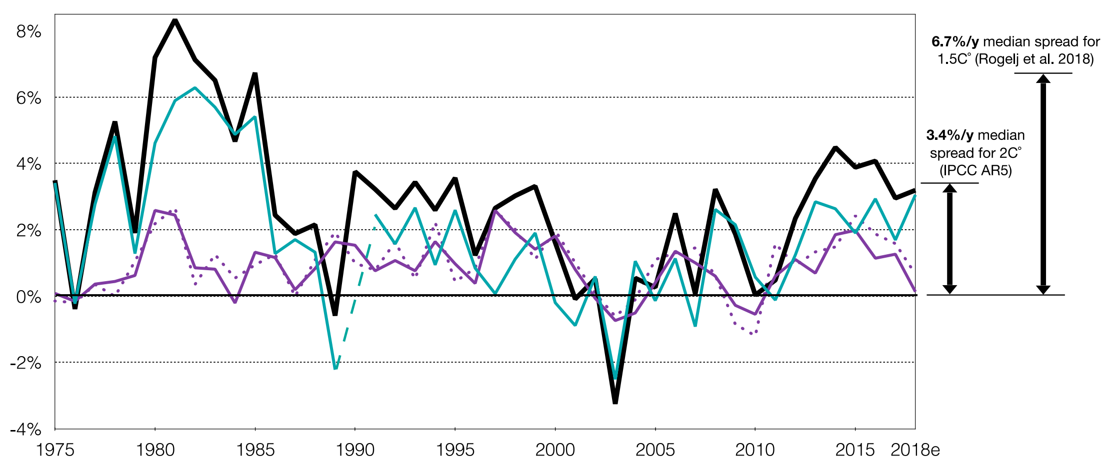
Supplemental Material

1. Additive version of Fig. 1, comparing synthetic with IEA energy intensities, and showing how rapid renewables growth helped offset slower recent savings

Fig. 1 shows the "spread" between upwards improvement in decarbonized supply and downwards improvement in energy intensity, so as to leave room to graph their respective regressions. Other purposes may instead merit the following additive graph, using the reciprocal (inverse) of energy intensity, *i e* energy productivity, so improvement in both variables is consistently upwards. This version also shows IEA primary energy intensity (dotted purple line) for comparison with synthetic intensity (purple line); their regressions are compared in Fig. 1 and its caption.

IEA's energy intensity drops slowed markedly in 2015–18 (Fig. 2), averaging 1.7%/y and dipping in 2018 to 1.2–1.3%/y (*cf* Fig. 2's caption)—still greater than the 1981–2010 average. The synthetic energy intensity drops (SM Part 1 n12–13) conservatively used in Fig. 1's regressions averaged 0.84%/y in 2015–18 and 0.13%/y in 2018—half IEA's average pace and with better statistical fit (Fig. 1's caption). Yet the savings slowdown was moderated, and in 2016 and 2018 was slightly more than offset, by decarbonized supply growth (Fig. 3), which in 2015–18 averaged 4.66%/y absolute or 2.56%/y in TFEC share—3× as important as decreased energy intensity. Both variables matter. During and despite the 2015–18 savings slowdown, their sum sustained since ~2010 the most impressive decarbonization in three decades, as shown by the heavy black line in the following graph:

Decarbonization shown as the sum (black) of the annual percent change in global non-carbon share of total final energy consumption, 1980–2018e (aqua), and additive inverse of the annual percent change in synthetic primary energy intensity of Gross World Product, 1980–2018 (magenta), checked against the same using IEA primary energy intensity, 1980–2018p (dotted magenta)



Sources: TFEC from IEA World Energy Balances (2017 extrapolated from 2016 by REN21 (2019) using 2016–17 growth rate declared in IEA (2018c), non-carbon TFEC from BP (2019), renewable heat consumption from IEA online database confirmed from IEA (2018c, p. 258, Fig. 6.6); all other sources from BP (2019). Synthetic primary energy intensity from BP, World Bank; 2 and 1.5 C° scenarios from IPCC AR5, Rogelj et al (2018), and Climate Interactive. Data point for 1990 supply is omitted to avoid singularity when biofuels data series begin. Energy intensity series is synthesized from BP primary energy consumption divided by World Bank GWP_{PPP} data to avoid technology-inconsistent primary-energy accounting conventions in the IEA series (2019 and online database), whose behavior, shown in the dotted purple line, differs modestly from the synthetic series (see notes 12 and 13).

