Long-Term Macroeconomic Effects of Climate Change: An Introduction to the Theory and Application of Dynamic Panel Models

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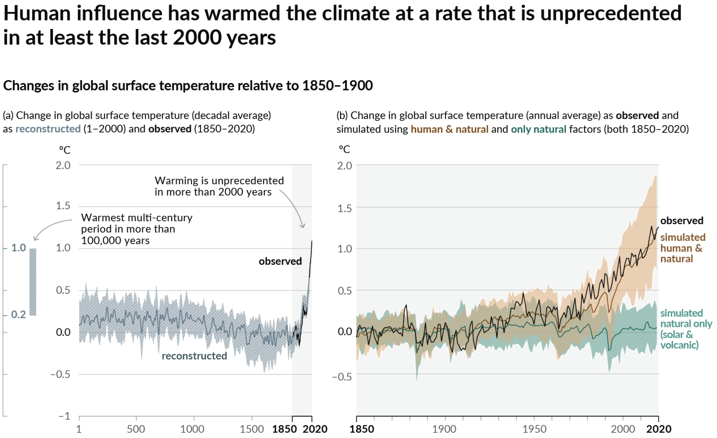
- Global temperatures have increased significantly in the past half century possibly causing a wide range of impacts.
  - Cold snaps and heat waves, droughts and floods, hurricanes, higher sea levels, and weather whiplash.



Source: Intergovernmental Panel on Climate Change (IPCC, 2021)

- By 2100, the global mean temperature will probably be 1–6 degrees Celsius higher than the pre-industrial temperature, depending on scenario and model.
- A persistent rise in temperatures, changes in precipitation patterns and/or more volatile weather events can have longterm macroeconomic effects by adversely affecting labour productivity, slowing investment and damaging human health.

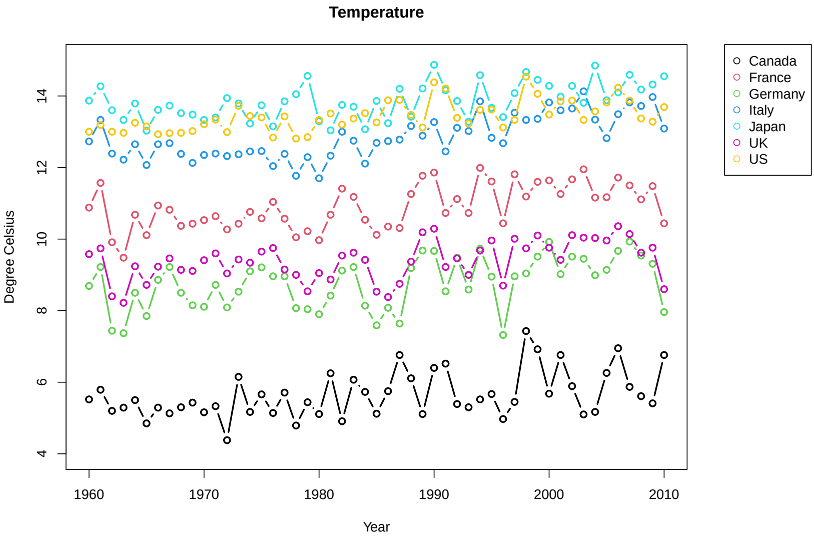
SSP	2041 — 2060	2081 — 2100	Very likely (90%) range
SSP1-1.9	1.6 $^\circ C$	1.4 $^\circ C$	[1.0, 1.8]
SSP1-2.6	1.7 $^\circ C$	1.8 $^\circ C$	[1.3, 2.4]
SSP2-4.5	2.0 $^\circ C$	2.7 $^\circ C$	[2.1, 3.5]
SSP3-7.0	2.1 $^\circ C$	3.6 $^\circ C$	[2.8, 4.6]
SSP5-8.5	2.4 $^\circ C$	4.4 $^\circ C$	[3.3, 5.7]

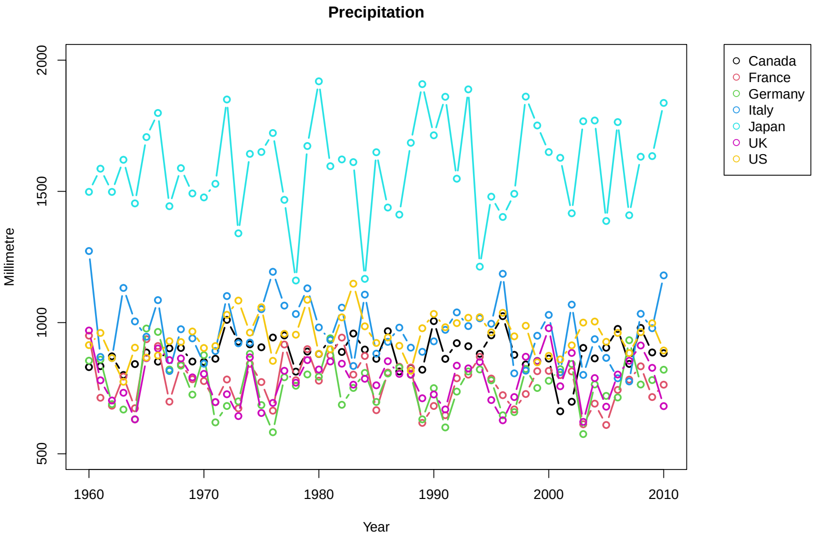
Source: Intergovernmental Panel on Climate Change (IPCC, 2021)

