Macroeconometrics

Lecture 22 Less than 2°C warming by 2100 unlikely

Topics in Climate Change
Forecasting CO_2 Emissions for the 21st Century

Tomasz Woźniak

Less than 2°C warming by 2100 unlikely

Bayesian predictive model

Hierarchical prior distributions

Lecture is based on:

Raftery, Zimmer, Frierson, Startz, Liu (2017), Less than 2°C warming by 2100 unlikely, Nature Climate Change, Vol. 7.

Other references:

Gerland, Raftery, Ševčíková, Li, Gu, Spoorenberg, Alkema, Fosdick, Chunn, Lalic, Bay, Buettner, Heilig, Wilmoth (2014) World population stabilization unlikely this century, Science, Vol. 346.

Less than 2°C warming by 2100 unlikely

Less than 2°C warming by 2100 unlikely: **objectives**

to develop probabilistic forecast of CO2 emissions and temperature change to 2100

to assess the credibility expert projections of the underlying quantities

Less than 2°C warming by 2100 unlikely: **methods**

IPAT equation

$$\text{Impact} \;=\; \text{Population} \;\times\; \text{Affluence} \;\times\; \text{Technology}$$

Kaya identity expresses future emission levels in a country as a product of: population, GDP per capita, and carbon intensity

$$\underset{[\text{Gt } CO_2]}{CO_2 \text{ emissions}} = \underset{[\text{persons}]}{\text{population}} \times \underset{[\text{US\$/pp}]}{\text{GDP per capita}} \times \underset{[\text{Gt } CO_2/\text{US\$}]}{\text{carbon intensity}}$$

Probabilistic forecasts of population, GDP per capita, and carbon intensity for individual countries that are subsequently aggregated over countries and time

Less than 2°C warming by 2100 unlikely: **challenges**

credibility of 90-year-ahead forecasts using 50 years of historical data can only partially be validated by forecast performance techniques

quality and comparability of data for all of the countries over sufficiently long period

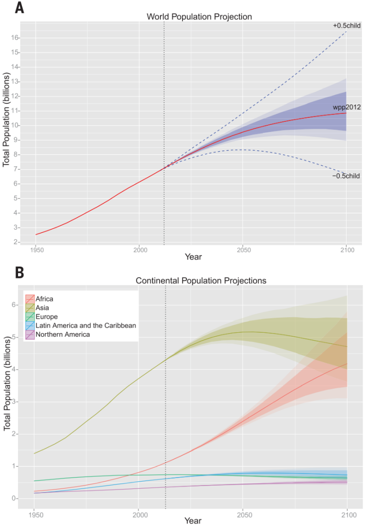
efficient information extraction applying panel data techniques

simplifying assumptions reducing estimation standard errors

calibration of the models to assure fit to the data and informative forecasts

Less than 2°C warming by 2100 unlikely: **results**

Population prediction based on Gerland et al. (2014)



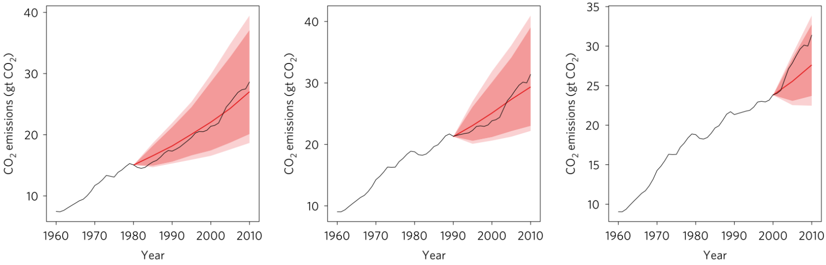
median population forecast:
increase of 4 billion to 2100, from the current 7.2 billion to 11.2 billion in 2100

the largest contribution from
Sub-Saharan Africa: increase from 1 billion to 3.9 billion.

GDP is to increase 21 times:
in this area which translates into 6% increase in CO_2 emissions

Less than 2°C warming by 2100 unlikely: **results**

Validation of emissions predictions.



