science for global insight

Assessing the improvement of greenhouse gases inventories: can we capture diagnostic learning?

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Table of contents

I. Diagnostic learning

I.1. Motivation

- Reductions targets for parties to a post-Kyoto emissions reduction treaty need to take into account uncertainty of emissions estimates.

- Uncertainty may render veryfing compliance with reductions targets impossible.

- By understanding diagnostic learning we may be able to reduce uncertainty.

I.2. Notion of diagnostic learning

- Revisions of greenhouse gases (GHG) inventories reflect the advancement of knowledge about emissions

- **Diagnostic learning** – process of improvements of GHG inventories (i.e., increase of accuracy of emissions estimates)

- Following *Marland et al. (2009)* we understand diagnostic learning as a convergence

$$E_{n,y} \to E_n \ as\ y \to \infty,$$

where E_n is a true but unknown value of emissions that occurred in the year n and $E_{n,y}$ denotes estimate of emissions in year n revised in year y. (As estimates are published with two-year lag, $y \geq n + 2$.)

I.3. Approaches to diagnostic learning

Method	Learning reflected by	Influence of structural changes
Hamal (2010)	Total uncertainty: differences between most recent and most initial estimates (plus precision estimates)	✓
Jarnicka, Nahorski	Changes of emissions paths from revision to revision	✓
Our method	Convergence of sequences of revised emissions estimates $E_{n,y}$ for each fixed year of emissions *n.*	✗

II. The data

II.1. Data description (1)

- We demonstrate our method on the case example of Austria's CO_2 emissions inventories.
- The data set has been compiled from the Austria's National Inventory Reports (NIRs) submitted to the UNFCCC in the years 2003-2014.

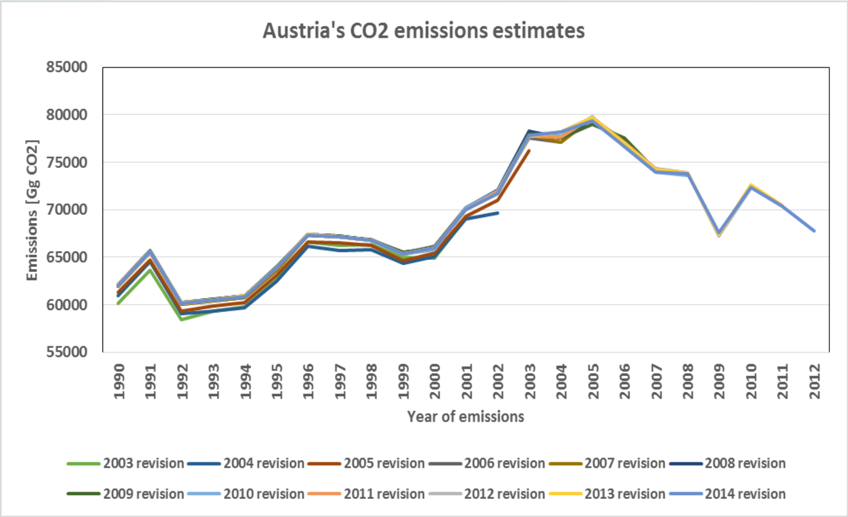
Year of emissions	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Year of NIR publication	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2	Gg CO_2
1992																							
...					Part I														Part II				
2002																							
2003	60113	63595	58455	59307	59744	62627	66629	66208	66333	65020	64928	69120											
2004	60899	64535	59080	59310	59704	62474	66147	65713	65808	64336	65064	69037	69671										
2005	61263	64752	59348	59900	60203	63115	66562	66527	66218	64614	65454	69280	70994	76213									
2006	61933	65486	60044	60415	60766	63664	67331	67155	66837	65444	66186	70179	71943	77562	77103								
2007	61930	65483	60042	60411	60763	63661	67327	67148	66812	65337	65960	70045	71709	77972	77140	79650							
2008	62085	65674	60229	60544	60930	63965	67407	67198	66773	65541	65928	70200	72115	78271	77529	79515	77283						
2009	62082	65671	60226	60543	60930	63965	67407	67200	66775	65554	65951	70056	72015	78055	77591	79009	77586	74177					
2010	62068	65656	60212	60528	60915	63951	67394	67188	66763	65353	65799	70191	72040	77840	77723	79773	76687	73972	73630				
2011	62068	65656	60212	60528	60915	63951	67394	67188	66772	65349	65984	70009	71890	77773	77688	79719	77084	74377	73929	67536			
2012	62060	65644	60138	60516	60900	63944	67384	67180	66763	65345	65972	70005	71720	77758	78216	79724	77033	74363	73922	67226	72290		
2013	62060	65644	60138	60516	60900	63944	67384	67180	66763	65345	65970	69999	71714	77758	78216	79724	77033	74275	73922	67397	72591	70455	
2014	62018	65602	60100	60482	60877	63924	67365	67162	66744	65343	65993	70029	71748	77801	78229	79393	76633	73980	73804	67568	72366	70354	67733