- The literature which attempts to quantify the effects of weather and/or climate on economic performance is growing fast.
- The more recent literature largely uses **panel data** models to estimate the economic effects of weather shocks.
  - See, for example, Burke et al. (2015), Dell et al. (2009, 2012, 2014), Hsiang (2016), Schlenker and Auffhammer (2018), Newell et al. (2021), and Kahn et al. (2021).
- In this talk we will discuss:
  - the fixed effects (FE) estimator for panel models,
  - the Nickell bias in dynamic panel models,
  - the Generalized Method of Moments (GMM) estimator for panel models, and
  - the Half-Panel Jackknife Fixed Effects (HPJFE) Estimator.

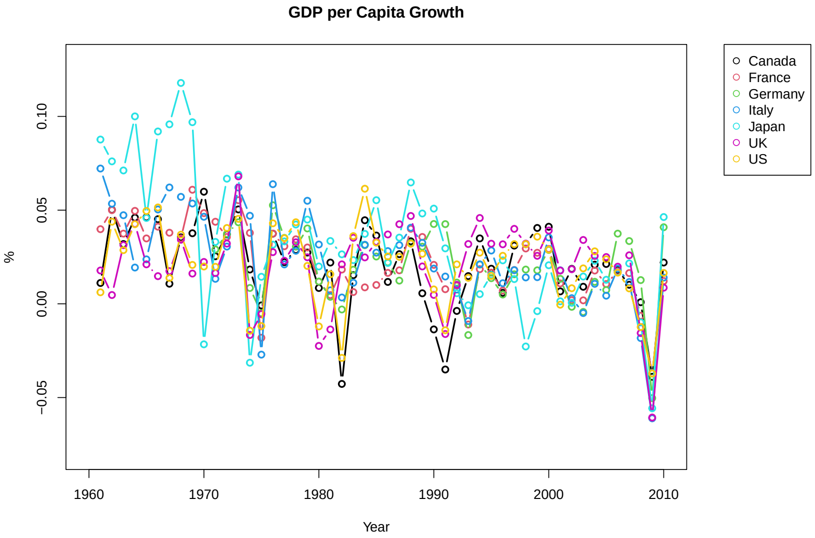
Panel Data

- A **cross-sectional** data set consists of a sample of individuals, households, firms, cities, states, countries, or a variety of other units, taken at a given point in time.
- A **time series** data set consists of observations on a variable or several variables over time.
  - E.g., stock prices, money supply, consumer price index, gross domestic product, annual homicide rates, and automobile sales figures.
- A **panel data** set (a.k.a. a **longitudinal** data set) consists of a sample of the same individuals, families, firms, cities, states, or whatever, across time.
  - Having both a cross-sectional and a time series dimension, a panel data set differs in some important respects from an independently pooled cross section or a time series.


Temperature
Degree Celsius
Year
4
6
8
10
12
14
1960
1970
1980
1990
2000
2010
Canada
France
Germany
Italy
Japan
UK
US



Precipitation
Millimetre
Year
500
1000
1500
2000
1960
1970
1980
1990
2000
2010
Canada
France
Germany
Italy
Japan
UK
US


GDP per Capita Growth
%
0.10
0.05
0.00
−0.05
1960
1970
1980
1990
2000
2010
Year
Canada
France
Germany
Italy
Japan
UK
US

- To estimate the effect of climate on the global economy, one way is to regress the economic growth rate on the temperature and precipitation:

$$g_{it} = \beta_0 + \beta_1 temp_{it} + \beta_2 prec_{it} + \varepsilon_{it}.$$

- For country $i = 1, 2, \ldots, N$ and year $t = 1, 2, \ldots, T$,
  - g_{it}: growth rate of per-capita output
  - $temp_{it}$: annual average temperature.
  - $prec_{it}$: annual accumulated precipitation.

