_t$  are year-specific effects,
- $\alpha_i$  are municipality-specific constants,
- $\epsilon_{it}$  is a vector of error terms and

#### Model Comparisons - Cross-sectional Censored Regressions

		Depend	dent variable: Ef	ficiency Score (VI	RS)	
	2006	2009	2011	2013	2015	2017
gini	-0.228	$-0.447^{**}$	$-0.393^*$	-0.242	-0.189	$-0.371^*$
$\log(\text{income})$	$0.119^{*}$	$0.249^{***}$	$0.208^{***}$	$0.164^{**}$	$0.221^{***}$	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
$\operatorname{mcf}$	$0.002^{*}$	$0.002^{**}$	$0.002^{**}$	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

_	Pa			variable - Efficie	ency Score (VRS)		
		censo regres.		$instrumental \ variable$			
	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**	
cadeation			(0.008)	(0.008)	(0.008)	(0.010)	
IDD			-0.004***	-0.005***	-0.002**	-0.003**	
IDD			(0.001)	(0.001)	(0.001)	(0.001)	
professional			0.001*	-0.00004	0.0004	0.0008	
professional			(0.0005)	(0.0005)	(0.0004)	(0.0005)	
mcf			0.001***	0.002***	0.001***	0.001**	
inci			(0.0003)	(0.002)	(0.0003)	(0.0004)	
I FET marray			-0.001	0.006	-0.007	-0.005	
LEFT mayor			-0.001 $(0.011)$	(0.010)	-0.007 $(0.009)$	-0.005 $(0.011)$	
DIGHT			0.017	0.005	0.000	0.010	
RIGHT mayor			0.017 $(0.012)$	0.005 $(0.011)$	0.003 $(0.010)$	0.013 $(0.012)$	
			` '	` '	. ,	` ′	
reg_cap			$-0.047^{**}$ $(0.023)$	-0.069** $(0.034)$	0.024 $(0.022)$	-0.021 (0.028)	
			` ,	` '	, ,	` ′	
Centre South	$-0.089^{***}$ $(0.012)$	$-0.086^{***}$ $(0.019)$	$0.058^{***}$ $(0.014)$	0.022 $(0.022)$	0.123*** (0.028)	$0.113^{**}$ $(0.035)$	
	(0.012)	(0.013)	(0.014)	(0.022)	(0.020)	(0.050)	
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		

## 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 **cyclical behaviour** and, on average, has remained stable in the period 2006 2017.

#### Regression analysis

- Empirical evidence of a negative relationship between inequality and efficiency.
- 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.
- Negative association with **Education**.

## 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

- How to capture **quality** in the provision of public services
- Is the negative coefficient for *education* explained by the reduction in **electoral participation**?
- Modelling spatial dependence-heterogeneity in LGE. Predictive analytics (Machine Learning?) for the probability to get an efficient performance.
- Given the current situation: 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 estate 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 Hypotheses

 $H_1$ : 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.