Table 1. Austria's CO_2 emissions estimates published in NIRs in the period 2003-2014.

We split the data into two parts:

- Part I: revised estimates of emissions for years 1990-2001 (12 sequenes (columns) of equal length)
- Part II: revised estimates of emissions for years 2002-2012 (11 sequences of decreasing length)

II.1. Data description (2)



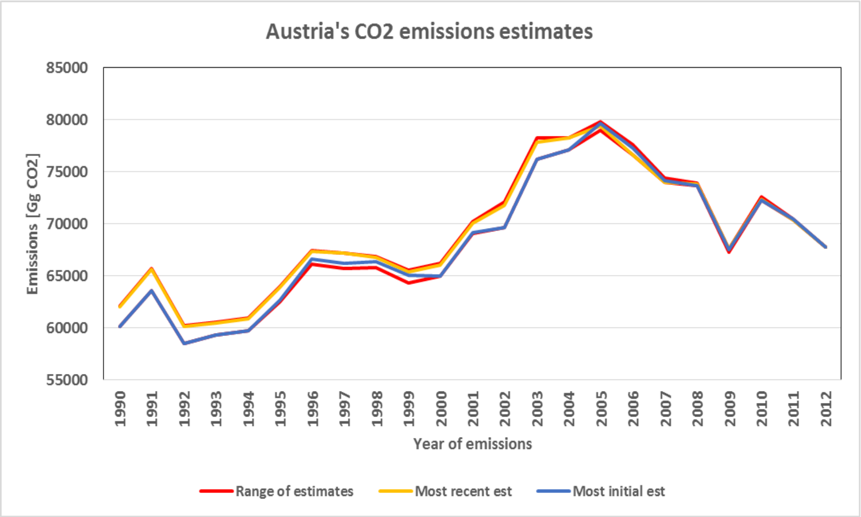


Fig. 1. Paths of Austria's CO_2 emissions plotted revision-wise

Fig. 2. Variability of Austria's CO_2 emissions: most recent and most initial estimates, highest and lowest estimates.

- Differences between emissions ocurred in different years are much bigger than corrections of estimates.
- It is difficult to compare in absolute terms the changes in estimates of emissions that occurred in different years.

II.2. Data transformation

To see the effect of consecutive estimates corrections more clearly we transform the data.

- We take the most recent revision as a refernce level.
- We normalize the data by dividing emissions estimates by the most recent ones:

