The Cost of Reducing Greenhouse Gas Emissions

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Abstract

This paper reviews the cost of various interventions that reduce greenhouse gas emissions. As much as possible we focus on actual abatement costs (dollars per ton of carbon dioxide avoided), as measured by 50 economic studies of programs over the past decade, supplemented by our own calculations. We distinguish between static costs, which occur over the lifetime of the project, and dynamic costs, which incorporate spillovers. Interventions or policies that are expensive in a static sense can be inexpensive in a dynamic sense if they induce innovation and learning-by-doing.

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What is the most economically efficient way to reduce greenhouse gas emissions? The principles of economics deliver a crisp answer: reduce emissions to the point that the marginal benefits of the reduction equal its marginal costs. This answer can be implemented by a Pigouvian tax, for example a carbon tax where the tax rate is the marginal benefit of the emissions reduction or, equivalently, the monetized damages from emitting an additional ton of carbon dioxide (CO_2). The carbon externality will then be internalized and the market will find cost-effective ways to reduce emissions up to the amount of the carbon tax.

However, most countries, including the United States, do not place an economy-wide tax on carbon, and instead have an array of greenhouse gas mitigation policies that provide subsidies or restrictions typically aimed at specific technologies or sectors. Such climate policies range from automobile fuel economy standards, to gasoline taxes, to mandating that a certain amount of electricity in a state comes from renewables, to subsidizing solar and wind electrical generation, to mandates requiring the blending of biofuels into the surface transportation fuel supply, to supply-side restrictions on fossil fuel extraction. In the world of a Pigouvian tax, markets sort out the most cost-effective ways to reduce emissions, but in the world we live in, economists need to weigh in on the costs of specific technologies or narrow interventions.

This paper reviews the costs of various technologies and actions aimed at reducing greenhouse gas emissions. Our aim is twofold. First, we seek to provide an up-to-date summary of costs of actions that can be taken now using currently available technology. These costs focus on expenditures and emissions reductions over the life of a project compared to some business-as-usual benchmark—for example, replacing coal-fired electricity generation with wind or weatherizing a home. We refer to these costs as static because they are costs over the life of a specific project undertaken now, and they ignore spillovers. In the environmental economics literature, these static costs are an element in creating what is called a marginal abatement cost (MAC) curve, which plots out the marginal costs of achieving a cumulative level of emissions abatement in order from the lowest- to highest-cost technology or measure.

To economists not in the energy-environment field, these marginal abatement costs might contain some surprises. Although we are skeptical of most "free lunch" static estimates, for some technologies the cost of emissions reductions is remarkably low. For example, blending corn ethanol into gasoline up to a 10 percent ratio provides essentially costless emissions reductions (our point estimate is in the "free lunch" range) in the United States because ethanol is a less-

expensive octane booster than alternatives derived from petroleum. Another low or negative static cost source of emissions reductions is replacing coal-fired electricity generation with natural gas, a switch that has been widely adopted by power generators located where gas prices are low because of the fracking revolution. On the other hand, some actions that might seem green are, from a static perspective, anything but. For example, driving a Ford Focus electric vehicle in a region in which electricity is generated by coal has approximately the same CO_2 footprint as a Ford Explorer sport utility vehicle that averages 25 miles per gallon, and costs nearly as much. We find a wide range of costs for interventions currently being employed, both across and within different types of interventions. This heterogeneity in costs implies that we could achieve the same amount of greenhouse gas emissions reductions that we are achieving now at a much lower static cost, or greater emissions reductions for the same cost. Possible reasons for the use of more expensive policies include the chosen policies having less transparent costs, individual policies having justifications beyond just climate policy, differences in the marginal costs across locations, and lobbying by businesses that could potentially be affected by lower-cost policies. In some cases, especially policies aimed at developing nascent technologies, the policies are developed with a longer-term vision in mind.

These estimates of static costs help to inform discussions about climate policy, but they miss the important consideration that climate change is a long-term problem.

As a result, the proper answer to our opening question is not necessarily what is least expensive mitigation strategy among options available today, but what are the actions if, taken today, will minimize the cost of mitigation both today *and* into the future, recognizing that actions taken today can influence future costs. We refer to such costs as dynamic, because they outlive the life of a specific project.

Our second aim is to distinguish between dynamic and static costs and to argue that some actions taken today with seemingly high static costs can have low dynamic costs, and vice versa. We make this argument at a general level and through two case studies, of solar panels and of electric vehicles. The cost of both technologies has fallen sharply, arguably driven in part by demand-side incentives that in turn stimulated learning-by-doing and technological improvements, the benefits of which are only partially captured by the manufacturing firm. In addition, purchasing an electric vehicle today drives the demand for charging stations, which in effect reduces the cost (here, the cost of time and worry) to potential future purchasers. Under the

right circumstances, such dynamic effects can offer a justification for policies that a myopic calculation suggests have high costs.

Estimates of Static Abatement Costs

Before we begin, we briefly digress on units. The standard units of emissions costs and benefits are dollars per metric ton (1000 kilograms) of CO_2 emissions avoided. As a point of comparison, the social cost of carbon is an estimate of the net present value of monetized social damages from emission of an additional metric ton of CO_2; under the Obama administration, the US government estimated the social cost of carbon to be approximately $46 in 2017 dollars for a ton of emissions in 2017 (IWG 2016).[1] Burning one gallon of petroleum gasoline produces roughly 9 kilograms of CO_2, so a social cost of carbon value of $46/metric ton CO_2 corresponds to $0.41 per gallon. Also, carbon dioxide is only one of many greenhouse gases; others include methane, nitrous oxide, and hydrofluorocarbons. To facilitate comparisons, it is conventional to convert costs for reducing non-CO_2 greenhouse gases into CO_2-equivalent units, and we adopt that convention here.[2]

Brief Background on Marginal Abatement Cost Curves

The marginal abatement cost curve plots measures to abate emissions in order from the least to most expensive. For each, there is a cost per ton of emissions reduced and a quantity of emissions reductions available at that cost. The use of MAC curves to support climate policy analysis dates back at least a quarter century; see Grubb et. al. (1993) for an early review. All models that estimate the mitigation costs of climate policy either implicitly or explicitly use a MAC curve.

