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Use of McKinsey abatement cost curves for climate economics modeling

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Abstract

Integrated assessment models (IAMs) of climate economics require projections of the future costs of greenhouse gas abatement. The work of McKinsey & Company, an international consulting firm, provides global estimates of marginal abatement cost curves, based on data on the costs of numerous emission-reducing technologies. This article describes the use of the McKinsey data in an IAM, the Climate and Regional Economics of Development (CRED) model.

The McKinsey studies identify a large potential for abatement with negative net costs, a finding which is controversial among economists and problematic for modeling purposes. We avoid this issue by using only the positive-cost McKinsey data, assigning a near-zero but positive cost to all reportedly negative-cost abatements. The results are broadly comparable to abatement cost estimates from MIT's EPPA model, although lower than those from some other IAMs. Even the positive-cost portion of the McKinsey data suggests that emission reduction may be cheaper than IAMs have often projected.

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Introduction

Integrated assessment models (IAMs) of climate economics are complex endeavors, requiring long-term projections of the changing global climate, trends in economic growth, and interactions between the two. One of the key interactions involves abatement: what will be the cost of additional steps toward emission reduction? In many IAMs, abatement cost estimates must be differentiated by year, location, and/or economic sector. Thus the development of the necessary abatement cost curves is a data-intensive process.

McKinsey & Company, an international consulting company, has become well known for its reports on marginal abatement costs, now covering every region of the world. McKinsey has recently made its Climate Desk database, the data behind its reports, available for nonprofit academic research.[1] The database provides a quantitative assessment of the greenhouse gas abatement potential and associated costs for measures with net costs below a threshold of €60 (about $80) per ton of CO_2-equivalent (CO_2e) reduction.[2] Data are reported for more than 100 technology and policy options spanning 11 economic sectors, with separate estimates of abatement costs and technical potential in each of 21 world regions.

This article describes what may be the first attempt to use the McKinsey abatement cost curves in an IAM. Section 2 presents an overview of the McKinsey results and discusses the controversy about the meaning of negative-cost abatement opportunities. Section 3 explains our solution to the negative-cost problem, along with other steps we took to convert the McKinsey data into manageable abatement cost curves for modeling purposes. Section 4 contrasts our estimates of abatement costs to others in the IAM literature. Section 5 offers concluding thoughts about the implications of our abatement cost estimates for IAMs and their evaluations of climate policy options.

Are negative-cost abatements possible?

McKinsey reports on greenhouse gas abatement costs reach relatively optimistic conclusions. The 2009 report, "Pathways to a Low-Carbon Economy," presenting Version 2 of the global abatement cost curve, estimates that by 2030 business-as-usual (BAU) emissions of greenhouse gases would reach 70 gigatons (Gt) CO_2e worldwide – of which 38 Gt could be avoided at a cost of €60 per ton or less (McKinsey 2009).The total cost for the entire 38 Gt agenda is €150 billion, an average of €4 per ton. Transaction and program costs, which are not included, are estimated to add another €1 to €5 per ton (McKinsey 2009, p. 16).

Average costs are low, in part, because the report identifies a significant potential for abatement with negative net costs, or net economic benefits: for 11 Gt of abatement in 2030, lifetime energy savings are estimated to outweigh the cost of upfront investment. Many of the negative-cost opportunities involve energy efficiency measures; some involve land use, especially in countries with large areas of tropical forests.

[1] See the McKinsey Climate Desk, https://solutions.mckinsey.com/climatedesk, for more information. We thank McKinsey & Company for making its data available for our research.

[2] For Version 2.1 of McKinsey's greenhouse gas abatement cost curve, released in 2010, the threshold was changed to €80 per ton CO_2e.

Similar results appear in McKinsey reports for individual countries and regions. A 2007 study of the United States found that, although BAU emissions in 2030 would be 9.7 Gt CO_2e, abatement measures costing less than $50 per ton could abate as much as 4.5 Gt – of which 2.0 Gt could be achieved at negative cost (Creyts et al. 2007).

Negative-cost abatement opportunities present a challenge to economic theory, reflected in the old saying about $20 bills on the sidewalk. If energy savings are available at a net economic benefit, why hasn't someone already found it profitable to invest in them? Yet McKinsey is not alone: bottom-up studies of the technical potential for energy savings and emission reductions have often identified extensive negative-cost options.