$$\frac{E_{n,y}}{E_{n,Y}}$$

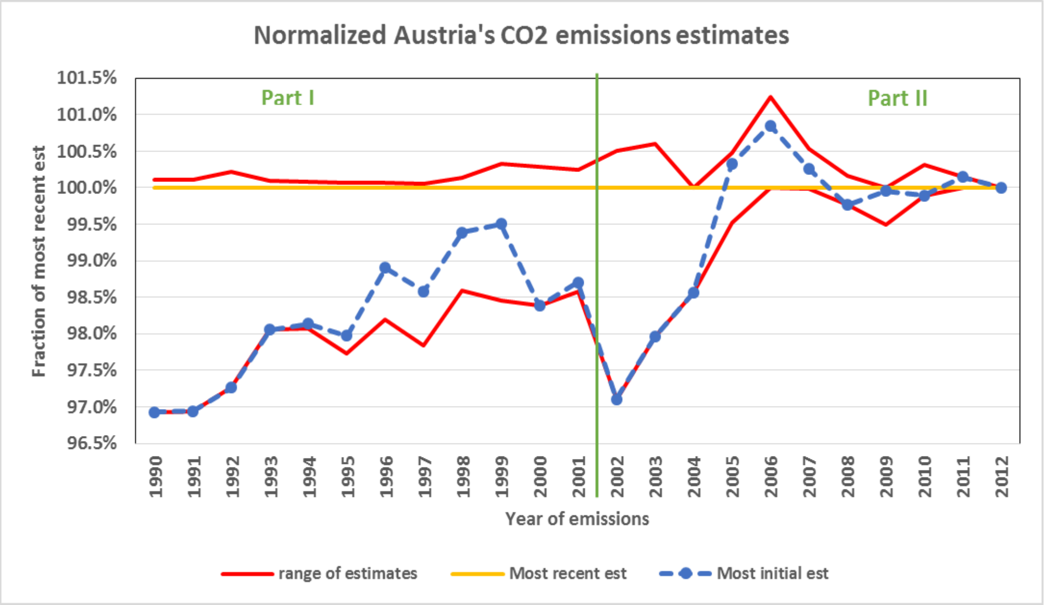


Fig. 3. Figure 2. after normalization transformation

III. Modeling diagnostic learning

III.1. Detecting diagnostic learning (1)

Assumptions:

- Emissions estimates $E_{n,y}$ are inaccurate and imprecise.
- The most recent estimates $E_{n,Y}$ are the most accurate and close to true emissions E_n.

How to detect diagnostic learning in the data?

- We say that diagnostic learning takes place if $E_{n,y} \rightarrow E_n \; as \; y \rightarrow \infty$.
- In practice we observe only a few (at most 12 at this point) first elements of sequence $E_{n,y}$.
- If $E_{n,Y} \approx E_n$ then we should be able to detect stabilization of $E_{n,y}$ around $E_{n,Y}$ as $y \rightarrow Y$. Equivalently, we should see

$$\frac{E_{n,y}}{E_{n,Y}} \rightarrow 1 \text{ as } y \rightarrow Y.$$

III.1. Detecting diagnostic learning (2)

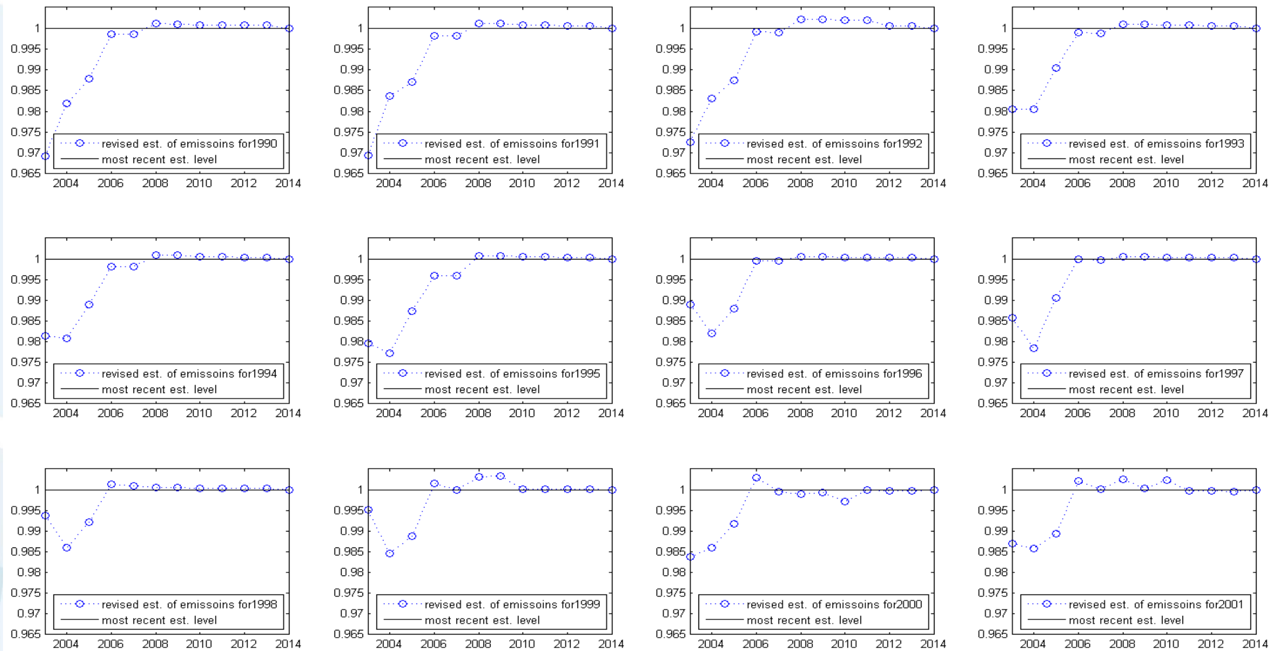


Fig. 4. Consecutive corrections of normalized emissions estimates for years 1990-2001 (Part I of the data)

- Bulk of learning is complete after just a few revisions.
- Later revisions of emissions estimates „oscilate” around level of the most recent ones.