Calibrated and estimated model assigns considerable predictive density mass to data corresponding to the forecast period in a pseudo-out-of-sample forecasting exercise

Less than 2°C warming by 2100 unlikely: **results**

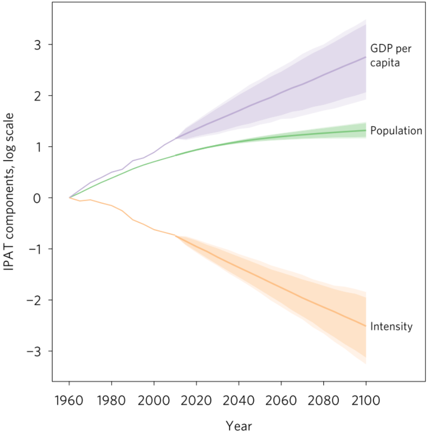
Kaya identity components predictions.

Decline in intensity balanced out by the increase in GDP

Population contributes very little to emissions forecast error variance

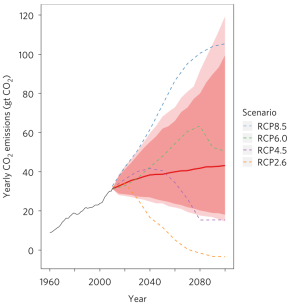
GDP growth reduction is an unlikely policy target

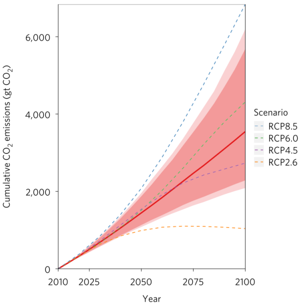
Reduction in intensity contributes a lot to emissions forecast error variance and is a feasible policy target



Less than 2°C warming by 2100 unlikely: **results**

CO_2 emissions predictions and assessment of projections.





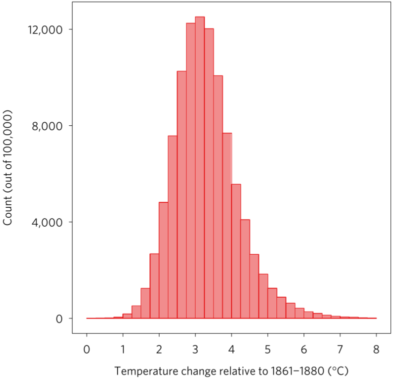
Annual emissions are predicted to increase

High- and low-level emissions scenarios are unlikely

Mid-level emissions scenarios are confirmed with probabilistic forecasts

Less than 2°C warming by 2100 unlikely: **results**

Predicted temperature increase.



median increase is equal to 3.2°C

likely range is between 2 and 4.9°C

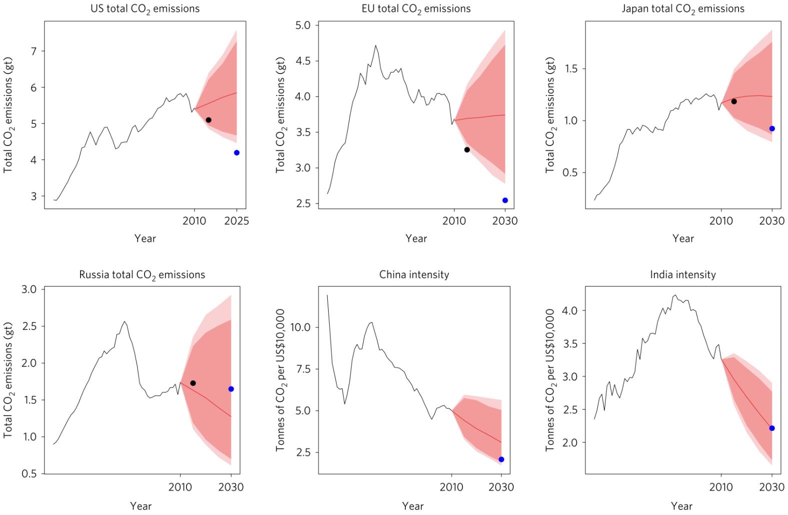
less than 2°C warming is assigned 5% chance

5% chance is assigned more than 4.9°C warming

less than 1.5°C warming is assigned 1% chance

Less than 2°C warming by 2100 unlikely: **results**

Emissions predictions and Paris agreement.