The rapid progress in the first half of the 1980s resulted from surges in early renewable supply (Fig. 3b) and global energy productivity in the wake of the 1979 oil-price shock, plus completion of major nuclear-power additions (Fig. 3b) ordered after the milder 1973 oil-price shock and before the pre-Three Mile Island market-driven collapse of US orders. Subsequent nuclear developments disappointed (Fig. 3b and Schneider et al (2018, 2019)); global and national nuclear installation rates were later outstripped by renewables (Lovins 2018b, Schneider et al 2019). Renewables' recent absolute additions (Fig. 3b) are larger than either version of Fig. 1 shows as changes in *share* of [rising] total final energy consumption, so the larger aqua and black values on the left than on the right of Fig. 1 and its additive variant do not indicate larger absolute additions; those can be viewed directly in Fig. 3ab.

2. Nearly all IAMs have been inadequately modeling energy efficiency

Even in IAM modeling studies that encompass low-energy demand scenarios, energy efficiency measures are generally much less characterized (Kriegler et al 2018). Those historic limitations, however, offer rich opportunities to narrow and even eliminate the "reality gap" by improving analysis faster than technical efficiency potential grows. A special issue of the journal *Energy Efficiency* is specifically devoted to this need (Mundaca et al 2018).

A few recently published IAM scenarios represent a step-change in closing this gap, and the results already reveal major implications for the realism and attainability of ambitious climate targets. These new state-of-the-art IAM scenarios confirm that falling energy intensity is not only a critical enabling condition for meeting stringent mitigation goals (Clarke et al 2014, Riahi et al 2015, Rogelj et al 2015, Kriegler et al 2018); it is *the* most important variable. For instance, in comparing the Shared Socioeconomic Pathway scenarios SSP1 and SSP2, Marangoni et al (2017) showed that declining energy intensity is about twice as important as the runner-up, economic growth. Riahi et al (2017) found that seemingly modest differences in forecast energy intensity reduction therefore cause *most of the 2–3-fold spread* in 2100 energy demand among the SS1–SS5 scenarios. The modeling community broadly agrees (*e g* Kriegler et al 2014, EMF27 2011) with conclusions like AR5's (IPCC 2014, pp 136–137) that reducing energy intensity *can halve the gross mitigation costs* of achieving nominal 450 or 550 ppmCO_{2eq} by 2100. And efficiency doesn't only displace costlier supply-side mitigations on the long-run margin; it also saves short-run operating costs because efficiency nearly always costs less than fuel, and it may cut energy-using systems' capital costs too.

Yet until about the past decade, when certain modeling groups' attention to demand-side opportunities started to rise (*e g* Riahi et al 2017, Grübler et al 2018), most IAMs treated decarbonization in detail but energy efficiency[i] sparsely, shaping the persistent misperception that effective mitigation is costly and nearly impossible. Even in 2014, "Many IAMs [still had]…only one equation each for representing energy use in the residential building, commercial building, industrial, and transportation sectors…[and are] very simplistic in their treatments of technological change" (Rosen & Guenther 2015). Similarly, some models like AIM/GCE (see §2.2 in Fujimori et al 2016) appear still to use the Autonomous Energy Efficiency Improvement approach criticized in literature cited by Gillingham et al (2008). Some still-cited models compared by Barker (2006) did "not even allow for…increased…energy efficiency in the mitigation scenarios…except implicit changes due to energy price elasticity…."

