Migration Policy Data across Time and Space

Part II

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What this session is about

- Part I: What are cross-national migration policy data and what do they measure?

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- Part I: What are cross-national migration policy data and what do they measure?
- Part II: What can I do with them and how do I do that?

What you will get out

- For users: Tools to undertake your own large-N comparative research
- For consumers & reviewers: A better ability to the evaluate the quality of large-N comparative research

What we are going to do

1. Introduce TSCS data
2. Talk about important estimation problems
3. Introduce modeling options for TSCS data
4. Look briefly at more advanced aspects

- All analyses are based on data from the IMPIC (Helbling et al. 2017) and CPDS (Armingeon et al. 2018) datasets (or simulated data)

What we are (unfortunately) not going to do

- Non-metric outcome variables (logit, etc.)

  (see Beck, Katz, and Tucker 1998; Carter and Signorino 2010; Jones and Branton 2005)

- Dyadic data (e.g. peace & conflict or trade relations)

  (see Erikson, Pinto, and Rader 2014; Green, Kim, and Yoon 2001)

- Dynamic models

  (see Beck and Katz 2011; Box-Steffensmeier and Helgason 2016; De Boef and Keele 2008)

- Spatial modeling

  (see Beck, Gleditsch, and Beardsley 2006; Franzese and Hays 2007)

What are TSCS data and what are they good for?

What are TSCS data?

TSCS data

- Repeated observations of the same units over time
- Units are typically political or geographical entities (countries, states, cantons,...)
- Time is usually measured in years
- Time is usually the dominant dimension (e.g. 20 countries over 50 years)

Example

Country	Year	Immigration policy
	[...]	
Austria	2008	0.4100881
Austria	2009	0.4257131
Austria	2010	0.4257131
Australia	1980	0.5954028
Australia	1981	0.6037361
Australia	1982	0.6037361
	[...]	

Source: The immigration policy indicator is from Helbling et al. (2017). The scale of the original indicator is reversed: Higher scores mean less stringent immigration controls.

Why use TSCS data?

- TSCS data allow us to learn substantively important information about policies and their causes and effects

  E.g. on the effects of labor market policy (Bradley and Stephens 2006), the effects of gun control legislation (Dube, Dube, and García-Ponce 2013), or the politics of immigration policy (Koopmans and Michalowski 2017; Römer 2017).

- TSCS data can allow us to use models that control for unobserved heterogeneity

  (Halaby 2004)

Relation to 'Nexus'

We can use TSCS data, migration policy data in particular, to investigate:

- ...the reasons why migration & mobility are restricted or liberalized
- ...whether liberal migration policies result in more migration (i.e. mobility)
- ...whether restrictive migration policies result in less migration