There are a number of possible explanations for the "efficiency gap" (between the cost-minimizing level of investment in energy efficiency and the actual level) or the "efficiency paradox." Market failures and barriers may discourage investment in low-cost efficiency measures; examples include misplaced incentives, unpriced costs and benefits, incomplete information, capital market barriers, and incomplete markets for efficiency (Brown 2001). Consumer reluctance to invest in efficiency measures could reflect extremely high discount rates for such purchases, possibly due to uncertainty and incomplete information. That is, households may avoid investments in efficiency unless they offer very rapid payback times. Business investment in energy efficiency may be shaped by organizational and institutional factors which, in practice, cause systematic deviations from profit-maximizing behavior (DeCanio 1998).

Whatever the explanation, negative-cost abatement does not fit comfortably into an IAM. In any optimizing model, all negative-cost investments would be made immediately, yielding a surge of additional capital (the negative costs, or net benefits) available for other investments. Perhaps this *should* happen – households and firms should pay more attention to picking up $20 bills (or energy efficiency measures) from the sidewalk. It seems, however, quite remote from what actually does happen; incorporating this feature would decrease the realism and policy relevance of an IAM.

Adapting the McKinsey cost curves for use in an IAM

We adapted the McKinsey marginal abatement cost (MAC) curves for use in the development of a new IAM. Our model, Climate and Regional Economics of Development (CRED), is designed at the same level of complexity as the simpler existing IAMs, for policy relevance and ease of use (Ackerman et al. 2010). It offers two principal innovations that set it apart.

The first major innovation in CRED is the treatment of utility maximization and international equity. Like many other IAMs, CRED is an optimization model that calculates the welfare-maximizing scenario under specified assumptions and inputs. It differs from other models in calculating the level of resource transfers between regions that would maximize global welfare. The standard assumption of diminishing marginal utility of consumption implies that, all else being equal, global well-being is improved when resources are transferred from richer to poorer regions; this egalitarian implication of conventional welfare economics is obscured by the technical apparatus of some complex models (Stanton 2010).

The other major innovation in CRED is its use of the McKinsey MAC curves to estimate the costs of abatement. Several steps were required to convert the wealth of disaggregated McKinsey data for 2030, the final year of their analysis, into MAC curves that could be used in CRED. Additional assumptions were made to allow reasonable changes in abatement costs over time.

Abatement cost curves for 2030

We began by aggregating McKinsey's 21 geographic regions into nine broader regions, and collapsing their eleven economic sectors into just two. Our sectoral classification was based on long-term patterns of growth: emissions, and therefore abatement opportunities, in agriculture and forestry are tied to land area, which is constant; emissions and abatement opportunities in all other sectors can grow along with population and GDP. We refer to agriculture and forestry as "land use" sectors, and the remaining sectors as "industry" – with the understanding that "industry" includes transport, household and commercial energy use, and waste management as well as industrial activity per se. The result of this aggregation is 18 empirical abatement cost curves for 2030, for land use and industry in each of nine world regions.

To avoid issues regarding the meaning of negative-cost abatements, we decided to omit these data, modeling only the positive-cost portion of the curves. Visual inspection of the data found that the curves become increasingly vertical as the quantity of abatement increases; they appear to have vertical asymptotes, reflecting the maximum technical potential for abatement in 2030. We created approximations to each of the 18 data sets with a two-parameter equation:

(1)
$$MAC(q) = \frac{Aq}{B-q}$$

Here q is the cumulative quantity of abatement, MAC(q) is the marginal cost of abatement, B is the vertical asymptote, or maximum technically feasible abatement potential, and A is a cost parameter (equal to the marginal cost at $q = B/2$).