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III.1. Detecting diagnostic learning (3) - - Range of estimates

Definition: Let

$$m_{n,y} = min\{E_{n,y}, \dots, E_{n,Y}\} \text{ and } M_{n,y} = max\{E_{n,y}, \dots, E_{n,Y}\}$$

denote the lowest and the highest of estimates of emissions in year *n* that were published between years *y* and *Y*.

Interpretation: All revised estimates published in year *y* or later lay in the range $[m_{n,y}, M_{n,y}]$.

- Width of this interval indicates the inaccuracy range of estimates published in year *y* or later.

- $M_{n,y}$ - $m_{n,y} \searrow 0$ as $y \to Y$. This may be interpreted as the increase of accuracy of emissions estimates.

III.1. Detecting diagnostic learning (4)

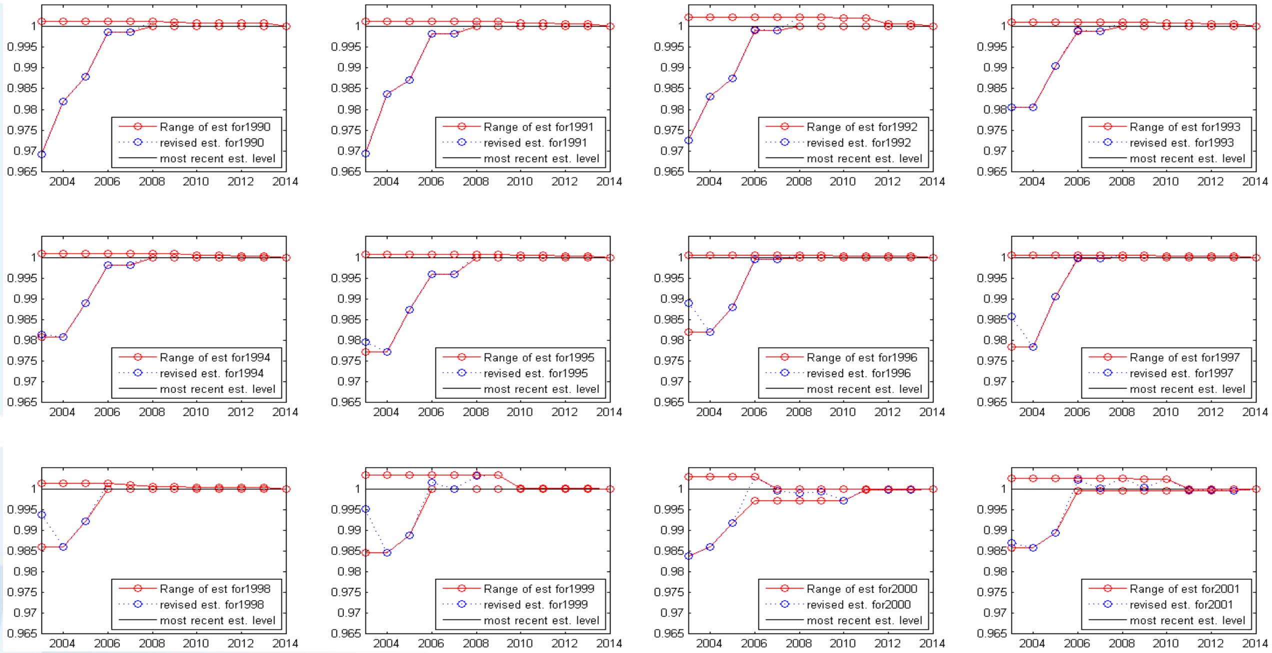


Fig. 4. Consecutive corrections of normalized emissions estimates for years 1990-2001 (Part I of the data)

- Upper ranges of emission estimates $M_{n,y}$ are nearly constant and close to most recent estimates $E_{n,Y}$.
- Lower ranges of emissions estimates $m_{n,y}$ carry most information about increase of estimates accuracy.

III.2. Model of diagnostic learning (1)

- Fig. 4. suggests that $m_{n,y}$ approaches level $E_{n,Y}$ more rapidly at the beginning and gradually slows down and stabilizes as $y \rightarrow Y$.

