Marginal Emissions Pathways: Drivers and Implications

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Governments frequently use policies that target the expansion of a clean technology to achieve greenhouse gas emissions mitigation goals, such as those submitted by countries under the Paris Agreement. As a result of direct and indirect market adjustments induced by a particular policy, marginal emissions from expanding a clean technology may vary in the amount of clean technology, reflecting a marginal emissions pathway. This paper analyzes the economic and policy drivers of marginal emissions pathways and the implications when such pathways are non-constant. We show numerically that marginal emissions pathways for a mandate and subsidy to promote biofuels in the U.S. are non-constant in the amount of biofuel and, due to differential impacts on output markets, move in opposite directions and eventually have opposite signs. We also show that explicitly or implicitly treating marginal emissions as constant can generate significant errors in the prediction of mitigation from clean technology policies and can make it difficult to attribute mitigation from decentralized efforts to address climate change, such as the Paris Agreement.

Keywords: marginal emissions; climate change; clean technology policies; emissions prediction

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Policies that incentivize the expansion of perceived clean technologies at the expense of dirty alternatives, such as mandates, fractional targets, and subsidies are central to decentralized efforts to mitigate greenhouse gas (GHG) emissions. For example, of Nationally Determined Contributions (NDCs) submitted through July 2021 as part of the Paris Agreement, measures to achieve domestic mitigation by expanding renewable energy were "most frequently mentioned" by countries, followed by measures to improve energy efficiency (UNFCCC 2021). Policymakers need accurate estimates of emissions reductions expected to be achieved by these efforts both individually—to inform the level of mitigation sought by any given nation, as well as collectively—to attribute national contributions to global mitigation.

Evaluating mitigation from clean technology policies is difficult because each unit of clean technology added by a policy need not result in the same change in emissions. Clean technologies only indirectly reduce emissions by displacing dirty alternatives. As a result, the change in emissions from policies that expand clean technologies depend on the policy-induced response of markets linked to the production and use of the clean technology as well as dirty alternatives, conditional on baseline economic conditions. These policy and economic drivers create a relationship between the quantity of clean technology added by a particular policy and the resulting marginal emissions or a *marginal emissions pathway*. The shapes of marginal emissions pathways have important policy implications because the total change in emissions from a clean technology policy is the integral under the marginal emissions pathway, but many standard methods explicitly or implicitly assume that marginal emissions pathways are constant in the amount of clean technology and/or the policy driving the clean technology expansion.

In this paper we explore the drivers of marginal emissions pathways and assess how the shapes of marginal emissions pathways affect the prediction and attribution of mitigation from clean technology policies. To illustrate the drivers of marginal emissions pathways, we first use a simple conceptual model to show that marginal emissions from a mandate and a subsidy—the most common clean technology policies (International Energy Agency 2017)—can be decomposed into input and output effects (this decomposition follows the previous literature, such as Lapan and Moschini (2012)). The input effect captures changes in emissions from adjustments in input markets linked to the production of the clean and dirty technologies assuming one-for-one displacement and is therefore the same for any policy. The output effect is the change in emissions that arises given how policies alter output markets and thus depends on the rate at which the clean technology displaces the dirty technology. Since input and output effects depend on economic conditions in affected markets, such as the market shares of the inputs used in the production of the clean or dirty technologies, and the output effect depends on how a particular policy distorts markets, marginal emissions may vary with respect to the amount of clean technology and/or the policy driving the clean technology expansion.

We then couple a rich sectoral economic model with a detailed emissions model to evaluate the marginal emissions pathways arising from a mandate and subsidy to promote corn ethanol in the United States. Marginal emissions pathways from each policy are not only non-constant but have different shapes due to divergent output effects. More precisely, marginal emissions are increasing for the subsidy at a nearly constant rate whereas marginal emissions are decreasing at an increasing rate for the mandate. At low ethanol quantities marginal emissions for both policies are between 1-3 gCO_2e/MJ, meaning these policies slightly raise emissions. Marginal emissions for the subsidy steadily rise as the quantity of ethanol increases, reaching 20 gCO_2e/MJ, whereas marginal emissions become negative under the mandate for quantities above 15 billion gallons. The same drivers that cause marginal emissions pathways to be non-constant, also explain the sensitivity of marginal emissions pathways to alternative parameter assumptions.

Finally, we explore the implications of non-constant marginal emissions pathways for predicting and attributing mitigation. Efforts to predict emissions reductions that explicitly or implicitly ignore the channels by which marginal emissions vary (e.g., amount of clean technology in the baseline and/or added, policy driving the expansion) can give rise to significant prediction errors. Similarly, with respect to decentralized efforts to address climate change such as the Paris Agreement, simple estimates of collective mitigation, such as the sum of mitigation from all countries' NDCs, are unlikely to provide accurate predictions of expected collective mitigation which, in turn, may make it difficult to attribute the precise contribution of each nation's mitigation effort. Our numerical analysis shows that failing to account for non-constant marginal emissions can give rise to predicted changes in emissions that are of the wrong sign and/or that diverge by an order of magnitude from true estimates. It is especially notable that these errors differ drastically across policies, due to differences in the shapes of the marginal emissions pathways. Ultimately this raises concerns about a number of methods used to predict changes in emissions such as: the use of (constant) lifecycle analysis or econometric point estimates of marginal emissions to infer large-scale changes in emissions, and the wide range of quantification strategies used by nations in their NDCs. Fewer than 10% of NDCs mention the use of models to estimate emissions reductions, fewer still consider the explicit role of policies, and not a single NDC reports how other countries' mitigation efforts affect their own predicted mitigation (UNFCCC 2021).

