Econometric Forecasting of Climate Change

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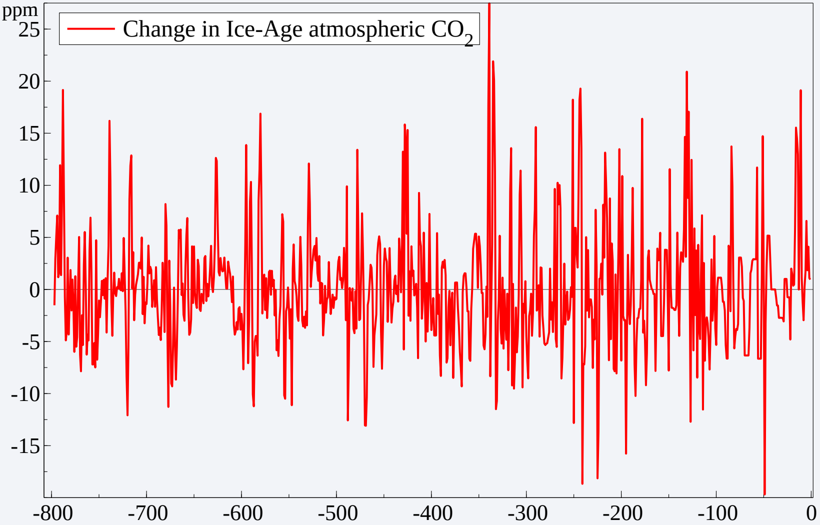
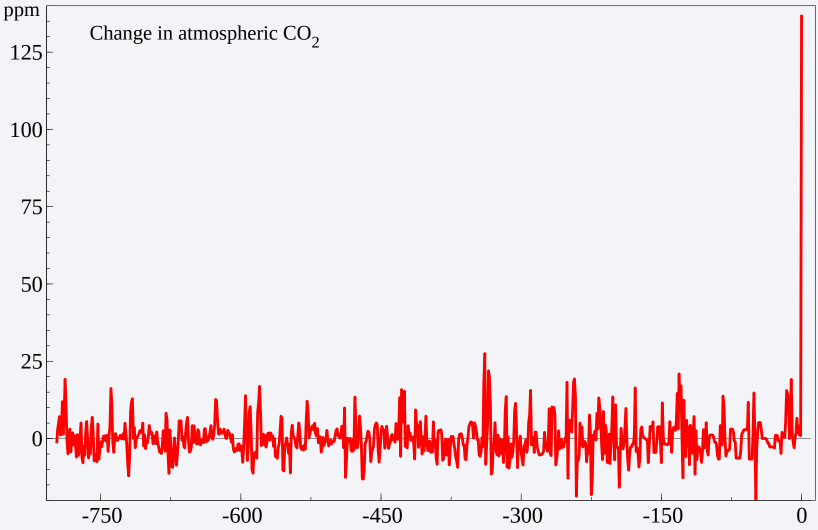
Let's start with some data...



Thousand-year changes in parts per million (ppm) CO_2 in atmosphere varying over $\pm$25ppm: 1 ppm = 7800 billion kg of CO_2

And now!



Now: atmospheric CO_2 changes of 130ppm in under 250 years.

And now!

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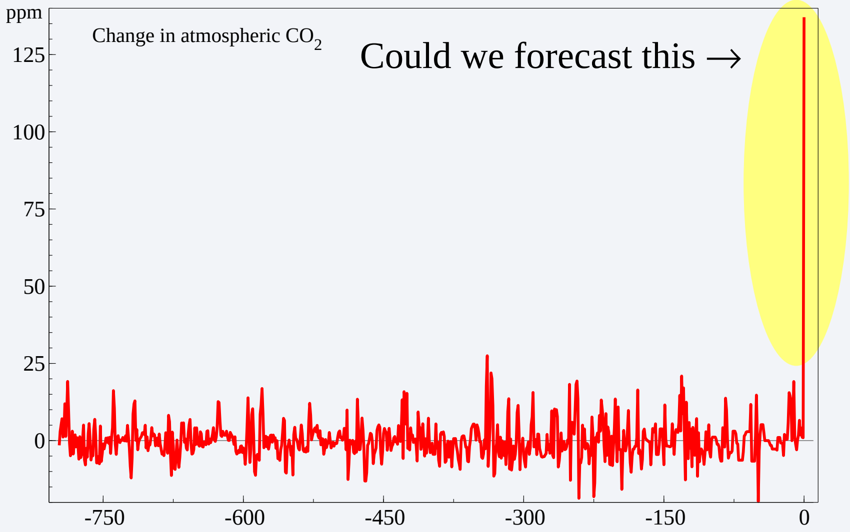

Now: atmospheric CO_2 changes of 130ppm in under 250 years.

Forecasting the jump in CO_2 from 1760 to now would have required a forecast of economies continuing to be dependent on coal then oil and natural gas and grow substantially world wide.

In turn, that would need to ignore the knowledge by 1900 that increased CO_2 would cause a warming climate (see Foote, 1856, Arrhenius, 1896), yet no counter action was taken.

Also that by 1900, Climate Change could be prevented by discoveries about generating electricity and the inventions of solar cells, wind turbines and electric vehicles with rechargeable batteries (Castle and Hendry, 2022, provide a brief history).

So Climate Change was not inevitable.

What determines the success of econometric model-based forecasts?

Their success depends upon (see Hendry, 1997):

(a) there are regularities in the system being modeled;

(b) those regularities are informative about the future;

(c) the estimated model captures the regularities; yet:

(d) excludes irregularities that might swamp regularities.

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There are regularities in both climate and macroeconomic data, many of which are informative about the future
some embodied in empirical systems.

However, sudden unanticipated changes are not rare and can be large, leading to forecast failure (see Castle et al., 2021a, 2021b, for principles of forecasting applicable to non-stationary processes and model selection when forecasting).

Recent examples with substantial impacts on climate-related economic variables include the 'Financial Crisis', COVID pandemic and Russia's invasion of Ukraine.

Route Map

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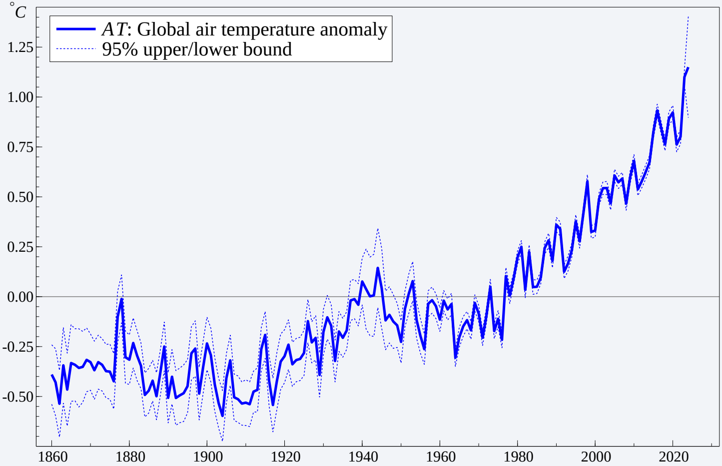
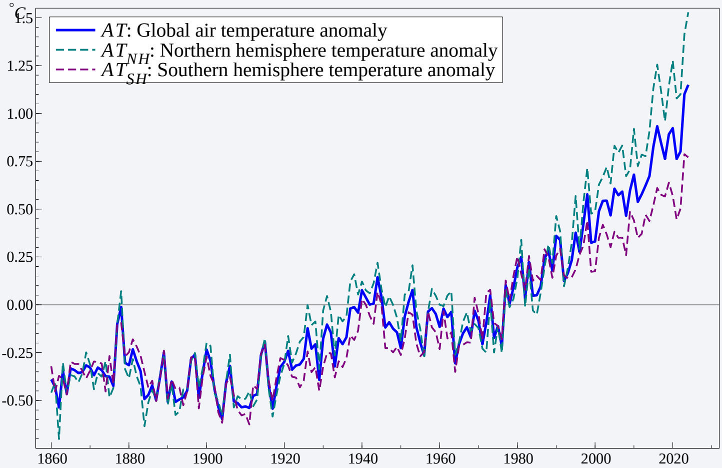
Global temperature anomalies



Global temperature anomaly shows increasing trend

Global temperature anomalies



Northern and southern hemispheres warming at different rates

Global temperature anomalies

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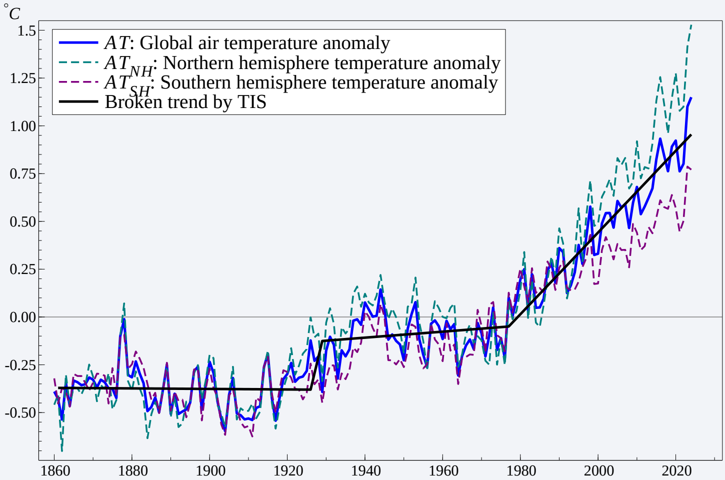

Broken linear trends reveal increasing trend in temperature rise

Global temperature anomalies

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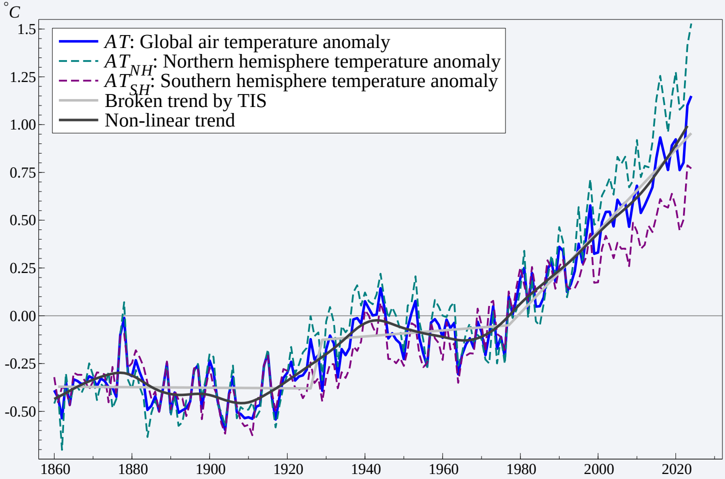
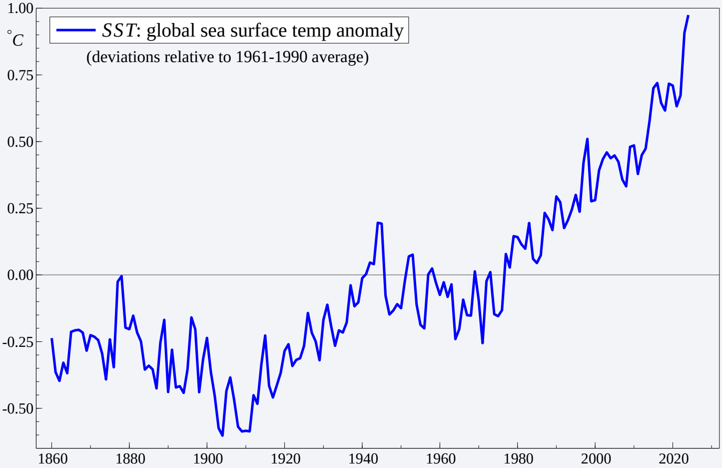


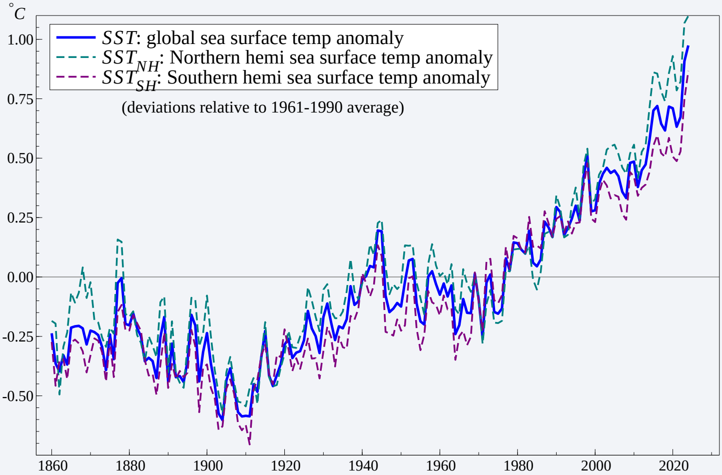
Broken linear or non-linear trends show similar rise

Sea surface temperature anomalies



Oceans are also warming rapidly

Sea surface temperature anomalies



Northern and southern hemisphere oceans also warming at varying rates

Ocean heat content anomalies

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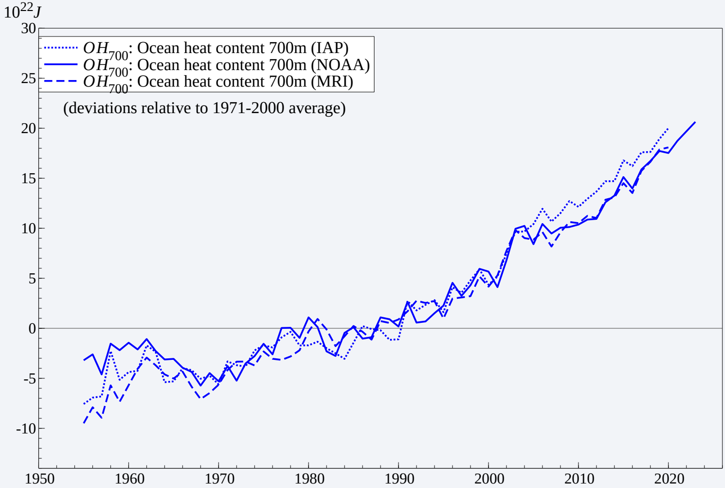
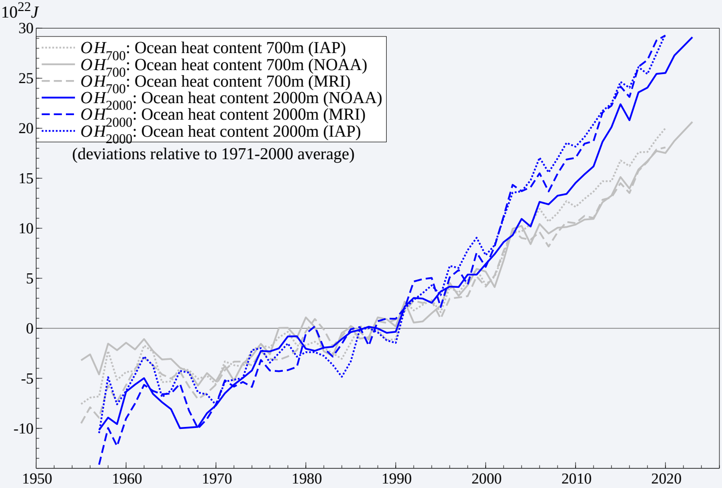


The warming extends to the shallow and deep oceans

Ocean heat content anomalies



Estimates vary but consistently predict rising heat content

Non-constant change

A common feature is non-constant change: changes keep changing, sometimes accelerating, sometimes slowing and occasionally dropping.

