International Non-CO_2 MACC Model Development - Incorporating Technological Change

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Motivation

- As governments and international parties pursue mid-century strategies to achieve carbon reduction targets established under the Pairs Agreement, there is an increased need for improved characterizations of future mitigation potential from GHG emitting sources.
- Anthropogenic non-CO_2 emissions are recognized as an important source of cost-effective mitigation that can contribute to countries' decarbonization efforts.
- Improves the quantification of the residual emissions.
  - Enabling larger integrated assessment models to evaluate the suite of advanced mitigation measures and approaches to that will be required to achieve a net zero carbon future.

Objective

Develop a methodology for modeling technological change (TC) in the non-CO_2 GHG marginal abatement cost curves (MACCs).

General Approach:

1. Identify a learning rate to model cost reductions overtime
2. Identify removal efficiency improvement rate
3. Categorize mitigation measures based on technological maturity
4. Adjustment for heterogeneity across countries for input prices over time.

MACC Model – Background

- Bottom up techno-economic model
  - Over 200 mitigation measures
  - 195 countries
  - Mitigation Technology Characteristics
    - Investment and operating costs (i.e. CAPEX, Fixed and Var O&M costs)
      - Costs are delineated by KLEM share
    - Projected annual revenues
      - Energy offsets (gas sales, electricity generation, avoided gas losses)
      - Non-Energy cost savings (labor, fuel, other production inputs)
    - Technical lifetimes
    - Emissions reduction efficiency (%)

Marginal Abatement Cost Equation

$$\sum_{t=1}^{T}\left[\frac{(1-TR)(P\cdot ER_t+R)+TB_t}{(1+DR)^t}\right]=CC_t+\sum_{t=1}^{T}\left[\frac{(1-TR)\cdot AC_t}{(1+DR)^t}\right]$$

Where:

P	=	the breakeven price of the option ($/t$CO_2$e);
ER	=	the emissions reduction achieved by the technology (tCO_2e);
T	=	the abatement measure's technical lifetime (years);
DR	=	the selected discount rate (5%);
TR	=	the tax rate (0%);
R	=	the revenue from sale of captured CH4 or other hydrocarbons;
TB	=	the tax break equal to the capital cost divided by the measures technical lifetime, multiplied by the tax rate ($);
CC	=	the one-time capital cost of the measure ($); and
AC	=	the recurring (O&M) cost of the measure ($/year).

Marginal Abatement Cost Equation

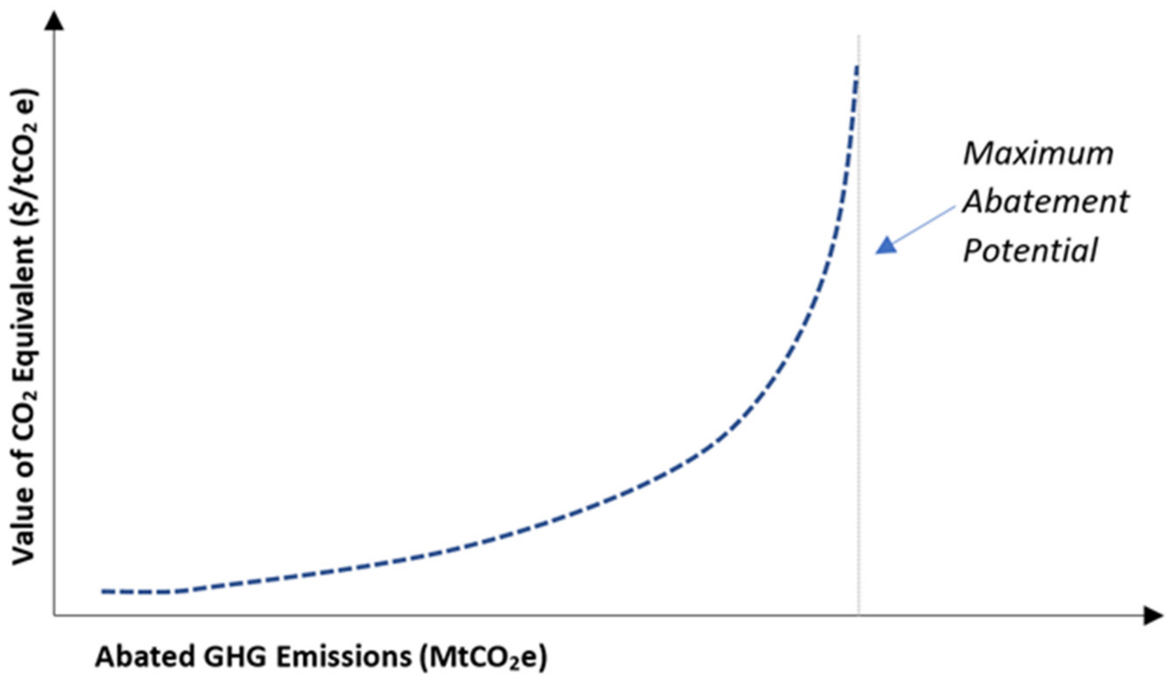
$$P = \underbrace{\left[\frac{CC}{df \cdot (1 + TR) \cdot ER}\right] + \frac{AC}{ER}}_{Annualized\ Cost} - \underbrace{\frac{AR}{ER} - \left[\frac{CC}{T \cdot ER} \cdot \frac{TR}{1 - TR}\right]}_{Annual\ Benefits}$$