- For each fixed n we assume the following model time evolution of $m_{n,y}$:

$$\frac{m_{n,y}}{E_{n,Y}} = 1 - c_n e^{-\lambda_n (y-n-2)}$$

  for $y = \{y_0, \dots, Y\}$, where $y_0 \geq n + 2$ is the year of publication of the most initial available estimate of emissions in the year n.

- Parameter λ_n is interpreted as the **learning rate** in the period between y_0 and Y.

III.2. Model of diagnostic learning (2)

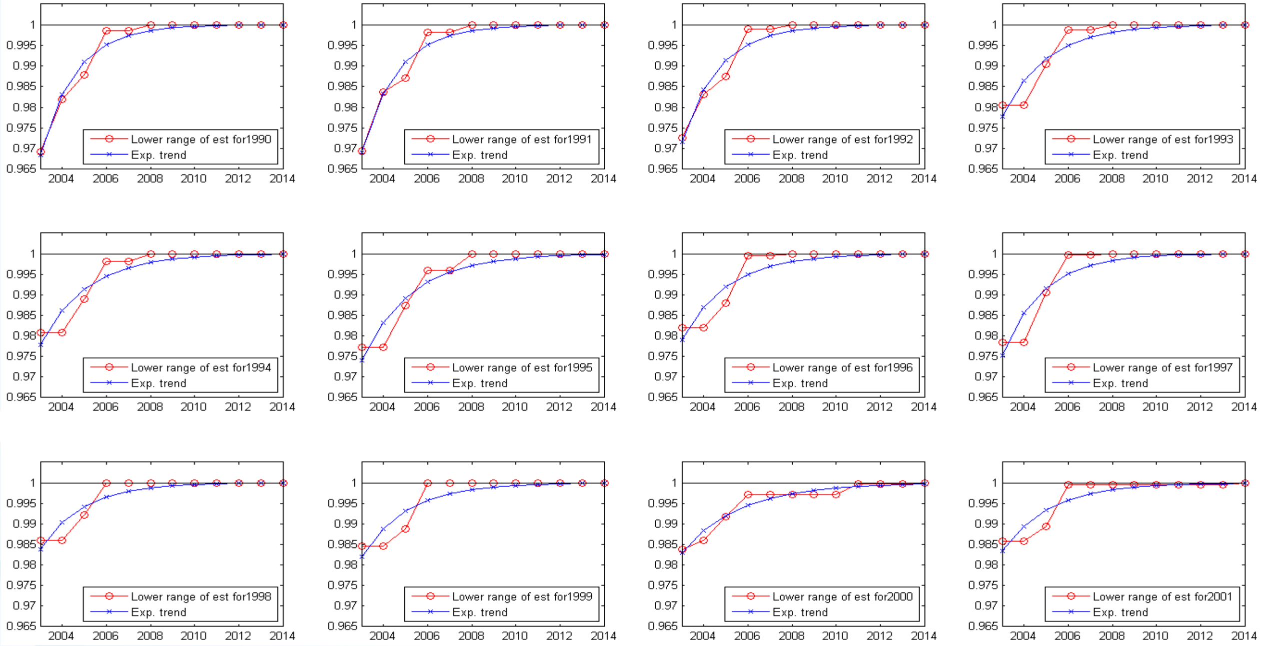
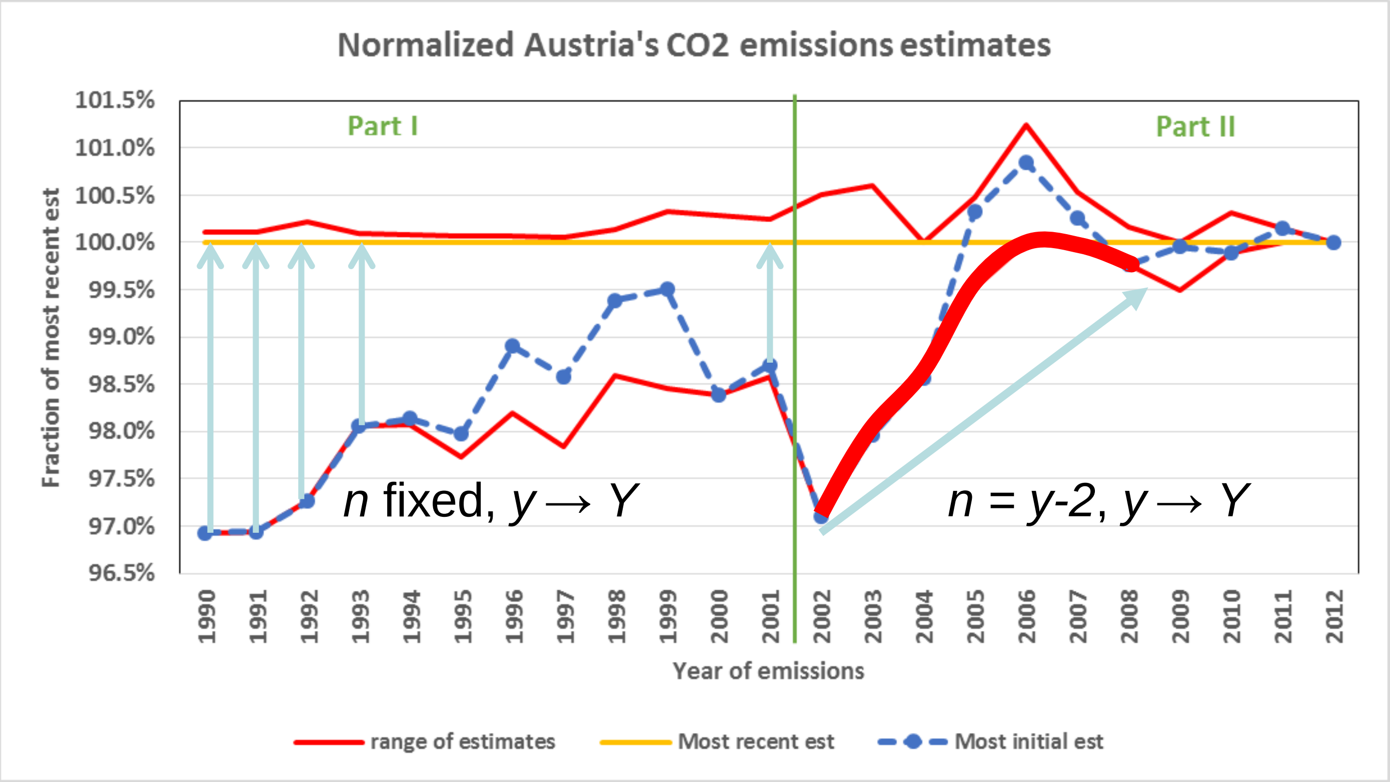