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[1] The Trump administration withdrew this estimate by executive order and forbid using the underlying research for regulatory purposes; as of this writing EPA is using two estimates, $1 and $6 per ton, depending on the discount rate (3% or 7%) (Newell 2017). The estimate of $46/ton is in the range of the academic literature, although some estimates are much higher; see Gillingham et. al. (2018). There is currently a cross-institutional, cross-disciplinary effort to provide a comprehensive update to the social cost of carbon based on recommendations made by the National Academy of Sciences (2017), see http://www.rff.org/research/collection/rffs-social-cost-carbon-initiative.
[2] A complication in developing CO_2-equivalent estimates is that the atmospheric residence time of greenhouse gases varies. The most common approach, the global warming potential approach is only an approximation when used to calculate the social cost of non-CO_2 greenhouse gases. See Marten and Newbold (2011) for a more comprehensive approach to calculating the social cost of non-CO_2 greenhouse gases.

The most prominent attempt at developing a comprehensive marginal abatement cost curve is the well-known McKinsey curve, which is constructed using engineering estimates of the cost of implementing new technologies or other measures.

Figure 1 displays the global version of the McKinsey curve (McKinsey 2009). A striking feature of the McKinsey curve, which is shared by MAC curves more generally (for example, see Figure 2 in Grubb 1993), is that some interventions have negative abatement costs: emissions can be reduced, and money saved, at the same time. Economists, including ourselves, are often skeptical of these "free lunch" estimates, unless they are supported by convincing evidence and explanations. Negative costs require institutional entities, such as firms, not to be optimizing, or require the existence of behavioral failures in consumer decision-making (like consumers acting myopically). In some cases, entities such as governments are institutionally complex and/or not minimizing costs, so these free-lunch savings are potentially valid but institutionally difficult to realize. When these negative costs are for energy efficiency programs, this is often called the "energy efficiency gap" and there is a continued debate in the literature on whether there is a real gap or whether the gap can be explained by unaccounted-for costs (Gerarden et al. 2017; Gillingham and Palmer 2014; in this journal, Allcott and Greenstone 2012).

Figure 1. The McKinsey marginal abatement cost curve

Global GHG abatement cost curve beyond business-as-usual – 2030

Note: The curve presents an estimate of the maximum potential of all technical GHG abatement measures below €60 per tCO₂e if each lever was pursued aggressively. It is not a forecast of what role different abatement measures and technologies will play.
Source: Global GHG Abatement Cost Curve v2.0

Source: McKinsey (2009), reproduced with permission of McKinsey & Company.

The concern over negative costs highlights a limitation of marginal abatement curves like the McKinsey curve in Figure 1: specifically, that they are based on engineering estimates, which have their own assumptions and typically do not include behavioral considerations. An example of such a behavioral effect is turning the heat up because the cost of doing so has declined because of weatherization. Economists are typically interested in the combined effect of behavioral responses and the engineering costs.

Static Cost Comparisons

In addition to these and other methodological concerns, the cost estimates in the McKinsey curve in Figure 1 are out of date. We therefore turn to more current estimates of marginal costs. These estimates are drawn from the economics and trade literatures, supplemented by our own calculations.

Table 1. New source generation costs when compared to existing coal generation

Technology	Cost Estimate ($2017/ton CO_2)
Onshore Wind	25
Natural Gas Combined Cycle	27
Utility-scale Solar Photovoltaic	29
New Natural Gas with Carbon Capture and Storage	43
Advanced Nuclear	59
Coal Retrofit with Carbon Capture and Storage	85
New Coal with Carbon Capture and Storage	95
Offshore Wind	105
Solar Thermal	133
Source: Author's calculations updating methodology from Clean Air Task Force (2013) based on Energy Information Administration estimates from the 2018 Annual Energy Outlook. CCS refers to carbon capture and storage technology. Costs are projected for facilities that come on line in 2022. Costs do not incorporate federal renewable tax credits.	

To fix orders of magnitude, we begin with some "bottom-up" or engineering cost estimates for the power sector, presented in Table 1. These estimates compare the cost per ton of CO_2 abated by replacing electricity generated by an existing coal-fired power plant with electricity generated by a cleaner alternative. The estimates are based on the Energy Information Administration's (2018) so-called "levelized" cost of electricity for the different sources, which combines discounted capital, operating, and maintenance expenses to produce a cost of energy per megawatt-hour, given the typical utilization rate or capacity factor for each generation type. These estimates are similar to private sector estimates, such as those by Lazard (2017).

According to these estimates, the least expensive technologies to reduce emissions relative to existing coal are natural gas combined cycle, onshore wind, utility-scale solar photovoltaics, and natural gas with carbon capture and storage technology. Advanced nuclear technologies and utility-scale solar photovoltaics are more expensive, followed by other carbon capture and storage technologies, offshore wind, and solar thermal. The technologies in this set

of estimates that are less expensive (when replacing existing coal) than the Obama administration's social cost of carbon estimate of $46 per ton of CO_2 are onshore wind, natural gas combined cycle, utility scale photovoltaic, and new natural gas with 90 percent carbon capture and storage. In comparison, offshore wind and solar thermal are currently quite expensive ways to reduce emissions (although offshore wind costs are falling). These estimates only consider climate benefits of switching from coal, not any other health co-benefits arising from reductions in local air pollutants.

From a policy perspective, engineering cost estimates such as those in Table 1 have important limitations. Some of these technologies are in wide current use, so cost estimates are reasonably reliable (onshore wind, natural gas combined cycle), whereas other technologies have demonstrated technical feasibility but current projects are subject to large cost overruns, so the engineering costs could be underestimates (for example, advanced nuclear, carbon capture and storage). Another limitation is that these are national averages, and costs vary regionally depending on local conditions (for example local fuel prices, wind conditions, and insolation). In addition, these are costs of switching technologies, which differs from the costs of a policy designed to encourage technology switching. These engineering estimates do not incorporate behavioral responses, either.