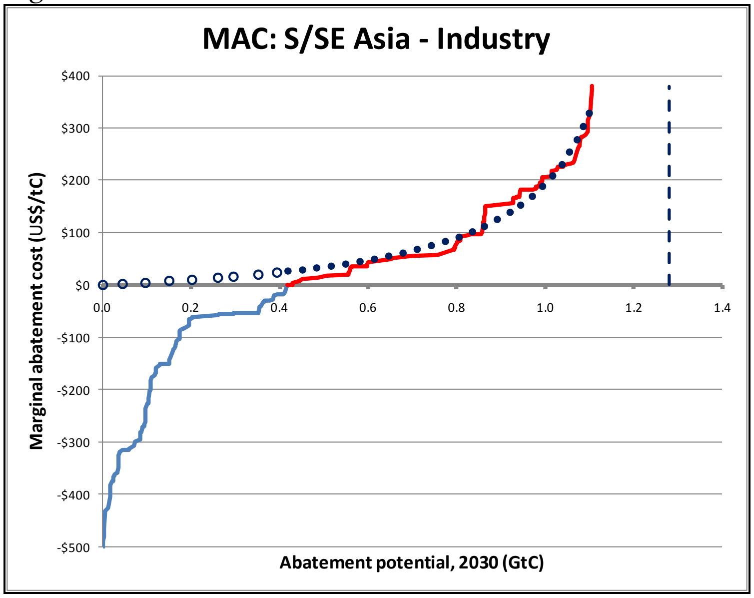
Correlation between the empirical data and the curves estimated with (1) was very good, with $r^2 > 0.9$ in 13 of the 18 cases, and $r^2 > 0.8$ in 17 cases.[3] The greatest differences between the empirical and fitted curves occur where the data are "lumpy," with a few measures accounting for large fractions of the total abatement potential.

We then extrapolated (1) across the negative-cost region of the McKinsey curves. Note that (1) is, by definition, constrained to go through the origin, with zero marginal cost for zero abatement. The extrapolation thus amounts to assigning near-zero but positive marginal costs to the measures for which McKinsey reported negative costs. (With such low costs, our model typically carries out the McKinsey negative-cost abatements quickly – but with costs always slightly positive, there is no surge of additional capital released by those abatements.)

An example is presented in Figure 1, for the industry sector of South and Southeast Asia. The solid lines are the negative-cost (blue) and positive-cost (red) portions of the McKinsey data. The solid dots are the curve fitted to the positive-cost data, using equation (1), and the open dots are the extrapolation of that curve across the negative-cost portion of the curve, assigning low but positive costs to the initial stages of abatement. The dashed vertical line is the estimated B parameter for the fitted curve.

[3] Here and in the curve-fitting for (3), described below, we used the Excel Solver to find the values of the constants that minimize the sum of squared differences between the empirical and estimated values.

Figure 1



The estimated values of A and B are presented in Table 1.

Table 1

Marginal Abatement Cost Curve Coefficients				
	Land Use Sector		Industry Sector	
	A	B	A	B
Africa	23.12	0.60	64.50	0.28
China	36.84	0.20	66.39	2.64
Russia/Eastern Europe	9.68	0.10	36.80	0.57
Europe	92.43	0.40	101.91	0.83
L. America/Caribbean	2.28	0.92	51.53	0.37
Middle East	6.79	0.05	46.53	0.37
Other high-income	30.54	0.09	107.41	0.54
S/SE Asia	26.23	1.36	53.90	1.28
U.S.A.	75.41	0.16	64.74	1.39
Units: A in $ / tC, B in GtC				

Use of (1) rather than the empirical curves simplifies cost calculations. For any carbon price p, (1) can be inverted to yield the quantity of abatement available at MAC(q) $\leq$ p

(2) $$q(p) = \frac{Bp}{A+p}$$

MAC gauges the total social cost of abatement, but it does not represent the investment needed to achieve that abatement. As defined by McKinsey, MAC is the average annual life-cycle cost impact of an abatement measure, combining annualized capital cost and all changes in operating costs. Fuel savings are often the most important change in operating costs, so that MAC is roughly the annualized capital cost net of annual fuel savings.

To estimate the investment cost of abatement, we used an additional set of McKinsey data. These data show the incremental investments, above BAU levels, required to achieve the full technical potential of each abatement measure. We associated each measure in the abatement cost curves with the corresponding investment costs. In a number of cases McKinsey reported positive marginal abatement costs but no investment costs; there we made the conservative assumption that the annualized capital cost equals the marginal abatement cost (which would be true only if there are no fuel savings or other changes in operating costs). Using McKinsey's 4 percent discount rate as the cost of funds, and assuming a 30 year lifetime, the inferred capital cost is roughly 17 times the marginal abatement cost.