Although several studies have analyzed the emissions implications of various clean technologies, this paper is the first to investigate the drivers of marginal emissions pathways and the implications of non-constant marginal emissions pathways for predicting and attributing mitigation. Previous work has relied on three broad approaches to assess marginal emissions. The first approach uses economic models to evaluate the impact of clean technology policies on emissions, or an outcome that may drive emissions for a particular clean technology. Simple analytical models have been developed to identify key parameters that alter the marginal impacts of clean technology policies at a particular quantity of clean technology (Fischer and Newell 2008; Holland, Hughes, and Knittel 2009). More detailed numerical models have been used to assess emissions impacts from non-marginal policy changes (Palmer and Burtraw 2005; Oladosu and Kline 2013; Fell and Linn 2013; Rajagopal and Plevin 2013; Chen et al. 2014; Allaire and Brown 2015; Bento, Klotz, and Landry 2015; Padella, Finco, and Tyner 2012; Goulder, Hafstead, and Williams III 2016; Thompson et al. 2018). We also rely on an economic model, but unlike these studies our focus is on characterizing the marginal emissions pathways of specific policies and investigating the implications of non-constant marginal emissions.

The second approach uses econometric methods to assess how emissions change in response to expansions in renewable electricity generation or changes in electricity demand (e.g., due to energy efficiency programs or electric cars) exhibit heterogeneity across space and time (see, for example, Graff Zivin, Kotchen, and Mansur (2014), Novan (2015), Holland et al. (2016), Callaway et al. (2017), and Holland et al. (2022)). These findings are in large part attributable to heterogeneity in the composition of marginal generation and demand profiles, which reflect the near-term economic conditions of a particular electricity market. However, by estimating the average marginal emissions impacts of changes in supply or demand conditional on observed economic conditions, these studies isolate only the input effect at a particular level of clean technology. Unlike our analysis, the emissions estimates from these studies do not account for the output effect and, with the exception of Novan (2015), do not show how the input effect changes with the amount of clean technology added.

The third approach uses lifecycle analysis (LCA) methods to evaluate the emissions impact of a clean technology, and possibly an assumed displacement of a dirty technology, through a bottom-up accounting of emissions across all phases of the technology's production and use (Farrell et al. 2006; Styles and Jones 2008; Lemoine et al. 2010; Hertwich et al. 2015). Our analysis of marginal emissions is comparable to consequential LCA, given its focus on market adjustments resulting from the addition of a unit of technology (Earles and Halog 2011; Rajagopal 2014; McManus and Taylor 2015; Rajagopal 2017). An important difference with most LCA studies is that we take a policy-based as opposed to a technology-based approach (Bento and Klotz 2014). Since technology-based LCAs only capture the input effect they cannot disentangle how marginal emissions vary across policies or with quantity. Unlike Bento and Klotz (2014), in this paper we show that marginal emissions vary with the amount of clean technology deployed and that traditional LCA approaches, which implicitly assume constant marginal emissions, lead to errors when predicting and attributing mitigation.

Taken together our findings illustrate the potential for sizeable harm from implicitly or explicitly ignoring non-constancy in marginal emissions pathways when predicting or attributing mitigation from non-marginal changes in a clean technology. This is similar in spirit to the problems of ignoring the general equilibrium effects of policies (e.g., Goulder and Williams (2003) and Fullerton and Heutel (2007)) or the use of marginal willingness to pay measures to value non-marginal changes in environmental goods (e.g., Toman (1998)).

Conceptual Model

Figure 1 introduces a general conceptual model that decomposes the change in emissions from a marginal expansion in a clean technology due to a clean technology policy. This model maps to a fully specified and general analytic model of the global economy (Section 2 of the Supplementary Information) consisting of multiple economic sectors and where emissions are tracked based on sectoral inputs and outputs. This framework is applicable to a diverse array of technology (e.g., electricity markets) and policy (e.g., Renewable Portfolio Standards) settings. Although this framework could also be applied to policies that target reductions in dirty technologies, we focus on policies that promote clean technologies due to their widespread adoption globally.