$$df = \sum_{t=0}^{T} \frac{1}{(1 + DR)^t}$$

- Set benefits equal to costs
- Solve for the breakeven price (P)

Marginal Abatement Cost Curve (MACC) Model

- Develop GHG reductions supply curves based on least cost ordering of mitigation technologies.



Common Approach

Empirically estimating technological change

The most common empirical approach in the literature to measuring technological change is to estimate the ***Learning Rate (LR)*, which can be interpreted as the percentage reduction in unit cost given a doubling of the experience metric.** The LR is typically estimated using the equations below.

(1) Linear Form: $$\boldsymbol{C = C_0 * X_t^{\beta}}$$

(2) Learning Rate: $$\boldsymbol{LR = 1 - PR = 1 - 2^{\beta}}$$

(3) Log-log form: $$\boldsymbol{\log C_t = \log \alpha + \beta \log X_t}$$

where:

C_t = unit cost

C_0 = cost of first unit

X_t = experience metric

β = Parameter measuring responsiveness of cost to the experience metric

PR = Progress ratio equal to the percent reduction in cost with each doubling in experience metric

α = constant

Learning Curve – Common Approach
IIASA GAINS Model

For the EU Reference Scenario, IIASA estimates the costs for mitigation of non-CO_2 GHGs, integrating cost reductions through learning and removal efficiency gains over time. The following assumptions were used to estimate the factors in the excerpted table below.

<u>Assumptions</u>

- Learning rate (*LR*): 15%
- Learning elasticity ($\boldsymbol{\beta}$): 23.4%
- Capacity growth (*X*): Doubling every 15 years
- Removal efficiency improvement: 1% annually (translates to a 1% annual reduction in emissions *not* captured)
- Learning curves applied globally
- Learning curves delayed depending on whether available cost data is current cost or forecasted future cost

Table 2: Adjustment factors for investment costs, operation and maintenance (O&M) costs, and emission factors used in GAINS to account for effects of technological development of non-CO_2 mitigation technology from 2020 to 2050.

