RESOURCES
for the FUTURE

Estimating the Emissions Reductions from Supply-side Fossil Fuel Interventions

Brian C. Prest, Harrison Fell, Deborah Gordon, and TJ Conway

Working Paper 23-12
April 2023
Updated March 2024

About the Authors

Brian C. Prest is an economist and fellow at RFF specializing in the economics of climate change, energy economics, and oil and gas supply. Prest uses economic theory and econometrics to improve energy and environmental policies by assessing their impacts on society. His recent work includes improving the scientific basis of the social cost of carbon and economic modeling of various policies around oil and gas supply. His research has been published in peer-reviewed journals such as *Nature*, the *Brookings Papers on Economic Activity*, the *Journal of the Association of Environmental and Resource Economists*, and the *Journal of Environmental Economics and Management*. His work has also been featured in popular press outlets including the *Washington Post*, the *Wall Street Journal*, the *New York Times*, Reuters, the Associated Press, and *Barron's*.

Harrison Fell is an associate professor in the Department of Agricultural and Resource Economics at North Carolina State University. His research focuses on environmental, energy, and natural resources economics, with an emphasis on policy-relevant work. Dr. Fell's recent work is related to energy systems with a focus on renewable energy, emissions trading systems, and electricity regulation.

Deborah Gordon is a senior principal in RMI's Climate Intelligence Program, where she coleads the Oil and Gas Solutions Initiative. Gordon serves as a senior fellow at the Watson Institute of International and Public Affairs at Brown University and is an affiliate at the Brown Climate Solutions Lab. Her research spearheaded the development of the Oil Climate Index plus Gas (OCI+), a first-of-its-kind analytic tool that compares the life-cycle climate impact of global oil and gas resources. The OCI+ is the topic of Gordon's new book, *No Standard Oil* (Oxford University Press, 2022).

TJ Conway is a principal in RMI's Climate Intelligence Program. He plays a leading role in the Oil and Gas Solutions Initiative, working with a range of stakeholders to help accelerate oil and gas firms' decarbonization efforts. Conway is also Professor of the Practice at Georgetown University, where he teaches an energy course through the Landegger Program in International Business Diplomacy at the Edmund A. Walsh School of Foreign Service.

Acknowledgments

Prest and Fell gratefully acknowledge the support of Onyx Transition. We appreciate thoughtful comments from Mike Braun, Seth Zimring, and Darius Nassiry.

About RFF

Resources for the Future (RFF) is an independent, nonprofit research institution in Washington, DC. Its mission is to improve environmental, energy, and natural resource decisions through impartial economic research and policy engagement. RFF is committed to being the most widely trusted source of research insights and policy solutions leading to a healthy environment and a thriving economy.

Working papers are research materials circulated by their authors for purposes of information and discussion. They have not necessarily undergone formal peer review. The views expressed here are those of the individual authors and may differ from those of other RFF experts, its officers, or its directors.

Sharing Our Work

Abstract

Supply-side interventions that retire highly emitting fossil fuel assets have received increased attention from policymakers and private actors alike. Yet concerns about market leakage—wherein reduced supply from one source is partially offset by increased production from other sources—have raised questions about how much emissions reductions they can achieve. In this paper, we estimate the effects of these supply-side interventions on global emissions, accounting for both market leakage as well as the relative greenhouse gas (GHG) intensity of different sources of supply. We account for uncertainty in market leakage rates and the emissions intensities of the curtailed and substitute sources of supply through a Monte Carlo analysis, drawing on supply and demand elasticities from the economics literature and emissions intensity data from the state-of-the-art Oil Climate Index plus Gas (OCI+) dataset on 586 oil and gas fields around the world. We find a rough band of central estimates for life-cycle emissions reductions from supply-side interventions in the range of 40–50 percent of the gross life-cycle emissions of each barrel curtailed, depending on the relative emissions intensity of the curtailed and substitute sources of supply. Further, across all of 1.53 million Monte Carlo simulations we conduct, we find very high confidence of net emissions reductions from supply-side interventions (nearly 99 percent of cases). Finally, targeting the most emissions-intensive sources of oil supply could achieve yet further emissions reductions. How one compares methane and CO2 emissions also has important consequences for which sources to target.