We therefore turn to a systematic review of costs of interventions – typically policies – aimed at reducing greenhouse gas emissions. This review draws on more than 50 recent articles in the economics literature. We selected papers based on a few criteria. First, the paper must be an economic analysis, so we draw most heavily from papers published in economics journals and economics working paper series. Second, the paper must either have enough information so that we can calculate a cost per ton of emissions reduction or include an explicit estimate of this cost. Most papers we review have an explicit estimate in dollars per ton CO_2. Third, we focus on papers published in the past decade, and nearly all of the papers included in our review are published after 2006. In some cases, we have supplemented the estimates from the economics literature with studies from the trade literature and/or our own calculations.

The results are summarized in Table 2. The table presents ranges of estimates whenever there are multiple estimates from either the same study or multiple studies; the Appendix provides an expanded version of Table 2 with sources and methods. As in a marginal abatement cost curve, we have ordered the estimates in Table 2 from lowest to highest cost.

Table 2. Static costs of policies based on a compilation of economic studies

Policy	Estimate ($2017/ton CO_{2e})
Behavioral Energy Efficiency	-190
Corn starch ethanol (U.S.)	-18 – +310
Renewable Portfolio Standards	0-190
Reforestation	1-10
Wind Energy Subsidies	2-260
Clean Power Plan	11
Gasoline Tax	18-47
Methane Flaring Regulation	20
Reducing Federal Coal Leasing	33-68
CAFE Standards	48-310
Agricultural Emissions Policies	50-65
National Clean Energy Standard	51-110
Soil Management	57
Livestock Management Policies	71
Concentrating Solar Power Expansion (China & India)	100
Renewable Fuel Subsidies	100
Low Carbon Fuel Standard	100-2900
Solar PV Subsidies	140-2100
Biodiesel	150-420
Energy Efficiency Programs (China)	250-300
Cash for Clunkers	270-420
Weatherization Assistance Program	350
Dedicated Battery Electric Vehicle Subsidy	350-640
Notes: Rounded to two significant digits. The authors have converted all estimates to 2017 dollars for comparability. See Appendix Table A-1 for sources and methods. CO_{2e} denotes conversion of tons of non-CO_2 greenhouse gases to their CO_2-equivalent based on their global warming potential.	

We highlight seven features of Table 2.

First, the range of costs of these interventions is extremely wide, from less than $10 per ton to over $1000 per ton. What is striking about this range is that all the interventions in Table 2 are either policy steps that have been implemented, at least in some jurisdiction, or have been actively proposed and considered. Most of the costs are relatively expensive, in the sense that they exceed $46/ton. Evidently, static cost is only one consideration when a policy is proposed or considered. This heterogeneity likely stems from multiple sources, including the carbon intensity of the displaced fuel (e.g., is the electricity on the grid coming from coal or hydropower?) and the other policies in place.

Second, there is a wide range of costs *within* a type of intervention. For example, subsidies to wind generation, such as the wind production tax credit in the United States, have estimated carbon abatement costs ranging from $2 to more than $260 per ton of reduced CO_2. For wind power, one reason for the large range is that there is large variation across sites in wind potential. The range is even wider for subsidies for solar photovoltaics, in part because there is wide variation in solar potential across locations (the solar power potential in southwestern Arizona is roughly twice that in upstate New York[3]), in part because of the timing of the programs (for example, earlier programs faced higher solar panel costs than later programs), and in part because of differences in scale (utility-scale arrays cost much less to install per kilowatt than rooftop arrays) (Baker et al. 2013). The wide ranges of estimates in Table 2 underscore that policies may have very different costs per ton of CO_2 depending on the empirical setting and/or the methodology of the study. The ranges of the estimates should not necessarily be taken as a proxy for uncertainty, for they simply show the ranges of estimates across study. Indeed, due to within-study uncertainty, values above and below the ranges are likely to occur with some probability. The ranges do provide evidence of the width of the range of estimates from different studies.

Third, some of the interventions that have negative economic costs in the McKinsey curve (and in other marginal abatement cost curves) have positive costs here. For example, engineering estimates of weatherization programs often suggest that they have negative costs (and so why such changes have not already been undertaken is the "energy efficiency paradox"). In a randomized controlled trial, however, Fowlie et. al. (2018) found that the actual costs of the weatherization exceeded the savings, leading to the $346/ton estimate of the mitigation cost reported in Table 2. They attribute the difference between the negative engineering costs for the homes in their study and the actual positive costs primarily to flaws in the engineering models.

Fourth, some of the costs in Table 2 *are* negative. A striking estimate arises from behavioral economics studies of how small nudges can get consumers to reduce their energy consumption, thereby saving money while reducing emissions; the estimate in Table 2 is taken from Allcott and Mullainathan's (2010) meta-analysis of behavioral interventions. An example of such a nudge is the OPOWER program, in which an insert in the residential electricity bill compares the homeowner's usage to that of her neighbors, costing the utility very little and

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[3] National Renewable Energy Lab NSRDB Data viewer.

leading to consumer savings. One concern, which we share, is that while the cost of such reductions is negative, the total emissions reductions from such nudges are likely to be relatively small and partially transitory. The other negative estimate in Table 2 is for corn ethanol, which some might find surprising. The California Air Resources Board (2018) estimates that ethanol from new corn ethanol plants has roughly 70% of the life-cycle CO_2 emissions of petroleum, including the carbon effects of induced land use change. Ethanol is the least-expensive additive for boosting the octane content of petroleum gasoline (Irwin and Good 2017), and in 2012, when the quantity mandate was not binding and there were no direct federal subsidies, ethanol comprised just under 10% of the US retail gasoline supply. Costs rise – and turn sharply positive – for blends exceeding 10 percent because of the lack of retail infrastructure, among other reasons.