This makes forecasting difficult as changes in the change are hard to anticipate.

A break during a forecast interval will later become a break in-sample so will contaminate estimation of the parameters of econometric models unless properly handled.

What can econometricians contribute?

Human behavior is key determinant of climate change, particularly from burning fossil fuels like coal, oil and natural gas, and agriculture releasing greenhouse gases (GHGs) such as carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH4), which cumulate in the atmosphere and reflect back radiation.

Macro-econometricians model aggregate human economic behavior which is non-stationary from evolving trends and breaks deriving from pandemics, wars, technical progress, financial innovation, demography, and economic policy regimes.

These have impacts on the climate, so climate data is also non-stationary, and in turn feeds back on economic outcomes, especially through extreme events like wild fires, cyclones, floods and droughts.

Econometricians have tools for jointly modelling interacting systems of non-stationary time series.

Characterised by complex interaction between atmosphere, oceans and land

Influenced by:

- natural forces: solar radiation; seasons; plate tectonics; volcanic eruptions; El Niño; etc.
- anthropogenic factors: burning fossil fuels; land use for agriculture & forestry; dams to store water; etc.
- and consequences of their interactions: reduced albedo from melting Arctic ice; aerosol pollution; changes in rainfall and cloud cover; wild fires; coastal erosion; etc.

Emissions of GHGs from natural and anthropogenic sources cumulate in the atmosphere and re-radiate energy from the sun back to the planet, hence the label greenhouse gases.

Natural and anthropogenic forcing

- ***Climate forcing*: an imposed change in Earth's energy balance (Hansen et al., 2017).**
- ***Total radiative forcing*: sum of all forcings, whether natural or anthropogenic.**

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IPCC provide estimates of total radiative forcing from anthropogenic sources.

Natural forcings due to solar irradiance and stratospheric aerosols from volcanic eruptions.

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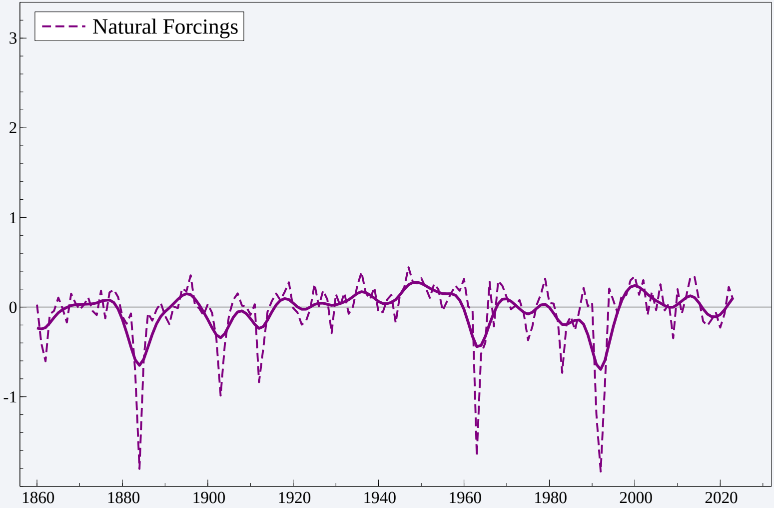

Radiative forcing estimated by CMIP6 Historical simulations using GISS-E2.1 (w/m^2)

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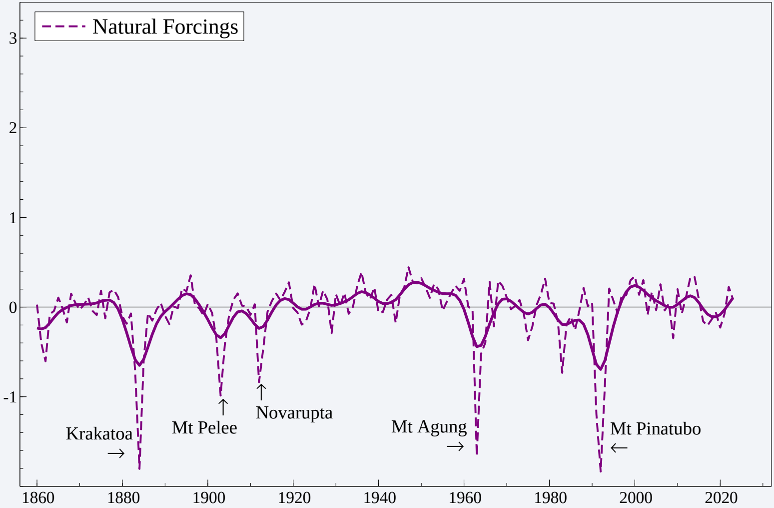
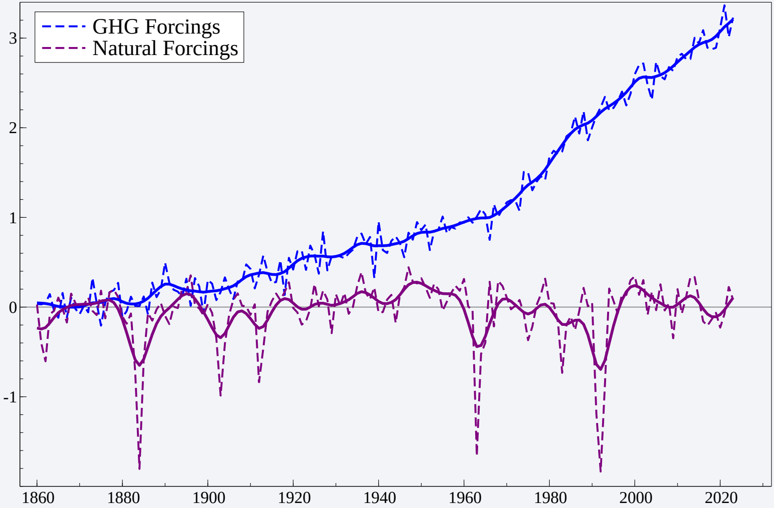


Radiative forcing estimated by CMIP6
Historical simulations using GISS-E2.1 (w/m^2)

Effective radiative forcing



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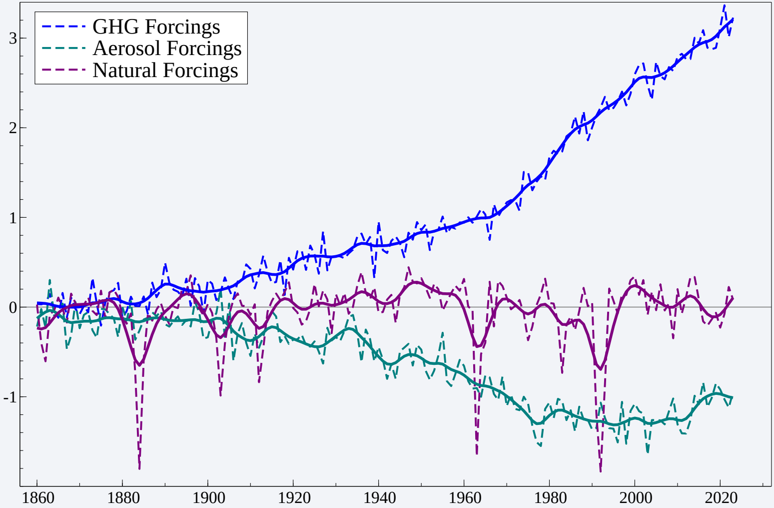

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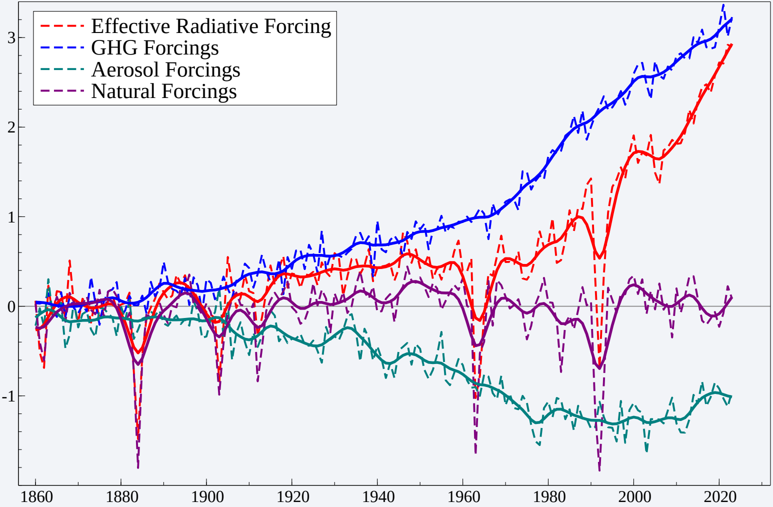

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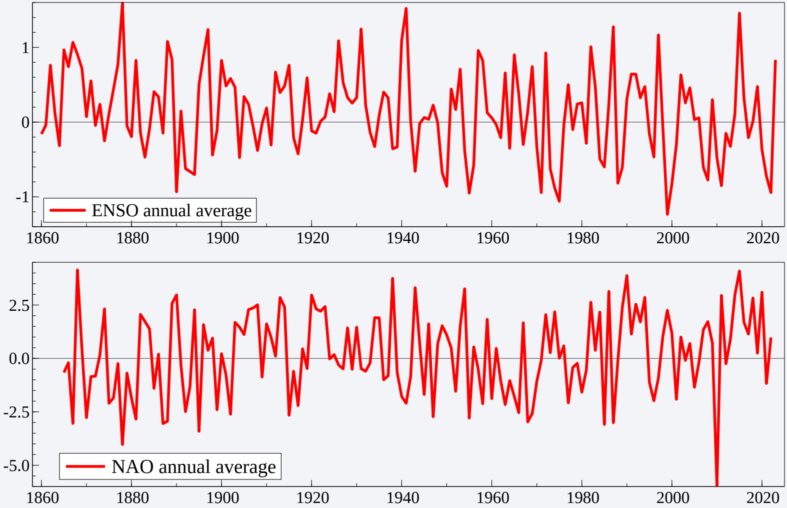
Natural cycles

- **Not all natural changes in Earth's energy balance are forcings: endogenous *natural variability* includes semi-periodic cycles like El Niño Southern Oscillation; Atlantic Multidecadal Oscillation; Pacific Decadal Oscillation.**
- **Changes in temperatures from cycles have magnitudes large enough to *temporarily* offset anthropogenic forcing & cause apparent hiatuses (Kosaka and Xie, 2013) so may confound policy analysis (Miller and Nam, 2020).**



El Niño-Southern Oscillation and North Atlantic Oscillation

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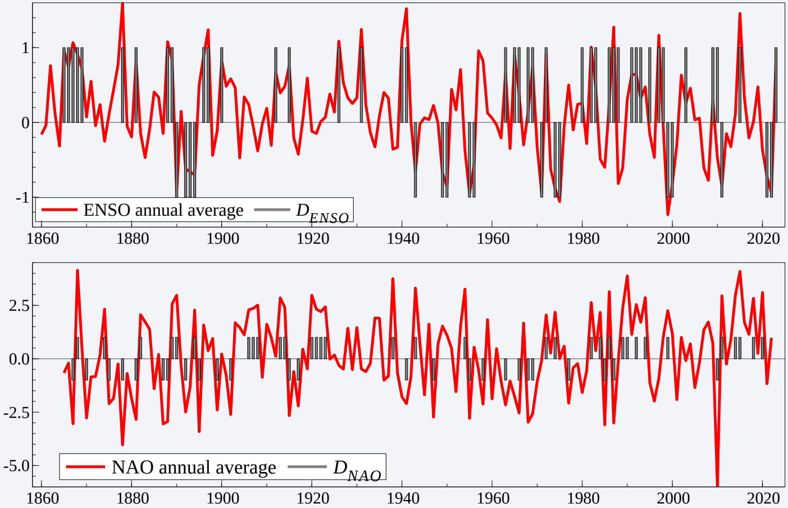

Indicators showing years with oceans warming or cooling

GHGs have been increasing rapidly

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Rapid increases in CO_2, N_2O, and CH_4 (Cheng and Redfern, 2022).

Atmospheric methane due to natural gas leaks, tundra melting, animal husbandry, and increase in wildfires (release carbon monoxide that nullifies hydroxl free radicals that help remove methane).

Latest IPCC report notes methane responsible for about $\frac{1}{3}$ of the $1.5^\circ C$ of global warming, offset in part by sulphur dioxide emissions cooling around $0.5^\circ C$, so total warming is now about $1^\circ C$, with half due to CO_2.