Keywords: supply-side interventions, oil, greenhouse gas emissions.
JEL Codes: Q5, Q31, Q35, Q41, Q54

Contents

1. Introduction

With numerous governments and corporations making increasingly ambitious carbon and methane emissions pledges, meeting now-ubiquitous "net zero" goals will require reducing not only the consumption of fossil fuels, but also their production and their emissions intensities. Winding down fossil fuel production has long been a policy lever considered in the academic literature (Harstad 2012; Erickson, Lazarus, and Piggot 2018; Lazarus and van Asselt 2018; Asheim et al. 2019; van der Ploeg and Rezai 2020; P. Newell and Simms 2020; Prest 2021; Prest and Stock 2021). Moreover, the life-cycle emissions intensity of oil and gas production—including Scope 1, 2, and 3 emissions—has been studied and found to be wide-ranging particularly when 20-year global warming potential (GWP) of methane is considered (Masnadi et al. 2018; Jing et al. 2020; Gordon 2023; Gordon, Tan, and Feldman 2016). In recent years these so-called "supply-side" climate policies have gained popularity among policymakers. For example, in the United States, President Joseph Biden campaigned on ending oil and gas leasing on federal lands, and his administration has slowed federal leasing activity.

More recently, private actors have begun to propose monetizing the retirement of emissions-intensive assets, starting with carbon. For example, newly proposed "carbon retirement portfolios" (Handler and Bazilian 2021) would purchase emissions-intensive assets like oil and gas wells or coal-fired power plants simply to retire them. The resulting reductions in GHG emissions could then be monetized, for example by generating and selling carbon credits, or receiving direct payments from governments per ton of emissions reduced.

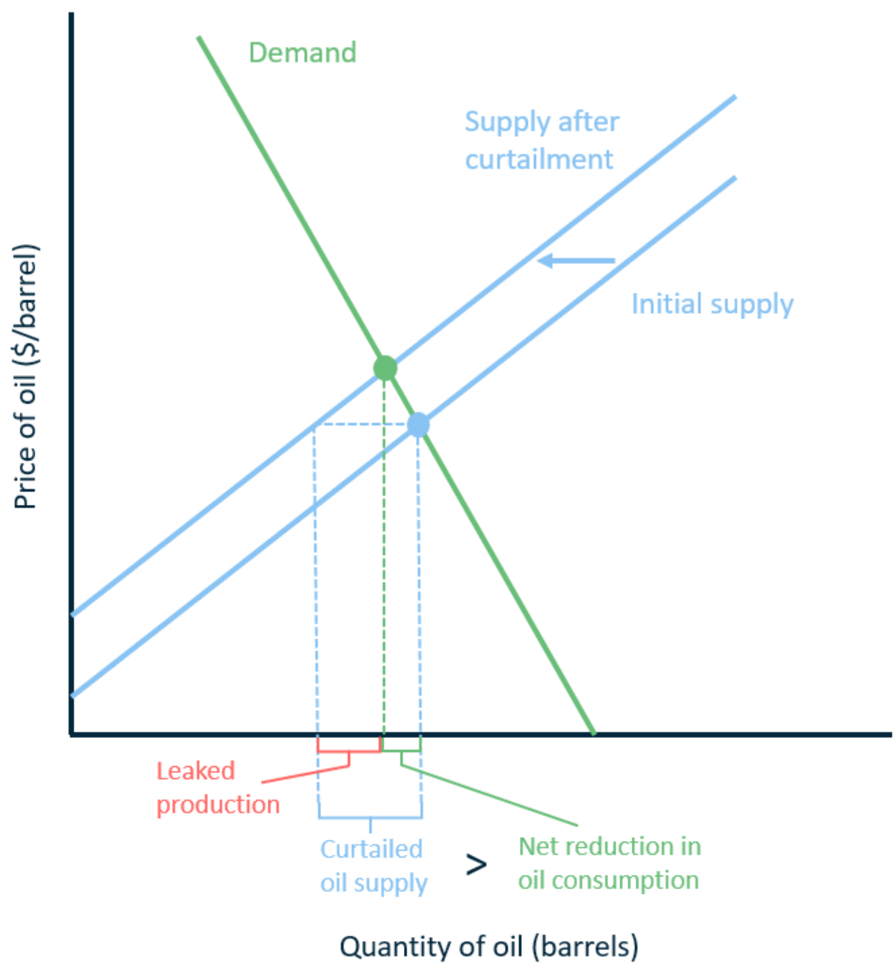
For those carbon credits or policies to be credible, their net impacts on emissions must be estimated as rigorously as possible. Even if one can compellingly demonstrate the emissions avoided directly from the asset in question (say, an oil field), the net impacts on global emissions will differ due to emissions "market leakage." The term "market leakage" as used in this paper, and in the economics literature more broadly, describes the phenomenon wherein reduced supply from one source is partially offset by increased production from other sources. This replacement production offsets some, but generally not all, of the emissions benefits from the supply-side intervention.