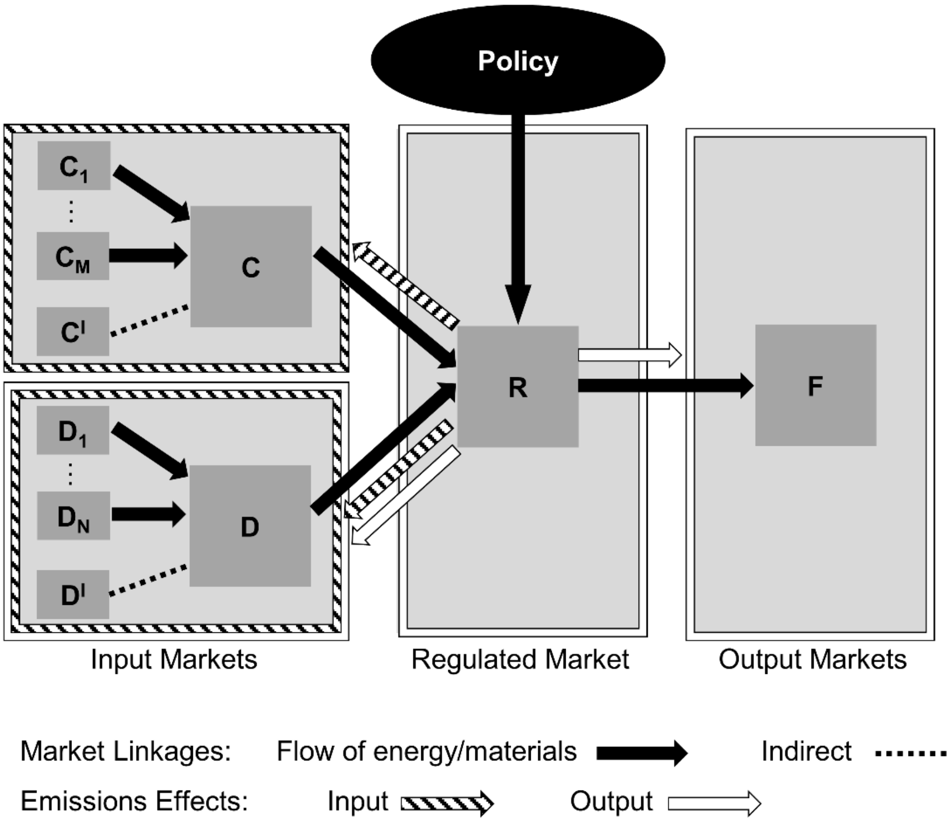

Figure 1. Economic and Emissions Impacts of Clean Technology Policies

Economic sectors are depicted by dark gray rectangles. The flow of energy and materials between sectors are indicated by black arrows. The production of clean and dirty technologies are the rectangles C and D. Each technology is itself directly produced from a variety of inputs (rectangles C_1, …, C_M and D_1, …, D_N linked by solid black arrows) and may indirectly affect markets for products that are not directly used as inputs (rectangles C^I and D^I linked by dashed black arrows), such as the conversion of land to agricultural production in response to biofuel expansion (Searchinger et al. 2008). Collectively, we refer to these as input markets. Clean and dirty technologies are combined to produce a composite consumption good (e.g., electricity or blended fuel). We focus on clean technology policies (oval) that directly encourage greater use of a clean technology, and therefore refer to this as the regulated market (rectangle R). The composite good is used in an output market (rectangle F), either as a final consumption good (e.g., in the case of electricity) or as an input to other production processes (e.g., the production of vehicle miles travelled in the case of blended fuel). Emissions are potentially generated linearly in each sector through production processes and/or the use of inputs.

Insights from the Conceptual Model

The conceptual model reveals the economic and policy drivers that may cause marginal emissions to vary with the amount of clean technology and/or policy driving the expansion in clean technology. In response to a clean technology policy, the quantity of clean technology in the economy increases but the quantity of dirty technology may decrease, stay the same, or increase. These changes cause economic sectors and the total level of emissions to adjust. The marginal change in emissions, across all sectors, due to a unit increase in the clean technology can be decomposed into input and output effects.

The input effect, depicted with the hatched arrows and boxes, is the change in emissions that arises due to equilibrium adjustments in input markets affected by the production of the clean and dirty technologies from a policy induced expansion of the clean technology. In order to isolate the emissions associated with the two technologies, we measure this effect assuming a one-for-one displacement of the clean technology for the dirty technology. As such, the input effect is the difference between the marginal emissions of the clean and dirty technologies. The marginal emissions of each technology reflect all changes in emissions arising from adjustments in input markets linked to the production of the technology as well as markets that compete with those inputs.[1]

By construction, the input effect is the same for any policy but need not be constant in the amount of clean technology. This is because marginal emissions of the clean and dirty technologies are determined by conditions in input markets, such as the prices of inputs or the share of inputs used in the production of either technology, and/or the emissions rates of inputs, any of which may change as more units of clean technology are added to the economy.

The output effect, depicted with white arrows and boxes, captures the change in emissions attributable to equilibrium adjustments in regulated and output markets. A clean technology policy may alter the prices of clean and dirty technologies and, in turn, the price of the composite good and prices in output markets that use the composite good. Conditional on the marginal increase in clean technology, these price changes will induce quantity changes in output and regulated markets, as well as the market for the dirty technology and associated input markets. The output effect captures any emissions associated with these quantity changes and can reinforce or erode the input effect.

If the production and use of clean and dirty technologies are the main sources of emissions, then the output effect is inversely related to the rate at which the clean technology displaces the dirty technology in equilibrium, or the displacement ratio. If the price of the composite good does not change in response to the policy, the displacement ratio will be one and

[1] The marginal emissions of a technology can be viewed as a consequential LCA measure, making the input effect the emissions savings identified by a technology-based consequential LCA (Earles and Halog 2011).

the output effect will be zero. A displacement ratio above (below) one implies more (less) emissions reductions from additional changes in the dirty technology than the one-for-one displacement assumed by the input effect and therefore a positive (negative) output effect.