Laudable recent efforts by some IAM groups to model energy efficiency are still far less granular than longstanding and extremely complex modeling of the less-important competition between energy supplies, such as detailed global supply curves for each fuel (Fricko et al 2017). Even the best efficiency analyses do not yet approach the detail and modernity common in the separate, large, and refined engineering-based literature on energy efficiency's empirical cost, performance, and prospects—regional, national, global[ii]. Most IAM teams make only limited use of that literature, so the causal factor most critical to model behavior rests on the sketchiest foundations. Although AR5 Working Group III, in Chapters 9–11, assembled strong data on the empirical cost and performance of energy efficiency[iii], that's scantily reflected in the sections of the report describing pathways (Chapter 6)—almost as if the two communities didn't converse.

Many IAMs, peering through a largely or wholly economic lens, still rely on indirect econometric representations of energy efficiency—like carbon pricing, often with far more effect on supply than on efficient use—as if inability to respond readily to price were not often more important than price itself (a reality that efficiency practitioners combat daily). Yet despite obeisance to economic theory, IAMs rarely if ever *compete* efficiency against energy supply as most actual economies do daily[iv]: supply is typically bought to meet projected demand, competing with other supply but not directly with even-more-efficient use. Nor can historic price elasticities, energy-system structures, operating rules, and business models foresee the disruptive technical and market discontinuities that dominate today's energy transformation and threaten to strand much of the existing asset base. Disquieting results of these deficiencies include:

- Some standard models predict energy demand will hold steady (*e g* Güneralp et al 2017) or grow even where it's shrinking, as in Europe.
- A highly influential IAM's 450-ppm scenario saves scarcely more energy in buildings than the baseline scenario, while the IAM's most ambitious scenario is higher in 2050 than a bottom-up model's *baseline* case (*id*)—an astounding discrepancy indicating an analytic framework misaligned with engineering reality.
- Many measure-by-measure efficiency analyses assume efficiency will add cost, even though IEA (2008 Fig. 2.14) found at least the first ~13 $GTCO_2$/y

had negative marginal cost, and Lovins (2018) marshalled empirical evidence that integrative design can achieve this in all sectors.

- Not analyzing end-use efficiency opportunities by sector, end-use, and device yields significantly higher energy use in, say, buildings than bottom-up studies do (Dhar et al 2016 Fig 5.1; Lucon, Ürge-Vorsatz et al 2014 Figs. 9.20 and 9.21). Indeed, IAMs often find little or no potential for improved efficiency (*e g* the BAU *vs.* "advanced efficiency" cumulative heating and cooling energy 2010–50 in Güneralp et al 2017), while physically explicit, empirically grounded, bottom-up studies find demand reductions of around one-third despite greatly improved services delivered to more than doubled floorspace (Güneralp et al 2016 Fig. 3, Lucon, Ürge-Vorsatz et al 2014 Fig. 2).

The 2014 Working Group III report's Buildings chapter reinforces this last point by plotting bottom-up and top-down models in the same Fig. 9.20 (Lucon, Ürge-Vorsatz et al 2014). The top-down models are more widely used. Yet strikingly illustrating the difference, deep-savings bottom-up scenarios, at least for buildings, find *lower* total investment costs and *greater* lifecycle savings than moderate-efficiency scenarios in several important regions, and materially larger in only one region (Ürge-Vorsatz et al 2015, Fig. 1). This is consistent with the microeconomic "tunneling through the cost barrier" typically found with integrative design, and with the German government's conclusions that deep retrofits and passive newbuilds will yield far lower energy use and lifecycle cost for Germany's building stock than incremental improvements (Umweltbundesamt 2017). IPCC AR5 Working Group III, too, confirms (Lucon, Ürge-Vorsatz et al 2014 pp 702–704) that deep retrofits can have lower lifecycle costs than shallow retrofits and that "very high performance new construction can be achieved at little, or occasionally even at negative, additional [capital] costs." Such bottom-up insights often reflect integrative design (Lovins 2018) which, being invisible to top-down models, could invalidate the finding (van Vuuren et al 2009) that the two approaches, despite large sectoral divergences, tend to yield similar aggregate savings.