We then created marginal capital cost curves, listing emission-reducing measures in the same order as in the MAC curves (i.e., in order of increasing MAC), but showing the investment required for each measure. Since the marginal capital cost curves were noisy in appearance, we integrated them to obtain smoother curves for the cumulative capital costs of reaching each level of abatement. The cumulative capital cost curves were well approximated by a quadratic function

$$K(q) = Eq + Fq^2 \tag{3}$$

The absence of a constant term reflects the fact that there is zero cumulative capital cost for reaching zero abatement. The marginal capital cost of the first unit of abatement is E; our estimate of E was zero in 8 of the 9 regions (all but Europe) for land use, but was never zero for industry. The estimated values of E and F are presented in Table 2.

Table 2

Cumulative Capital Cost Curve Coefficients

	Land Use Sector		Industry Sector	
	E	F	E	F
Africa	0	929	729	5,385
China	0	5,713	469	639
Russia/Eastern Europe	0	5,408	998	1,165
Europe	118	2,740	2,680	902
L. America/Caribbean	0	231	1,422	3,161
Middle East	0	10,062	1,102	3,104
Other high-income	0	8,158	2,193	1,213
S/SE Asia	0	467	417	1,183
U.S.A.	0	7,278	2,246	273

Units: E in \$ / tC, F in \$ / Billlion $(tC)^2$

Long-run changes in abatement costs

The analysis described so far, resulting in equations (2) and (3), provides only a snapshot of abatement costs in 2030. For long-term modeling in CRED (or any IAM), additional assumptions are needed about the evolution of abatement costs over time. The maximum potential in 2030, represented by B in (1), falls far short of complete elimination of carbon emissions in industry.[4] We assumed that technical progress would result in steady growth of the B parameter in each region's industry sector, reaching a level that allows complete abatement of regional emissions in 2105, a century after our base year. Thereafter, we assumed each industry-sector B would grow at the same rate as BAU emissions, thus continuing to allow complete abatement.

The estimate of a century to reach the potential for complete abatement is an arbitrary one – the pace of future technical change is of course unknown and unknowable – based in part on our subjective prior beliefs about the expected results. With technical progress much slower, climate stabilization would be impossible; but with complete abatement achievable within 50 years, climate stabilization appears implausibly easy.

In modeling the future evolution of abatement costs, we also held A and E constant over time. The former means that the MAC of getting halfway to the maximum potential for abatement is constant, even as the potential grows; the latter means that the marginal investment required for the lowest-cost abatement measure is constant. Finally, we held the product FB constant over time. The meaning of this assumption can be seen by combining (2) and (3). The average capital cost of all abatements with MAC $\leq$ p is

(4) $$\frac{K(q)}{q} = E + Fq = E + \frac{FBp}{A+p}$$

In the final form of (4), the parameters E, A, and FB are all constant. So for any fixed p, the average capital cost of all abatement with MAC $\leq$ p is constant.

Our image of technical change, in short, is that the maximum technical potential in each region and sector grows steadily from the level implied by the McKinsey curves for 2030, up to complete abatement by the end of the century. At any given carbon price, there is a steadily growing quantity of abatement that is cost-effective, available at a constant average capital cost.

In CRED, the model selects "optimal" regional carbon prices, which determine the level and pace of abatement – separately for high-income and developing regions – on the basis of equation (2) and the required capital stock for abatement on the basis of equation (3). Capital invested in abatement leads to lower productivity growth, but also lower emissions and climate damages, than conventional investment. The tradeoff between these rival goals shapes the pattern of investment and incomes, and the climate outcomes, which maximize global welfare.

[4] In the land-use sectors, the maximum potential generally equals or exceeds business-as-usual emissions; in some regions the 2030 MAC includes not only complete abatement, but also some potential for net sequestration. We assume that B is constant over time in land-use sectors, reflecting an abatement potential that is based on land area, not on industrial growth.