Fifth, a few of the interventions have very low costs. Some, like the Clean Power Plan—the Obama administration's rulemaking for CO_2 emissions standards in the electric sector—and regulations to reduce methane flaring from fracked oil wells that co-produce natural gas, are examples in which the regulation intensity was chosen with cost in mind. The Clean Power Plan is notable for its low cost per ton of emissions reductions (this estimate is taken from the Regulatory Impact Analysis of the Clean Power Plan, U.S. Environmental Protection Agency 2015). This cost per ton is less than the engineering costs in Table 1, in part because the regulation drives a switch in generation from existing coal-fired plants to existing gas-fired plants, which does not require building a new plant as in Table 1. In addition, because the Clean Power Plan allowed interstate trading of emissions permits, new low-greenhouse gas generating facilities would be built where it is most economically efficient to do so, yielding lower costs than the generic plant replacement costs in Table 1. The Clean Power Plan is also notable because its projected CO_2 emissions reductions are the largest, or nearly so, among the interventions in Table 2.

Sixth, some of the interventions have very high static costs. The United States and Europe have programs that require blending biodiesel into the diesel fuel supply. Biodiesel can be made from many oil feedstocks, including waste grease, but on the margin it is made from food-competing feedstocks such as soybean oil oil. These food oils are expensive and production of soy biodiesel requires a large subsidy, which is provided in the United States primarily through a tax credit and through the Renewable Fuel Standard. In other cases, the high costs are

a result of inefficiencies in program design. For example, the temporary Cash for Clunkers program was installed at the depth of the financial crisis recession to provide an infusion of demand for new cars to support the auto industry and to provide countercyclical fiscal stimulus. Because the program exchanged old vehicles for more efficient new ones, it boosted fleet fuel economy. However, it had substantial temporary inframarginal transfers that were not a problem for its primary purpose – to pull forward auto demand – but made it a costly way to reduce emissions.

Seventh, the literature suggests that the cost of reducing carbon with some land use policies are low. Jayachandran et al. (2016) used a randomized controlled experiment to find that cash payments for forest conservation in Uganda substantially reduced deforestation at a cost of $1/ton. Their experiment lasted only two years and without the payments one might expect reversion to the deforestation baseline, so that the emissions reduction is temporary not permanent, and thus has only modest effects.[4] This distinction between permanent and temporary sequestration, along with the difficulty of ascertaining whether the payments actually induce incremental retention in practice (something that was in fact found in Jayachandran et al.'s (2016) experiment), are at the heart of the controversy over the use of carbon offsets (for example, van Benthem and Kerr 2013; Bento, Kanbur, and Leard 2016).

One sobering insight from the estimates in Table 2 is that many of the least-expensive interventions cover a small amount of CO_2 reductions, whereas the scalable technologies that that are at the center of discussions about a transformation to a low-carbon economy— electric vehicles, solar photovoltaic panels, and offshore wind turbines—are among the most expensive on the list. Behavioral nudges are a very small step towards deep decarbonization. In contrast, the more expensive scalable technologies have a much greater potential for substantial emissions reductions. For these technologies, what matters most are not the static costs today, but the costs and consequences of these interventions over time, that is, the dynamic costs of the intervention. It is informative to know what are the cheapest interventions to do today, but we would argue that it is even more important to know what interventions might most effectively drive down the price of large-scale reductions in emissions in the future.

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[4] The distinction between temporary and permanent forest sequestration is important. Temporary rainforest sequestration is equivalent to storing emissions, then releasing them later. Analogously to how generating electricity from wind displaces retired coal-fired electricity, permanent sequestration permanently keeps the CO_2 in question out of the atmosphere.

Dynamic Costs

The long residence time of CO_2 in the atmosphere makes climate change a long-term problem, in which (to a first approximation) what matters is the total number of tons emitted over some long horizon. As a result, the key to reducing emissions in the future is to have low-cost alternatives to fossil fuels that are zero- or low-carbon. The true total cost of investments or interventions today therefore must include both their static, or face-value cost, and any spillovers those investments have for future costs of emissions reduction. The importance of a dynamic perspective is hardly new—see Popp, Newell, and Jaffe (2010) for a review—but it is often neglected both in the public debate and in the literature on costs of abatement. Yet, the welfare benefits of even small growth rates in the efficiency of clean technologies may be large, as suggested by simulations in Hassler et al. (2017).

Conceptual Framework

The static cost estimates of the previous section focus on direct reductions in emissions in the relatively short-run. However, expenditures on certain kinds of short-run reductions in emissions today can also affect emissions in the future, above and beyond direct emissions from the project. There are at least four reasons why this second component of emissions reduction could be nonzero and possibly large for some green technologies. Three of these stem from externalities, while the fourth is the difference between myopic and dynamic cost minimization.

First, many of these low-carbon technologies are nascent, and there could be substantial gains in production efficiency as more units are produced. Such gains can arise from engineering and managerial improvements made as production increases, a channel referred to as learning by doing, and from scale economies. To the extent that such gains are only partially appropriable by the firm, an expenditure today provides a positive externality that reduces costs in the future. The first case study that we discuss in the next subsection, solar panels, focuses on this learning-by-doing effect.

Second, a related externality arises from research and development (R&D) spillovers because research results are only partially appropriable. These spillovers also represent a market

failure, and economists have argued that the spillovers are likely to be particularly large for emerging clean technologies (Nordhaus 2011). To the extent that purchases today spur additional research, which then reduces costs, expenditures today reduce emissions tomorrow. It can often be difficult to separate the effects of R&D spillovers from learning-by-doing spillovers, for as a firm ramps up production, it also may ramp up research. For this reason, economists have often encouraged caution in relying too heavily on learning-by-doing to model technological change (Nordhaus 2014).

Third, a separate externality that is present for some technologies is a network or "chicken and egg" externality, in which an expenditure today influences the options that are available to others in the future. For example, purchases of electric vehicle today will, on the margin, stimulate demand for charging stations, which once installed will lower the effective cost for future potential purchasers of electric vehicles. Our second case study, of electric vehicles, in principle includes both learning-by-doing and network externalities.