In standard models' defense, it is complicated and challenging to model integrative design, human behavior, and societal value shifts. The resulting preference for analytic simplicity and for fewer, larger individual projects mirrors institutional investors' preferences. Energy supply is familiar, comes in tractably large and slow-to-build chunks, has relatively transparent and easily measured transactions and prices, is sensitive to policies, and (until this decade's fracking and renewables revolutions) has deployed and evolved rather slowly. In contrast, energy efficiency is less well-known, highly granular and situational, very diverse (thorough analyses can include thousands of technologies), often opaque and challenging to measure rigorously, complex in policy and behavioral interactions, irregular in deployment pace, and often presumed to innovate slowly. Industry has particularly complex and shifting mixes of processes, feedstocks, products, and by- or coproducts, so at late 2016, "hardly any study has looked into the industrial end-use sector" (Edelenbosch et al 2017). However, the widespread belief that industrial process heat (like heavy transport —*cf* Lovins 2015, Lovins & RMI 2011) is very hard and costly to decarbonize (*e g* Shell 2018 p 15, ETC 2018) will probably prove wrong once analysts pay proper attention to widening system boundaries on the demand side. These sectors represent the next great analytic, policy, and practice frontier.

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i. Shifting composition of economic output can also cut energy intensity but, like technical energy efficiency, is traditionally modeled more econometrically than physically.

ii. Some basic references are in Lovins (2018). IEA's early global efficiency supply curves (IEA 2008, 2015) are very conservative, showing 11% potential savings in 2040 with average payback <2 y. Another important line of literature relies not on Best Available Technology and emerging ones but on benchmarking national process intensities (e g Worrell & Carreon 2017).

iii. Regrettably, this evidence of measured cost and savings was reportedly published only at the plenary's insistence and was not allowed to be distilled into "supply curves of the efficiency resource" (a practice common for decades among efficiency analysts), apparently due to some leaders' fondness for empirically unsupportable large-rebound theories (see rebound discussion in our main paper) and personal belief that no significant cost-effective efficiency remains unbought. If compelling empirical evidence of efficiency's potential cannot be fully presented by the Working Group charged with assessing it, the IPCC's process and balance on this topic need deep reform. One test of reforms' success could be whether AR6 properly considers modern all-sectors integrative-design evidence such as Lovins (2018) compiled.

iv. Analogously, few IAMs model economic dispatch (Rosen & Guenther 2015), so each coal-fired power plant, once built, is often assumed to produce its rated output for its rated lifetime, rather than being run ever less as it's outcompeted by renewables. That merit-order shift has cut Chinese thermal (nearly all coal) plants' average capacity factor by 16.6 percentage points during 2013–16, regaining 4.6 points during 2016–18 (China Electricity Council 2019), but formal adoption of economic dispatch, for impressive benefits (IEA 2019a, Lin & Wetzel 2019), is likely to send it much lower. This analytic gap substantially overstates coal plants' future CO_2 and other emissions; yet even a new review (Edenhofer et al 2018) assumes coal plants "will emit at a constant rate over their entire life-time," and its proposed mitigation options don't mention economic dispatch, which China is in fact moving to adopt. However, the latest version of the MESSAGE model (Huppmann et al 2019) does model both baseload and flexible operation of thermal power stations, and can therefore reflect their merit-order displacement by variable renewables (Johnson et al 2016). Other IAMs would benefit from this feature.

3. Key features and pathways of 1.5C° pathways

Table 1: Key global features of mitigation pathways (MP) that limit global warming to 1.5 C°. Based on Grübler et al. (2018), Riahi et al. (2017) and Rogelj et al. (2018), these pathways' narratives can be

described thus: MP1: Multiple innovations across diverse systems generate lower energy demand while living standards rise. In turn, meeting growing energy service demands with lower energy use allows rapid decarbonization of energy supply with far less investment. Reliance on carbon dioxide removal (CDR) options is minimized and only afforestation is needed. MP2: Focusing on a sustainability path and encompassing low challenges to mitigation, this scenario emphasizes *inter alia* human development and well-being, economic convergence, equality, consumption towards low material growth, lower energy intensity, educational investments, effective international collaboration, and respect for environmental boundaries. Land systems are effectively managed and social acceptability for CDR options is limited. MP3: With medium challenges to mitigation, socio-technical systems follow historical (incremental) patterns. Economic growth and human development continue to improve but unfold unequally with slow advancement towards sustainable development goals. Decarbonization is primarily achieved by altering how energy is produced and products are manufactured. Reduced demand also moderately mitigates emissions. MP4: With high challenges to mitigation. economic growth and globalization generate widespread adoption of carbon-intensive lifestyles, with high demand for livestock products and transportation fuels. Decarbonization is mainly achieved through supply-side technologies, with marked use of CDR.