Fig. 5. Exponential model of diagnostic learning (Part I of the data)

Year of emissions n	1990	1991	1992	1993	1994	1995
Learning rate λ_n	0.6251	0.6210	0.5954	0.5043	0.4722	0.4425
Year of emissions n	1996	1997	1998	1999	2000	2001
Learning rate λ_n	0.4815	0.5405	0.5147	0.4786	0.3761	0.4497

Table 2. Values of learning rates

III.3. Model validation (1)



- In Part I of the data we fit the model of learning for each year of emissions separately.
- In Part II we grasp diagnostic learning across both emission years and revisions.

III.3. Model validation (2)

- Negligible structural changes. Learning is uniform across emissin years *n*.
- Diagnostic learning has exponential dynamics with learning rate $\bar{\lambda}$.
- Using Part I of data we estimate $\bar{\lambda} \approx \frac{1}{12}\sum_{n=1990}^{2001} \lambda_n$.
- Accuracy of all estimates published after year *y* increase uniformly as $y \to Y$.
- $M_{n,y}$ - $m_{n,y}$ ≈ $M_{y-2,y}$ - $m_{y-2,y}$ ≈ $E_{y-2,y}$ - $m_{y-2,y}$ for $n \leq y-2$.
- we estimate $\bar{\lambda}$ from Part II of the data using formula

$$\frac{m_{y-2,y}}{E_{y-2,Y}} = 1 - \bar{c}\, e^{-\bar{\lambda}\,(y-y_0)}$$

for all $y = \{y_0 = 2003, \ldots, 2014\}$

$\bar{\lambda}$ derived from Part I of the data (as the average of λ_n)	0.5085
$\bar{\lambda}$ derived from Part II of the data	0.4948

Table 3. Two independent estimates of the uniform learning rate $\bar{\lambda}$

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Summary

- Diagnostic learning is reflected by the increase of accuracy.
- We quantify diagnostic learning by the rate (speed) of convergence of revised estimates.
- Diagnostic learning exhibit exponential dynamics

References

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