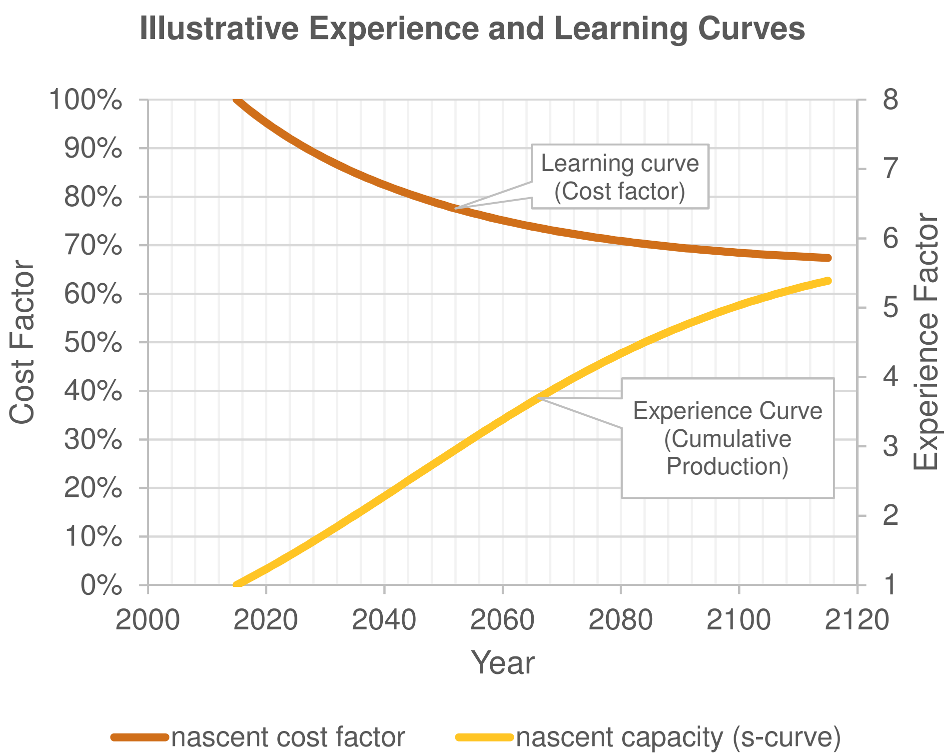
Year	Technologies with current costs and removal efficiencies provided in literature		Technologies with future expected costs and removal efficiencies provided in literature	
	Investment and O&M costs	Emission factors	Investment and O&M costs	Emission factors
2020	1	1	1	1
2025	0.88	0.95	1	1
2030	0.82	0.9044	1	1
2035	0.765	0.8601	0.88	0.95
2040	0.72	0.8179	0.82	0.9044
2045	0.68	0.7778	0.765	0.8601
2050	0.651	0.7397	0.72	0.8179

Source: *Non-CO_2 GHG emissions in the EU-28 from 2005 to 2050 (Gains Model Methodology)*

Selecting and applying learning curves

- In order to articulate learning curves for our model, we apply the linear equation $\boldsymbol{C = C_0 * X_t^{\beta}}$ where
  - C_0 (Cost of first unit) = 1
  - X_0 (Learning metric) = 1
  - β (Learning elasticity) is calculated using $\boldsymbol{Learning\ Rate} = \boldsymbol{1 - 2^{\beta}}$ = 23.5%
- Capacity growth (X_t) is exogenously imposed using a sigmoidal diffusion curve, which is modeled after the innovation adoption curve, rather than a static doubling rate, which is exponential in the long run.
- Using a diffusion curve results in a cost factor curve that naturally flattens over time to model a decline in incremental cost reductions achievable through learning.
- Sigmoidal Curve Equation:

$$X(t) = \frac{max}{1 + e^{-\propto(t-m)}}$$



Assumptions

Technological maturity and socioeconomic development status

- We use one average learning rate that is supported by the literature; the resulting learning curve was adjusted based on two factors:
  - **Maturity of a given abatement technology**
  - **Socioeconomic development status of a given country**
- The learning curve were adjusted by shifting the year in which the learning curve starts.
  - The table to the right shows start years and assumed removal efficiency improvement for different combinations of maturity and development stage
  - Mature technologies are shifted earlier (2000 or 2005) on the assumption that a large portion of cost reductions and efficiency improvements have already been achieved by the model start year.
  - We also assume that emerging economies will lag behind due to a number of factors
- Some important assumptions include:
  - Cost savings achieved through learning applies to annual recurring costs.
  - Rate of change in removal efficiency applied based on technology maturity.