Some make the extreme claim that market leakage from supply-side interventions is 100 percent on a global scale—for example, implying that taking a barrel of oil production off the market has no net impact on global oil consumption because it is offset one-for-one by increased production elsewhere. This claim is sometimes referred to as "perfect substitution" and has historically been cited as an argument in favor of domestic development of fossil fuels in the United States.[1] However, this argument is contradicted by basic economic theory. In economic theory, the price and consumption of a product such as oil are driven by the intersection of supply and demand curves. If a supply-side intervention removes production from an inframarginal field (i.e., a field with a marginal cost production below the current market price), this shifts the supply curve to the left, as shown in Figure 1. The shift in the supply curve results in a new, higher equilibrium price. As can be seen in Figure 1,

[1] See, e.g., Richards, Heather, "Would Biden's oil freeze increase emissions?", E&E News, Washington, D.C., (2021). https://www.eenews.net/articles/would-bidens-oil-freeze-increase-emissions/, and Bureau of Ocean Energy Management, "OCS Oil and Natural Gas: Potential Lifecycle Greenhouse Gas Emissions and Social Cost of Carbon" (2016).

the retirement of an inframarginal field concurrently leads to a reduction in the equilibrium quantity, though this reduction is typically less than the quantity of oil retired. Figure 1 represents a stylized example, but reality is more complex, with supply curves that are not simply straight lines and that change shape over time as new oil fields are discovered and developed. However, Figure 1 nonetheless represents the key factors driving market leakage: the slopes of supply and demand curves around their point of intersection.

Figure 1. Stylized Illustration of the Leakage Mechanism



For the retirement of the inframarginal field to have no effect on the equilibrium quantity, demand for oil would have to be perfectly insensitive to price, meaning the demand curve does not slope downwards, but rather is a vertical line.[2] This contention is implausible, particularly in the context of increased availability of oil substitutes in certain demand segments—such as electric vehicles (EVs),

[2] Leakage could also be 100 percent if oil supply were infinitely elastic—that is, a perfectly flat supply curve—which is even more implausible because it would imply that the price of oil is a constant value that is unaffected by fluctuations in demand.

just one example of how consumers can respond to price changes by using less petroleum products. The mechanism by which curtailed oil supply reduces consumption is straightforward: a reduction in supply shifts the supply curve up and to the left; this increases the price of oil,[3] and since demand curves in general slope downwards, oil consumers respond by using less (moving up and to the left along the demand curve). Figure 1 shows this mechanism in a simple supply and demand diagram, demonstrating that some, but not all, of curtailed supply is offset by leakage; only in the unrealistic case where the demand curve is perfectly vertical ("perfectly inelastic") will leakage be 100 percent.