Comparison to other models

Since we are introducing a new strategy for modeling abatement costs, it seems useful to compare it to existing approaches. How much difference do our McKinsey-based cost curves make, relative to established modeling techniques? In this section we compare our MAC curves to estimates derived from the MIT Emissions Prediction and Policy Analysis (EPPA) model, and then discuss a comparison of our results to other models, in recent work by William Cline.

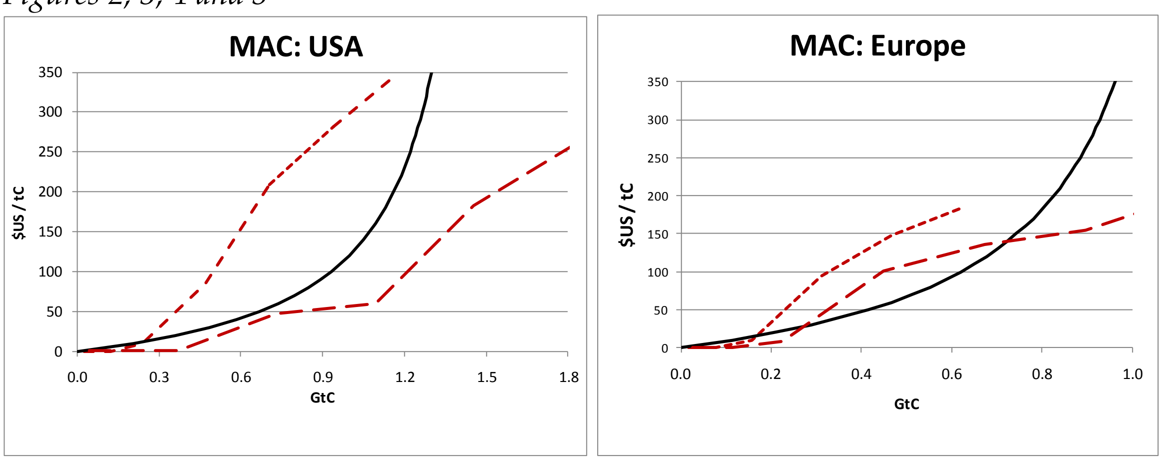
MAC curves in the EPPA model

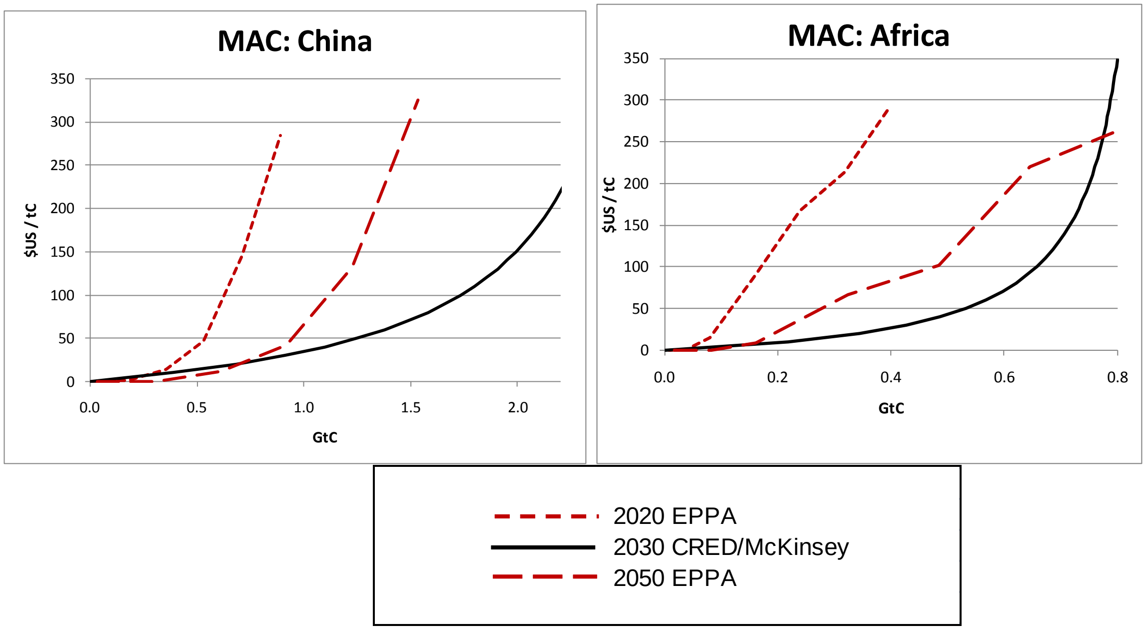
The EPPA model is part of the MIT Integrated Global Systems Model. EPPA combines a multi-regional general equilibrium model of the world economy with bottom-up estimates of energy supply and technology costs, in order to develop projections of economic growth and greenhouse gas emissions (Paltsev et al. 2005). EPPA has been used for a number of climate analyses, including a study projecting MAC curves and discussing their use in climate policy (Morris et al. 2008). That study includes a comparison of EPPA results to the McKinsey cost curves, emphasizing their differences. Yet the EPPA MAC curves turn out to be similar to the positive-cost portion of the McKinsey curves, which form the basis for the MAC estimates used in CRED.