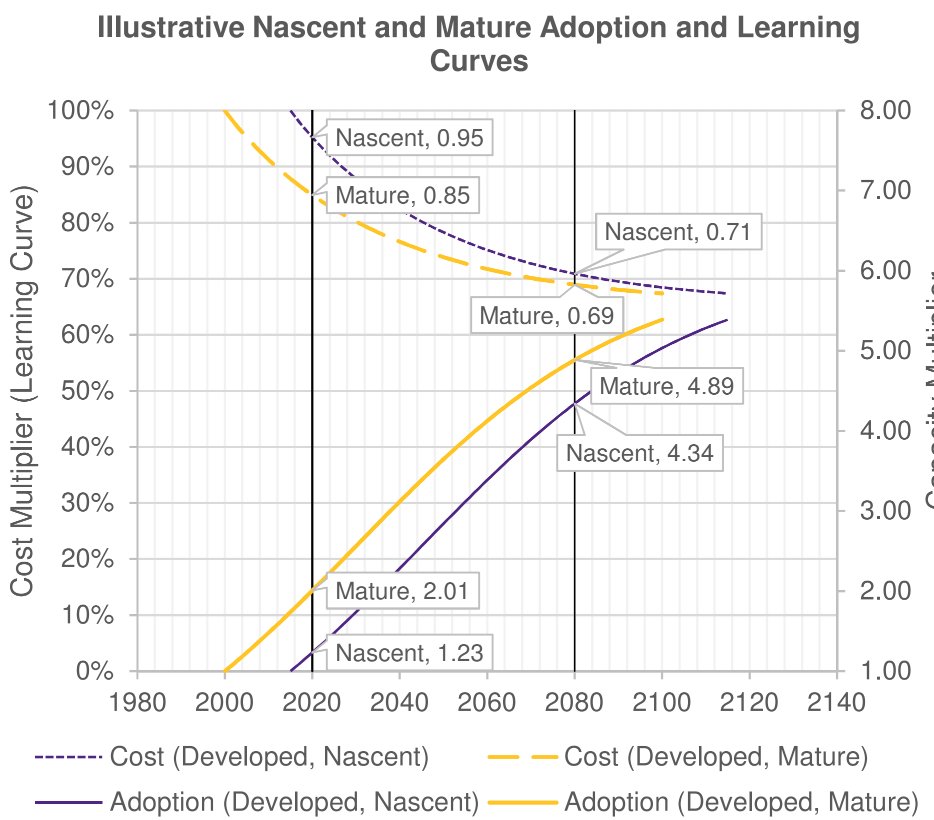
Learning start year by development and technological stage

Tech. Stage	Developed	Emerging	RE Improvement
	Country development stage		
Nascent	2015	2020	1.0%
Mature	2000	2005	0.5%

Introducing differentiation in technology maturity

In order to model differing levels of maturity among abatement technologies, we retain the same learning and diffusion curves, but shift the curves in time based on the maturity of the technology.

- Technology cost fall quickly in early years, driving increased adoption.
- Over time cost reductions slow.
- While each technology is unlikely to follow an identical learning curve and adoption curve, the lack of data makes it necessary to generalize.