- But *different countries are different*!
- The simple model likely suffers from *omitted variable* problems.
  - E.g., culture, history, age distribution, gender distribution, education levels, law enforcement efforts, and so on.
- One possible solution is to try to control for more factors.
  - However, many factors might be hard to control for.
- Most panel data models view the unobserved factors affecting the dependent variable as consisting of two types, α_i^* and u_{it}:

$$\begin{aligned} g_{it} &= \beta_0 + \beta_1 temp_{it} + \beta_2 prec_{it} + \varepsilon_{it} \\ &= \beta_0 + \beta_1 temp_{it} + \beta_2 prec_{it} + \alpha_i^* + u_{it}. \end{aligned}$$

- α_i^* controls the constant differences between countries.

Random Effects vs Fixed Effects

$$
\begin{aligned}
y_{it} &= \beta_0 + \mathbf{x}_{it}^\top \beta + \alpha_i^* + u_{it} \\
&= \alpha_i + \mathbf{x}_{it}^\top \beta + u_{it}.
\end{aligned}
$$

- When the unobserved variables $\{\alpha_i^*\}$ are **uncorrelated** with the observed variables ($\mathbf{x}_{it}$), the model is known as a *random effects model*.
  - In the random effects models, to simply regress y_{it} on $\mathbf{x}_{it}$ is actually fine.
- When the unobserved variables $\{\alpha_i^*\}$ are allowed to have any associations whatsoever with the observed variables ($\mathbf{x}_{it}$), the model is known as a *fixed effects model*.

Estimation of Fixed Effects Models

$$y_{it} = \alpha_i + \mathbf{x}_{it}^\top \beta + u_{it}.$$

- Let $\bar{y}_i = T^{-1} \sum_{t=1}^{T} y_{it}$, $\bar{\mathbf{x}}_i = T^{-1} \sum_{t=1}^{T} \mathbf{x}_{it}$, and $\bar{u}_i = T^{-1} \sum_{t=1}^{T} u_{it}$.

$$\bar{y}_i = \alpha_i + \bar{\mathbf{x}}_i^\top \beta + \bar{u}_i.$$

- Combining two equations yields

$$y_{it} - \bar{y}_i = \left(\mathbf{x}_{it} - \bar{\mathbf{x}}_i\right)^\top \beta + \left(u_{it} - \bar{u}_i\right).$$

  - The unobserved variables $\{\alpha_i\}$ vanish!
- That is, to identify β β, we may regress $y_{it} - \bar{y}_i$ on $\mathbf{x}_{it} - \bar{\mathbf{x}}_i$.
- The **fixed effects** estimator is also known as the **within** estimator.

```r
library(plm)
temp$UDel_temp_popweight_2 <- temp$UDel_temp_popweight^2
BHM <- plm(growthWDI ~ UDel_temp_popweight + UDel_temp_popweight_2 +
             I(UDel_precip_popweight/1000) + I(UDel_precip_popweight_2/1000000) +
             I(year) + (iso*time) + (iso*time2),
           data=temp, index=c("iso","year"), model="within")
summary(BHM)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = growthWDI ~ UDel_temp_popweight + UDel_temp_popweight_2 +
##     I(UDel_precip_popweight/1000) + I(UDel_precip_popweight_2/1e+06) +
##     I(year) + (iso * time) + (iso * time2), data = temp, model = "within",
##     index = c("iso", "year"))
##
## Unbalanced Panel: n = 166, T = 8-50, N = 6584
##
## Residuals:
##       Min.    1st Qu.     Median    3rd Qu.       Max.
## -0.6354166 -0.0188812  0.0016402  0.0219689  0.6638493
##
## Coefficients: (2 dropped because of singularities)
##                                    Estimate  Std. Error t-value  Pr(>|t|)
## UDel_temp_popweight              0.01271774  0.00324787  3.9157 9.113e-05 ***
## UDel_temp_popweight_2           -0.00048708  0.00010294 -4.7317 2.277e-06 ***
## I(UDel_precip_popweight/1000)    0.01440048  0.01024661  1.4054   0.15996
## I(UDel_precip_popweight_2/1e+06) -0.00473187  0.00249887 -1.8936   0.05833 .
## I(year)1962                     -0.07154891  0.37842535 -0.1891   0.85004
## I(year)1963                     -0.14955184  0.74831439 -0.1999   0.84160
## I(year)1964                     -0.20721736  1.10981228 -0.1867   0.85189
## I(year)1965                     -0.28330201  1.46293200 -0.1937   0.84645
## I(year)1966                     -0.36112138  1.80764344 -0.1998   0.84166
## I(year)1967                     -0.42675258  2.14395270 -0.1990   0.84223
## I(year)1968                     -0.48229613  2.47186222 -0.1951   0.84531
## I(year)1969                     -0.53640639  2.79137655 -0.1922   0.84762
## I(year)1970                     -0.59488337  3.10247293 -0.1917   0.84795
## I(year)1971                     -0.66733501  3.40517327 -0.1960   0.84463
```