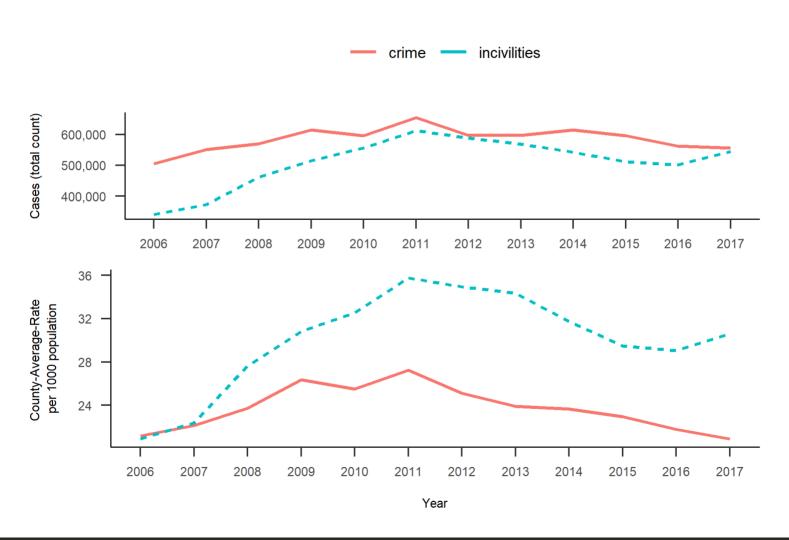
### Data

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

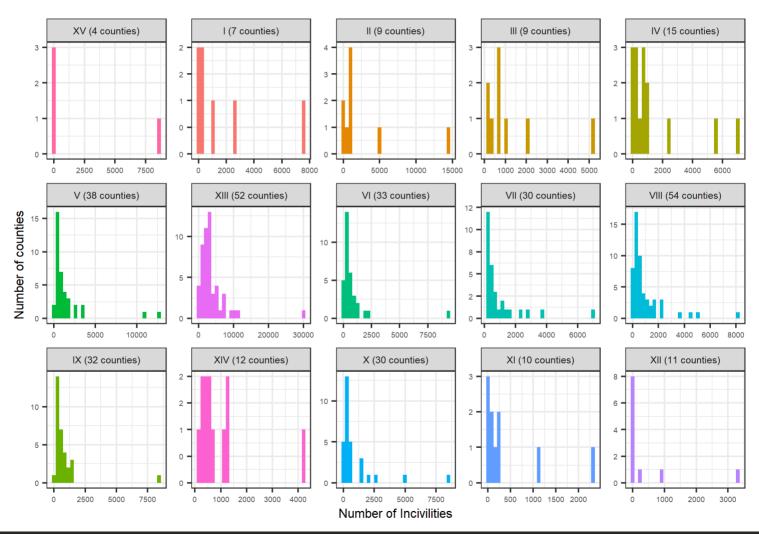
$$inciv\_rate = rac{incivilities_{it}}{n_{it}} * 1000;$$

- 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



## Annual Average Number of Incivilities per County



## Method: Panel Count Data models

• Considering as the response variable the count of incivilities:

$$\lambda_{it} = exp(eta_0 + eta_1 gini_{it} + X\gamma + lpha_i + heta_t)$$

- where
  - $\circ \lambda$  is the rate of incivilities,
  - *X* is our vector of controls,
  - $\circ \ lpha's$  are county-specific constants and
  - $\circ$   $\theta's$  are time-specific constants.
- To account for differences in county population, we have:

$$rac{\lambda_{it}}{(rac{population_{it}}{1000})} = exp(eta_0 + eta_1 gini_{it} + X\gamma + lpha_i + heta_t)$$

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

$$log(\lambda_{it}) = eta_0 + eta_1 gini_{it} + X\gamma + lpha_i + heta_t + log(rac{population_{it}}{1000})$$

### **Results: Poisson Regression**

	Dependent variable: Number of Incivilities  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***
og(income)	(0.001) 0.395*** (0.011)	(0.001) -0.317*** (0.012)	(0.001) -0.186*** (0.013)	(0.002) 0.275*** (0.017)	(0.002) 0.100*** (0.018)	(0.002) 0.125*** (0.018)	(0.001) 0.277*** (0.017)	(0.002) 0.101*** (0.018)	(0.002) 0.112*** (0.018)
poverty	-0.0004*** (0.0001)	0.0003**	0.0001 (0.0001)	-0.0003*** (0.0002)	0.003*** (0.0002)	0.001*** (0.0002)	0.003*** (0.0001)	0.003*** (0.0002)	0.001*** (0.0002)
inemployment	-0.006*** (0.0003)	0.003*** (0.0002)	0.005***	0.006***	0.007*** (0.0002)	0.008***	0.006***	0.007*** (0.0003)	0.008***
youth	(0.0000)	-0.059*** (0.0004)	-0.050*** (0.0004)	(0.000)	-0.032*** (0.003)	-0.002 (0.003)	(0.0000)	-0.031*** (0.003)	-0.010*** (0.003)
foreign		0.119*** (0.0004)	0.083*** (0.0005)		0.028*** (0.0006)	0.044*** (0.0007)		0.028*** (0.0006)	0.041*** (0.0007)
autonomy		0.004*** (0.00004)	(0.00004)		-0.003*** (0.0001)	-0.001*** (0.0001)		-0.003*** (0.0001)	-0.002*** (0.0001)
nousing		(, , ,	-0.010*** (0.0001)		(*****)	-0.0003 (0.0002)		(*****)	-0.0002 (0.0001)
og(density)			-0.009*** (0.001)			-0.469*** (0.017)			-0.268*** (0.017)
women			-0.026*** (0.0003)			(0.001)			(0.001)
community_org			(0.002***			(0.002***			(0.002***
leterrence			(0.007***			(0.00007)			(0.0007)
capitalYes			(0.001)			, ,			(0.080)
mayorLEFT			0.010*** (0.002)			0.044*** (0.002)			0.041*** (0.002)
mayorRIGHT			0.021*** (0.002)			0.034*** (0.002)			0.031*** (0.002)
gini:log(income)	-0.006*** (0.0002)	0.003*** (0.0002)	0.001*** (0.0003)	-0.007*** (0.0003)	-0.004*** (0.0004)	-0.004*** (0.0004)	-0.007*** (0.0003)	-0.004*** (0.0004)	-0.004*** (0.0003)
Constant	0.380*** (0.062)	5.521*** (0.067)	6.737*** (0.071)				1.409*** (0.105)	3.208*** (0.127)	2.802*** (0.185)
Year Dummies? Region Dummies?	Yes Yes	Yes Yes	Yes Yes	Yes No	Yes No	Yes No	Yes Yes	Yes Yes	Yes Yes
Observations Log Likelihood	1,944 -285,168.100	1,944 -189,792.700	1,944 -167,855.800	1,944 -73,068.100	1,944 -71,772.252	1,944 -68,801.188	1,944 -75,895.29	1,944 -74,599.891	1,944 -71,802.581

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## Discussion and Recommendations

- 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.

## 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