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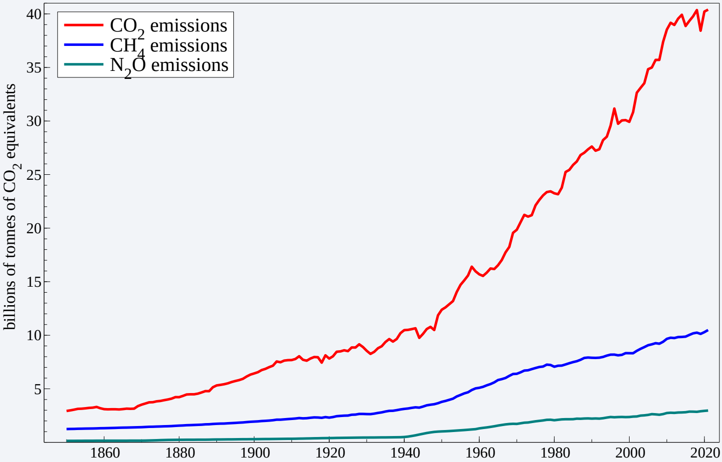
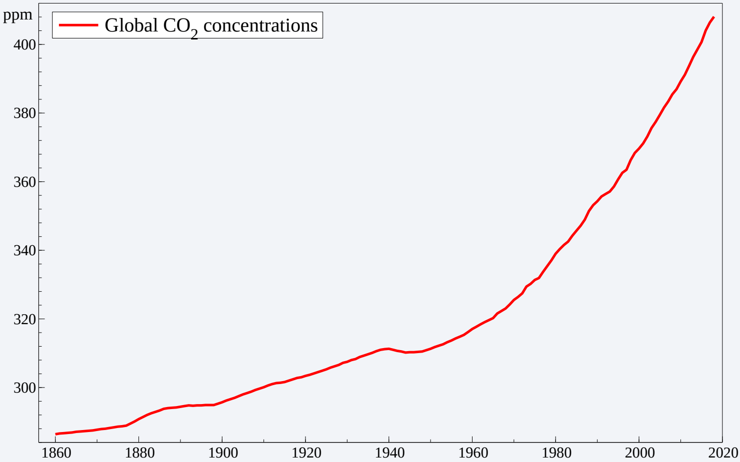
All GHGs including chlorofluorocarbons (CFCs), hydroCFCs, HFCs and sulfur hexafluoride (SF_6) contribute to radiative forcing so the Earth receives more incoming energy from sunlight than it radiates back to space.

Emissions of greenhouse gasses



Global greenhouse gas emissions by gas



Global CO_2 concentrations in parts per million (ppm)

Global CO_2 concentrations

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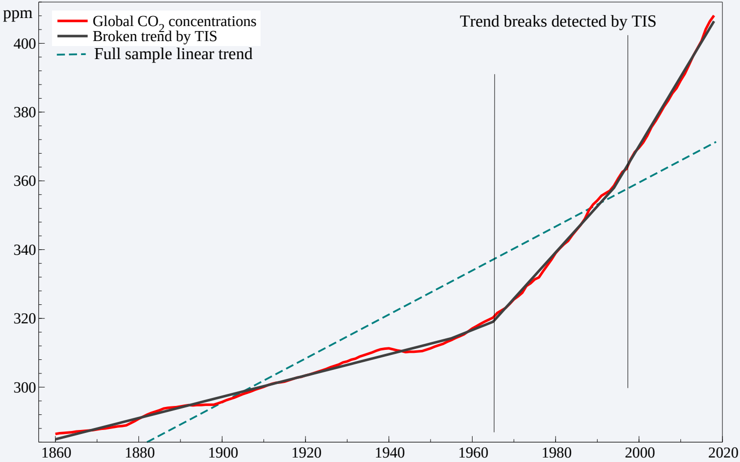
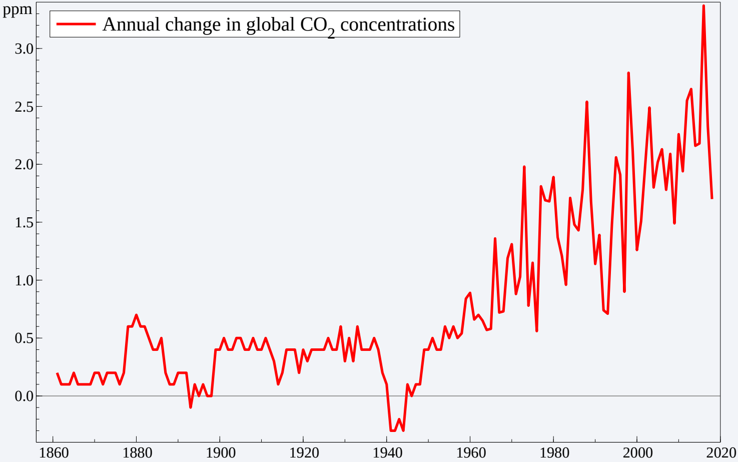


Comparing to an overall linear trend highlights that the trend is increasing.

Annual change in CO_2 concentrations



Annual change in global CO_2 concentrations in parts per million (ppm)

Annual change in CO_2 concentrations

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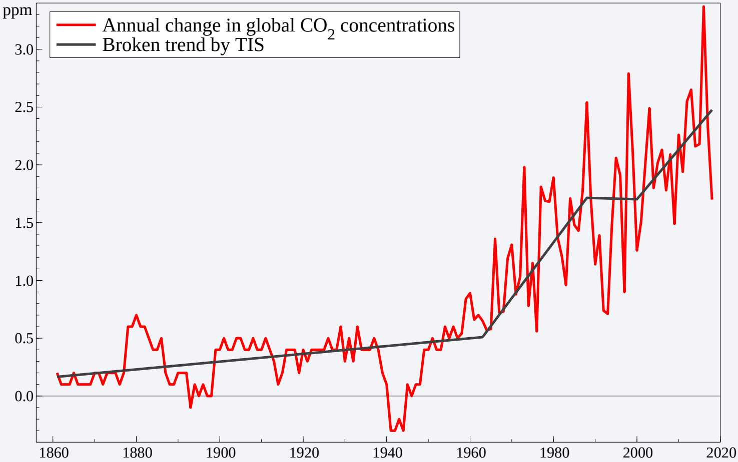

Change in measurement leading to increased volatility.

Rapidly increasing trend despite Paris Agreement.

Pandemic lockdowns reduced GHG emissions but still emissions greater than can be absorbed, leading to increased concentrations.

Controling GDP growth is not likely to get society to climate neutrality.

Global CO_2 emissions over the COVID pandemic

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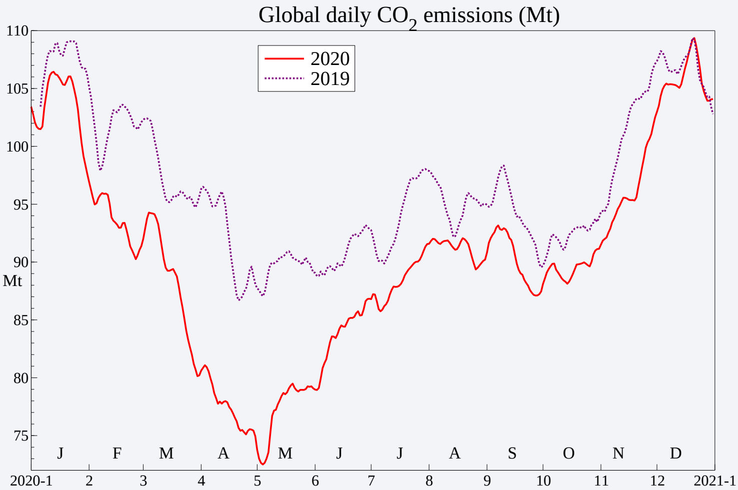

Reductions in CO_2 emissions in millions of tonnes (Mt) during 2020 from the SARS-Cov-2 pandemic compared to 2019.

Global CO_2 emissions over the COVID pandemic

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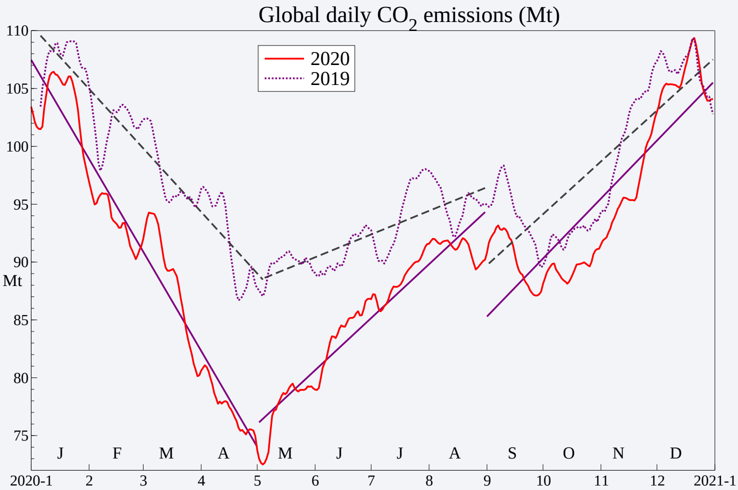

Even the drastic lockdowns during 2020 from the pandemic barely dented emissions (in Mt so tiny compared to 4ppm).

Climatic outcome depends on physical properties (energy balance etc.) and human behavior

Climate time series are non-stationary; exhibiting inertia; stochastic trends and distributional shifts from changing means and variances over time.

Forecasting change is insufficient as many features of climate change depend on levels of variables like atmospheric CO_2, which requires cumulating changes to levels when changes are forecast.

Reasonably accurate forecasts of changes may cumulate to poor forecasts of levels: if an average growth rate of 2% per annum is forecast by 1.6% per annum, after five years the level is underpredicted by 2%.

Most excess energy stored in climate system is taken up by oceans, leading to thermal expansion & sea level rise, 'baked in' by slow adjustment to past temperatures (Jackson et al., 2018).

∴ forecasts of future serious coastal flooding are reliable (Vousdoukas et al., 2018), although outcomes differ across RCPs much worse if West Antarctic & Greenland ice masses melted faster (Jackson et al., 2021).

Contribution from thermal expansion to sea level rise is substantial (Jevrejeva et al., 2020).

Storm surge heights dependent on local conditions–and resulting economic damages more so (Martinez, 2020; Jevrejeva et al., 2018).

But sea-level rise will intensify coastal flood risk by changing amplitude and occurrence of storm surges.

Sea level rise and Arctic ice melt

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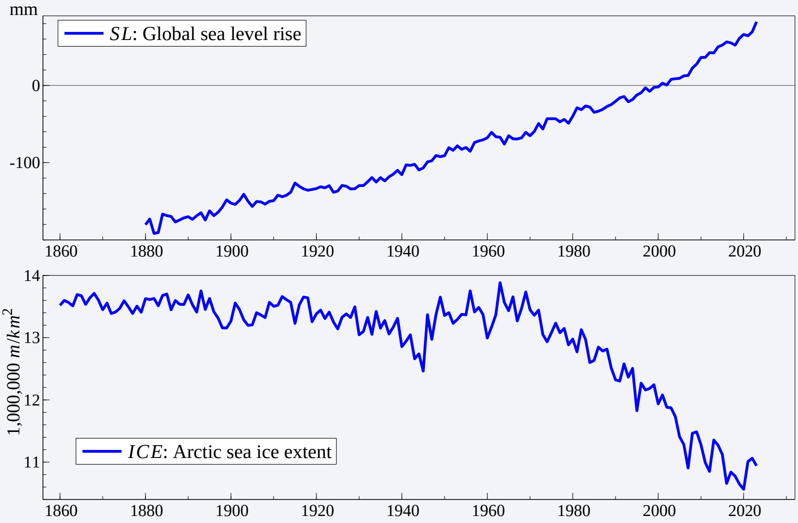

Sea level rise (OWID) and Arctic Ice melt (Copernicus)

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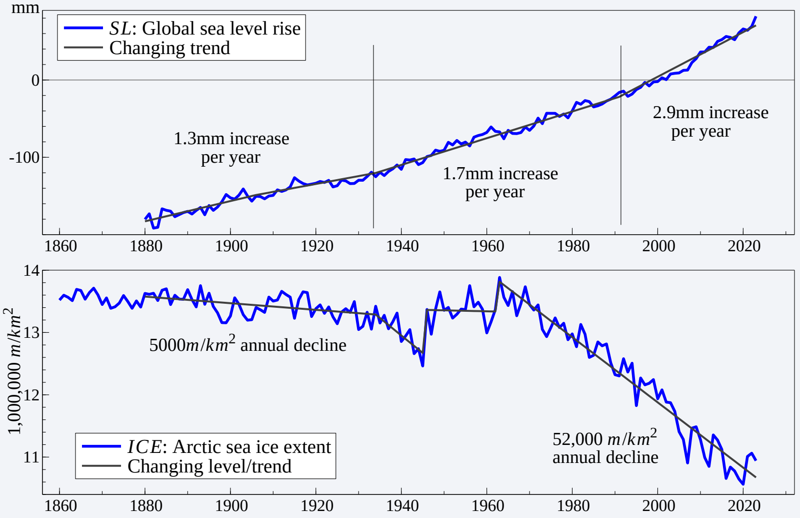

Sea level rise (OWID) and Arctic Ice melt (Copernicus)

Complexity of physical climate models grown with computing power, based on energy budgeting 1st law of thermodynamics

- First Generation: Zero-dimensional EBM equates global temperature change to a proportion of difference between incoming solar energy & outgoing energy radiated by Earth.
- 1960s: one-dimensional EBMs explicitly model horizontal latitudinal net heat transport (Budyko, 1969, Sellers, 1969).
- 1970s: One-and-a-half-dimensional/two-dimensional EBMs allow horizontal net heat transport to be driven by more complex forces so temperatures vary over latitude & longitude (Sellers, 1976).

Early EBMs either omitted anthropogenic components entirely or had stochastic forcings that were weakly stationary but anthropogenic forcings are not stationary!

Direct links between climate models and econometric systems

Cointegration applied to climate (Stern and Kaufmann, 2000).

Energy-balance model of global temperature, ocean heat content and radiative forcing equivalent to cointegrated system estimated from discrete time data (Pretis, 2020a).