- The **fixed effects** estimator, a.k.a. the **within** estimator, regresses $y_{it} - \bar{y}_i$ on $\mathbf{x}_{it} - \bar{\mathbf{x}}_i$.

$$\hat{\beta}_{FE} = \left[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)(\mathbf{x}_{it} - \bar{\mathbf{x}}_i)^\top \right]^{-1} \left[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)(y_{it} - \bar{y}_i) \right].$$

- Alternatively, the model can be written as:

$$\begin{aligned} y_{it} &= \alpha_i + \mathbf{x}_{it}^\top \beta + u_{it} \\ &= \alpha_1 \mathbb{I}(i = 1) + \alpha_2 \mathbb{I}(i = 2) + \cdots + \alpha_N \mathbb{I}(i = N) + \mathbf{x}_{it}^\top \beta + u_{it}. \end{aligned}$$

  - The function $\mathbb{I}(\cdot)$ is the indicator function.
- The **least squares dummy variables** (LSDV) estimator, which regresses y_{it} on $\mathbf{x}_{it}$ and $\{\mathbb{I}(i = 1), \mathbb{I}(i = 2), \ldots, \mathbb{I}(i = N)\}$, is numerically identical to the *within* estimator.

- It is easy to show that

$$\hat{\beta}_{FE} - \beta = \left[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\mathbf{x}_{it} - \bar{\mathbf{x}}_i \right) \left(\mathbf{x}_{it} - \bar{\mathbf{x}}_i \right)^\top \right]^{-1} \left[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\mathbf{x}_{it} - \bar{\mathbf{x}}_i \right) u_{it} \right].$$

- As $N \to \infty$ (and T is fixed,) by the *law of large numbers*,

$$\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\mathbf{x}_{it} - \bar{\mathbf{x}}_i \right) u_{it} = \frac{1}{T} \sum_{t=1}^{T} \left[\frac{1}{N} \sum_{i=1}^{N} \left(\mathbf{x}_{it} - \bar{\mathbf{x}}_i \right) u_{it} \right]$$

$$= \frac{1}{T} \sum_{t=1}^{T} \left[\frac{1}{N} \sum_{i=1}^{N} \mathbf{x}_{it} u_{it} - \frac{1}{N} \sum_{i=1}^{N} \bar{\mathbf{x}}_i u_{it} \right]$$

$$\xrightarrow{p} \frac{1}{T} \sum_{t=1}^{T} \left[\mathbb{E} \left(\mathbf{x}_{it} u_{it} \right) - \mathbb{E} \left(\bar{\mathbf{x}}_i u_{it} \right) \right].$$

Strict/Strong Exogeneity

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\mathbf{x}_{it}-\bar{\mathbf{x}}_i\right)u_{it}\xrightarrow{p}\frac{1}{T}\sum_{t=1}^{T}\left[\mathbb{E}\left(\mathbf{x}_{it}u_{it}\right)-\mathbb{E}\left(\bar{\mathbf{x}}_i u_{it}\right)\right].$$

- For $\hat{\beta}_{FE}$ to be consistent, we need not only $\mathbb{E}\left(\mathbf{x}_{it}u_{it}\right)=0$, but also $\mathbb{E}\left(\bar{\mathbf{x}}_i u_{it}\right)=0$.
- A sufficient condition is that $\mathbf{x}_{it}$ is **strictly/strongly exogenous**, *i.e.*, $\mathbb{E}\left(\mathbf{x}_{i\tau}u_{it}\right)=0$ for any t and τ.

First-Difference Estimator

- Besides the fixed effects (FE) estimator, an alternative is the **first-differenced** (FD) estimator.

$$
\begin{aligned}
y_{i,t} &= \alpha_i + \mathbf{x}_{i,t}^\top \beta + u_{i,t}, \\
y_{i,t-1} &= \alpha_i + \mathbf{x}_{i,t-1}^\top \beta + u_{i,t-1}.
\end{aligned}
$$

- Combining two equations yields

$$
\Delta y_{i,t} = \Delta \mathbf{x}_{i,t}^\top \beta + \Delta u_{i,t}.
$$

  - The unobserved variables $\{\alpha_i\}$ vanish, again!
- The **first-difference** (FD) estimator regresses $\Delta y_{i,t}$ on $\mathbf{x}_{i,t}$.
- Being less efficient than *FE*, *FD* is rarely used.
- We will talk about it later.