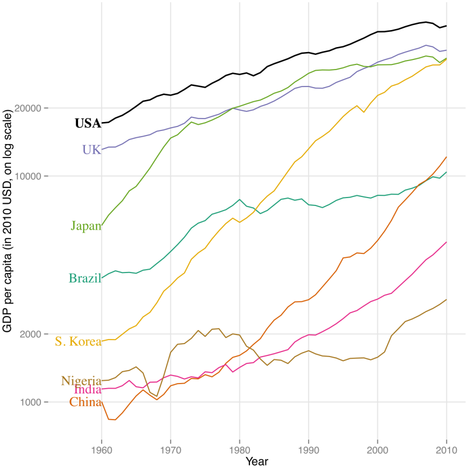


• preliminary estimate 2015, • Paris climate agreement target for 2030

Bayesian predictive model

Bayesian predictive model

Model for the frontier economy.



Bayesian predictive model

Model for the frontier economy.

$$F_t = F_{t-1} + \gamma + \gamma_{pre1973}\mathcal{I}(t \leq 1973) + \epsilon_t^{(f)}$$
$$\epsilon_t^{(f)} \sim \mathcal{N}\left(0, \sigma_f^2\right)$$

Model: gaussian random walk with structural break in the drift

Dependent variable: the logarithm of US annual GDP per capita

Sample period: 1960 - 2010 ($T = 50$)

Data source: The Maddison Project: www.ggdc.net/maddison/maddison-project/

Bayesian predictive model

Model for other economies.

$$(F_t - G_{c.t}) = \phi_c(F_{t-1} - G_{c.t-1}) + \epsilon_{c.t}^{(g)}$$
$$\epsilon_{c.t}^{(g)} \sim \mathcal{N}\left(0, \sigma_{g.c}^2\right)$$

$$\text{for } c = 2, 3, \ldots, N$$

Model: convergence to the frontier at a stationary AR(1) rate

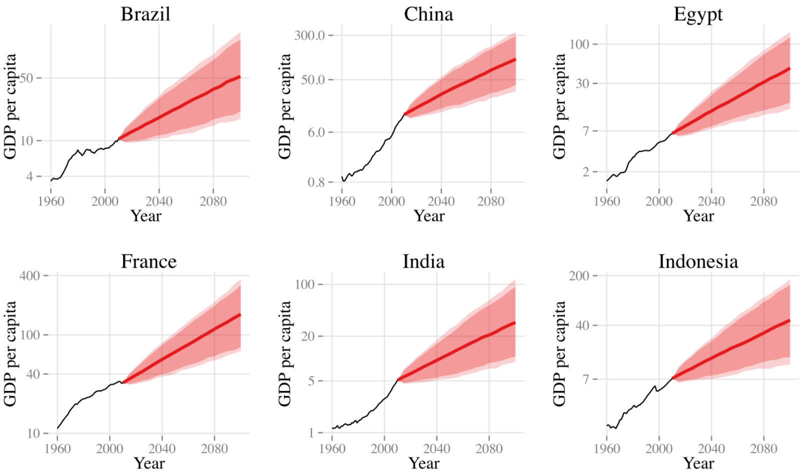
Dependent variable: the difference between F_t and the logarithm of annual GDP data in 1990 US dollars converted to 2010 US dollars by multiplying by 1.52 based on the OECD price deflator

Sample period: 1960 - 2010 ($T = 50$)