The total area under the MAC curves, an estimate of the total cost of abatement, is quite different for McKinsey and EPPA. For McKinsey's U.S. MAC curve, the cost of 3 Gt CO_2e of reductions is negative \$54 billion for the negative-cost portion of the curve, plus \$37.5 billion for the positive-cost portion, totaling negative \$16.5 billion. The comparable area under EPPA's U.S. MAC curve is \$33 billion, or roughly \$50 billion higher (Morris et al. 2008, Appendix B). Notice, however, that the area under the positive-cost portion of the McKinsey curve – that is, the portion that is used in CRED – is similar to the area under the EPPA curve.

The EPPA analysis also provides numerical estimates of MACs by region for 2010, 2020, and 2050 (Morris et al. 2008, Appendix A). Figures 2, 3 compare the CRED/McKinsey MACs for 2030 to the EPPA MACs for 2020 and 2050 (after conversion to the same units, 2005 dollars per ton of carbon (tC)) for four regions.

Figures 2, 3, 4 and 5





The EPPA analysis generally finds the MAC shifting rightward over time, implying that more abatement is available at the same carbon price. Thus one would expect to find the 2030 MAC (not presented by EPPA) bracketed by the 2020 and 2050 curves. For the United States, this is essentially where the 2030 CRED/McKinsey curve falls, suggesting that the two analyses are presenting quite similar pictures of abatement costs. For Europe, our 2030 curve is roughly at the level of EPPA's 2050 curve, except at high carbon prices. For Africa and even more for China, our analysis identifies considerably greater abatement opportunities in 2030 than EPPA projects for 2050, at all but the lowest carbon prices.

The EPPA curves, especially for 2050, are shaped differently than the McKinsey curves. This is due in part to EPPA assumptions about biofuel options that become available after 2025. Yet in terms of overall levels, Figures 2, 3, 4 and 5 show that CRED and EPPA are making roughly similar projections of the near-term cost of abatement for developed countries; CRED is somewhat more expansive about opportunities in developing countries.

CRED, RICE, and EMF

A recent analysis by William Cline compares three sets of estimates of the costs of a global emission reduction scenario (Cline 2010). Cline analyzes what he calls the "Copenhagen Convergence" scenario, based on the national abatement targets for 2020 adopted at the UNFCCC conference in Copenhagen in December 2009, followed by straight-line reductions from 2020 to uniform worldwide per capita emissions of 1.43t CO_2 per year in 2050. He compares estimates of the cost of this scenario from three sources: the 2010 version of William Nordhaus' RICE model (Nordhaus 2010a; 2010b); Cline's own analysis of the results of the Energy Modeling Forum (EMF)-22 studies (Clarke et al. 2009); and our own McKinsey-based MAC curves.

The calculation of abatement costs in RICE, and in Cline's analysis of EMF results, is quite different from our approach. RICE assumes (as does the DICE model) that k, the cost of abatement as a fraction of GDP, is related to μ, the fraction of business-as-usual emissions abated (both measured at time t), by

(5) $$k_t = \alpha_t \mu_t^{\beta}$$

In (5), α and β are parameters governing the cost of abatement: α, specified separately for each region, declines over time, while β is set to 2.8 in RICE for all regions and time periods. The declining trend in α implies that any given amount of abatement becomes less expensive over time. The curvature created by β = 2.8 – an almost-cubic curve – means that at any point in time, abatement of a small fraction of emissions is inexpensive, but higher levels of abatement are much more costly.