Fourth, energy investments typically have substantial irreversible components, which in general implies state dependence so that the dynamically optimal path may differ from a sequence of myopic optimizations each chosen at a point in time. This potential for lock-in is at the heart of the debate about the merits of natural gas as a bridge fuel towards decarbonizing the power sector, in which renewable proponents argue that natural gas is cheaper only if one optimizes myopically and fails to recognize that the power sector will eventually need to be decarbonized. This intuition underlies Vogt-Schilb et al. (2018), who show that if abatement is achieved through investment in long-lived capital, it can be optimal to begin emissions abatement with expensive abatement investments that have large emissions reduction potential because they crowd-out dirtier long-lived investments. Irreversibility (state dependence) also underlies the results of Fischer and Newall (2008), Acemoglu et al. (2012), and Acemoglu et al. (2016), who show that a carbon price combined with research subsidies for low- greenhouse gas technologies may be desirable to attain dynamically efficient outcomes.

Of course, long-term considerations may not always lower the cost of emissions reductions. For example, nuclear power has long had major federal research subsidies but its cost has gone up, not down (Davis and Hausman 2016). Additionally, as the marginal ton of displaced electricity becomes cleaner (e.g., gas instead of coal), the cost per ton abated by low-carbon renewables will tend to increase. One major reason why dynamic considerations are often

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ignored is that they tend to be highly uncertain. But that uncertainty should be viewed as a research challenge rather than an excuse to ignore dynamic considerations, and there is some evidence from the recent literature to draw from.

Dynamic Cost Case Study 1: Solar Panels

From 2010 to 2015, the price of solar photovoltaic panels fell by two-thirds, while annual global panel installations grew by 250 percent, as shown in Figure 2. The fact that panel sales increased when their price fell is hardly surprising, but more intriguing is that the steepest decline in panel prices after about 2007 post-dated the initial growth in panel sales, which began around 2002. The growth in sales in the mid-2000s was associated with policies that provided aggressive financial support for installing rooftop photovoltaic arrays through the German Energiewende, which provided a substantial feed-in tariff that allowed solar installations to be compensated at a very high rate for electricity fed into the grid, and the California Solar Initiative, which provided generous upfront subsidies for solar installations.[5] These early panel purchases were very expensive and account for some of the high photovoltaic cost estimates in Table 2. As stressed by a number of researchers (for example, Borenstein 2017), the static cost per ton of CO_2 reduced from policies to encourage solar installations tends to be high. Our literature review finds costs ranging from more than \$100 per ton of CO_2 to in the thousands per ton of CO_2. On the lower end, Hughes and Podolefsky (2105) estimate costs of the California Solar Initiative at between \$130 and \$196 per ton. On the high end, Abrell et al. (2017) find a static cost per ton of €500-1300 (roughly \$574-1492 in 2017 dollars) for solar feed-in tariffs in Germany and Spain (a solar feed-in tariff is a long-term fixed price contract for purchasing electricity from a solar array).

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[5] Many US states have generous net metering policies that act as implicit subsidies by compensating solar fed into the grid at the retail rate. Some states have Renewable Portfolio Standards that require utilities to procure certain amounts of renewable power (sometimes with a solar carve-out) by certain dates. At the federal level, since 2008, there has been a 30% investment tax credit for the installation of a residential solar system.

**Figure 2. Solar panel price indexes (left, excluding subsidies)
and cumulative worldwide installed capacity (right), 1983-2015**

Sources: International Energy Agency (2017), Navigant Consulting (2009),
Gerarden (2017)
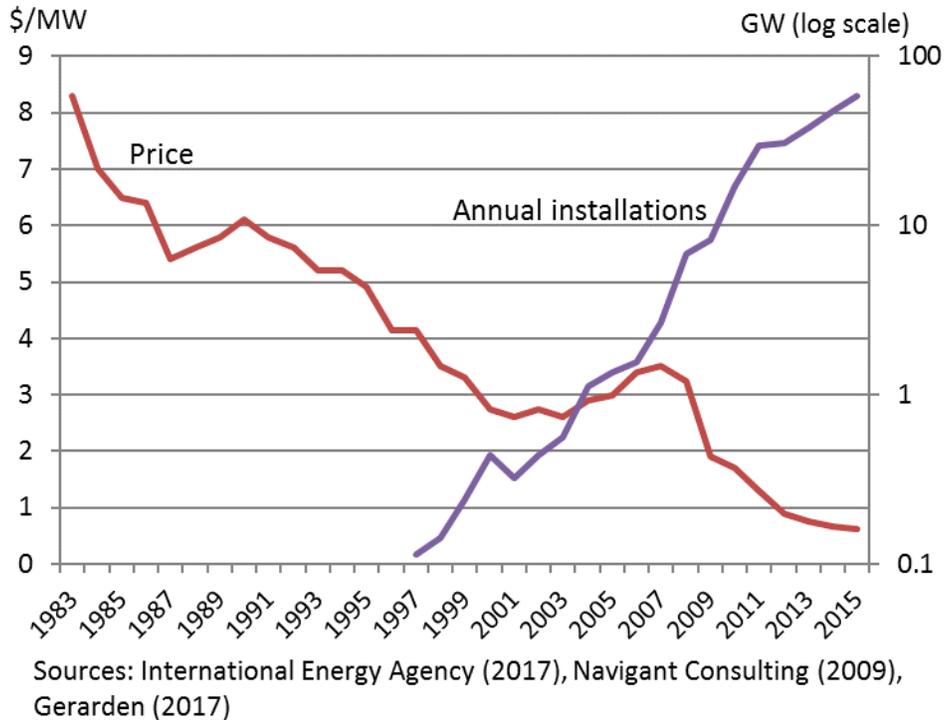
However, both the timing shown in Figure 2 and recent research suggests that the early
push in demand, stimulated by deep government subsidies, did in fact help to drive down the
price of solar panels. One channel is that current subsidies may encourage firms to innovate to
reduce their future costs. Gerarden (2017) estimates that this induced innovation effect, which
does not include learning-by-doing, contributed to the decline in solar array prices and increased
the external social benefits from global solar adoption by at least 22 percent. His results further
suggest an important spillover from any single country that subsidizes solar to the rest of the
world due to the investment in innovation by international firms. In this sense, the German
Energiewende subsidized lower-cost solar for the rest of the world.