Dynamic Panel Models

- The *strong exogeneity* condition is actually *strong*.
  - **Strict/Strong exogeneity**: $\mathbb{E}\left(\mathbf{x}_{i\tau} u_{it}\right) = 0$ for any t and τ.
- *E.g.*, consider a *dynamic panel model*,

$$\begin{aligned} y_{i,t} &= \alpha_i + \beta x_{i,t} + u_{i,t} \\ &= \alpha_i + \beta y_{i,t-1} + u_{i,t}. \end{aligned}$$

  - That is, $x_{i,t} = y_{i,t-1}$.
  - $|\beta| < 1$.
- Since $y_{i,t}$ and $u_{i,t}$ are correlated for sure,

$$\mathbb{E}\left(x_{i,t+1} u_{it}\right) = \mathbb{E}\left(y_{i,t} u_{it}\right) \neq 0$$

- consider the dynamic panel model,

$$
\begin{aligned}
y_{i,t} &= \alpha_i + \beta x_{i,t} + u_{i,t} \\
&= \alpha_i + \beta y_{i,t-1} + u_{i,t}.
\end{aligned}
$$

- The *fixed effects* estimator regresses $y_{it} - \bar{y}_i$ on $x_{it} - \bar{x}_i$.

$$
y_{i,t} - \bar{y}_i = \beta \left(y_{i,t-1} - \bar{y}_{i,-1} \right) + u_{i,t} - \bar{u}_i.
$$

  - Note that $\bar{y}_i = T^{-1} \sum_{t=1}^{T} y_{i,t}$, and $\bar{y}_{i,-1} = T^{-1} \sum_{t=1}^{T} y_{i,t-1}$.

$$
\begin{aligned}
\hat{\beta}_{FE} = & \left[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(y_{i,t-1} - \bar{y}_{i,-1} \right)^2 \right]^{-1} \\
& \left[\frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(y_{i,t-1} - \bar{y}_{i,-1} \right) \left(y_{i,t} - \bar{y}_i \right) \right].
\end{aligned}
$$

Nickell's Bias

- It can be easily shown that

$$\hat{\beta}_{FE} - \beta = \left[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{i,t-1} - \bar{y}_{i,-1}\right)^2\right]^{-1} \left[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{i,t-1} - \bar{y}_{i,-1}\right)u_{i,t}\right].$$

in which, by the law of large numbers,

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{i,t-1} - \bar{y}_{i,-1}\right)u_{i,t} \xrightarrow{p} \frac{1}{T}\mathbb{E}\left(y_{i,t}u_{i,t}\right).$$

- That is, in dynamic panel models, the *fixed effects* estimator $\hat{\beta}_{FE}$ is not consistent.
- **Nickell's bias** (1981, *Econometrica*).

Endogeneity

- The *fixed effects* estimator regresses $y_{it} - \bar{y}_i$ on $\mathbf{x}_{it} - \bar{\mathbf{x}}_i$.

$$y_{it} - \bar{y}_i = \left(\mathbf{x}_{it} - \bar{\mathbf{x}}_i\right)^\top \beta + \left(u_{it} - \bar{u}_i\right).$$

- In general, in a regression model, when an *explanatory variable* is correlated with the *error*, the explanatory variable is known to be **endogenous**.
- Ignoring endogeneity in the estimation leads to *inconsistent* estimates.
- When the *strict exogeneity* assumption is violated, the explanatory variable after the within transformation is usually correlated with the error.

First-Difference (FD) Estimator

- The *first-difference* (FD) estimator regresses $\Delta y_{i,t}$ on $\mathbf{x}_{i,t}$.

$$y_{it} - y_{i,t-1} = \left(\mathbf{x}_{it} - \mathbf{x}_{i,t-1}\right)^\top \beta + \left(u_{it} - u_{i,t-1}\right).$$

- Again, when the *strict exogeneity* assumption is violated, $\mathbf{x}_{i,t-1}$ can be correlated with u_{it}, and the *first-difference* explanatory variable is usually correlated with the error.
  - The *first-difference* estimator $\hat{\beta}_{FD}$ is also inconsistent.

Weak Exogeneity

- The dynamic panel model is a leading example of the **weak exogeneity**.
- The explanatory variable $\mathbf{x}_{i\tau}$ is *weakly* exogenous if $\mathbb{E}\left(\mathbf{x}_{i\tau}u_{it}\right) = 0$ for all $\tau \leq t$, but

$$\mathbb{E}\left(\mathbf{x}_{i\tau}u_{it}\right) \neq 0 \text{ for some } \tau > t.$$

- *E.g.*, in a dynamic panel model, when $x_{i,t} = y_{i,t-1}$, $x_{i,t+1} = y_{i,t}$ is correlated with $u_{i,t}$.

Macroeconomic Effects of Climate Change

- To estimate the effect of climate on the global economy, one usually regresses the economic growth rate on the temperature and precipitation:

$$g_{it} = \alpha_i + \beta_1 temp_{it} + \beta_2 prec_{it} + u_{it}.$$

- There is a bi-directional feedback effects between growth and climate change (Kahn et al., 2021).
  - Faster economic activity increases the stock of greenhouse gas (GHG) emissions and thereby the average temperature (possibly with a long lag, say, a 10-year lag).
- That is, u_{it} may be correlated to $temp_{i,\tau}$ for some $\tau > t$.