Exploring TSCS Data: Descriptive Analysis

Plotting TSCS Data – Changes over time in each country

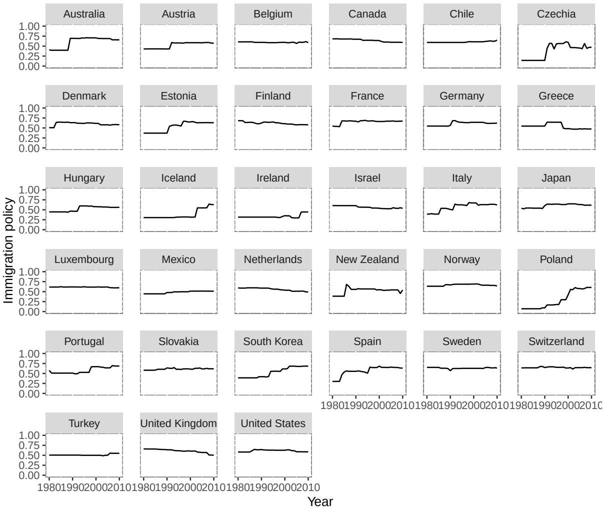

Figure 1: The development of immigration policy across countries over time

Plotting TSCS Data – Average change over time

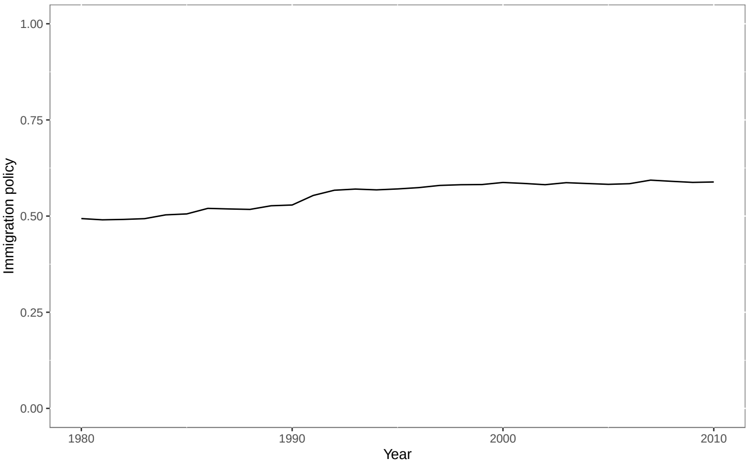

Figure 2: The development of immigration policy across countries over time

Plotting TSCS Data – The variation across countries

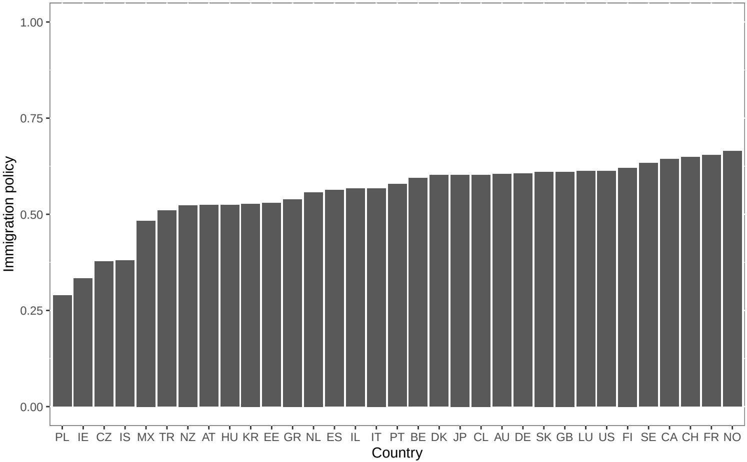

Figure 3: Differences in immigration policy across countries

Lessons from the descriptive analysis

- The generosity of voting rights for immigrants varies across countries and over time
- The variation across countries is greater than the variation over time

How do we explain this variation?

Our guiding hypothesis

Relaxed immigration policies are associated with more generous welfare states.

(cf. Römer 2017)

Can we now simply regress our immigration policy indicator on some measure of welfare state generosity and some controls?

$$\text{ImmPolicy}_{i,t} = \beta_0 + \beta_1 \text{Generosity}_{i,t} + \boldsymbol{\beta}\mathbf{x_{i,t}} + \epsilon_{i,t}$$

Modeling TSCS data:
Estimation issues

TSCS data compared

Table 1: TSCS Data

Country	Year	Imm. policy
AT	2008	0.4100881
AT	2009	0.4257131
AT	2010	0.4257131
AU	1980	0.5954028
AU	1981	0.6037361
AU	1982	0.6037361

Table 2: Survey data

ID	Gender	Income
1	M	2345
2	F	8764
3	M	234
4	F	7654
5	F	1234
6	D	9876

- What differences between TSCS and survey data can you identify?
- How might they affect regression estimations?

Requirements for valid regression estimations

Key Gauss-Markov assumptions

1. Independent error terms: Cov($\epsilon_i \epsilon_j$)$= 0$
2. Identically distributed ('homoscedastic') error terms: Var(ϵ)=σ^2_ϵ; $\sigma^2_{\epsilon\ i} = \sigma^2_\epsilon$ for all i

Gauss-Markov assumptions and TSCS data

Likely violations:

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- Observations can be correlated over time (*serial correlation*):
  Cov$(y_t y_{t+1}) \neq 0 \qquad \rightarrow \qquad$ Cov$(\epsilon_t \epsilon_{t+1}) \neq 0$

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- Observations can be correlated across countries (*contemporaneous correlation*):
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- Observations can be correlated across countries (*contemporaneous correlation*):
  Cov$(y_i y_j) \neq 0 \quad \rightarrow \quad$ Cov$(\epsilon_i \epsilon_j) \neq 0$
- Some countries are better explained than others – which means non-constant error terms (*heteroscedasticity*)

What happens to our estimates?