Other channels for cost reduction in the production of solar panels include learning by
doing and economies of scale. Nemet (2006) decomposes the reduction in cost into the
manufacturing plant size, module efficiency, and cost of silicon, finding that between 1980 and
2001, economies of scale from a larger manufacturing plant sizes accounted for 43 percent of the
cost reduction. Most of the remaining cost reduction could be attributed to improvements in

module efficiency due to research and development investment. The substantial cost declines in solar module prices over the past decade are often attributed to economies of scale (Carvalho, Dechezleprêtre, Glachant 2017). Economies of scale and learning-by-doing can in many cases be appropriable by the firms making decisions to scale up (this appears to be the case for learning-by-doing among rooftop solar installers, as Bollinger and Gillingham 2018 explain), so that learning-by-doing and scale economies do not by themselves necessarily constitute reasons for policy intervention. Absent a carbon price however, the demand for solar panels will be less than it would be were there a carbon price. As a result, second-best policies that are initially expensive (like the German Energiewende) can in principle stimulate production that would not normally happen because fossil fuels are cheaper than they would be, were their externality priced. For solar panels, at least, all this seems to have been the case.

Going forward, we may continue to see policy-induced cost reductions for solar technology. As the penetration of solar rises, and as the rest of the electricity system decarbonizes, such cost reductions will have to continue to be substantial to offset the higher potential costs of additional storage because of solar intermittency.


Dynamic Cost Case Study 2: Electric Vehicles

Like solar panels, the static costs of CO_2 reductions obtained by using electric vehicles in Table 2 is high. Today, many electric vehicles in the United States are charged using electricity that on the margin is produced by fossil fuels. Holland et al. (2016) use Graff Zivin et al.'s (2014) method for computing marginal emissions to examine the static optimal second-best purchase subsidy on electric vehicles accounting for both greenhouse gases and local air pollution. Holland et al. (2016) find that the subsidy ranges from a subsidy of $2,785 in California (with relatively clean electricity on the margin) to a *penalty* of $4,964 in North Dakota, where electricity is generated from coal. Archsmith et al. (2015) perform similar calculations that additionally include lifecycle considerations, and find that on average electric vehicles currently only slightly reduce greenhouse gases relative to gasoline-powered vehicles.

From a dynamic perspective, however, the case against programs to support electric vehicle purchases is far less clear. The static calculations ignore the fact that the grid is evolving and becoming cleaner. Moreover, the general issues raised for solar panels—induced innovation, learning by doing, and economies of scale that would not otherwise be achieved because carbon

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is not priced—apply to electric vehicles as well. Unlike the case of solar panels, however, we are not aware of any research that investigates drivers of price dynamics for electric vehicles, perhaps because the cost declines and sales growth are so recent. The available data are, however, suggestive that the analogy to demand-pull effects for solar panels could well apply to electric vehicles.

Figure 3 plots electric vehicles that entered the market from model years 2011-2018 based on their suggested retail price (y-axis) and battery range (x-axis). The price-range frontier has strikingly shifted out: more recent market entrants have greater battery range at lower cost, underscoring this rapid improvement in technology.

Figure 3. Electric vehicle MSRP plotted against the battery range shows impressive technology improvements within a short time
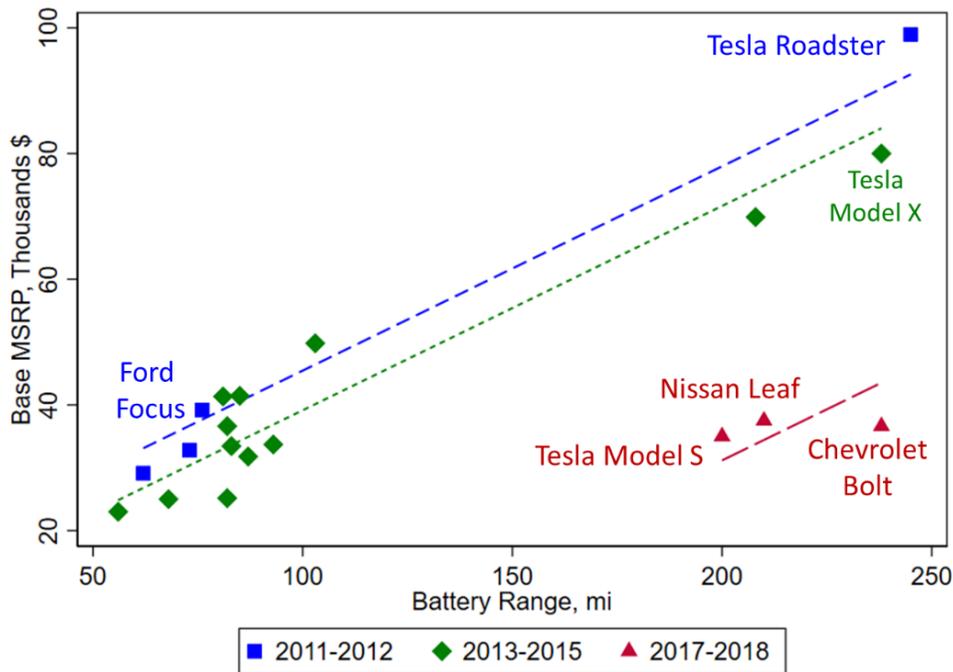
Notes: Dates indicate year the model is introduced. Regression lines are fit with a common slope and different intercept for each group of model years. Source: Li (2018) and authors' calculations.