We obtain two important insights regarding a clean technology mandate and subsidy from the conceptual model. First, consistent with other studies (Lapan and Moschini 2012) the output effect differs across the two policies. While the sign of the output effect is ambiguous for the mandate, it is always positive for the subsidy. By increasing demand for the clean technology the mandate causes the marginal cost of the clean technology to increase. If the mandate displaces the dirty technology, then the marginal cost of the dirty technology will fall. When input markets are perfectly competitive these changes in marginal costs are fully passed through into the input prices facing the composite (regulated) good producer. Depending on the relative changes in clean and dirty input prices and other economic conditions (e.g., the shares of clean and dirty technologies), the price of the regulated good may increase or decrease. Equivalently, the displacement ratio may be above or below one and the output effect may be positive or negative. In contrast, a subsidy drives a wedge between the marginal cost of production and the price of the clean technology paid by the composite good producer, or clean input price. The subsidy therefore raises the marginal costs of the clean technology while lowering its input price. Since the clean technology can be used relatively more cheaply in the production of the composite good, demand for the dirty technology will fall causing a decline in the marginal cost (and input price) of the dirty technology. The fall in both input prices are passed through into the price of the composite good which also falls, causing demand for the composite good to rise and a positive output effect.

Second, the mandate implies a relationship between the input effect and the output effect that is absent for the subsidy. Economic conditions in the clean and dirty input markets determine the input effect, as well as the extent to which the marginal costs and input prices of the two technologies change. In turn, these input price changes determine the change in the producer price of the composite good. Marginal costs of producing the clean technology are increasing in the amount of clean technology added in many contexts (e.g., as inputs become scarcer or given a decreasing returns to scale technology). Increasing marginal costs imply that each additional unit of the clean technology added by a mandate has a gradually larger positive impact on the change in the price of the composite good, which lowers the output effect. However, for the subsidy, conditions in clean technology input markets have no bearing on the output effect because the additional subsidy required to increase the clean technology by one unit offsets the rise in the marginal costs of the clean technology.

How input and output effects vary with the amount of clean technology added by a particular policy determine the marginal emissions pathway for each policy, which is just the sum of these two effects.

Numerical Model

Our numerical analysis uses a multi-market equilibrium model developed to evaluate U.S. policies to support corn ethanol that has been coupled to a detailed emissions model (Bento, Klotz, and Landry 2015; Bento and Klotz 2014; Landry and Bento 2020). The model, whose predictions have been validated in prior work (Bento, Klotz, and Landry 2015), accounts for direct and indirect adjustments in domestic and international input markets related to the production of ethanol (the clean technology) and gasoline (the dirty technology), which are combined to produce blended fuel (the composite good).[2] Corn used as an input to ethanol production competes with other crops and non-cropland land uses both domestically and internationally. Crude oil is used to produce gasoline for the domestic market, while international demand for crude oil responds to price changes. Therefore, the marginal costs of ethanol and gasoline production depend on conditions in the respective input markets (e.g., the share of corn used for ethanol production) and will change as ethanol quantities expand. The model calculates lifecycle greenhouse gases, in terms of carbon dioxide equivalent (CO_2e) based on 100-year global warming potentials, resulting from agricultural production, land use change, ethanol production, crude oil recovery, gasoline refining, and the combustion of gasoline and crude products. A full description of the sectors represented and functional forms are provided in Section 2 and 3 of the Supporting Information whereas Section 4 details the data sources, parameters, and emissions factors used by the model.[3]

We use this model to examine how marginal emissions from ethanol change with the

[2] Blended fuel together with other inputs is subsequently used to produce vehicle miles travelled, which together with a food composite and a numeraire are the final consumption goods. The model also accounts for interactions with several pre-existing policies.

[3] There are three potential limitations of our numerical framework. First, although our model explicitly captures trade in crops and crude oil, we do not allow for trade in biofuels, which could alter the input effect depending on the emissions associated with foreign biofuels. Second, it abstracts from other possible market distortions such as market power and/or price regulation, so changes in marginal costs of the clean and dirty technologies are passed into the price of the regulated good. Third, our analysis does not consider the dynamic effects of policies through induced innovation that may lower technology costs in the future.

quantity of ethanol supported by a mandate and subsidy. Our analysis starts from a baseline that represents the year 2015 with no ethanol policies in place. The total quantity of ethanol in this baseline is 6 billion gallons which reflects the amount of ethanol produced under perfect competition in the absence of ethanol policies but given all other pre-existing policies. As a result, this is lower than observed U.S. ethanol quantities in 2015 due to the absence of a mandate on conventional biofuels of 15 billion gallons implied by the U.S. Renewable Fuel Standard (RFS).

To construct marginal emissions pathways, we simulate incremental increases in a mandate and subsidy for ethanol in the production of blended fuel. We increase each policy to expand ethanol quantities from 6 billion gallons to 20 billion gallons over 100 increments. For the mandate this is relatively straightforward, but changes in the subsidy entail identifying subsidy levels necessary to simulate incremental changes in ethanol quantities. For example, to achieve an expansion of 2 billion gallons, the subsidy is $0.13 per gallon. To achieve a 4 billion gallon expansion the subsidy is $0.34 per gallon. To approximate marginal emissions, we compute the average change in emissions per unit of ethanol added over each increment. The resulting series of marginal emissions and ethanol quantity pairs characterize the marginal emissions pathway for each policy.