- Coefficient estimates are still unbiased, but some observations are better predicted than others; out-of-sample predictions are more likely to be wrong
- OLS standard errors are computed under assumption of homoscedasticity & independence – and therefore highly likely to be wrong

  (Beck and Katz 1995, 1996; see also Hayes and Cai 2007)

This means: A simple OLS regression of some y on one or more x will likely give us wrong results if we are using TSCS data

Taking care of contemporaneous correlation & heteroscedasticity

Panel-corrected standard errors (Beck and Katz 1995, 1996)

- Special type of ‘robust’ standard errors
- Correct for contemporaneous correlation & heteroscedasticity – but not serial correlation!
- Requires T of at least 15 (usually not a problem)
- In Stata: `xtpcse`; in R: `pcse`-package

  See also Bailey and Katz (2011) on the R-package

Taking care of serial correlation (I)

Two options:

- Option A: Further transform error term: $\epsilon_{t,i} = \rho\epsilon_{t-1,i} + \upsilon_{t,i}$

  (e.g. Prais-Winsten regression)
- Option B: Include lagged dependent variable $y_{t-1,i}$ as predictor into regression equation
- *Nowadays, we prefer Option B*

  (Beck and Katz 1996)

Taking care of serial correlation (I)

Testing for remaining serial correlation

1. Run the regression model you want to estimate
2. Save the residuals
3. Regress the residuals on their lags and all other covariates included in the original model
4. The coefficient for the lagged residuals should not be statistically significant

(Beck 2001, 279)

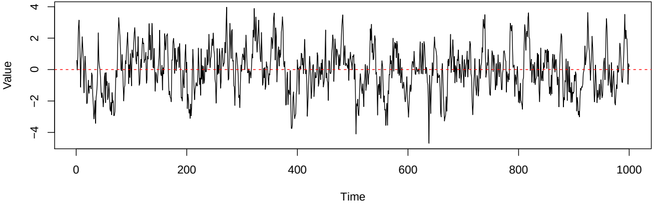
Now we have taken care of our error terms – but we are not done yet

Verifying (non-)stationarity

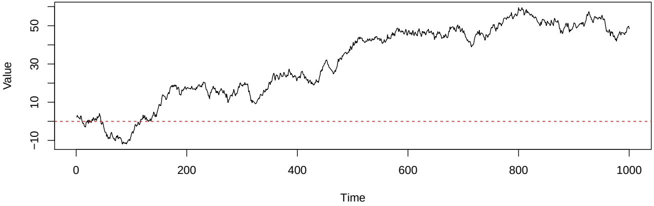
- The models we are going to talk about work on the assumption that our data are *stationary*
- Stationarity means that variables are 'mean-reverting', i.e. they may change over time but their variation is bounded within some limits that are stable over time
- Non-stationary variables (a.k.a. 'integrated', I(1), unit-roots, or 'random walks') tend to meander aimlessly over time

See also Beck and Katz (2011, 333) or Box-Steffensmeier et al. (2014); see Murray (1994) for an intuitive illustration.

Examples



(a) Stationary series



(b) Non-stationary series

Testing for stationarity

- A range of tests is available to test for stationarity or non-stationarity
- For single time-series data, one would use an Augmented Dickey-Fuller test

  (Dickey and Fuller 1981)
- Tests are also available for panel or TSCS data, but many of them are designed for typical panel data (large N, small T), not TSCS data

  (Birkel 2014; Hlouskova and Wagner 2006)
- The latter tests also tend to be not overly reliable

  (Hlouskova and Wagner 2006)

What if my data are not stationary?

- Option A: Transforming the data from levels to changes and estimating a first-difference model (see below) often works
- Option B: One can also use models specifically designed for non-stationary data (e.g. the Error-Correction Model)

(Birkel 2014)

Summary

1. TSCS data very likely violate core regression assumptions (i.i.d. errors)
2. Simply running an OLS regression (`reg` or `lm()`) on TSCS data will likely produce wrong results
3. We use panel-corrected standard errors (PCSE) and include a lagged dependent variable (LDV) to take care of contemporaneous and serial correlation and panel-heteroscedasticity
4. We need to check that our variables are stationary; if they are not, we can either transform the data or apply models for non-stationary data

Modeling TSCS data:
Specification options

Possibility I: Pooled regression

- We leave the data in their original ('pooled') TSCS format
- We apply panel-corrected standard errors & include a lagged dependent variable
- We run a regression on the pooled data