Beneath the "Projected temperature overshoot line," average compound rates of change are calculated by dividing the natural logarithm of the ratio of primary intensity or fossil-fuel primary supply share (modeled final-energy shares are unavailable) by 20 or 40 years respectively; actual trajectories will not follow those idealized patterns. Please see 2005–2100 model data in the accompanying spreadsheet iamc15_energy_carbon_data_ALL_MP_v2.xlsx, "data" tab from https://data.ene.iiasa.ac.at/iamc-1.5c-explorer.
Data sources: Grübler et al (2018), Huppmann et al (2018), Rogelj et al (2018).

Selected global indicators	MP1 'Low energy demand'	MP2 'Sustainability'	MP3 'Middle-of-the-road'	MP4 'Resource and energy-intensive'
Final energy demand in 2030 (EJ/yr)	309	325	424	494
Final energy demand in 2030 (relative to 2010)	–15%	–5%	17%	39%
Final energy demand in 2050 (EJ/yr)	245	349	438	512
Final energy demand in 2050 (relative to 2010)	–32%	2%	21%	44%
Primary energy intensity in 2030 (EJ/million US$2010)	2.38	2.6	3.28	3.56
Primary energy intensity in 2030 (relative to 2010)	–64%	–61%	–51%	–47%
Final energy intensity in 2030 (EJ/million US$2010)	1.95	2.01	2.73	2.76
Final energy intensity in 2030 (relative to 2010)	–60%	–58%	–44%	–43%
Primary energy intensity in 2050 (EJ/million US$2010)	1.13	1.46	2.24	1.92
Primary energy intensity in 2050 (relative to 2010)	–83%	–78%	–67%	–72%
Final energy intensity in 2050 (EJ/million US$2010)	0.96	1.15	1.78	1.37
Final energy intensity in 2050 (relative to 2010)	–80%	–76%	–63%	–71%
Renewable energy share in 2030 (relative to 2010)	60%	58%	48%	25%
Renewable energy share in 2050 (relative to 2010)	77%	81%	63%	70%
CO_2 emissions in 2030 (relative to 2010)	–58%	–47%	–41%	4%

CO_2 emissions in 2050 (relative to 2010)	−93%	−95%	−91%	−97%
Fossil-free primary energy in 2030	42%	34%	33%	17%
Fossil-free primary energy in 2050	81%	63%	64%	75%
Land area of bioenergy crops in 2050 (million hectares)	22	93	283	724
Cumulative CCS until 2100 ($GtCO_2$)	0	348	687	1218
of which BECCS ($GtCO_2$)	0	151	414	1191
Projected temperature overshoot	No or less than 0.1˚C	No or <0.1˚C	<0.1˚C	>0.2˚C
Av. compound %/y change in pri. en. intensity, 2010–30	−5.1	−4.7	−3.6	−3.2
Av. compound %/y change in pri. en. intensity, 2010–50	−4.4	−3.8	−2.8	−3.2
Av. compound %/y change in pri. en. fossil-free share, 2010–30	4.7	4.1	3.5	0.1
Av. compound %/y change in pri. en. fossil-free share, 2010–50	4.0	3.6	3.4	3.8

4. Supporting model-data spreadsheet

For the data behind Table 1, please see the accompanying spreadsheet ERL_LovinsEtAl_database _v5_28Nov2019.xlsx, sourced in its README tab.

5. References cited here but not in main paper, doi: 10.1088/1748-9326/ab55ab

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