Estimated parameters quantify uncertainties in IAMs of economic impacts of climate change.

Accounting for structural breaks from volcanic eruptions highlights parameter uncertainties, previous estimates of temperature response to increased CO_2 concentrations too low.

Moist energy-balance models allowing for horizontal net heat transport equivalent to cointegrated system & allow for more warming near poles than Equator (Brock and Miller, 2023).

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Most climate econometric time-series analyses do not strictly impose energy balance properties, allowing for measurement error, etc., they seek to be consistent with conservation of energy required by principles (first law) of thermodynamics.

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VAR specification

$$\begin{aligned}\mathbf{y}_t &= \sum_{j=1}^{4} \mathbf{\Pi}_j \mathbf{y}_{t-j} + \mathbf{\Gamma}_u \mathbf{z}_{u,t} + + \mathbf{\Gamma}_r \mathbf{z}_{r,t} \\ &+ \sum_{k=2}^{T-1} \lambda_{s,k} S_{1881+k} \sum_{k=3}^{T-1} \lambda_{\tau,k} \tau_{1881+k} + \boldsymbol{\nu}_t\end{aligned}$$

$\mathbf{y}_t = (AT, ERF, SST, SL, ICE)_t$.
$\mathbf{z}_{r,t}$: restricted regressors including t (full sample deterministic trend).
$\mathbf{z}_{u,t}$: unrestricted stationary regressors including $(const, ENSO, D_{Krakatoa}, D_{MtAgung}, D_{Pinatubo}, D_{MtPelee}, D_{Novarupta})_t$.
S_{xxxx}: step indicator; 1 till date $xxxx$ and 0 otherwise.
τ_{xxxx}: trend indicator; $(-t, -t+1, -t+2, \ldots, 0, 0, 0 \ldots)$.

Note: AT temperature; ERF effective radiative forcing; SST sea surface temperature; SL sea level; ICE Arctic ice.

Indicator saturation estimators designed to detect outliers, shifts in mean or in trends at any point in data sample without relying on knowledge of their number, signs, magnitudes or timing.

Principle involves generating an indicator variable for every observation in sample for adding to set of regressors to search for their significance.

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Indicator variables could be:

- impulse dummies (IIS): $\iota_j = 1$ for $t = j$ and 0 otherwise $\forall j \in T$.
- step dummies (SIS): $S_{j,t} = 1_{t \leqslant j}$ and 0 otherwise.
- trend breaks (TIS): cumulation of step indicators designed to be zero in the forecast period.
- multiplicative dummies (MIS): step indicators interacted with conditioning regressors.

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Adding all indicators at once results in perfect fit, but using tree search algorithm with expanding & contracting block searches allows all possible indicators to be investigated.

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Trend indicators cumulate step indicators up to each next observation.
Many equivalent forms, we use $\text{ø}'_1 = (-1, 0, 0, \ldots, 0)$, up to $\text{ø}'_T = (-T, -(T-1), -(T-2), \ldots, -1)$ (implemented in *Autometrics*, Doornik, 2009).
Conditioning variables $\mathbf{z}_t$ could be retained without selection.

Differences between Step indicator saturation (SIS) and TIS:

- **trend indicators rapidly become highly collinear.**
- **orders of convergence of estimators differ from $\sqrt{T}$.**

Trend indicator saturation (TIS)

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Split-half approach (Hendry et al., 2008):

1. **Add first $T/2$ trend indicators, record those significant at α.**
2. **Replace first half with remaining set of trend indicators, again recording which are significant in that subset.**
3. **Combine recorded indicators from two stages, select at α.**

Distributional shifts

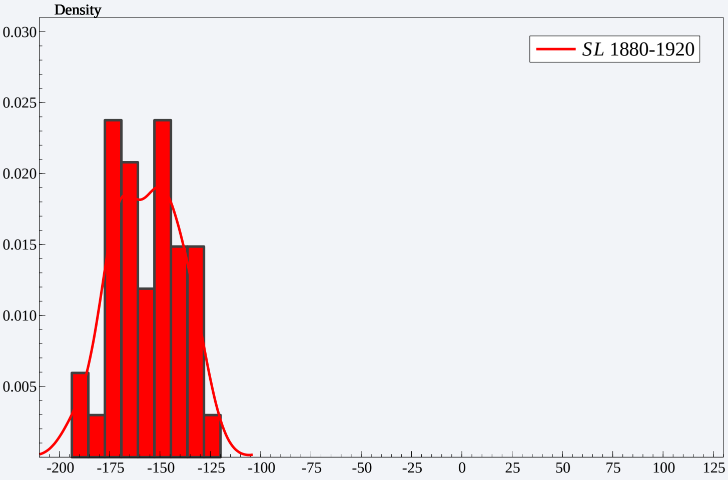
Climate change is not happening at a constant rate, so forecasters need to handle non-stationarities caused by shifts and breaks as well as smoothly-varying deterministic functions.

Arctic ice cover disappearing at increasingly rapid rates. Accelerating ocean heat content and global sea-level rises. Deterministic trends shown on plots are descriptive, not components of DGPs, reflecting responses to increasing atmospheric levels of GHGs.

Changes in dynamics as well as location shifts like impacts of COVID-19 lockdowns on economic outcomes & ∴ GHGs.

Little can be done when unanticipated shifts occur after forecasts made (sudden onset of COVID-19). Difficult even when antecedents that might predict a shift (information going beyond relevant discipline's information on 'regular forces', e.g. advance warning of El Niño.)

Distributional shifts sea level rise



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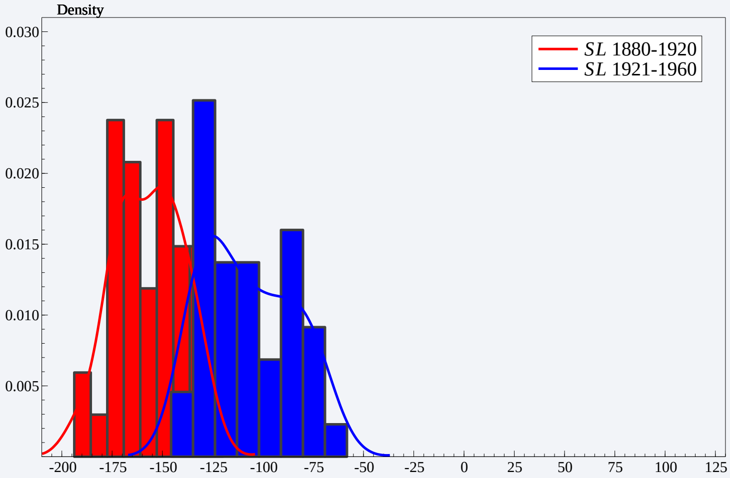

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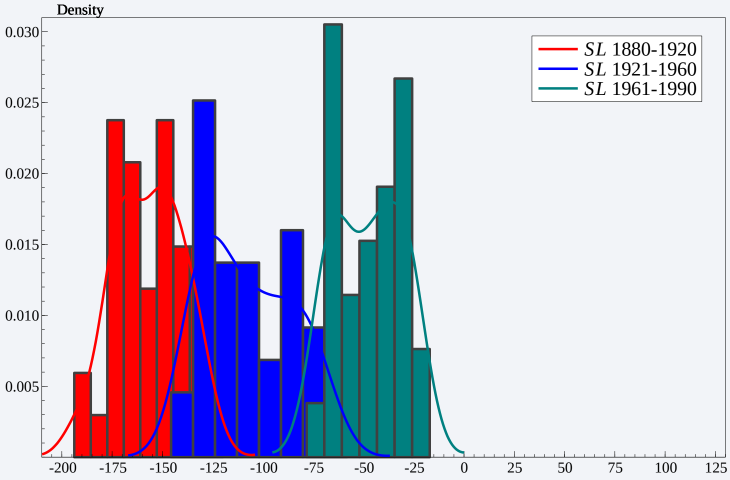

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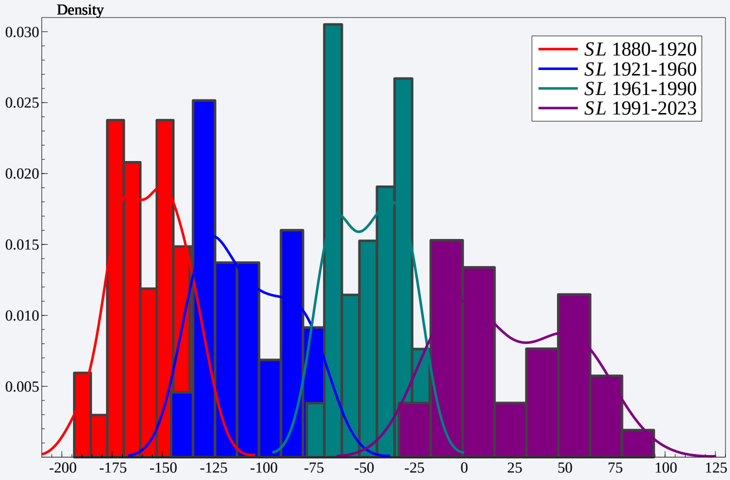
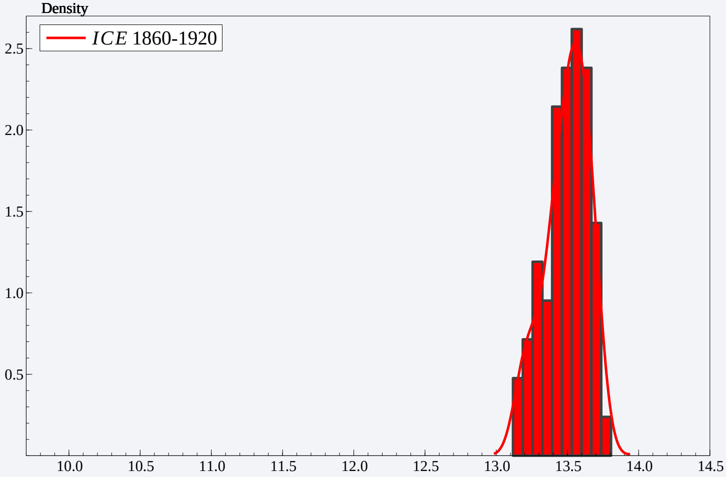
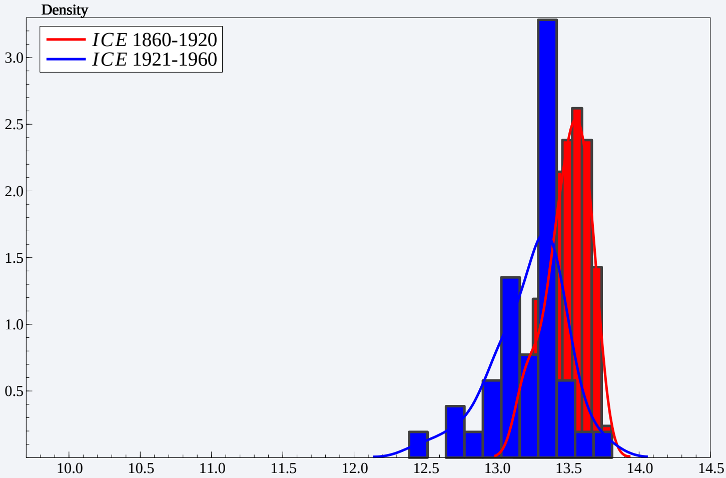


Distributional shifts in Arctic sea ice extent



Distributional shifts in Arctic sea ice extent



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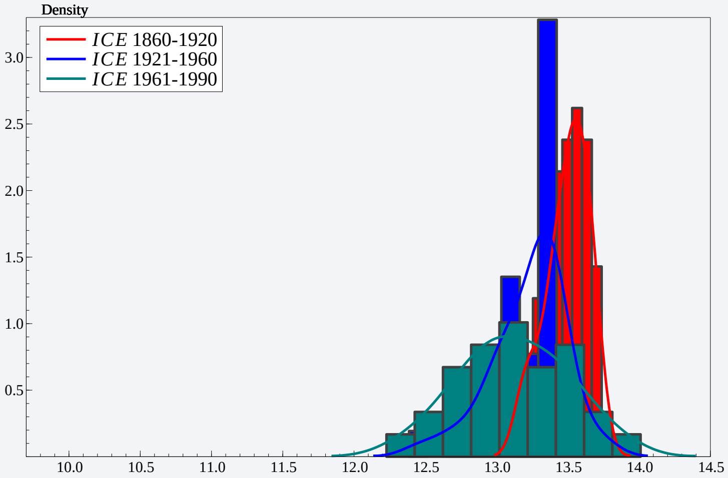

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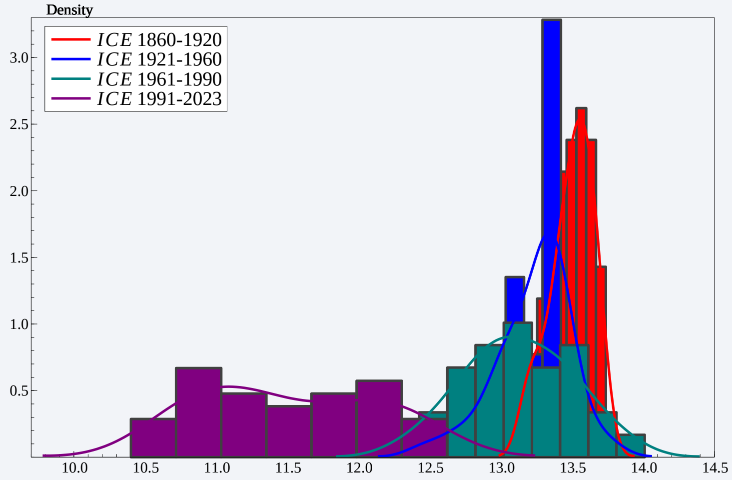

VAR specification

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- SIS & TIS applied at $\alpha = 0.01\%$ keeping all other regressors.
- $S_{1947}; \tau_{1903}; \tau_{1938}; \tau_{1945}; \tau_{1946}; \tau_{1978}$ retained. Reductions to combine the indicators in 1945, 1946 and 1947 rejected.
- Lagged variables selected at 1%, reduced lag length to 1.
- 19 variables in each equation of system.