We consider a large total expansion in ethanol production in order to highlight the differences in emissions changes that could potentially emerge. The range of ethanol quantities we consider is meant to illustrate the economic mechanisms identified in our conceptual framework. Technical limitations (e.g., the blend wall) may need to be overcome to achieve ethanol quantities at the higher end of the range we consider. With respect to the mandate, corn ethanol quantities through 15 billion gallons align with the historical implementation of the RFS. Quantities beyond this are largely illustrative but within the scope of discussions regarding future implementation of the RFS, i.e., if the conventional biofuel standard continues to be enforced and the Advanced and Cellulosic biofuel standards continue to receive significant waivers by the U.S. Environmental Protection Agency.

Results

Next, we use insights from the conceptual model and results from our numerical model to characterize marginal emissions pathways for an ethanol mandate and subsidy in the U.S.

Input Effect

The input effect is the difference between the marginal emissions from ethanol and gasoline and is the same across policies. Panel A of Figure 2 displays the marginal emissions from ethanol and gasoline as ethanol quantities increase from 8 to 20 billion gallons. At 8 billion gallons, marginal emissions from ethanol (circle markers) are 72 gCO_2e/MJ. This total includes emissions from ethanol production, expanded corn production, displaced production of other crops, and direct and indirect land use change. Marginal emissions from gasoline (star markers) total 78 gCO_2e/MJ and include emissions from the extraction and refining of crude oil and the combustion of gasoline, less indirect emissions reductions from displaced crude oil products used outside the U.S. This estimate of the marginal emissions from gasoline are similar in magnitude to other studies that account for fuel market effects (Rajagopal 2013; Rajagopal and Plevin 2013).

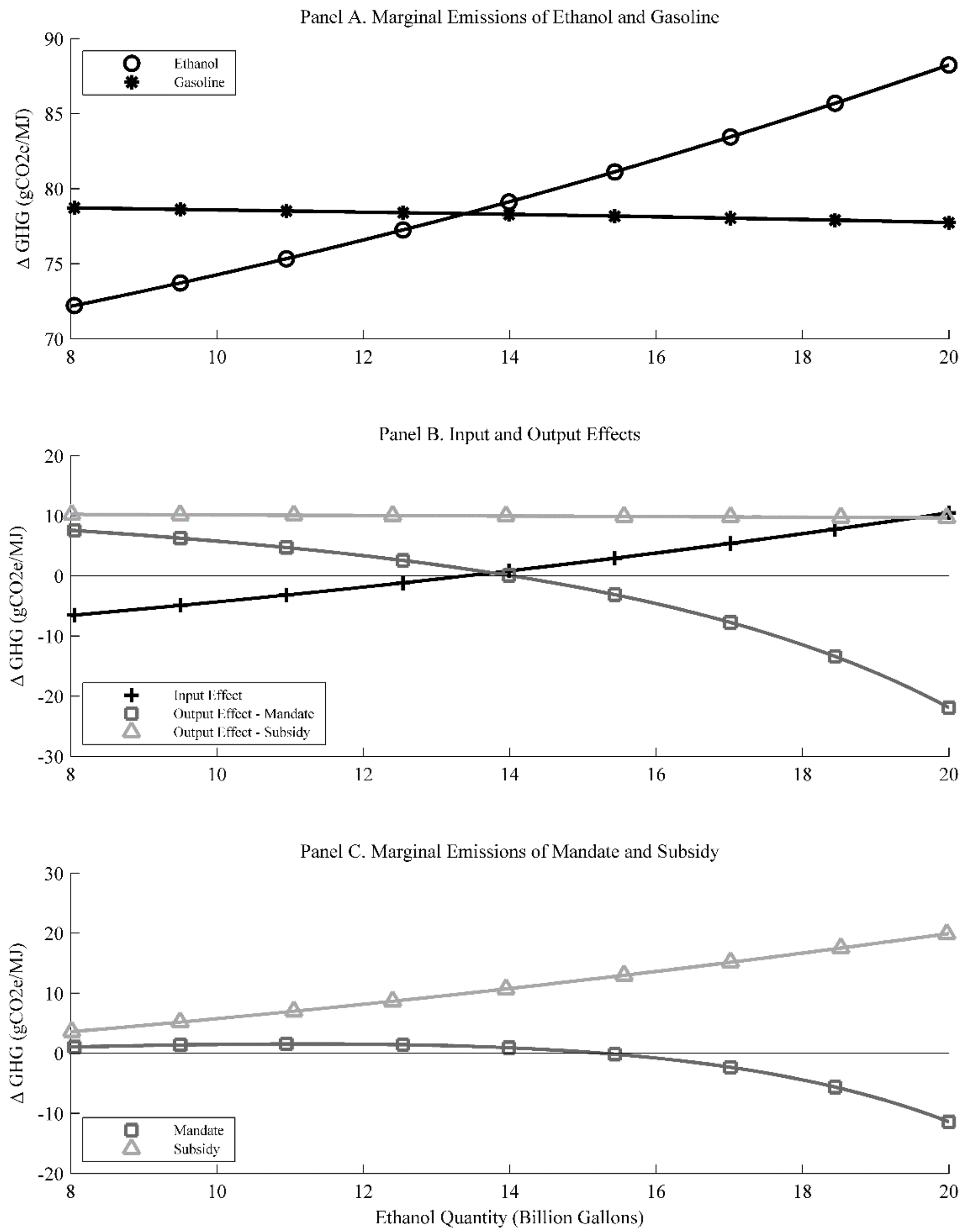

Figure 2. Decomposition of Marginal Emissions Pathways

The input effect for both policies is the hashmarked line in Panel B of Figure 2. It is negative, but small at low ethanol quantities and increases as input markets tighten in response to expansions in ethanol. At 8 billion gallons the input effect represents only an 8 gCO_2e/MJ reduction in emissions. The input effect increases at a nearly constant rate with the amount of ethanol added and is positive after 13.5 billion gallons because the marginal emissions of ethanol are larger than the marginal emissions of gasoline for large quantities of ethanol.