Endogeneity

- In linear regressions, a regressor is said to be **endogenous** if it is correlated with the regression error.

$$y_i = \mathbf{x}_i^\top \beta + \epsilon_i,\ i = 1, 2, \ldots, n,\ \text{where } \mathbb{E}\left(\mathbf{x}_i \epsilon_i\right) \neq \mathbf{0}.$$

- The OLS estimator is *inconsistent* when an endogenous regressor is present.

$$\begin{aligned} \hat{\beta} - \beta &= \left(\frac{1}{n} \sum_{i=1}^{n} \mathbf{x}_i \mathbf{x}_i^\top \right)^{-1} \frac{1}{n} \sum_{i=1}^{n} \mathbf{x}_i \epsilon_i \\ &\xrightarrow{p} \mathbb{E}\left(\mathbf{x}_i \mathbf{x}_i^\top \right)^{-1} \mathbb{E}\left(\mathbf{x}_i \epsilon_i \right) \\ &\neq \mathbf{0}. \end{aligned}$$

Instrumental Variable Estimation

- Suppose that $y_i = \mathbf{x}_i^\top \beta + \epsilon_i$, where $\mathbf{x}_i$ is $(k+1) \times 1$ and contains some endogenous regressors such that $\mathbb{E}\left(\mathbf{x}_i \epsilon_i\right) \neq \mathbf{0}$.
- Let $\mathbf{z}_i$ be another $(k+1) \times 1$ vector such that $\mathbb{E}\left(\mathbf{z}_i \epsilon_i\right) = \mathbf{0}$ and $\mathbf{z}_i$ is correlated with $\mathbf{x}_i$.
  - The variables in $\mathbf{z}_i$ are known as the **instrumental variables**, **instruments**, or simply **IV**.
- Instead of solving the normal equations $\mathbf{X}^\top\left(\mathbf{y} - \mathbf{X}\beta\right) = \sum_{i=1}^n \mathbf{x}_i(y_i - \mathbf{x}_i^\top \beta) = \mathbf{0}$, the IV method solves:

$$\mathbf{Z}^\top\left(\mathbf{y} - \mathbf{X}\beta\right) = \sum_{i=1}^n \mathbf{z}_i(y_i - \mathbf{x}_i^\top \beta) = \mathbf{0}.$$

Given that $\mathbf{Z}^\top\mathbf{X}$ is of full rank (so that it is invertible), the solution is the **IV estimator**:

$$\hat{\beta}_{IV} = \left(\mathbf{Z}^\top\mathbf{X}\right)^{-1}\mathbf{Z}^\top\mathbf{y} = \left(\sum_{i=1}^n \mathbf{z}_i\mathbf{x}_i^\top\right)^{-1}\sum_{i=1}^n \mathbf{z}_i y_i.$$

Over-Identification

- No reason to assume $\mathbf{z}_i$ to be $(k+1) \times 1$.
- What if $\mathbf{z}_i$ is $(\ell + 1) \times 1$, where ℓ may be different from k?
- $\ell + 1$ equations. $k + 1$ parameters.

$$\mathbf{Z}^\top (\mathbf{y} - \mathbf{X}\beta) = \mathbf{0}.$$

  - As $\ell = k$, number of equations = number of parameters. *Just-identified*.
  - As $\ell < k$, number of equations < number of parameters. *Under-identified*. *No unique solution*.
  - As $\ell > k$, number of equations > number of parameters. *Over-identified*. *No solution*!

Two-Stage Least Squares Estimation

- As $\ell > k$, instead of $\mathbf{Z}^\top(\mathbf{y} - \mathbf{X}\beta) = \mathbf{0}$, we solve the following *just-identified* system of $k+1$ equations:

$$\mathbf{X}^\top\mathbf{Z}\left(\mathbf{Z}^\top\mathbf{Z}\right)^{-1}\mathbf{Z}^\top(\mathbf{y} - \mathbf{X}\beta) = \mathbf{0},$$

  and obtain the following estimator:

$$\hat{\beta}_{2SLS} = \left[\mathbf{X}^\top\mathbf{Z}\left(\mathbf{Z}^\top\mathbf{Z}\right)^{-1}\mathbf{Z}^\top\mathbf{X}\right]^{-1}\mathbf{X}^\top\mathbf{Z}\left(\mathbf{Z}^\top\mathbf{Z}\right)^{-1}\mathbf{Z}^\top\mathbf{y}.$$

- The **Two-Stage Least Squares Estimator** (**TSLS**, or **2SLS**).