Data source: The Maddison Project

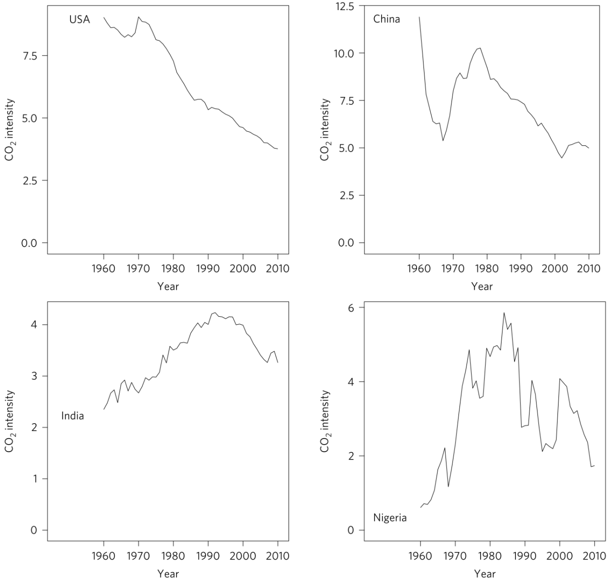
Bayesian predictive model

Model for other economies.



Bayesian predictive model

Carbon intensity data.



Bayesian predictive model

Model for carbon intensity.

$$\tau_{c.t} = \eta(t - \bar{t}) + \beta\tau_{c.t-1} - \delta_c + \epsilon_{c.t}$$

$$\epsilon_{c.t}|\epsilon_{c.t}^{(g)} \sim \mathcal{N}\left(\rho\frac{\sigma_c}{\sigma_{g.c}}, (1-\rho^2)\sigma_c^2\right)$$

Model: panel AR(1) model with common deterministic trend, autoregressive and correlation parameters, and country-specific fixed effects

ρ – common correlation coefficient between $\epsilon_{c.t}$ and $\epsilon_{c.t}^{(g)}$

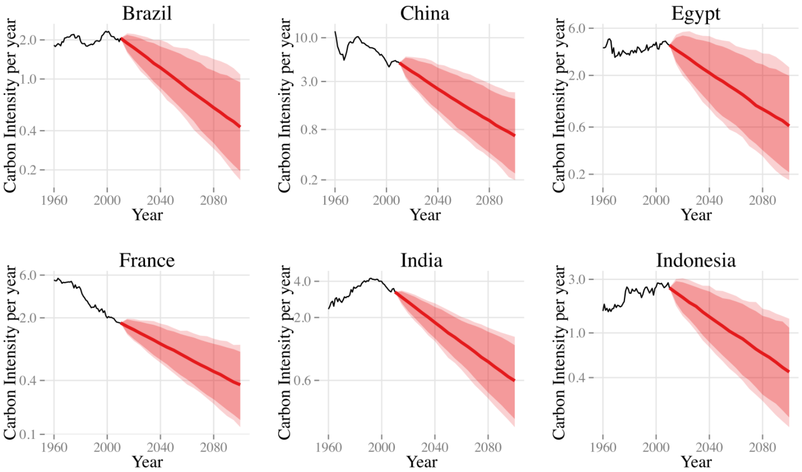
Dependent variable: the logarithm of fossil fuel and cement production emissions for each country, excluding emissions from land-use change, in tonnes of CO_2 per US$10,000 in 2010 Purchasing Power Parity

Sample period: post-peak series for each country – the peak is the maximum of smoothed series using loess smoother with span 0.25

Data source: Global Carbon Budget: www.globalcarbonproject.org

Bayesian predictive model

Model for other economies.



Bayesian predictive model

Joint modeling: error term specification.

$$\begin{bmatrix} \epsilon_t^{(f)} \\ \epsilon_{1.t} \\ \epsilon_{2.t}^{(g)} \\ \epsilon_{2.t} \\ \vdots \\ \epsilon_{N.t}^{(g)} \\ \epsilon_{N.t} \end{bmatrix} \sim \mathcal{N}_{2N} \left(\mathbf{0}_{2N}, \begin{bmatrix} \sigma_f^2 & \rho\sigma_f\sigma_1 & 0 & 0 & \dots & 0 & 0 \\ \rho\sigma_f\sigma_1 & \sigma_1^2 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \sigma_{g.2}^2 & \rho\sigma_{g.2}\sigma_2 & \dots & 0 & 0 \\ 0 & 0 & \rho\sigma_{g.2}\sigma_2 & \sigma_2^2 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \sigma_{g.N}^2 & \rho\sigma_{g.N}\sigma_N \\ 0 & 0 & 0 & 0 & \dots & \rho\sigma_{g.M}\sigma_N & \sigma_N^2 \end{bmatrix} \right)$$