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- Lagged variables selected at 1%, reduced lag length to 1.
- 19 variables in each equation of system.
- System is well-specified: all system diagnostic tests pass apart from functional form at 5% (see non-linearity below).

Table: System diagnostic tests

$F_{ar}(50, 505) = 1.22$	second-order vector residual autocorrelation
$\chi^2_{nd}(10) = 5.84$	vector residual non-normality
$F_{het}(160, 525) = 1.03$	vector residual heteroskedastcity
$F_{reset}(50, 505) = 1.42^*$	RESET functional form
$F_{nl}(240, 363) = 1.21$	non-linearity index test

Recursive residuals and constancy tests

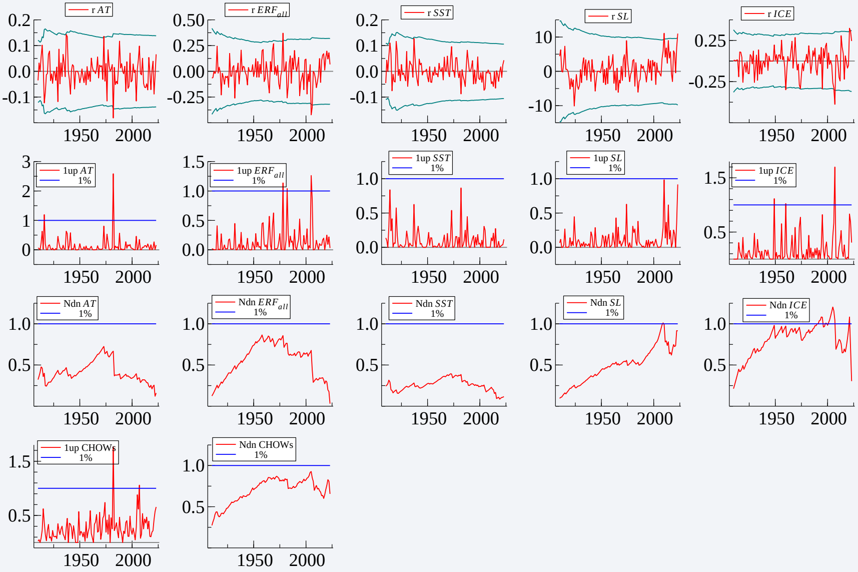

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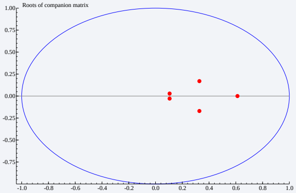
Table: Correlations between residuals (standard deviations on diagonal)

	AT	ERF	SST	SL	ICE
AT	0.07				
ERF	0.09	0.16			
SST	0.77	0.22	0.05		
SL	0.09	-0.02	0.03	4.91	
ICE	-0.30	0.16	-0.15	-0.01	0.18



Eigenvalues of dynamics less than unity but we proceed to undertake cointegration analysis on the system.

Cointegrating relationships

Let $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$ where $\boldsymbol{\alpha}$ is a $(p \times r)$ matrix of adjustment coefficients describing which equations adjust, and $\boldsymbol{\beta}$ is a $(p \times r)$ matrix of coefficients describing r long-run relations $\boldsymbol{\beta}'\mathbf{x}_t$.

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$$\boldsymbol{\beta}' = \begin{bmatrix} 1 & -\lambda_2 & 0 & -\lambda_4 \\ 0 & 1 & \lambda_3 & 0 \\ -\lambda_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} AT \\ ERF \\ SST \\ SL \\ ICE \end{pmatrix}$$

- CI_a relates temperature to sea surface temperature (following Pretis (2020b) who relates mixed layer temperature anomaly to deep compartment temperature anomaly).
- CI_b relates temperature anomaly to effective radiative forcing, also similar to Pretis (2020b).
- CI_c captures effect of radiative forcing on level of arctic ice.
- CI_d maps relationship between temperatures and sea levels.

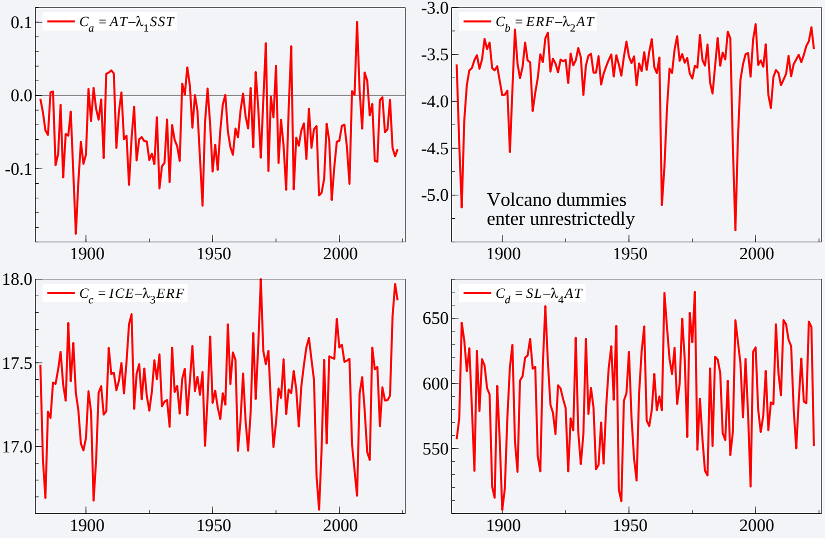
Imposing theoretical constraints on β matrix along with data-based restrictions on α matrix results in $\chi^2_{LR}(13) = 8.63$ ($p - value = 0.80$) so restrictions are comfortably accepted.

$$\alpha\beta' =$$

$$\begin{bmatrix} \underset{(0.063)}{-0.72} & \underset{(0.231)}{-0.74} & 0 & 0 & 0 \\ \underset{(0.019)}{0.09} & \underset{(0.045)}{-0.76} & \underset{(0.015)}{0.08} & \underset{(1.60)}{3.11} & \underset{(0.064)}{0.50} \\ 0 & 0 & 0 & 0 & \underset{(0.073)}{-0.87} \\ \underset{(0.0001)}{0.002} & \underset{(0.0003)}{0.002} & \underset{(0.0001)}{0.002} & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & \underset{(0.126)}{-0.60} & 0 & \underset{(28.1)}{-368} \\ 0 & 1 & \underset{(0.055)}{0.52} & 0 \\ \underset{(0.049)}{-1.23} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

Map to cointegrated system and undertake model reduction by eliminating regressors in each equation that were insignificant at 1%. Allow for more complex short-run dynamics and non-linearities.

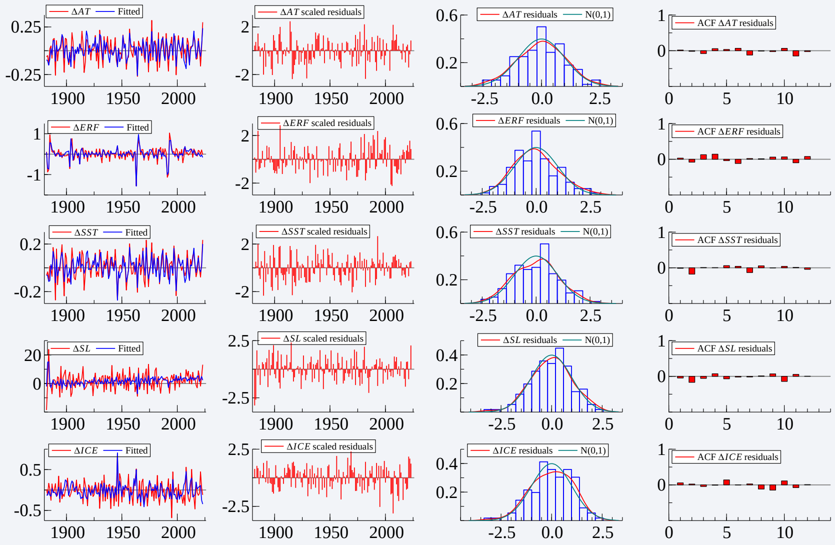
Stationary cointegrating relationships



Model of climate variables

$$
\begin{aligned}
\Delta AT_t &= \underset{(0.07)}{-0.81}CI_{a,t-1} + \underset{(0.02)}{0.15}CI_{b,t-1} - \underset{(0.004)}{0.018}CI_{c,t-1} + \underset{(0.0001)}{0.0013}CI_{d,t-1} \\
&\quad \underset{(0.01)}{+0.09}ENSO_t + \underset{(0.07)}{0.31}I_{1946} \\
\Delta ERF_t &= \underset{(0.05)}{-0.73}CI_{b,t-1} - \underset{(0.0004)}{0.002}CI_{d,t-1} - \underset{(0.25)}{3.57} + \underset{(0.14)}{1.35}D_{Krakatoa} + \underset{(0.16)}{0.83}D_{MtPelee} \\
&\quad \underset{(0.14)}{+1.52}D_{Pinatubo} + \underset{(0.14)}{1.55}D_{MtAgung} + \underset{(0.14)}{0.58}D_{Novarupta} + \underset{(0.16)}{0.36}I_{1946} \\
\Delta SST_t &= \underset{(0.01)}{+0.15}CI_{b,t-1} + \underset{(0.00009)}{0.0009}CI_{d,t-1} + \underset{(0.009)}{0.09}ENSO_t + \underset{(0.01)}{0.04}\Delta ERF^2_{t-1} \\
&\quad \underset{(0.06)}{-0.35}I_{1946} \\
\Delta SL_t &= \underset{(0.23)}{-1.29}CI_{b,t-1} - \underset{(0.08)}{0.32}\Delta SL_{t-1} - \underset{(4.47)}{18.26}D_{Krakatoa} + \underset{(1.63)}{5.05}\Delta ERF^2_{t-1} \\
&\quad \underset{(0.01)}{+0.036}\tau_{2011} \\
\Delta ICE_t &= \underset{(0.06)}{+0.42}CI_{b,t-1} - \underset{(0.08)}{0.81}CI_{c,t-1} + \underset{(1.54)}{15.55} - \underset{(0.16)}{0.55}D_{MtAgung} + \underset{(0.18)}{0.85}I_{1946}
\end{aligned}
$$

Model fit, residuals, residual density and correlogram



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Forecasts or scenario projections

Climate scientists produce *simulations* of an underlying physical climate model: *conditional* forecasts with certain anthropogenic scenarios in mind.

Global Climate Models

Forecasts or scenario projections

Climate scientists produce *simulations* of an underlying physical climate model: *conditional* forecasts with certain anthropogenic scenarios in mind.

Climate forecasts now produced by *global climate models*. High level of complexity & spatial/temporal disaggregation.

- ***Representative Concentration Pathways* (RCPs): focus on concentrations of GHGs rather than emissions (Moss et al., 2010).**
- ***Shared Socioeconomic Pathways* (SSP): expand on RCPs by allowing for alternative scenarios in economic and population growth (Riahi et al., 2017).**

Uncertainty around initial conditions of climate forecasts. Slight mistakes in measured state of atmosphere can grow rapidly over time leading to large errors in future.
Ensemble forecasts (computer model run a number of times from slightly different initial conditions) used to estimate uncertainty around central forecast (Palmer, 2006, 2022).

Future path of GHGs highly uncertain (dependent on human use of fossil fuels & agriculture) so projections conditional on concentration pathways rather than unconditional outcomes.

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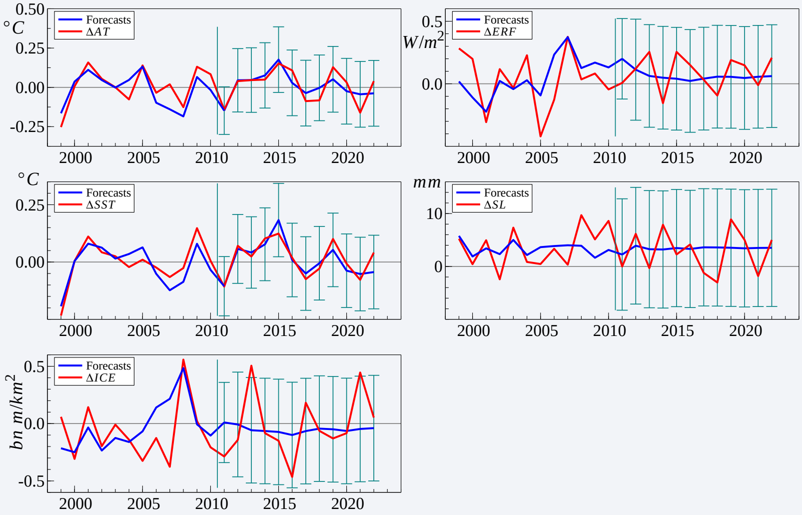
Interpretation of uncertainty from climate models differs to that of economic or statistical models:

- Climate models: uncertainty based on common set of input data but different models and different initial conditions.
- Statistical models: uncertainty from known model with unknown coefficients and error specification for unobserved determinants.

Why use statistical forecasting methods for predicting climate?

- **forecast horizon typically longer than traditional economic forecasting;**
- **for longer horizon forecasts non-stationarity plays a key role;**
- **breaks in trend over forecast period inherently unpredictable, depending on exogenous shocks and distant policy changes;**
- **conditional forecasts based on assumptions regarding future policy and events are feasible;**
- **key feature of forecasting models is whether they are closed (all their variables are modeled), or open (some variables are unmodeled and conditional forecasts are made);**
- **exogeneity of conditioning variables matters concerning linking economic outputs to temperature, or the opposite;**
- **invariance of model parameters to policy interventions and environmental changes crucial.**

Dynamic forecasts of changes in climate variables



Forecasts for 2011-2022, using model estimated up to 2010.