Cline fits equation (5) to results from 11 different models which participated in the EMF-22 modeling exercise, including three to eight abatement scenarios and corresponding sets of costs from each model. A single equation is estimated for each of seven countries or groups of countries (United States, European Union, China, India, and three groupings, roughly based on income, which include the rest of the world). The estimated values of α are much higher than in RICE; the estimates of β average 1.46, about half the RICE value. Thus Cline's EMF abatement cost estimates start out much higher than the RICE estimates, for low levels of abatement, but the gap narrows at higher levels of abatement due to the lower value of β in the EMF equations.

The overall result of Cline's comparisons is that our CRED estimates project the lowest emissions abatement costs, while the EMF estimates are by far the highest. Table 3 presents the three sets of estimates for abatement costs as a percent of GDP in 2030, for selected countries and regions:[5]

Table 3

Abatement costs as percent of GDP, 2030

Abatement costs in 2030 under Cline's "Copenhagen Convergence" scenario, selected countries and regions

	CRED	RICE	EMF-22
China	0.12	0.36	2.42
EU	0.12	0.23	0.80
India	0.00	0.01	0.25
Russia	0.07	0.27	2.44
Saudi Arabia	0.08	0.19	1.89
South Africa	1.08	0.69	4.19
USA	0.07	0.23	1.18
All industrial	0.11	0.28	1.11
All developing	0.06	0.19	1.47
World	0.08	0.22	1.33

Source: Cline (2010), *Tables 13, 14, 15.*

[5] Additional data analysis, described in (Cline 2010), is required to turn regional estimates into single-country estimates for Cline's comparisons.

Cline discusses other estimates of abatement costs, many of them roughly comparable to the RICE estimates, with a scattering of both higher and lower numbers. His principal focus in the comparisons is on explaining the surprisingly high EMF estimates, especially for developing countries. Cline offers an alternate interpretation of the EMF cost curves, assuming that countries could buy emission reductions at the global carbon price (as estimated in the EMF scenarios). This suggests that with global emissions trading, the EMF total worldwide costs could be cut in half – although still leaving them well above the RICE, let alone CRED, estimates. The gap between the CRED and RICE figures, roughly a 3:1 ratio, may simply represent the difference between bottom-up and top-down modeling of costs and technologies. In this respect, it is interesting that EPPA, with a very different bottom-up analysis of energy costs, produces MAC curves which are in some cases comparable to CRED, i.e. comparable to the positive-cost portion of the McKinsey curves.

Conclusions

Our adaptation of the McKinsey curves for the CRED model offers a new method for incorporating an extensive database on abatement costs into an IAM. Our major innovation is to omit McKinsey's negative costs, treating those measures as having roughly zero cost. By doing this we avoid the academic controversy about the interpretation of negative-cost investment opportunities, and obtain estimates which are in some respects comparable to EPPA, another detailed, bottom-up analysis of energy costs. Our two-parameter approximations of the McKinsey data, in equations (1) and (3), summarize the mass of detailed data in a tractable algebraic form.

As Cline demonstrates, our estimates are well below those of well-known models using more aggregated, top-down approaches to abatement costs. The optimism of bottom-up studies about low-cost abatement potential comes through in this comparison – and, evidently, does not depend solely on negative-cost opportunities. Even with the negative costs reset roughly to zero, our McKinsey-based cost estimates are at the low end of reported abatement costs. There are only two ways to reconcile the difference between estimates: either the McKinsey studies are systematically too low about abatement costs, positive as well as negative; or the standard approaches in top-down models are systematically too high.

This is more than a purely academic disagreement, since the projected costs of emission reduction are one of the most policy-relevant outputs from IAMs. Political debate about the costs of climate policy should, ideally, be informed by the best available economic analysis. Mistakes can be, and are being, made in both directions, from the "win-win" optimism of some environmental advocates about costless emission reduction, to the pessimistic fears of some conservatives about the ruinous economic burdens of abatement. The goal of economic research should be to narrow the range of uncertainty, and produce better cost estimates as an input to the ongoing discussion of climate policy. We hope that our study contributes to this goal.

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