Model: block-diagonal structure of the error term covariance matrix presuming common correlation coefficient and country-specific variances

Hierarchical prior distributions

Hierarchical prior distributions

Model for the frontier economy – prior distributions.

$$\begin{aligned} F_t &= F_{t-1} + \gamma + \gamma_{pre1973}\mathcal{I}(t \leq 1973) + \epsilon_t^{(f)} \\ \epsilon_t^{(f)} &\sim \mathcal{N}\left(0, \sigma_f^2\right) \end{aligned}$$

$$\begin{aligned} \gamma &\sim \mathcal{U}[0, 1] \\ \gamma_{pre1973} &\sim \mathcal{U}[-0.1, 0.1] \\ \sigma_f &\sim \log \mathcal{N}(-3, 20) \end{aligned}$$

Hierarchical prior distributions

Model for other economies – prior distributions.

$$(F_t - G_{c.t}) = \phi_c(F_{t-1} - G_{c.t-1}) + \epsilon_{c.t}^{(g)}$$
$$\epsilon_{c.t}^{(g)} \sim \mathcal{N}\left(0, \sigma_{g.c}^2\right)$$

$$\phi_c | \mu_\phi, \sigma_\phi \sim \mathcal{TN}_{[0,1]}\left(\mu_\phi, \sigma_\phi^2\right)$$
$$\mu_\phi \sim \mathcal{U}[0, 1]$$
$$\sigma_\phi \sim \mathcal{U}[0, 1]$$

$$\sigma_{g.c} | \mu_g, \sigma_g \sim \log \mathcal{N}\left(\mu_g, \sigma_g^2\right)$$
$$\mu_g \sim \mathcal{N}(-6, 40)$$
$$\sigma_g \sim \mathcal{U}[0.05, 5]$$

Hierarchical prior distributions

Model for carbon intensity.

$$\tau_{c.t} = \eta(t - \bar{t}) + \beta\tau_{c.t-1} - \delta_c + \epsilon_{c.t}$$

$$\epsilon_{c.t}|\epsilon^{(g)}_{c.t} \sim \mathcal{N}\left(\rho\frac{\sigma_c}{\sigma_{g.c}}, (1-\rho^2)\sigma_c^2\right)$$

$$\eta \sim \mathcal{N}\left(0.1, 0.01\right)$$

$$\beta \sim \mathcal{U}[0, 1]$$

$$\delta_c|\mu_\delta, \sigma_\delta \sim \mathcal{N}\left(\mu_\delta, \sigma_\delta^2\right)$$

$$\mu_\delta \sim \mathcal{N}(0, 1)$$

$$\sigma_\delta \sim \log\mathcal{N}(-5, 1.15)$$

$$\sigma_c|\sigma_\mu, \sigma_{SD} \sim \log\mathcal{N}\left(\sigma_\mu, \sigma_{SD}^2\right)$$

$$\sigma_\mu \sim \mathcal{N}\left(-2, 100\right)$$

$$\sigma_{SD} \sim \mathcal{U}[0.05, 5]$$

$$\rho \sim \mathcal{U}[-1, 1]$$

Less than 2°C warming by 2100 unlikely

Long-run forecasting of quantities that are essential for decision-makers faces multiple challenges

Probabilistic forecasting is crucial for realistic assessment of future tendencies

Hierarchical Bayesian modeling provides additional tools to calibrate the model to the objective of the research

Much stricter policies constraining carbon intensity of economies are required to keep the increase in global temperatures below the level triggering multiple climate change tipping points