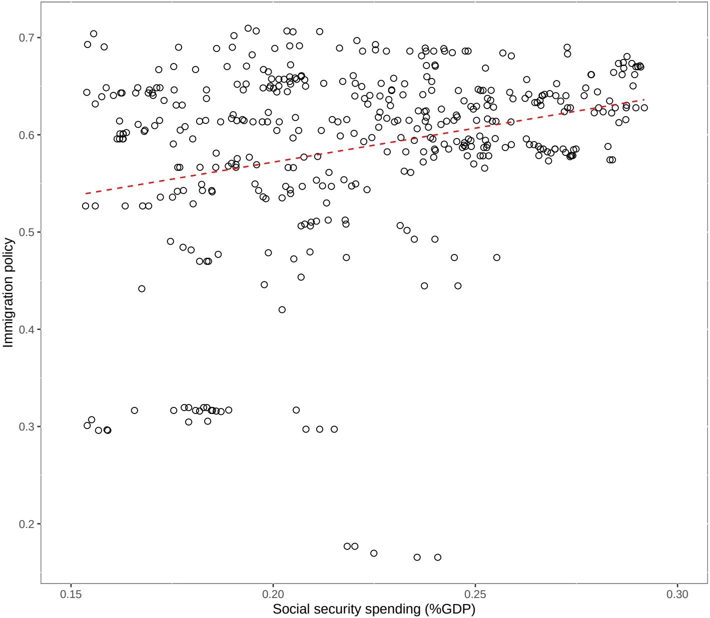
Formally:

$$y_{i,t} = \beta_0 + \gamma y_{t-1,i} + \boldsymbol{\beta}\mathbf{x_{i,t}} + \epsilon_{i,t}$$

Pooled regression results

	Coefficient	PCSE	p-value
Constant	0.03	0.01	0.00
Immigration policy (lag)	0.93	0.02	0.00
Social spending	0.06	0.03	0.05
EU	-0.01	0.00	0.09
Left govnmt.	0.00	0.00	0.76

This is, in essence, the regression we are running



What could be an issue here?

Recall

TSCS data include variation...

- ...*between* countries and...
- ...*within* countries over time

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- ...*between* countries and...
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Problem

OLS does not differentiate between cross-sectional and longitudinal variation – it simply draws a line through the data

See also Stimson (1985)