Generalized Method of Moments (GMM)

$$\mathbb{E}\left(\mathbf{z}_i\epsilon_i\right) = \mathbb{E}\left[\mathbf{z}_i\left(y_i - \mathbf{x}_i^\top\beta\right)\right] = \mathbf{0}.$$

- When $\mathbf{z}_i$ is a $(k+1)\times 1$ vector, the IV estimator solves the sample counterpart:

$$\frac{1}{n}\sum_{i=1}^{n}\mathbf{z}_i(y_i - \mathbf{x}_i^\top\beta) = \mathbf{0}.$$

- The IV estimator is a **method of moments** estimator.
- When $\mathbf{z}_i$ is a $(\ell+1)\times 1$ vector with $\ell > k$, the sample moment conditions have no solution.
- Instead of solving the sample moments, the 2SLS estimator minimizes

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \mathbf{x}_i^\top\beta)\mathbf{z}_i^\top\left(\mathbf{z}_i\mathbf{z}_i^\top\right)^{-1}\mathbf{z}_i(y_i - \mathbf{x}_i^\top\beta).$$

- The 2SLS estimator is a **generalized method of moments** (GMM) estimator (Hansen, 1982, *Econometrica*).

Real-World Examples

- Returns to schooling (Angrist and Krueger, 1991, *Quarterly Journal of Economics*):
  - Treatment variable X: education.
  - Outcome variable Y: wage.
  - Instrumental variable Z: quarter of birth.
- Returns to schooling (Card, 1995, *Quarterly Journal of Economics*):
  - Treatment variable X: education.
  - Outcome variable Y: wage.
  - Instrumental variable Z: college in the county.
- Effect of smoking during pregnancy (Evans and Ringel, 1999, *Journal of Public Economics*):
  - Treatment variable X: smoking during pregnancy.
  - Outcome variable Y: birth weight.
  - Instrumental variable Z: cigarette taxes.

IV Approach for Dynamic Panel

- Coming up with more convincing IVs usually involves a rigorous process of selection and validation.
- ChatGPT: a 12-step procedure.
- Scott Cunningham: *Causal Inference: The Mixtape* (2021): **Be clever!**
- In panel models, however, the IV can be **free**!

- Anderson and Hsiao (1982, *Journal of Econometrics*).
- Consider a dynamic panel model:

$$y_{i,t} = \alpha_i + \beta y_{i,t-1} + u_{i,t}.$$

- Taking the first difference yields

$$\Delta y_{i,t} = \beta \Delta y_{i,t-1} + \Delta u_{i,t}.$$

- Since $y_{i,t-1}$ is correlated with $u_{i,t-1}$, $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ is correlated with $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$.
- Anderson and Hsiao (1982) propose using $z_{i,t} = y_{i,t-2}$ or $z_{i,t} = \Delta y_{i,t-2}$ as instruments.
  - Since both $y_{i,t-2}$ and $\Delta y_{i,t-2}$$ are correlated with $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ but uncorrelated with $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$.
- Arellano and Bond (1991, *Review of Economic Studies*) propose to use not only one lag, but *all* lags.

$$
\begin{aligned}
g_{it} = & \theta_i + \theta_{rt} + \beta_1 temp_{it} + \beta_2 temp_{it} \times Poor_i \\
& + \gamma_1 prec_{it} + \gamma_2 prec_{it} \times Poor_i + \varepsilon_{it}.
\end{aligned}
$$

- Dell, Jones, and Olken: *Temperature Shocks and Economic Growth: Evidence from the Last Half Century* (2012, *American Economic Journal: Macroeconomics*.)
  - g_{it}: growth rate of per-capita output of country i at year t.
  - $temp_{it}$: annual average temperature.
  - $prec_{it}$: annual precipitation.
  - $Poor_i = 1$ if country i is a poor country. $Poor_i = 0$ otherwise.
  - θ_i: country fixed effects.
  - θ_{rt}: year fixed effects (interacted separately with region dummies and a poor country dummy).
- DJO estimated that a $1^\circ C$ rise in temperature in a given year reduced economic growth in that year by about 1.3 percentage points in poorer countries.

$$
\begin{aligned}
g_{it} =& \theta_i + \theta_t + \alpha_{i.1} T + \alpha_{i,2} T^2 + \beta_1 temp_{it} + \beta_2 temp_{it}^2 \\
& + \gamma_{p,1} prec_{it} + \gamma_{p,2} prec_{it}^2 + \varepsilon_{it}.
\end{aligned}
$$

- Burke, Hsiang, and Miguel: *Global Non-Linear Effect of Temperature on Economic Production* (2015, *Nature*.)
  - g_{it}: growth rate of per-capita output of country i at year t.
  - $temp_{it}$: annual average temperature.
  - $prec_{it}$: annual average precipitation.
  - θ_i: country fixed effects.
  - θ_t: year fixed effects.
- BHM: unmitigated warming is expected to reshape the global economy by reducing average global incomes roughly 23% by 2100.