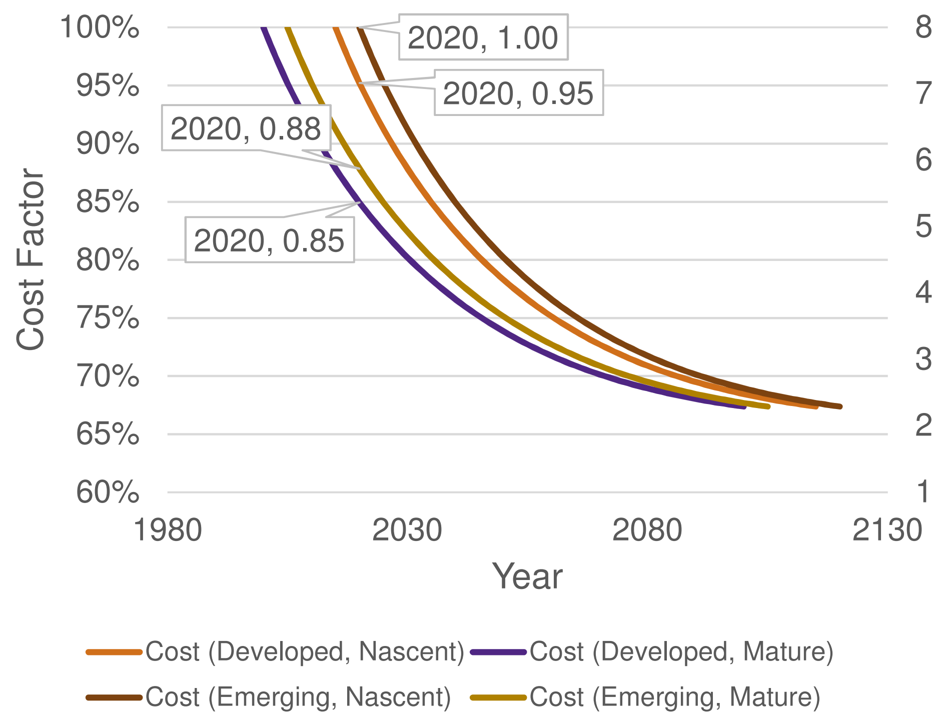


Cost Factor Heterogeneity

In addition to modeling two levels of technology maturity, we also adjust learning curves for developed and emerging economies.

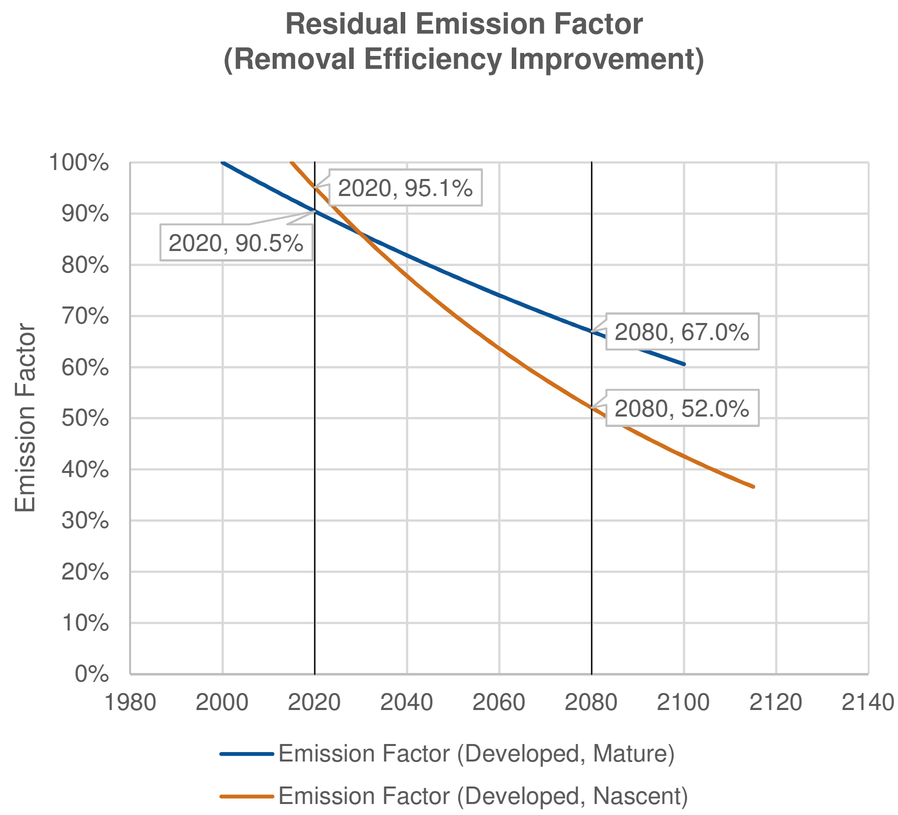
- The end result is four learning curves that reflect the same learning rate, but different starting points in time.