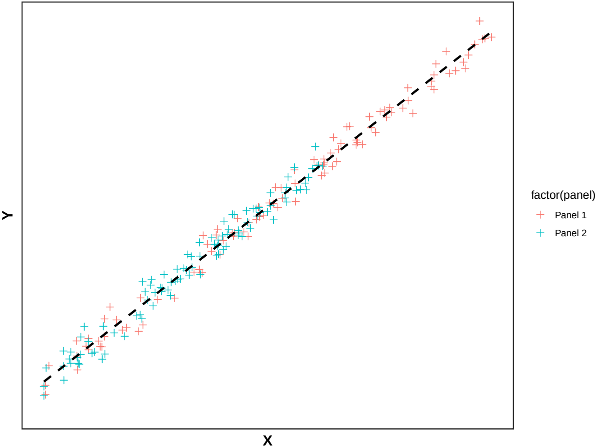


Figure 5: The ideal case

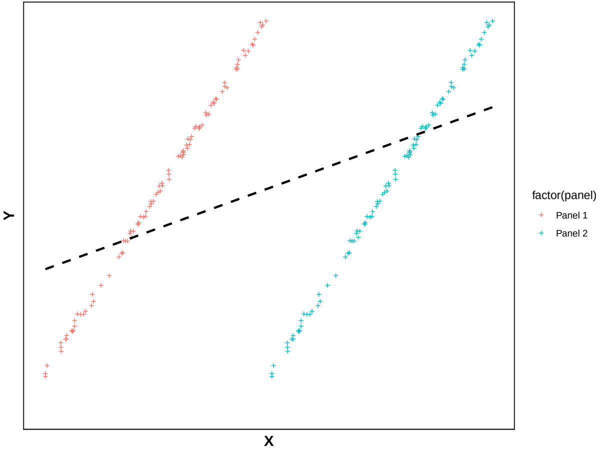


Figure 6: Underestimating the true relationship

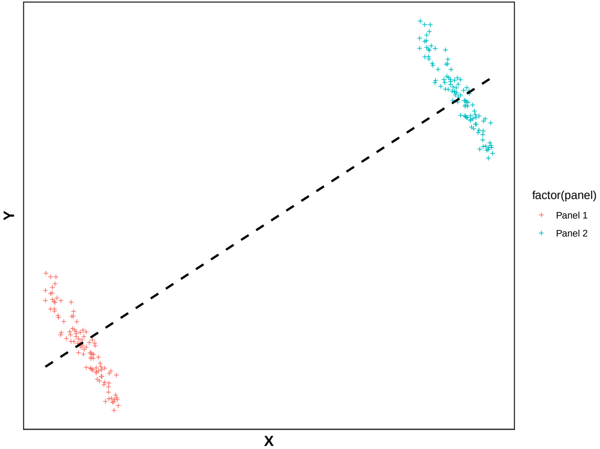
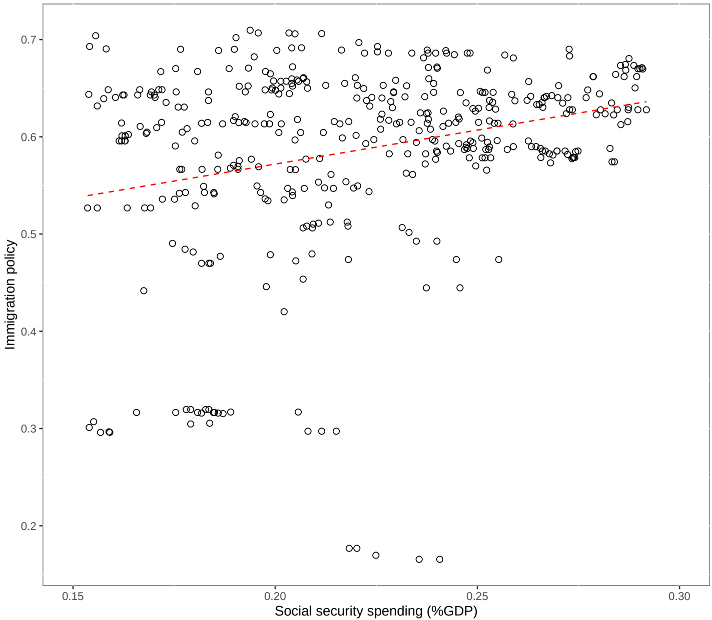


Figure 7: Entirely wrong relationship

With this in mind, what exactly do we learn here?



Lesson

- A pooled TSCS regression simply fits a line to the data – it does not differentiate between cross-country and longitudinal variation in the data
- This only delivers correct results if countries are sufficiently homogeneous and can be pooled
- If this is not the case, our results may be misleading

(Wilson and Butler 2007)

Possibility II: Fixed-effects model

- If we are doubtful about the degree of homogeneity between countries, we can include N-1 country-specific intercepts
- We can then also run an F-test for the joint significance of the country dummies to test the pooling assumption

  See also Wilson and Butler (2007, 105)
- (Alternative: transforming all observations into deviations from their country-specific means)

  This is what 'canned' FE-models do, e.g. `xtreg, fe` in Stata
- Important: We are now looking only at the variation **within** countries!

Formally

Country dummies:

$$y_{i,t} = \beta_0 + \gamma y_{i,t-1} + \boldsymbol{\beta}\mathbf{x_{i,t}} + \omega_i + \epsilon_{i,t}$$

where ω_i represents $N-1$ country dummies

Deviations from mean:

$$(y_{i,t} - \overline{y_{i,.}}) = \beta_0 + \gamma(y_{i,t-1} - \overline{y_{i,.}}) + \boldsymbol{\beta}(\mathbf{x_{i,t}} - \overline{\mathbf{x_{i,.}}}) + \epsilon_{i,t}$$

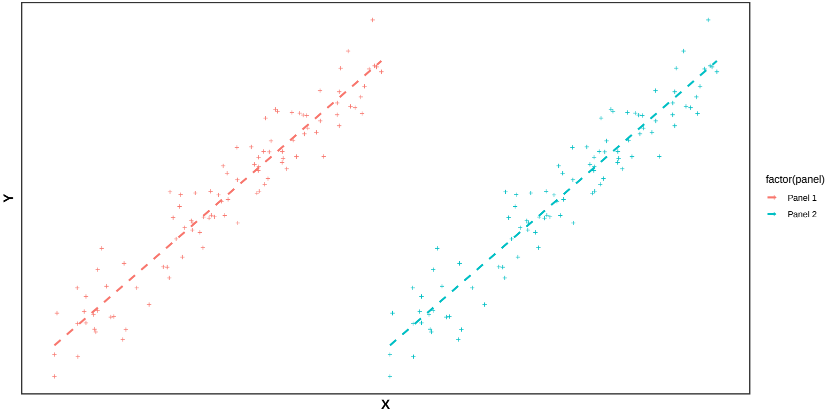


Figure 9: Fixed-effects estimation illustrated

Results from Fixed-effects model

	Coefficient	PCSE	p-value
Constant	0.08	0.03	0.01
Immigration Policy (lag)	0.90	0.04	0.00
Social spending	-0.06	0.06	0.29
EU	-0.01	0.01	0.10
Left govnmt.	0.00	0.00	0.76

Notes: Country intercepts are omitted.