Dynamic forecasts of climate variables

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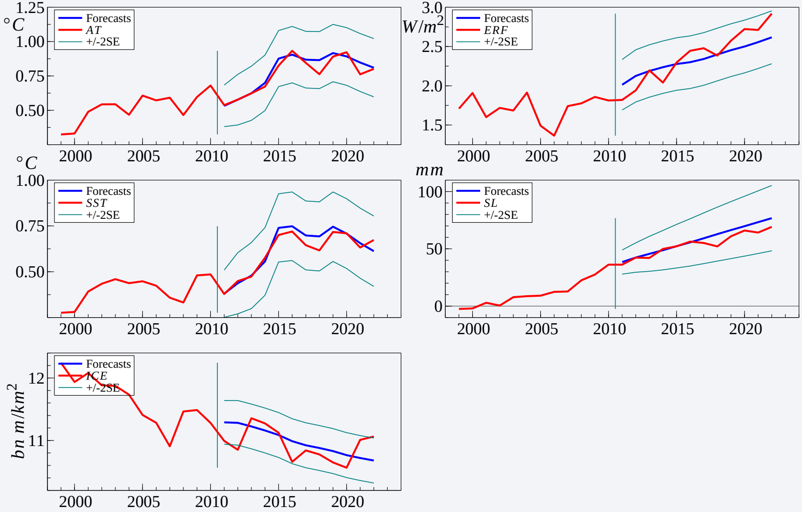

Integrated forecasts from VEqCM over 2011-2022. model estimated to 2010.

Dynamic forecasts of cointegrating relations

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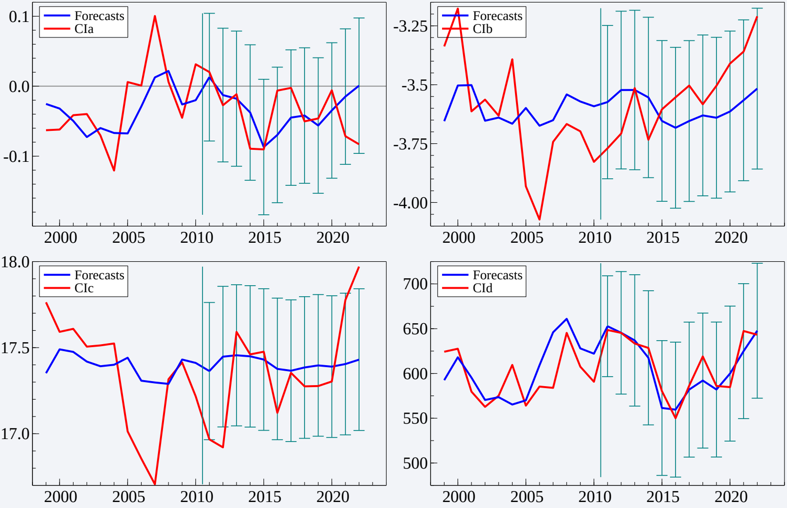

Dynamic forecasts of the cointegrating relations over 2011-2022.

Long-run information matters for forecasts

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	VEqCM	VAR levels		VAR diffs	
			ISE		ISE
AT	**0.04**	0.06	0.16	0.12	0.05
ERF	**0.17**	0.38	0.64	0.22	0.21
SST	**0.04**	0.07	0.13	0.16	0.08
SL	5.29	10.63	30.93	9.81	**4.63**
ICE	**0.25**	0.35	0.52	0.35	0.28

RMSFEs for 12 dynamic forecasts over 2011-2022.

- **VAR levels**: VAR in (AT, ERF, SST, SL, ICE) with 2 lags (selected from 4), conditioning on ENSO & volcano dummies.
- **VAR diffs**: VAR in $(\Delta AT, \Delta ERF, \Delta SST, \Delta SL, \Delta ICE)$ with 1 lag (selected from 3), conditioning on ENSO & volcano dummies variables. Level forecasts from integrating differenced forecasts.
- **ISE**: Indicator saturation estimators. For levels IIS & TIS at $\alpha = 0.01\%$; for differences IIS & SIS at $\alpha = 0.1\%$

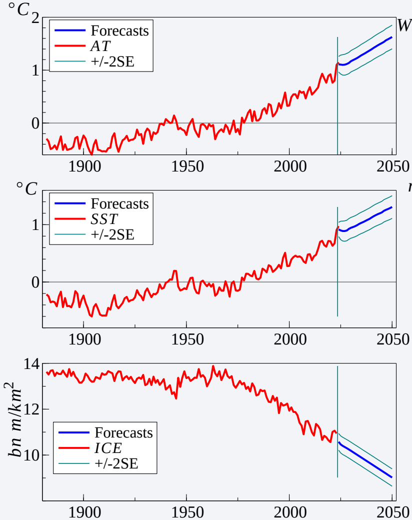
System forecasts outperform univariate forecasts

	VEqCM	AR(1)	TIS	RW
AT	**0.04**	0.36	0.09	0.15
ERF	**0.17**	1.51	0.32	0.65
SST	**0.04**	0.34	0.08	0.16
SL	5.29	**3.70**	13.15	20.22
ICE	**0.25**	0.83	0.29	0.42

RMSFEs for 12 dynamic forecasts over 2011-2022.

- **AR(1)**: Univariate AR(1) model for each endogenous variable, estimated over 1882-2010.
- **TIS**: Trend indicator saturation applied at $\alpha = 0.01\%$ with fixed constant and trend, estimated over 1882-2010.
- **RW**: Random walk forecast.

Forecasts to 2050



System closed apart from ENSO which is assumed to be zero over forecast horizon

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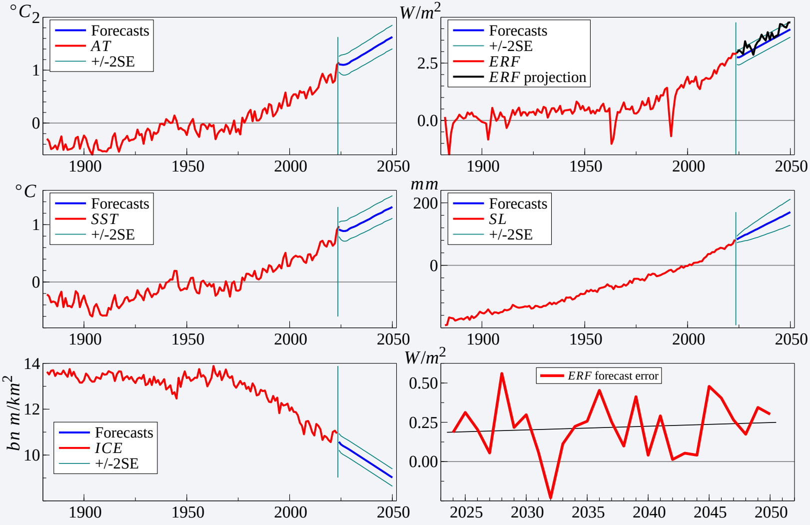

Evaluate ERF forecasts relative to physical model projections.
Systematic forecast bias suggesting structural break.

All stochastic variables are endogenous (trend shift variables are zero after their end dates) apart from ENSO.
If ENSO can be accurately forecast, could condition on those forecasts but Hendry and Mizon (2011) show many additional problems for open models so often pays to omit.

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Absent future trend breaks, predictions for 2050 are:

- **Global temperatures will be $1.6^{\circ}\mathrm{C}$ above $1961-1990$ ave.**
- **Global sea surface temperatures will be $1.3^{\circ}\mathrm{C}$ above $1961-1990$ ave.**
- **Global sea level rise will be $170\mathrm{mm}$ above $1993-2008$ ave.**
- **Arctic Ice extent will be reduced to $9\mathrm{bn}\ \mathrm{m}/\mathrm{km}^2$.**

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- Arctic Ice extent will be reduced to $9\mathrm{bn\ m/km}^2$.

Forecasts are conditional on current trends, incorporating feedbacks from ocean warming, sea-level rise and ice melt.
The forecasts do not condition on the future path of radiative forcing.

Shared Socio-economic Pathways (SSPs) used by IPCC.

Five SSPs embody narratives on population, GDP and urbanization trajectories, & assumptions on energy and land use sectors, see O'Neill et al. (2017):

SSP1 Sustainability – taking the green road.

SSP2 Middle of the road.

SSP3 Regional rivalry – a rocky road.

SSP4 Inequality – a road divided.

SSP5 Fossil fuel development – taking the highway.

Provide baseline and mitigation scenarios based on Representative Concentration Pathways (RCPs) which impose forcing targets ($6.0; 4.5; 3.4; 2.6 W/\mathrm{m}^2$ in 2100).

SSPs recorded at decadal intervals from 2010. Linear interpolation using unobserved components model (STAMP; Koopman et al., 2013).

Projections for radiative forcing

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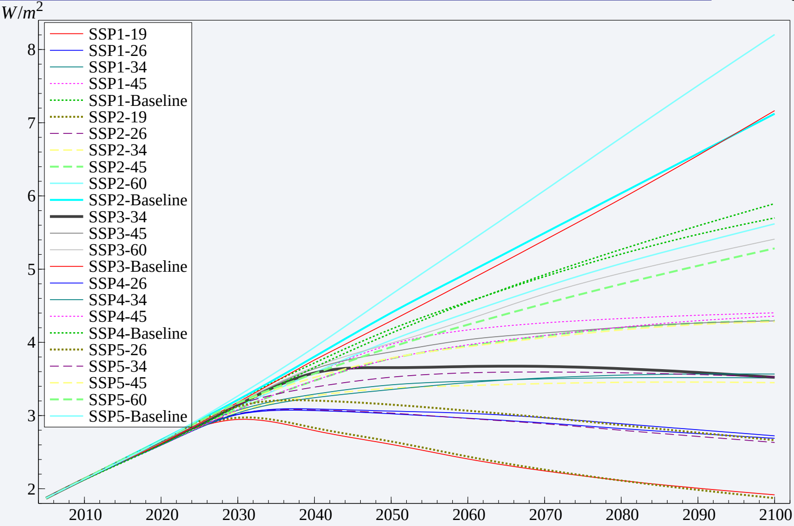


Projected radiative forcing under SSPs using AIM/CGE model, see Riahi et al. (2017).

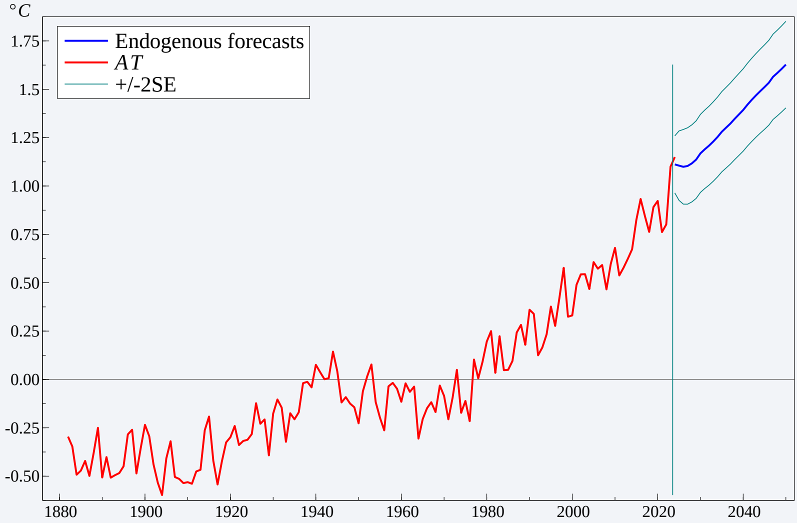
Conditioning on radiative forcing

To implement the forecasts assuming a projected path for radiative forcing change ERF from endogenous to exogenous and estimate a 4 variable system conditioning on ERF.

The quadratic term $\Delta \mathrm{ERF}^2_{t-1}$ is obtained from the scenario projections.

The cointegrating relations are identities based on the scenario projections and are forecast within the system.

The model is unchanged to 2023, but the forecasts condition on a known future path for ERF.



Forecasts of AT with endogenous ERF

Forecasts of global temperature to 2050

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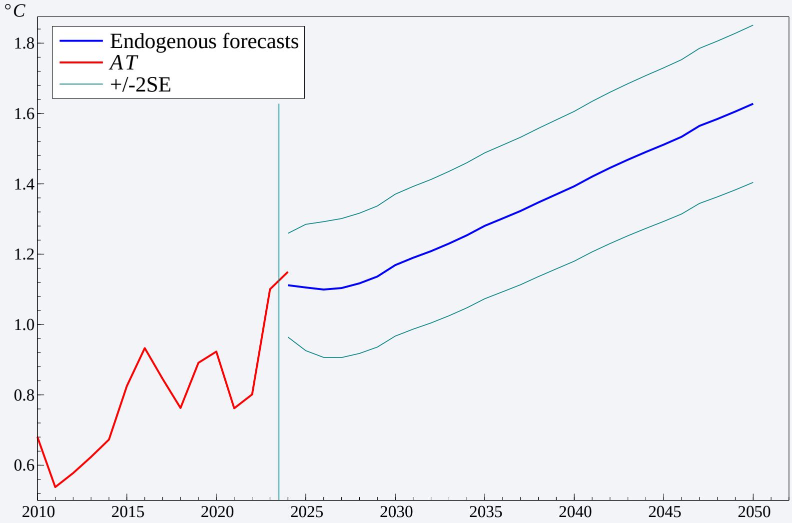

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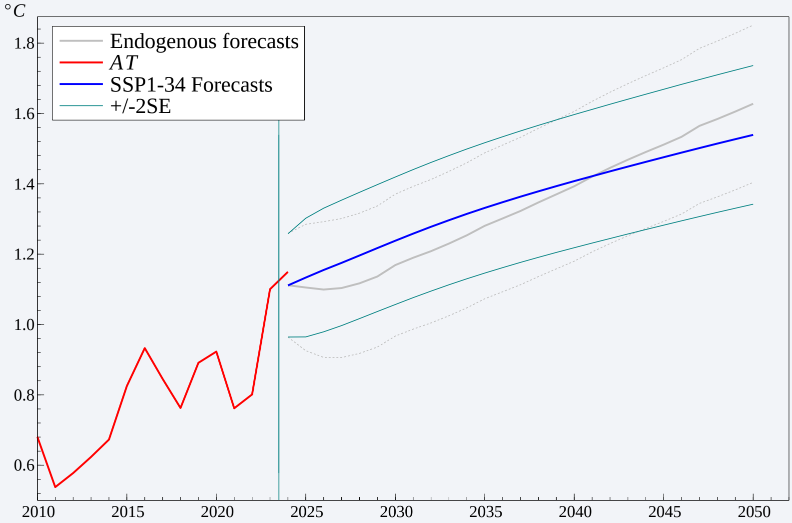