Cost Reductions by Technological Maturity and Economic Development



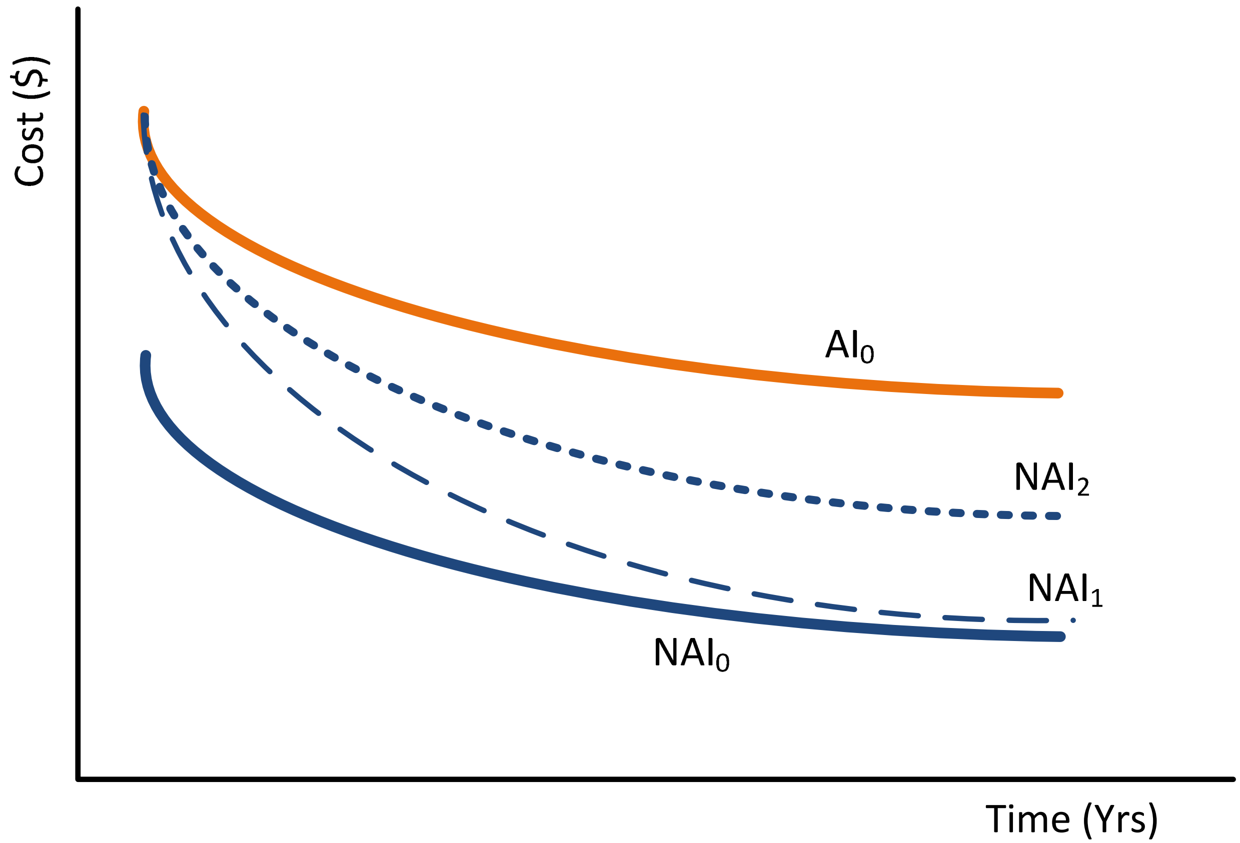
Applying rates of removal efficiency improvement

- In order to model improvements in removal efficiency, we select a rate of improvement that is supported by the literature and calculate a *residual emissions factor*.
- A 1% improvement in an emissions factor can be interpreted as a 1% annual increase in the percent of emissions captured by the abatement technology.
- The figure to the right shows a 1% annual improvement for nascent technologies and a 0.5% improvement for mature technologies.
- One could consider further differentiating by country but would require adjustments to the reduction efficiency.