The large declines in price for vehicles with the same range is mainly due to the ongoing decline in battery prices. From 2009 to 2015, the price of batteries for electric vehicles fell by 75 percent (US Department of Energy 2016). Like solar photovoltaic arrays, electric vehicles have

been a target of demand-pull subsidy programs. Since the Energy Policy Act of 2005, there has been a US federal income tax credit of $7,500 (which phases out with production by any given manufacturer). Many states have additional incentives, such as a $3,000 rebate in Connecticut, eligibility for driving in a high-occupancy lane with only a single occupant in California, and a zero-emissions vehicle mandate in 10 states that requires automakers to sell a certain number of zero tailpipe emission (including electric vehicles) vehicles for every non-zero-emissions vehicle sold. Numerous papers in the transportation literature have provided evidence suggesting that electric vehicle subsidies increase demand for electric vehicles, as one would expect (reviewed in Zhou, Levin, and Plotkin 2016). The general pattern of demand-pull policies combined with subsequent sharp declines in costs is similar to that found for solar panels. We note that it is consistent with learning-by-doing and scale economy effects, and that confirming or refuting this hypothesis is an important area for future research by economists.

Electric vehicles also exhibit network effects, whereby the purchase of an additional electric vehicles makes the installation of a charging station more profitable. Thus, a positive feedback can exist, leading to multiple equilibria. For example, there may be one equilibrium with few charging stations and few or no electric vehicles, and another with many charging stations and electric vehicles. There is a growing literature on electric vehicles and network effects. Zhou and Li (2017) point out the possibility of multiple equilibria in electric vehicles and argue that a targeted subsidy policy to encourage electric vehicle adoption can be much more efficient than a uniform policy. Yu et al. (2016) discuss how network effects can lead the market solution to under-invest in electric vehicles compared to what is socially optimal. Li (2017) develops a structural model of two-sided market estimated with vehicle registration data from the United States to find that mandating compatibility in charging stations would benefit consumers, enhance network effects, and increase the size of the electric vehicle market. Springel (2018) uses vehicle registration data from Norway—the country with the highest penetration of electric vehicles—to estimate a structural model showing that subsidies for charging stations are more effective for increasing electric vehicles uptake than are purchase subsidies for electric vehicles, but their effectiveness tapers off with increased subsidy.

The findings of these papers on network effects point to how a static perspective on policies to encourage technologies such as electric vehicles miss important aspects germane to the long-term cost-effectiveness of different policy approaches.

Static v. Dynamic Costs: Other Examples

Our two case studies present the sanguine view that seemingly expensive investments today result in lower costs in the future, a finding broadly akin to the theoretical work of Vogt-Schilb et al. (2018), Newbery (2018), Acemoglu et al. (2012), and Acemoglu et al. (2016). This happy result, however, is not preordained. For example, taking the dynamic approach may lead one to invest *less* in a carbon abatement technology if costs are expected to increase, rather than decrease, over time. Nuclear technology may fall into this category as construction costs of nuclear energy have risen, not fallen (Davis and Hausman 2016). Increasing costs of integrating renewable electricity into the electric grid can also work in this direction. In other cases, the static approach is perfectly appropriate. Consider policies to reduce methane leaks from the natural gas distribution system: the costs of sealing these leaks is likely to be similar in the near future as it is today as the process of sealing leaks is well understood but costly (digging up pavement and replacing pipes). Still other cases are less clear. Policies that would promote fuel switching to natural gas may reduce emissions in the short-run, but have potential to lead to investments in long-lived capital assets, and possibly even technological lock-in (Gillingham and Huang 2018).

Challenges

The costs of reducing carbon emissions discussed in this paper pose several challenges. One of these challenges is that some politically appealing programs, such as support for biodiesel through (for example) the federal Renewable Fuel Standard or subsidies for energy efficiency programs, can be quite costly either for technological reasons or because of behavioral responses. Because the costs for these programs are often masked and only apparent upon scrutiny by economists, they appear low-cost but are not.

A second challenge is the reverse, where highly visible programs are perceived as high-cost but are not. A prominent example is the Clean Power Plan, which would have resulted in large emissions reductions for a cost far below that of many other programs already in place.

A third challenge is that the static costs provide at best an incomplete picture of the true costs of a particular action, which must include the dynamic consequences. The sign of those dynamic consequences in general depends on the intervention. If the intervention is replacing

coal electricity generation by natural gas, low short-term costs might lead to higher longer-term costs if the result is long-lived natural gas infrastructure that is locked in and costly to abandon as the price of renewables drops. In contrast, if the intervention is providing subsidies for purchasing electric vehicles, the demand-pull effects of induced learning by doing and economies of scale can make dynamic costs much lower than a myopic static calculation would suggest. Because climate change is a long-term problem and the changes ultimately needed to reduce emissions are vast, the dynamic costs are far more important than the static ones.

A fourth challenge is to the economic research community, and it stems from the previous observation. As is clear from our review, most of the empirical studies of costs by economists focus on static costs, typically static costs of programs that have already been in place. This is natural because there is data on these programs, and understanding the costs of previous programs is a helpful guide to designing future programs. But particularly in the field of climate change research, more attention is needed on the determinants of dynamic costs. This exciting field of research merges environmental and energy economics with the extant literature on productivity, diffusion, and learning-by-doing. We have highlighted two areas – solar photovoltaics and electric vehicles – in which demand-pull policies appear to induced cost reductions, however that need not always happen and magnitudes surely vary from one case to the next.

Climate change is a long term problem, and the focus of policy must be on long-term solutions. To make major progress on climate goals, say, 80% decarbonization by 2050 in the United States, will require new technology deployed on a vast scale. Even if each technological step is evolutionary—cheaper electric vehicle batteries, connecting the grid to harness the wind potential in the Midwest, reducing the cost of offshore wind, developing and commercializing low-carbon fuels for air transport—the overall change will be revolutionary. If a price on carbon is not politically feasible—and arguably even if it is—these long-term considerations need to be incorporated into our short-term policy tradeoffs. From the perspective of the cost calculations in this paper, one clear implication is that choosing low-cost interventions without a future, including ones that lock in fossil fuel infrastructure, can result in too much emphasis being placed on what is cheapest to do today. We are always surprised by technological progress, but as economists we are not surprised that it occurs when the right incentives are in place.