The increasing input effect arises from the increase in the marginal emissions of ethanol in Panel A and corresponds to increases in the marginal costs of ethanol production. As more ethanol is added to the economy, land markets become progressively tighter, requiring ever larger increases in the prices of corn and other crops (Figure 1 in Supporting Information) and raising the marginal costs of producing ethanol. This in turn induces more emissions from land market adjustments. In contrast, marginal emissions from gasoline are nearly constant because the bulk of these emissions are due to final combustion, which is constant per unit of gasoline, and there is only a slight slackening of the crude oil market since the quantity of gasoline displaced is small in relation to global demand for crude oil.

Output Effect

In sharp contrast to the input effect, the output effect differs dramatically across policies. The output effect for the mandate (square markers) and subsidy (triangle markers) are plotted alongside the input effect in Panel B of Figure 2. The output effect for the subsidy is always greater than for the mandate. At 8 billion gallons, the output effects for both policies are positive, but slightly smaller for the mandate (8 gCO_2e/MJ) than for the subsidy (10 gCO_2e/MJ). Initially, both policies cause the price of blended fuel to fall and therefore less than one unit of gasoline is displaced for each unit of ethanol added. However, unlike the subsidy, the mandate ensures that the increase in the marginal costs of producing ethanol are passed through into the price of blended fuel resulting in a smaller decline in the price of blended fuel, followed by an eventual increase.

As ethanol quantities expand, the output effect for the mandate decreases at an increasing rate and eventually becomes negative. Since marginal emissions of gasoline are nearly constant with respect to ethanol added, the falling output effect reflects a rising displacement ratio (Figure 2 in the Supporting Information). This occurs for two reasons. First, the marginal costs of ethanol rise as land markets tighten and therefore each additional unit of ethanol induces a larger increase in the price of ethanol relative to the fall in the price of gasoline, which is nearly constant. Second, as the share of ethanol in blended fuel increases, the increase in the price of ethanol contributes more to the change in the price of blended fuel. Consequently, consistent with the sign of the displacement ratio, the output effect falls by 9 gCO_2e/MJ between 8 and 14 billion gallons, becomes negative at 14 billion gallons, and then falls further to 20 gCO_2e/MJ at 20 billion gallons. That the magnitude of the changes in the output effect are similar, if not bigger, than the input effect indicates its first-order importance in determining marginal emissions and illustrates the shortcomings of technology-based LCA metrics.

In contrast, the output effect for the subsidy changes very little with the quantity of ethanol added because the displacement ratio is nearly constant. The marginal subsidy required to induce a unit change in ethanol increases as the marginal costs of ethanol production rise, causing the price of blended fuel to be roughly constant. Moreover, across the range of ethanol quantities we simulate, the increasing share of ethanol in blended fuel only has a small negative impact on the displacement ratio.

Marginal Emissions Pathways

Panel C of Figure 2 displays the marginal emissions pathways for the mandate and subsidy, which are the sum of input and output effects from Panel B. At 8 billion gallons, positive output effects just offset negative input effects for both policies, leading to positive, but small, marginal emissions. Marginal emissions for the mandate are only 1 gCO_2e/MJ, but marginal emissions for the subsidy are slightly higher (3 gCO_2e/MJ) due to the larger output effect. These slight increases in emissions are consistent with results of similar modeling exercises that account for both domestic and international land and fuel market adjustments (EPA 2010; Rajagopal 2013; Hill, Tajibaeva, and Polasky 2016).

Due to divergent output effects, the marginal emissions pathways for the two policies move in opposite directions as ethanol quantities expand. Marginal emissions due to the mandate are nearly constant initially and then fall when the output effect dominates the input effect. In contrast, marginal emissions for the subsidy increase at a constant rate, reflecting increases in the input effect. The difference in marginal emissions between the two policies grows considerably, reaching 10 gCO_2e/MJ at 14 billion gallons and 30 gCO_2e/MJ at 20 billion gallons. After 15.5 billion gallons, marginal emissions for the two policies have different signs. At 20 billion gallons, a unit of ethanol added by the mandate reduces emissions by more than 10 gCO_2e/MJ, but a unit of ethanol added by the subsidy increases emissions by 20 gCO_2e/MJ.

The mandate establishes a negative linkage between input and output effects. Tightening input markets due to the expansion of ethanol drive the input effect up but push the output effect down. This linkage is absent for the subsidy since the subsidy neutralizes the impact of rising marginal costs of ethanol production on the output effect.

Despite a positive and increasing input effect, emissions reductions are possible at higher ethanol quantities if the output effect is sufficiently negative, as is the case eventually for the mandate. Since the emissions advantages of ethanol over gasoline, as reflected by the input effect, are small, the output effect essentially determines the sign on marginal emissions.