Stepwise Approach to Modeling Country Heterogeneity

- Introduce dynamic relative cost factors applied to inputs (KLEM).
- Historic Approach
  - AI_0 - cost of abatement with TC in Annex I country
  - NAI_0 - NonAnnex I cost assuming full domestic inputs.
- New adjustments for shifts and growth in domestic input prices.
  - NAI_1 – Shift from foreign to domestic inputs over time
  - NAI_2 – Shift from foreign to domestic over time *and* apply growth rates to input prices to reflect GDP, wage, and energy price growth.



Cost Factor and Emission Factor Results

	Developed Nations				Emerging Nations			
Year	Nascent Technology		Mature Technology		Nascent Technology		Mature Technology	
	Cost Factor	Emissions Factor	Cost Factor	Emissions Factor	Cost Factor	Emissions Factor	Cost Factor	Emissions Factor
2015	1.00	1.00	0.88	0.93	1.00	1.00	0.91	0.95
2020	0.95	0.95	0.85	0.91	1.00	1.00	0.88	0.93
2025	0.91	0.90	0.82	0.88	0.95	0.95	0.85	0.91
2030	0.88	0.86	0.80	0.86	0.91	0.90	0.82	0.88
2035	0.85	0.82	0.78	0.84	0.88	0.86	0.80	0.86
2040	0.82	0.78	0.77	0.82	0.85	0.82	0.78	0.84
2045	0.80	0.74	0.75	0.80	0.82	0.78	0.77	0.82
2050	0.78	0.70	0.74	0.78	0.80	0.74	0.75	0.80

Methodology
Application to existing MACC calculations

$$P = \frac{\boxed{CC_t}}{1 - TR \cdot \boxed{ER_t} \cdot \sum_{t=1}^{T} \frac{1}{(1+DR)^t}} + \frac{\boxed{RC_t}}{\boxed{ER_t}} - \frac{\boxed{R}}{\boxed{ER_t}} - \frac{\boxed{CC_t}}{\boxed{ER_t} \cdot T} \cdot \frac{TR}{1 - TR}$$

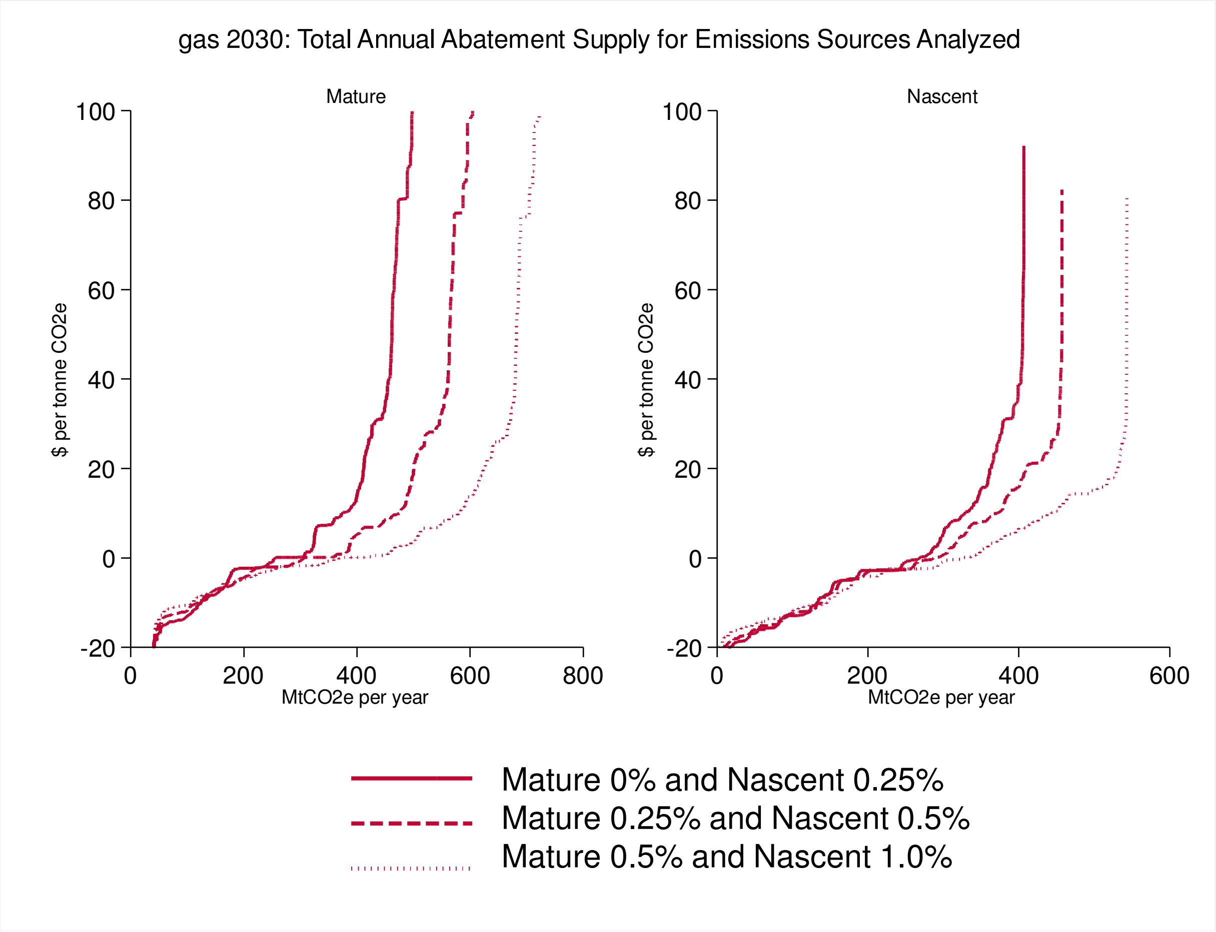
Impacted by learning *Impacted by removal efficiency improvement*