Forecasts of AT with exogenous ERF

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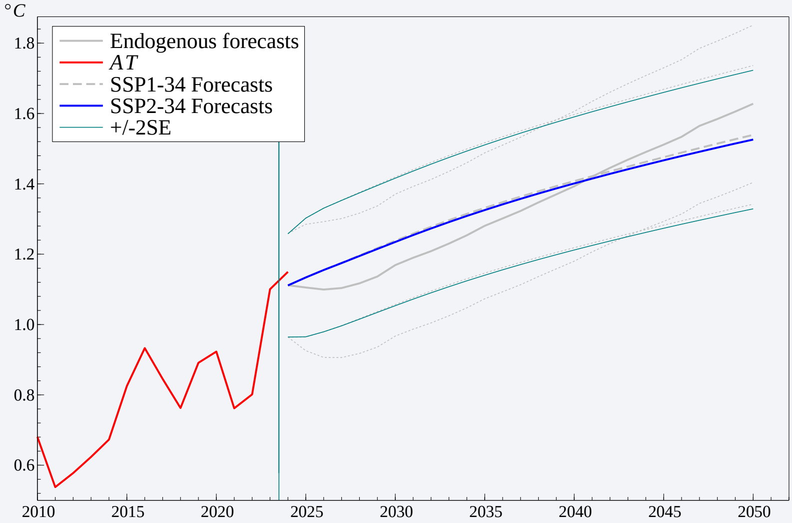

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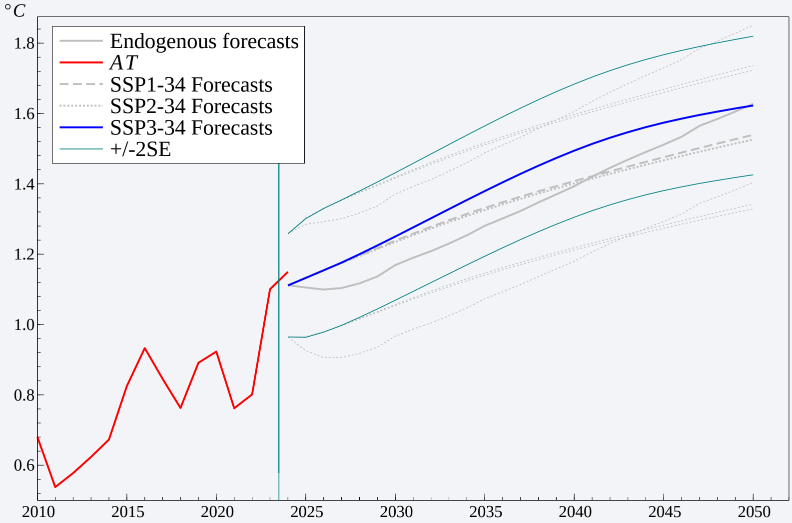

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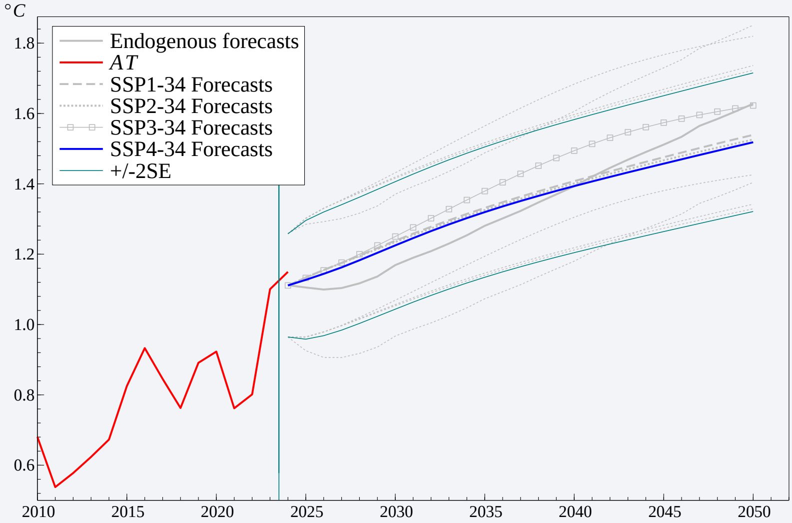

Forecasts of AT with exogenous ERF

Forecasts of global temperature to 2050

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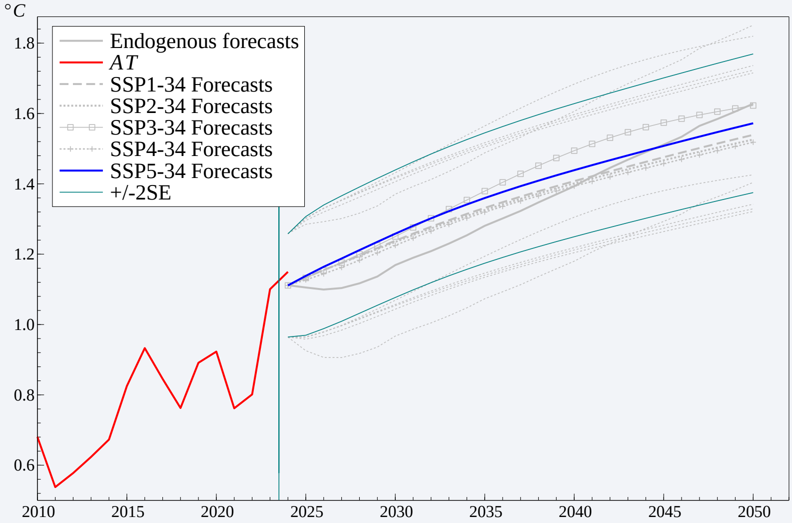

Forecasts of AT with exogenous ERF

	2050	2100
AT	$1.29 - 1.69°C$	$1.62 - 2.59°C$
SST	$0.96 - 1.37°C$	$1.0 - 2.02°C$
SL	$169 - 183mm$	$357 - 472mm$
ICE	$9.0 - 9.1bn\ m^2$	$6.1 - 6.7bn\ m/km^2$

Range of forecasts from SSP1-19–SSP5-60 in $°C$

Benchmarks

IPCC predicts AT of $1.5°C$ in 2050 and $2 - 4°C$ by 2100.
SST is predicted to rise to between $1.2°C$ and $3.2°C$ by 2100.
IPCC has a wide range for SL in 2100 of between $430 - 840mm$.
There are predictions that Arctic ICE could disappear by 2100.

Route Map

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1. A look at some climate data
2. A multivariate cointegrated VAR of climate variables
3. Forecasting climate change
4. Is there evidence of tipping points?
5. Conclusions

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Tipping points: a small change causes a large response (Lenton et al., 2008, Lenton, 2013).

Difficult to forecast occurrence of tipping points.
But short sequence of large one-sided 1-step ahead forecast errors occurring as forecast origin advances suggests sudden change from previous model.
Could be due to large measurement errors, step shift in mean of the process, or a sudden rapid change.

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Could be due to large measurement errors, step shift in mean of the process, or a sudden rapid change.

Use saturation estimation on Arctic ice equation to see if we can improve on forecasts.
Method: Test whether first two or three significant indicators can be replaced by broken linear or log-linear trend to capture sudden rapid changes.

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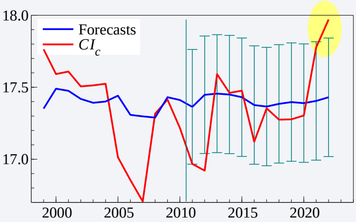
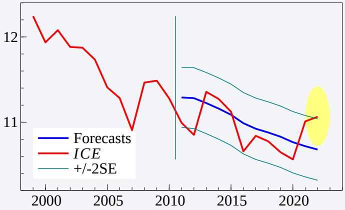
Forecasts for third cointegrating relation suggest a possible shift in 2021/22.





Equation for sea level estimated over 1882-2022

$$
\begin{aligned}
\Delta \mathrm{ICE}_t \quad = \quad & +\underset{(0.06)}{0.42}\,\mathrm{CI}_{b,t-1} - \underset{(0.08)}{0.81}\,\mathrm{CI}_{c,t-1} + \underset{(1.54)}{15.55} \\
& - \underset{(0.16)}{0.55}\,\mathrm{D}_{MtAgung} + \underset{(0.18)}{0.85}\,\mathrm{I}_{1946}
\end{aligned}
$$

Is there a break in the last few years of data?

- **Estimate the Arctic ice equation in levels up to 2021 including an impulse indicator for 2021 and test for significance:** $\widehat{t}_{I_{2021}} = 2.01$**.**
- **Extend sample by 1 observation test if impulse indicator in 2021 and 2022 is significant:** $\widehat{t}_{I_{2021}} = 2.01$**;** $\widehat{t}_{I_{2022}} = 1.8$**. Joint test** $F_{excl}(2, 155) = 3.6^*$**.**
- **Replace indicators with linear trend extending into forecast period and estimate with 2 observations:** $\widehat{t}_{\tau_{2021,22}} = 2.4$**.**
- **Replace indicators with log-linear trend extending into forecast period and estimate with 2 observations:** $\widehat{t}_{\log(\tau_{2021,22})} = 2.48$**.**
- **Compute out-of-sample forecasts and average across linear and log-linear trend.**

Forecasts for Arctic Ice in 2023

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	$Actual$	$VEqCM$	$\log(\tau)$	τ	$Ave(\tau)$	Ave
Fcast	10.94	10.70	11.19	11.29	11.24	11.06
$\widehat{e}_{2023}$		0.24	-0.24	-0.35	-0.29	**-0.12**

- $\log(\tau)$ estimates the Arctic ice equation in levels with a log-linear trend commencing in 2021.
- τ estimates the Arctic ice equation in levels with a linear trend commencing in 2021.
- $Ave(\tau)$ computes an equally weighted average of $\log(\tau)$ and τ.
- Ave computes an equally weighted average of the system forecasts of the level of Arctic ice from $VEqCM$ and $\log(\tau)$ and τ.

Forecasts for Arctic Ice in 2023

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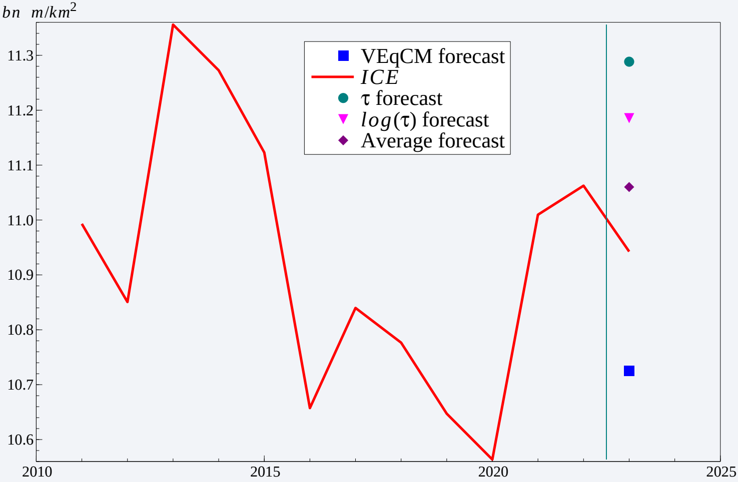

Summary of tipping point detection

- Significance of impulse indicators is marginal.
- Forecasts using trend correction show a reversal of trend in ice extent relative to system forecasts.
- No clear evidence of a positive tipping point (i.e. slow down in arctic ice melt).
- Need more observations to distinguish between measurement, outlier or changing trend.
- Operate detection methods sequentially as new data arrives.

Route Map

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Conclusions

Econometric methods have a useful role to play in climate modeling: outcomes are determined by human behavior interacting with physical properties of Earth's climate system.

Time-series data is non-stationary from stochastic trends & location and trend shifts making forecasts uncertain & prone to failure.

Unanticipated changes cannot be avoided but later become in-sample, so modeling must take account of them to avoid distortions in parameter estimates & resulting forecasts.

Climate change is not a given but an anthropogenic outcome. It is possible to get to net-zero GHG emissions by 2050: the speed and form of such a transition will impact on climate forecasting.

Thank you!

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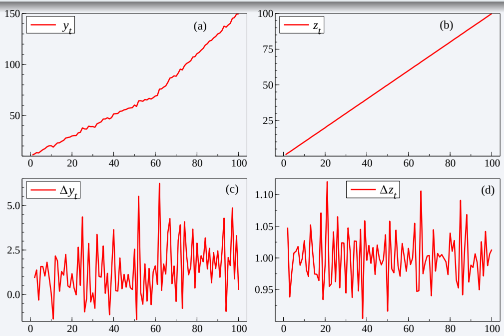
To investigate we use simulated data:

$$
\begin{aligned}
y_t &= \beta_{0,t} + \beta_{1,t} z_t + \epsilon_t \text{ where } \epsilon_t \sim \mathsf{IN}[0, \sigma^2_\epsilon] \\
z_t &= \gamma_0 + \gamma_1 t + \nu_t \text{ where } \nu_t \sim \mathsf{IN}[0, \sigma^2_\nu]
\end{aligned}
$$

$\beta_{0,t} = 10$ & $\beta_{1,t} = 1$ for $t = 1, \ldots, 60$; $\beta_{0,t} = -50$ & $\beta_{1,t} = 2$ for $t = 61, \ldots, 100$; $\gamma_0 = 0$, $\gamma_1 = 1$, $\sigma^2_\epsilon = 1$, $\sigma^2_\nu = 0.001$, deliberately set to a tiny value to mimic a trend.