These findings reinforce previous research that shows that accounting for policies is essential for evaluating the emissions impacts of clean technologies (Bento and Klotz 2014). In addition, we show here for the first time that marginal emissions may be non-constant with respect to the amount of clean of technology in the baseline or added by a policy and that this itself depends on policies.

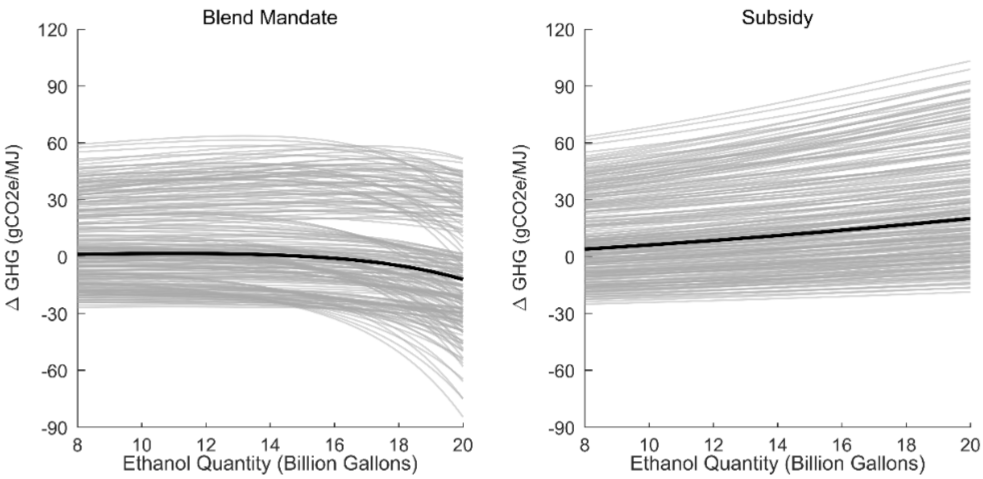

Figure 3. Global Sensitivity Analysis of Marginal Emissions Pathways

Sensitivity Analysis

As discussed in Section 6 of the Supplementary Information, we also explore the sensitivity of marginal emissions pathways to four key sets of parameters (elasticities of excess supply for crude oil, elasticities of crop demand for food production, elasticities of demand for blended fuel, and emissions factors for agricultural production and land use change). Marginal emissions pathways under all possible parameter combinations are displayed for both policies in Figure 3. Previous studies have also found considerable sensitivity in estimates of emissions from biofuels and biofuel policies (Plevin et al. 2010 and 2015), but our focus is on how the sensitivity in marginal emissions differs with ethanol quantities and/or policies. We briefly highlight three main findings. First, marginal emissions are non-constant across a wide range of parameter assumptions for both policies. Second, total variation in marginal emissions pathways (the difference between the highest and lowest marginal emissions at a given quantity) depends on the economic and policy drivers emphasized in our analysis above. Third, as discussed further in the in the Supplementary Information, the strong non-linearities in marginal emissions pathways under some parameter combinations for the mandate are the result of interaction effects arising from linkages between land and fuel markets, which do not emerge for the subsidy. Taken together, these results suggest that the same drivers that lead to non-constant marginal emissions pathways also explain sensitivity in marginal emissions which policymakers will need in order to credibly quantify uncertainty arising from their own and others' mitigation efforts.

Implications

So far our analysis has examined the drivers of marginal emissions pathways and has shown that marginal emissions may vary with the amount of clean technology and/or policy inducing the clean technology expansion. We next consider the implications of these findings for 1) predicting total mitigation from clean technology policies and 2) the attribution of mitigation to individual mitigation pledges. We illustrate these issues using our corn ethanol results, but more generally the signs of errors can be characterized based on the shape of the marginal emissions pathway.

The first implication of non-constant marginal emissions is that mitigation estimates that explicitly or implicitly (i.e., by not considering baseline quantities or the size of technology expansion) treat marginal emissions as if they are constant are unlikely to be correct. The total change in emissions from an expansion in clean technology can be obtained by integrating under the marginal emissions pathway for a particular policy starting from a baseline and given the amount of clean technology expanded. Methods that assume constant marginal emissions effectively approximate the total change in emissions as a rectangle, whereas methods that do not consider the correct baseline and/or amount of clean technology expansion calculate the wrong integral. As noted above, methods that make these types of assumptions are pervasive in the literature analyzing clean technology policies as well as in many of the NDCs that countries have submitted under the Paris Agreement.

In order to quantify the magnitude of prediction errors using our corn ethanol results, Table 2 reports differences between total emissions for a 3 BG expansion in ethanol from a

14 BG baseline and total emissions calculated using methods that fail to account for non-constant marginal emissions. Columns (3) through (5) report the errors from using constant marginal emissions, while columns (6) and (7) report errors when using the incorrect baseline quantity of ethanol. In almost all cases, there are notable errors in predicted total emissions and the percentage errors are especially large because corn ethanol policies tend to have small impacts on emissions.