P = the breakeven price of the option ($/tCO2e);
ER = the emissions reduction achieved by the technology (MtCO2e);
R = the revenue generated from energy production (scaled based on regional energy prices) or sales of by-products of abatement (e.g., compost) or change in agricultural commodity prices ($);
T = the option lifetime (years);
DR = the selected discount rate (%);
CC = the one-time capital cost of the option ($);
RC = the recurring (O&M) cost of the option (portions of which may be scaled based on regional labor and materials costs) ($/year);
TR = the tax rate (%); and
TB = annual tax benefit of depreciation = (CC/T)*TR

Results by Sector

Sector	Source	@ $0/tCO2e				@ $30/tCO2e			
		2015		2030		2015		2030	
		Baseline	TechChange	Baseline	TechChange	Baseline	TechChange	Baseline	TechChange
ENE	col	89	40	108	59	443	440	552	560
ENE	gas	408	397	512	771	692	691	833	1,328
WASTE	lan	166	150	206	231	252	252	301	376
WASTE	wwr	0	0	9	10	22	22	60	65
IND	naa	-	-	-	-	71	71	87	98
FGAS	al	9	4	13	6	13	18	18	22
FGAS	eps	15	15	21	32	29	27	41	92
FGAS	semi	6	6	4	4	26	26	17	19
FGAS	fpd	-	-	-	-	1	9	2	9
FGAS	hcfc	-	-	-	-	34	34	255	255
FGAS	mg	5	13	5	15	5	14	5	15
FGAS	pv	-	-	-	-	-	-	-	-
Totals		698	626	878	1,127	1,589	1,602	2,171	2,839
% Change			-10%		28%		1%		31%

Sensitivity Analysis



Conclusions

We expand on existing approaches to modeling technology change in the following ways:

- Global scope, covering 195 countries
- We employ a sigmoidal adoption curve rather than a static doubling rate in adoption of mitigation technologies, which more accurately models how innovations diffuse over time.
- Introduce heterogeneity in technology maturity constraining the potential impacts of cost reductions.

Findings

- Reductions in early years are constrained due to changes in assumptions about domestic and import inputs.
- By 2030, technology cost reductions lead to ~30% increase in mitigation potential at carbon prices below $30/tCO2e.
- Reduction efficiency improvement rate assumption has a significant impact on the mitigation results.