Results from Fixed-effects model

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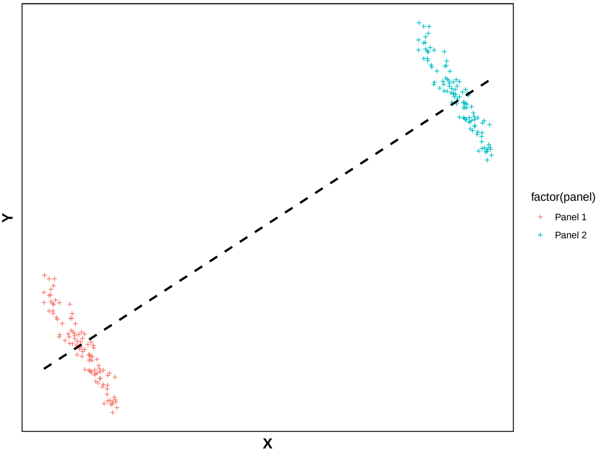
Left govnmt.	0.00	0.00	0.76

Notes: Country intercepts are omitted.

$\rightarrow$ **Note the reversed sign of the coefficient for social spending!**

This suggests that the relationship between welfare spending and immigration policy *within* each country looks something like this



- The Fixed-effects model provides a clearer picture of what is going on in the data
- Problem: We can only look at variation *within* countries – and we know from the descriptive analysis that there is more variation *between* than *within* countries!

Possibility III: The between-effects model

- We decide that we want to look only at differences **between** countries
- We therefore collapse the data by computing for each variable the average per country
- Our data are then simple cross-sectional data and we can now run a normal regression model
- Alternative: Run a between-effects model and let the computer do the math

  (e.g. `xtreg, be` in Stata)

Formally

$$\overline{y_{i.}} = \beta_0 + \boldsymbol{\beta}\overline{\mathbf{x_{i.}}} + \epsilon_{i,.}$$

This is not more complicated than this:

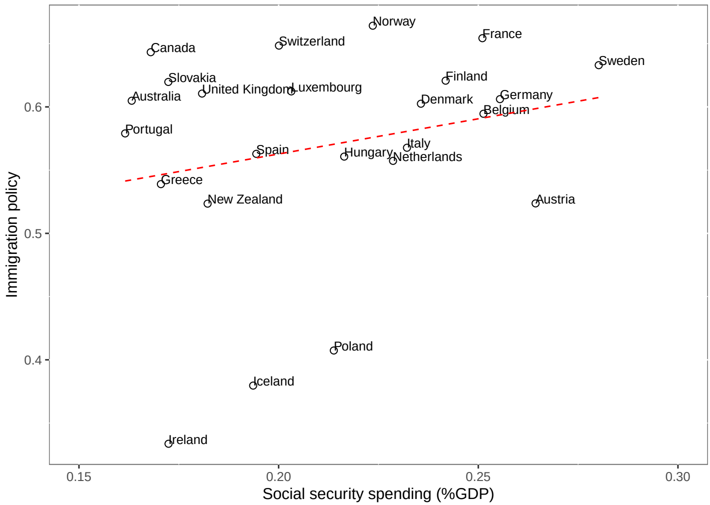


Figure 10: The association between welfare state spending and immigrant voting rights

Regression model comparison

Table 3: Comparison of OLS on country averages and between-effects estimator

	OLS on means	Between-effects
Constant	0.513 (0.090)*	0.513 (0.087)*
Social spending	0.287 (0.433)	0.307 (0.417)
R^2	0.018	0.022
Num. obs.	26	26

$^* p < 0.05$

- This is a quick and easy way to approach TSCS data
- But: It is not an efficient use of our data – we lose all the variation over time in the data!
- And: We cannot tell in which direction the relationships go!

Possibility IV: First-differences

- We look only at **year-to-year changes within** each country
- We therefore transform the data from levels to changes
- This removes all the variation between countries from the data
- This usually also deals with serial correlation and non-stationarity

Formally

$$\Delta y_{i,t} = \beta_0 + \boldsymbol{\beta} \boldsymbol{\Delta} \mathbf{x_{i,t}} + \epsilon_{i,t}$$

Important: We are now analyzing a different set of data!