More generally the shape of marginal emissions pathways (i.e., as captured by the first, second, etc. derivatives of the marginal emissions pathway over the interval characterized by the baseline and amount of clean technology added) directly inform the sign of prediction errors. For example, since the MEP is falling in the amount of clean technology under the mandate, fixing marginal emissions at the first unit or using a baseline that is too low yields an underestimate of total emissions. Conversely, since marginal emissions are increasing in the amount of clean technology, the subsidy generates errors of the opposite sign. Non-linearity of marginal emissions, such as non-zero rates at which marginal emissions rise or fall with the amount of clean technology, can also affect errors. For instance, since the MEP for the mandate is falling at an increasing rate in the amount of clean technology, the use of an average constant emissions factor (on the correct interval) generates a non-zero error. Conversely, since the MEP is approximately linear for the subsidy, no error is generated for this case.

Table 2. Prediction and Attribution Errors when Marginal Emissions are Non-Constant

	1	2	3	4	5	6	7	8	9
			Constant Emissions Factors			Incorrect Baseline		Attribution (J =2)	
	Actual	Wrong Policy	First	Last	Average	Too Low (9 BG)	Too High (17 BG)	Status Quo Baseline	Others' Policies Baseline
A. Mandate									
Change in CO_2e (Tg)	-0.1	3.2	0.2	-0.6	-0.2	0.4	-1.6	0.1	-0.3
Error		3.3	0.3	-0.5	-0.1	0.5	-1.5	0.2	-0.2
Error (%)		-3300	-300	500	100	-500	1500	-192	192
B. Subsidy									
Change in CO_2e (Tg)	3.2	-0.1	2.7	3.7	3.2	1.6	4.2	2.9	3.5
Error		-3.3	-0.5	0.5	0	-1.6	1	-0.3	0.3
Error (%)		-103	-16	16	0	-50	31	-10	10

A second implication of non-constant marginal emissions is that it makes it difficult to attribute changes in emissions to individual mitigation pledges. If marginal emissions are non-constant, the sum of countries' predicted mitigation pledges need not equal predicted total emissions reductions that account for all countries' policy actions. As predicted total emissions reductions are the best guess of the emissions reductions likely to be measured *ex post*, this gap in predicted mitigation indicates that it is likely to be difficult to attribute measured collective emissions reductions to an individual country's mitigation pledge. Similar to the discussion above, this 'attribution error' depends on the shape of marginal emissions pathways. To understand this, suppose two countries facing the same marginal emissions pathways individually pledge to reduce emissions by using a mandate to expand ethanol by 1.5 BG from a 14 BG baseline. If neither country anticipates the others' ethanol expansion, the sum of their individual predicted mitigation efforts is 0.1 $TgCO_2e$ (column (8) of Table 2), which exceeds the predicted total change in emissions of -0.1 $TgCO_2e$ (column (1)). If each country were to account for the others' mitigation pledge (column (9)), the sum of individual predicted mitigation efforts is less than predicted total emissions reductions. The different signs of these attribution errors again coincide with the fact that the marginal emissions pathway for the mandate is falling. For similar reasons, the subsidy yields attribution errors with opposite signs. These represent a 'best case' and if other prediction errors are also made, these attribution errors may be further compounded once emissions are subsequently measured *ex post*.

Conclusion

This paper examines the drivers of marginal emissions pathways and the implications of potentially non-constant marginal emissions pathways for the prediction and attribution of mitigation. Marginal emissions pathways can be decomposed into an input effect, which equals the difference in marginal emissions between the clean and dirty technologies from economic adjustments in input markets and is the same for any policy, and an output effect, which captures the change in emissions arising from economic adjustments in regulated and output markets that differ across policies. In the case of a subsidy and mandate to support corn ethanol in the U.S., we find that marginal emissions, and sensitivity of marginal emissions, can vary between policies and the baseline amount of ethanol in the economy.

Our analysis has shown that ignoring non-constancy in marginal emissions can create challenges for predicting total mitigation from clean technology policies and for attributing individual contributions to collective mitigation. We show that the signs of these prediction and attribution errors depend on the shape of the marginal emissions pathway and find that the magnitudes of these errors are potentially sizeable in the corn ethanol context. With respect to the Paris Agreement, these findings suggest that greater quantification and dissemination of marginal emissions pathways and their sensitivity through the NDC proposal and finalization process is likely to enhance the capacity for nations to make more credible and certain mitigation pledges.

While our numerical exercise focuses on policies to expand corn ethanol, non-constant marginal emissions pathways are likely to emerge in many other clean energy contexts, such as policies targeting the expansion of electricity generation from renewable sources or improvements in energy efficiency. Recent work tends to identify the emissions input effect in this sector (e.g., Callaway et al. (2017)), focusing especially on spatial and temporal heterogeneity in the types of fossil fuel generation that renewables and energy efficiency investments displace. The emissions output effect is less well understood, though it will depend on similar drivers that underlie our corn ethanol results as well as features specific to the sector under examination (e.g., in the case of electricity markets, demand variability, regulatory structure, market power, and transmission congestion).

Although our focus has been on assessing mitigation to address climate change, the challenges we emphasize are fundamental to understanding a plethora of policy outcomes in any highly non-linear economic system. In our context, non-constant marginal emissions emerge even though marginal emissions are (assumed to be) linear at each stage of a technology's lifecycle. These challenges may be amplified further by non-linearities in emissions dispersal (as in the context of local air or water pollution) or in the valuation of damages associated with GHGs or other pollutants.

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