- Newell, Prest, and Sexton: *The GDP-Temperature Relationship: Implications for Climate Change Damages* (2021, *Journal of Environmental Economics and Management*.)
  - Theory does not prescribe specific, estimable, structural relationships between climate and economic outcomes
  - Researchers, therefore, have made varying assumptions about the functional forms of these relationships.
- NPS estimated 800 plausible specifications of the temperature-GDP relationship and evaluated models by cross-validation.
  - Temperature-GDP *growth* vs temperature-GDP *level*, *linear* relationship vs *nonlinear* relationship, *static* models vs *dynamic* models with lags of temperatures and precipitations, etc.
- NPS identified models relating temperature to GDP *levels* as more often being the most accurate in out-of-sample validation.
  - The best such models imply GDP losses by 2100 of $1 \sim 3\%$.

- Kahn, Mohaddes, Ng, Pesaran, Raissi, and Yang: *Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis* (2021, *Energy Economics*.)
- To identify the *long-term* macroeconomic effects dynamics of macroeconomic variables should be allowed.
  - While weather could affect the level of output across climates, climate change, by shifting the long-term average and variability of weather, could impact an economy's ability to grow in the long-term, through reduced investment and lower labour productivity.
- *Trended* variables, such as temperatures, should not be used in output or output growth equations.
  - Temperatures have been trending upward strongly in almost all countries in the world, and its use as a regressor in growth regressions can lead to spurious results.

- Specifically, KMNPMY considered the following model:

$$g_{it} = \alpha_i \sum_{\ell=1}^{p} \phi_\ell g_{i,t-\ell} + \sum_{\ell=1}^{p} \beta_\ell^t \Delta \widetilde{temp}_{i,t-\ell} + \sum_{\ell=1}^{p} \beta_\ell^p \Delta \widetilde{prep}_{i,t-\ell} + \varepsilon_{it}.$$

  - $\widetilde{temp}_{it}$ and $\widetilde{prep}_{it}$ are measures of temperature and precipitation relative to their historical norms.
- However, the model is a *dynamic panel model* with lags of the dependent variable.
- Moreover, there is a bi-directional feedback effects between growth and climate change.
  - Faster economic activity increases the stock of greenhouse gas (GHG) emissions and thereby the average temperature (possibly with a long lag).
  - At the same time, rising average temperature could reduce real economic activity.
- Temperatures are not *strictly* exogenous.

Half-Panel Jackknife Fixed Effects

- Chudik, Pesaran, and Yang (2018. *Journal of Applied Econometrics*).
- FE has a Nickell's bias, *i.e.*,

$$\hat{\beta}_{FE} = \beta + \frac{1}{T} Bias + \cdots .$$

- We split the data set into two halves and apply the FE to both. $\hat{\beta}_{FE,a}$ uses the first half ($t = 1, 2, \ldots, T/2$), and $\hat{\beta}_{FE,b}$ uses the second half ($t = T/2 + 1, T/2 + 2, \ldots, T$).

$$\hat{\beta}_{FE,a} = \beta + \frac{1}{T/2} Bias + \cdots , \text{ and } \hat{\beta}_{FE,b} = \beta + \frac{1}{T/2} Bias + \cdots .$$

- The **Half Panel Jackknife Fixed Effects** (HPJFE) estimator:

$$\begin{aligned}
\hat{\beta}_{HPJFE} =& 2\hat{\beta}_{FE} - \frac{1}{2}\hat{\beta}_{FE,a} - \frac{1}{2}\hat{\beta}_{FE,b} \\
\approx& 2\beta - \frac{1}{2}\beta - \frac{1}{2}\beta \\
&+ \frac{2}{T} Bias - \frac{1}{T} Bias - \frac{1}{T} Bias = \beta.
\end{aligned}$$

- Kahn, Mohaddes, Ng, Pesaran, Raissi, and Yang: *Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis* (2021, *Energy Economics*.)
- KMNPRY show that climate change has a long-term negative impact on growth in most countries (rich or poor and hot or cold). If temperature deviates from its historical norm by $0.01^{\circ}C$ annually, economic growth will be lower by 0.06 percentage points per year.
- KMNPRY find that an increase in average global temperature of $0.04^{\circ}C$ per year (in the absence of mitigation policies) reduces world's real GDP per capita by around 7 percent by 2100. Limiting the increase to $0.01^{\circ}C$ per annum, which corresponds to the Paris Agreement, reduces the output loss to around 1 percent.
    - Adaptation helps but is not enough. More forceful mitigation e¤orts are needed.