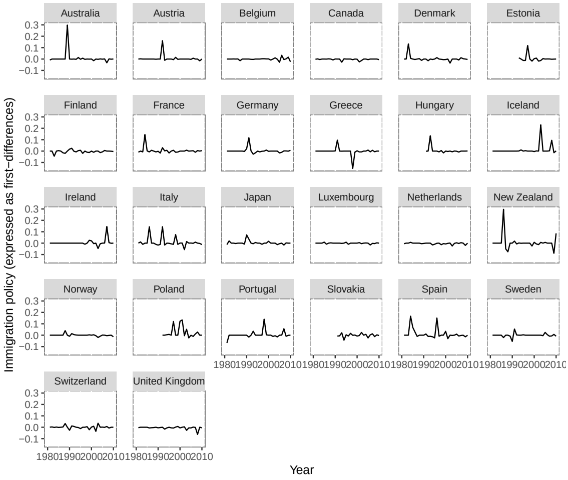


Figure 11: Immigrant voting rights across countries, expressed as first-differences

Results from first-differences model

	Coefficient	PCSE	p-value
Constant	0.00	0.00	0.27
Social spending (Δ)	0.04	0.12	0.73
EU (Δ)	-0.01	0.02	0.75
Left govnmt. (Δ)	0.00	0.00	0.42

Modeling TSCS data:
Other things to keep in mind

Fixed-effects and LDVs: Nickell-bias

- Combining a LDV with fixed-effects should only be done if T is sufficiently large ($>$20)!

  (Beck and Katz 2011)

- Otherwise the estimation **is** biased

  (Nickell 1981)

- If you absolutely need to combine FE and a LDV in shorter panels, you need to use specific "dynamic panel estimators". These are not designed for TSCS data, though!

  (Arellano and Bond 1991; Blundell and Bond 1998; Bond 2002; Wawro 2002)

FE, FD and institutions or 'sluggish' variables

- We are sometimes interested in the effects of variables that either never change or change very rarely, e.g. political institutions
- Some countries could, for instance, be 'kinder and gentler' to both immigrants and the poor alike because of their consensual political systems

  (Lijphart 1984, 1999)
- These institutions change very rarely, if ever
- **Both fixed-effects and first-difference models cannot estimate the effects of stable country-specific variable**

FE, FD and stable factors

- Assume that $\theta_{i,t}$ represents a variable that varies only between but never within countries (like political institutions)
- This means:

FE, FD and stable factors

- Assume that $\theta_{i,t}$ represents a variable that varies only between but never within countries (like political institutions)
- This means:

θ is constant over time within countries

$$\theta_{i,t=1} = \theta_{i,t=2} = [...] = \theta_{i,T}$$

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$$\theta_{i,t=1} = \theta_{i,t=2} = [...] = \theta_{i,T}$$

The year-to-year change in θ is 0 within each country

$$\theta_{i,t=t} - \theta_{i,t=t+1} = 0$$

FE, FD and stable factors

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The year-to-year change in θ is 0 within each country

$$\theta_{i,t=t} - \theta_{i,t=t+1} = 0$$

Each $\theta_{i,t}$ is the same as its average within each country, $\overline{\theta_{i,.}}$

$$\theta_{i,t} = \overline{\theta_{i,.}} \quad \rightarrow \quad \theta_{i,t} - \overline{\theta_{i,.}} = 0$$

First-differences & stable predictors

The first-difference model with a stable predictor, θ

$$\Delta y_{i,t} = \beta_0 + \boldsymbol{\beta}\boldsymbol{\Delta}\mathbf{x_{i,t}} + \lambda\Delta\theta_{i,t} + e_{i,t}$$

...can also be written like this:

$$(y_{i,t} - y_{i,t-1}) = \beta_0 + \boldsymbol{\beta}(\mathbf{x_{i,t}} - \mathbf{x_{i,t-1}}) + \lambda(\theta_{i,t} - \theta_{i,t-1}) + e_{i,t}$$

We know that $\theta_{i,t} - \theta_{i,t-1} = 0$ because θ never changes. The coefficient, λ, can never be significant in this model!

Fixed-effects & stable predictors

The fixed-effects model with a stable predictor, θ

$$(y_{i,t} - \overline{y_i}) = \beta_0 + \gamma(y_{i,t-1} - \overline{y_i}) + \boldsymbol{\beta}(\mathbf{x_{i,t}} - \overline{\mathbf{x_i}}) + \lambda(\theta_{i,t} - \overline{\theta_{i,.}}) + \epsilon_{i,t}$$

We again know that:

$$\theta_{i,t} = \overline{\theta_{i,.}} \quad \rightarrow \quad \theta_{i,t} - \overline{\theta_{i,.}} = 0$$

Here as well, the coefficient, λ, is therefore also never going to be significant!