TIS using split-half approach under the null

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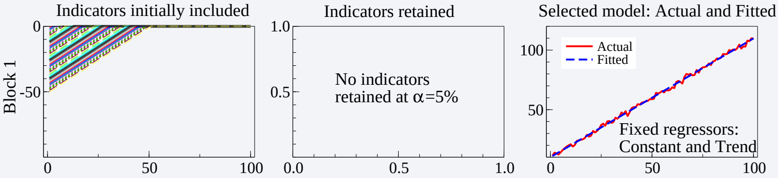
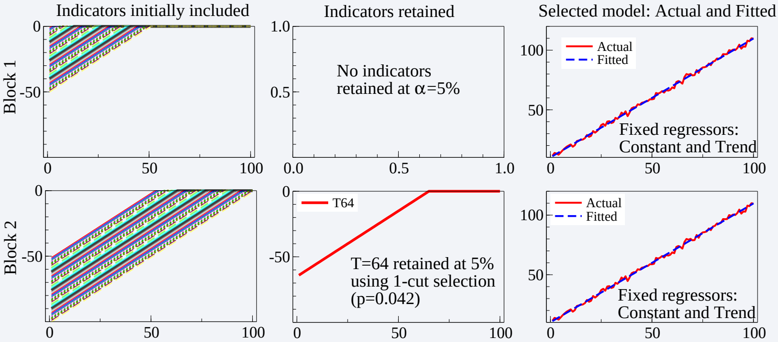


TIS using split-half approach under the null



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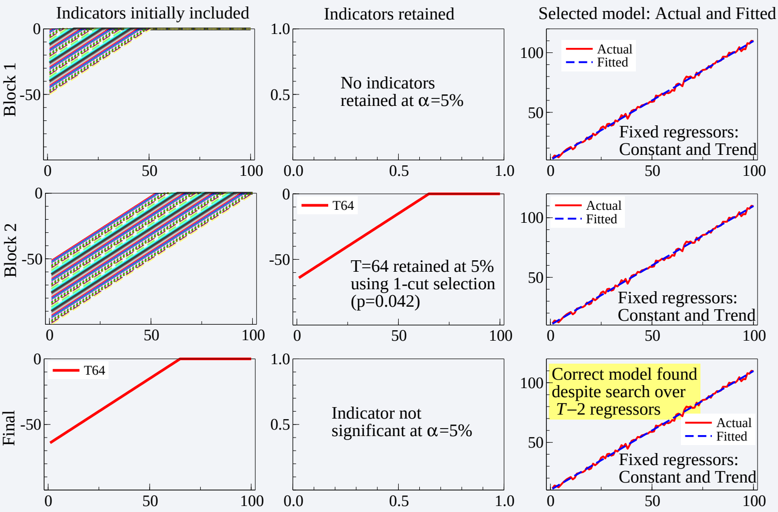
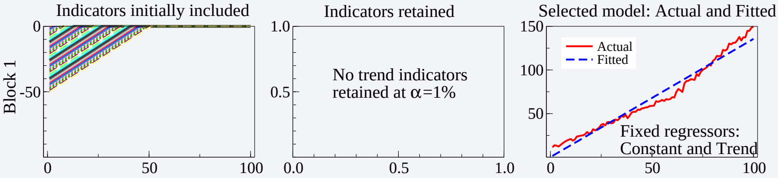
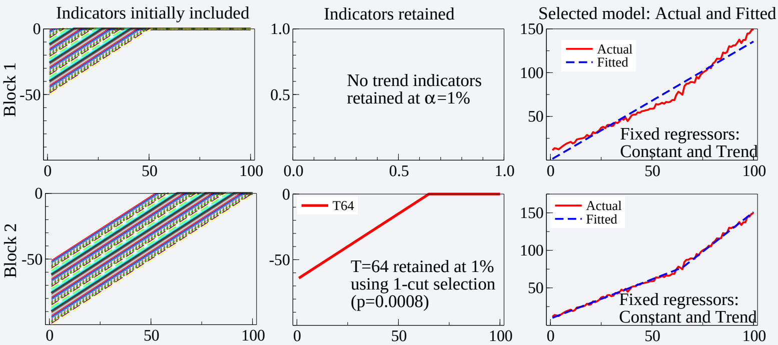
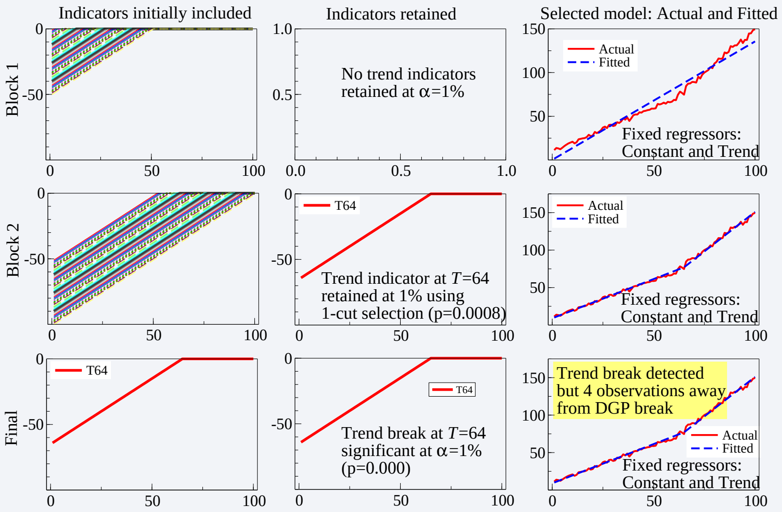


TIS under the alternative: a break in trend at T=60

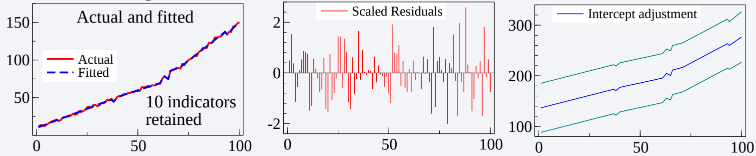



Indicators initially included
Indicators retained
Selected model: Actual and Fitted
Block 1
Block 2
No trend indicators retained at α=1%
Actual
Fitted
Fixed regressors: Constant and Trend
T64
T=64 retained at 1% using 1-cut selection (p=0.0008)
Actual
Fitted
Fixed regressors: Constant and Trend

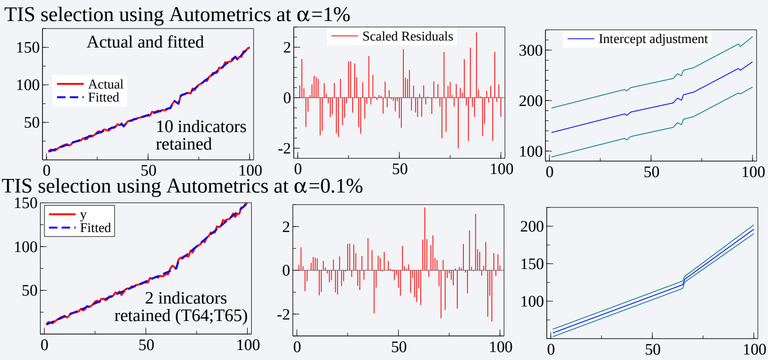
TIS under the alternative: a break in trend at T=60



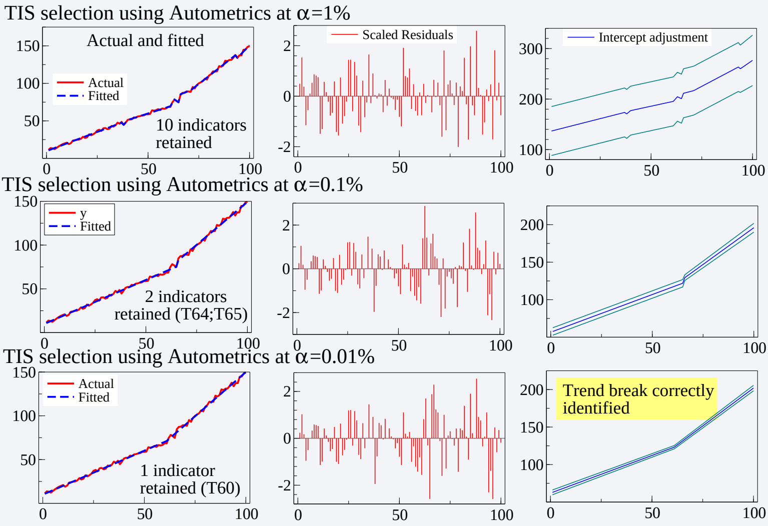
TIS selection using Autometrics at α=1%



Multipath search Autometrics



Multipath search Autometrics



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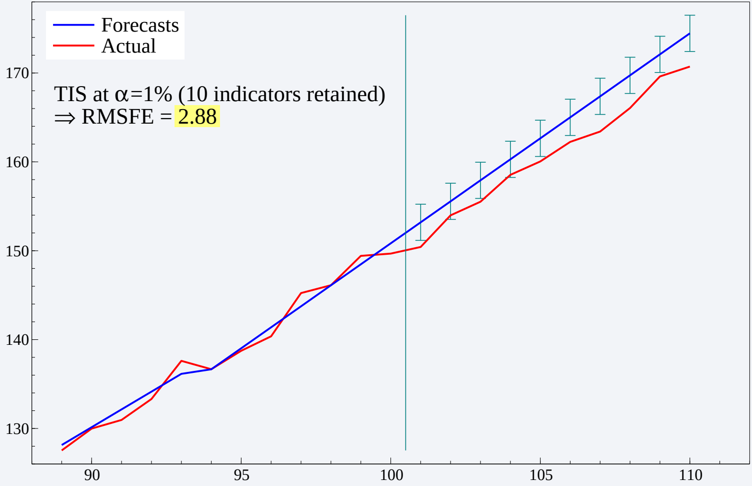
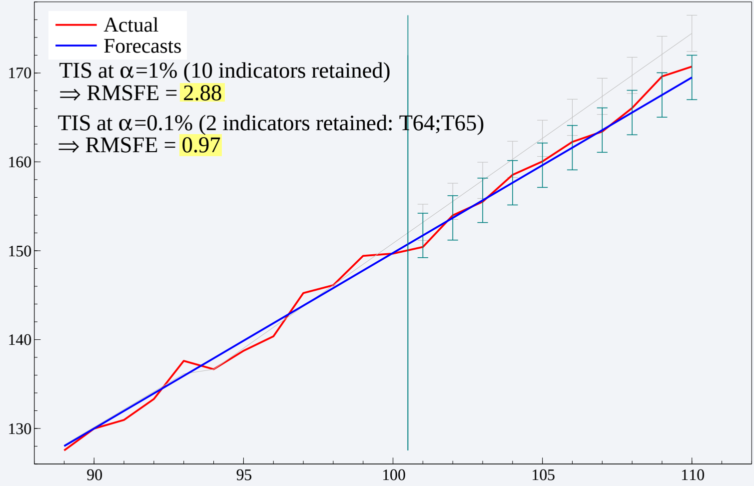
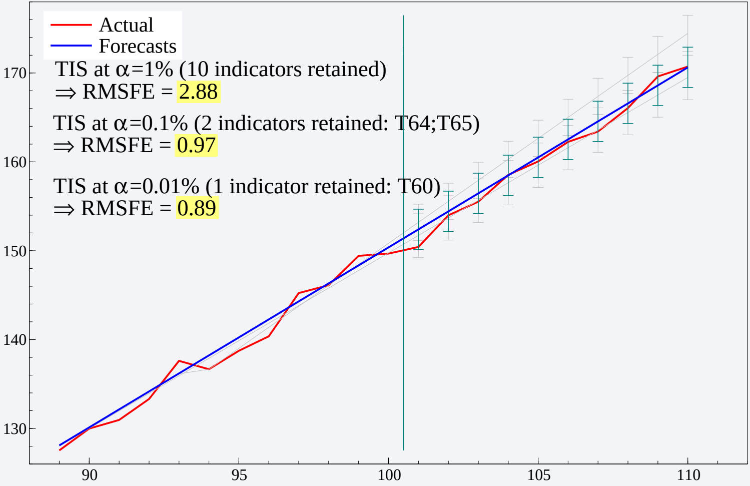


Trend break at T=60: Forecasting using TIS



Trend break at T=60: Forecasting using TIS



Trend break at T=60: Forecasting using TIS

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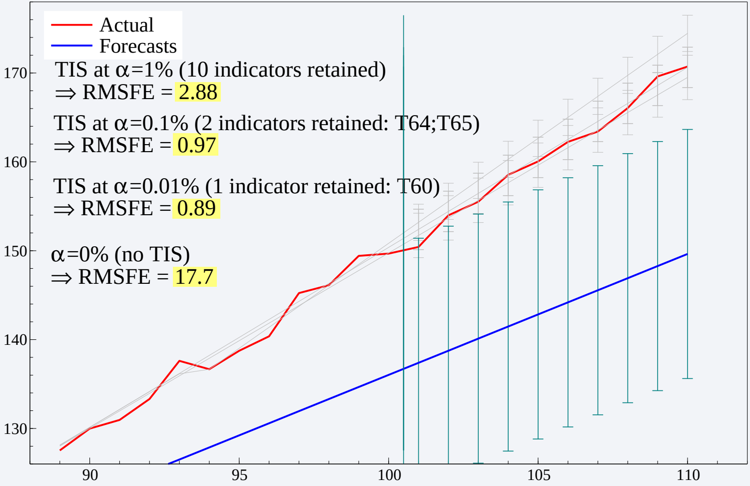
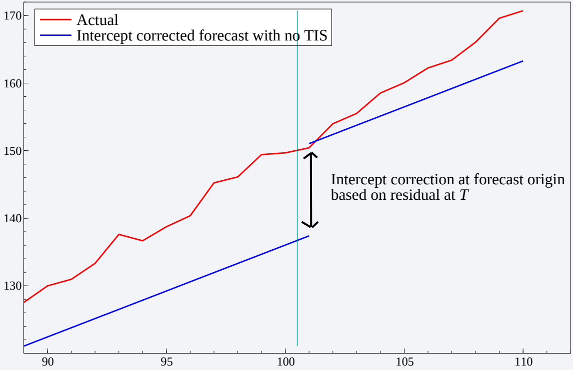


Intercept correction isn't sufficient

Not correctly modeling trend breaks in-sample leads to poor forecasts. Not sufficient to intercept correct at forecast origin.



Trend breaks must be modeled in-sample, even if long way from forecast origin. Use full sample rather than just post-break data.