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Appendix Table: Sources for estimates in Table 2.

Policy	Reference	Estimate ($2017/ton CO2)	Notes
A. Transportation			
Corn starch ethanol (U.S.)			Policies to blend ethanol with gasoline
	Irwin, Good (2017)	-$18	Below the E10 blend wall based on costs of non-ethanol oxygenates
	Authors' calculations	$312	Subsidy value based on 2017 actual average RIN value and CARB average pathway emissions
Biodiesel (U.S.)			Policies to blend ethanol with gasoline
	Waste oil - au calculations	$146-243	Subsidy value based on 2017 actual average RFS RIN value and CARB (2018) average pathway emissions. Range excludes or includes biodiesel tax credit (tax credit was reinstated retroactively for 2017). Excludes additional subsidies through the LCFS.
	Tallow - au calculations	$179-298	
	Soy oil - au calculations	$251-418	
Renewable Fuel Standard			Policies requiring transportation fuels to contain a minimum amount of renewable fuels
	Sarica, Tyner (2013)	$1.10 - $15.70	
	Holland, Hughes, Knittel, Parker (2011)	$72.70	
Renewable Fuel Subsidies			Policies to provide financial incentives for production of renewable transportation fuels
	Holland, Hughes, Knittel, Parker (2011)	$103.30	
Gasoline Tax			Per gallon tax on gasoline
	Knittel, Sandler (2013)	$18.20 - $46.70	
CAFE Standards			Policies to set fuel efficiency and greenhouse gas emissions standards for certain vehicles
	Kok, Annema, van Wee (2011)	-$107.40 to -$155.40	
	Sarica, Tyner (2013)	$224.80	
	Jacobsen (2013)	$307.30	
Low Carbon Fuel Standard			Policies to limit the average emissions intensity of transportation fuels
	Holland, Hughes, Knittel, Parker (2011)	$103.90	

	Holland, Knittel and Hughes (2009)	$385 - $2852	
Cash for Clunkers			Policy to provide financial incentives for consumers to trade in low efficiency vehicle and purchase new higher efficiency vehicle
	Knittel (2009)	$270.80 - $417	
Dedicated Battery Electric Vehicle Subsidy			Policy to provide financial incentives for consumers to purchase electric vehichles
	Archsmith, Kendall, Rapson (2015)	$347.5 - $637.30	
B. Power Sector			
Wind Energy Subsidies			Policies to provide financial incentives for wind energy projects
	Abrell, Kosch, Rausch (2017)	$126.30 - $264	
	Abrell, Kosch, Rausch (2017)	-$5.60 to -$8	
	Marcantonini, Ellerman (2013)	$66.60	
	Frondel, Ritter, Schmidt, Vance (2010)	$87.50	
	Metcalf (2009)	$14.00	
	Callaway, Fowlie, McCormick (2015)	$27 - $93.7	
Clean Power Plan			National regulation to limit emissions from electricity generation in US
	Original EPA RIA (2015)	$11	
Concentrating Solar Power Expansion (China & India)			Policies to provide financial incentives for new concentrating solar power projects in India and China
	Ummel (2010)	$101.20	
Renewable Portfolio Standards			State policies to mandate a certain percentage of renewables in overall energy mix
	Chen, Wiser, Mills, Bollinger (2009)	$0 - $241.10	
	Johnson (2014)	$13 - $189.20	
Solar PV Subsidies			Policies to provide financial incentives for solar PV energy projects
	Abrell, Kosch, Rausch (2017)	$574 - $1492.30	
	Abrell, Kosch, Rausch (2017)	$1102 - $2146.70	
	Hughes, Podolefsky (2015)	$138.80 - $209.30	

	Marcantonini, Ellerman (2013)	$813.40	
	Frondel, Ritter, Schmidt, Vance (2010)	$1,159.60	
	Callaway, Fowlie, McCormick (2015)	$224.10 - $763.90	
	Macintosh, Wilkinson (2011)	$242.80 - $287.70	
	Gillingham, Tsvetanov (2018)	$376.90 - $615	
C. Energy Efficiency			
Energy Efficiency Programs (China)			Potential for efficiency upgrades to urban production processes in different regions in China
	Wang, Bian, Cheng (2017)	$297.70	
Weatherization Assistance Program			Policy to fund energy efficiency improvements and lower heating fuel usage in low-income households
	Fowlie, Greenstone, Wolfram (2018)	$346.20	
Behavioral Energy Efficiency			Program focusing on home energy reports
	Allcott, Mullainathan (2010)	-$188.50	
D. Land Use			
Reforestation			Payments for ecosystem services to increase carbon sinks
	Jayachandran, de Laat, Lambin, and Stanton (2016)	$0.60	
	Jack (2011)	$9.70	
Agricultural Emissions Policies			Policies to limit greenhouse gas emissions from agricultural production
	De Cara, Jayet (2011)	$49.80 - $65.40	
Soil Management			Policies to limit greenhouse gas emissions through improved soil management techniques
	Beach, DeAngelo, Rose, Li, Salas, DelGrosso (2008)	$56.90	
Livestock Management Policies			Policies to limit greenhouse gas emissions through improved livestock management techniques
	Beach, DeAngelo, Rose, Li, Salas, DelGrosso (2008)	$71.20	
E. Extraction and Other			
Methane Flaring Regulation			State policy to limit methane flaring from natural gas production in North Dakota

	Lade, Rudik (2017)	$20.40	
Reducing Federal Coal Leasing			Policies to reduce coal leasing on federal lands
	Gillingham, Stock (2016)	$33 - $68	
National Clean Energy Standard			National policies to mandate a certain percentage of "clean" energy in overall energy mix
	Sarica, Tyner (2013)	$50.60 - $112.40	

Notes: Source cost estimates were adjusted to 2017 dollars using the PCE price index.

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