Summary on model selection

- **Pooled TSCS models are risky.** One should verify that countries are sufficiently homogenous
- **Alternative A**: Look at variation within countries using either a fixed-effects or a first-difference model

  (as e.g. Rueda 2015)
- **Alternative B**: Choose a between-effects model; recommended when one is primarily interested in stable or 'sluggish' variables like institutions

  (as e.g. Iversen and Soskice 2006)
- Also:
  - Be careful when combining FE and a LDV
  - When faced with unit-root variables, using a first-difference model might be a solution; otherwise think about co-integration

    (Birkel 2014; Murray 1994)

Checklist

1. Do I have a clear theoretical expectation of what variation and covariation (within countries, between countries, both) I expect to find?
2. Did I use descriptive statistics to get a first sense of what is happening in the data?
3. Did I make sure that my model deals with any serial or contemporary correlation and heteroscedasticity present?
4. Did I check that my variables are stationary?
    - If they are not, did I consider transforming the data to changes or running models for integrated data?
5. Did I verify that my regression model is capturing the patterns in the data correctly?

Extensions

Dynamics

- All the models we talked about have the built-in assumption that any effects of x on y are *instantaneous*
- An increase in welfare state generosity in one year, e.g., is supposed to lead to relaxed immigration policy *in the same year*
- This assumption can be problematic given that political reforms often take considerable time
- Dynamic models, which include lagged predictors, can be used to capture delayed and long-term effects

For details see Beck and Katz (2011) and De Boef and Keele (2008).

Two commonly used dynamic models for TSCS data

The Autoregressive Distributed Lag (ADL) Model

$$y_{i,t} = \beta_0 + \gamma y_{i,t-1} + \boldsymbol{\beta}\mathbf{x_{i,t}} + \boldsymbol{\lambda}\mathbf{x_{i,t-1}} + \epsilon_{i,t}$$

The Single-Equation Error-Correction Model (ECM)

$$\Delta y_{i,t} = \beta_0 + \gamma y_{i,t-1} + \boldsymbol{\beta}\boldsymbol{\Delta}\mathbf{x_{i,t}} + \boldsymbol{\lambda}\mathbf{x_{i,t-1}} + \epsilon_{i,t}$$

Spatial effects

- One of the problems we faced earlier and solved with PCSEs was that of contemporaneous correlation
- Two countries could for instance be connected in some way (e.g. the Dutch and Belgian economies)
- PCSEs 'control away' this variation, but we may be interested in precisely this – for instance if we are working on policy diffusion theories

  (Helmdag and Kuitto 2018; Jahn 2006; Lee and Strang 2006; Schmitt 2011)
- Spatial regression models allow us to analyze connections between countries

  See e.g. Beck, Gleditsch, and Beardsley (2006) or Franzese and Hays (2006, 2007)

Non-metric dependent variables

- All the models we talked about are for metric or linear dependent variables
- Sometimes we want to/need to use other variables such as binary indicators
- Logistic regression can be used to model binary dependent variables in TSCS data
- Important: Time dependence must be modeled as well
- This can be done by including a variable for time and its second and third polynomial

A TSCS model for binary dependent variables

$$y_{i,t} = \mathrm{logit}(\beta_0 + \boldsymbol{\beta}\mathbf{x_{i,t}} + \delta_1 \mathrm{time}_t + \delta_2 \mathrm{time}_t^2 + \delta_3 \mathrm{time}_t^3 + \epsilon_{i,t})$$

See Beck, Katz, and Tucker (1998) and Carter and Signorino (2010); see also Jones and Branton (2005) for an approach based on duration models.

Integrated variables & co-integration

- One of the important steps in our analysis was to test our data for stationarity – whether variables are mean-reverting and have stable variances over time
- Time-series analysts have developed a methodology for non-stationary variables, which centers on the concept of co-integration

  See Murray (1994) for a very easy and illustrative example; see Box-Steffensmeier et al. (2014) or Thome (2014) for a more thorough introduction
- Co-integration tests are also available for panel/TSCS data, but they are not widely used in the social sciences

  (Birkel 2014)

Missingness & inferences

Missing data

Honaker and King have developed AMELIA, a multiple-imputation package for TSCS data

Honaker and King (2010); see also Honaker, King, and Blackwell (2011)

Better inferences and analysis

Williams and Whitten have developed a package (for Stata) to maximize the amount of information you can get out of TSCS models (e.g. to simulate effects over time).

Williams and Whitten (2012); see also King, Tomz, and Wittenberg (2000); Tomz, Wittenberg, and King (2003)

Helpful resources

- Murphy (2014): Intro to TSCS analysis in R
- Torres-Reyna (2010): Getting started with Fixed/Random Effects Models using R
- Swirl (`https://swirlstats.com/`): Interactive learning tool for R

Replication code for today

Replication code (for R) is available on GitHub[1]

[1] The password for the data folder is the city we're in today (lowercase, no accents).


That's all Folks!

Thanks!
Questions?

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