The responses of consumers' quantity demanded to price signals are not limited to traveling less (say, through working remotely an additional day of the week); there are also other avenues of demand response, such as improving fuel efficiency or switching to alternatives such as EVs or other modes of transit. Beyond the transportation sector, oil is used in petrochemical and other industrial applications as well as heating, all of which could feature their own channels of demand response. Overall, unless consumers are completely insensitive to price, some of the effect of reduced supply is manifest by reduced consumption—that is, leakage is incomplete, implying that overall oil consumption and emissions decline.

While the theoretical basis for some level of leakage is clear, it is difficult to empirically estimate because it is generally not directly observable. If one were to reduce a barrel of supply from a well in New Mexico, and, in response, a producer ramps up its production by, say, half a barrel somewhere across the country or even the globe, it is not feasible to observe this specific response. Hence, estimates of leakage rates typically rely on economic modeling of the global oil market.

An additional challenge to measuring leakage is that the "leaked" replacement supply may have a higher or lower GHG intensity, which has implications for the net impacts of a supply-side intervention. For example, if a relatively emissions-intensive source of oil production is curtailed and that supply is partially substituted by cleaner sources, this would reduce emissions even if market leakage is 100 percent. Hence, one must also account for the relative emissions intensity of different sources of oil supply. Due to the variation in crude oil quality and the emissions intensity of supply chains, oils produced from different sources have different life-cycle climate impacts (Masnadi et al. 2018; Gordon 2021; RMI 2022).

Since there is a choice of where to engage in supply-side interventions, the emissions intensity of the oil curtailed is in part a choice variable. It is perhaps obvious that supply-side interventions should then target oils with the highest emissions intensities first, such as Canadian oil sands or heavy crudes in California or elsewhere.

Credible estimates of the two key components determining the emissions impacts of supply-side interventions—market leakage rates and relative emissions intensities—are key to ensuring that estimated emissions reductions are credible. This is particularly important when such calculations

[3] In practice, refineries operate as intermediaries between producers of crude oil and its end-users—primarily transportation fuels like gasoline and diesel—and refiners can adjust to make different products when the composition of petroleum product demand shifts. Nonetheless, the price of gasoline is closely linked to that of crude oil, so price increases in the market for crude oil are largely passed onto consumers.

have direct implications for market prices, carbon credit volumes, and hence financial flows between market participants.

This presents a challenge: how one can credibly and transparently estimate the emissions displaced by supply-side interventions when such calculations are necessarily abstract due to the infeasibility of directly observing realized emissions impacts. In this paper, we use standard tools of economics while invoking minimal assumptions to derive a mathematical formula representing the emissions impacts of a supply-side intervention (say, removing one barrel of oil supply from the market). We then show different applications of that formula using reasonable ranges of key inputs: namely, estimates of supply and demand elasticities and relative emissions intensities of curtailed and substitute sources of supply. Since estimates of these inputs are inherently uncertain and likely to change over time, no single number can credibly represent the emissions reductions; rather, we use Monte Carlo analysis to estimate central values and ranges for net emission impacts of curtailed oil supply, reflecting uncertainties in the key inputs (supply and demand elasticities and emissions intensity values) and potential sources of substitute supply.

In general, our central estimates find net emissions reductions regardless of the source of curtailed and substitute supply, although the magnitudes and uncertainty ranges vary considerably depending on those factors. We present estimated net emissions reductions and uncertainty ranges for a grid of types and sources of curtailed supply (e.g., heavy versus light oil, sweet versus sour) and potential sources of substitute supply (e.g., by region).

For example, if production from the relatively emissions-intensive Canadian oil sands is curtailed, and the source of substitute production is chosen randomly in proportion to a field's production, the expected net emissions reductions are 350 kilograms of carbon dioxide per barrel of oil equivalent[4] (using a 100-year global warming potential, [GWP]), or kgCO_2e/boe, (95 percent range: 170 to 520, accounting for uncertainty in the leakage rate and uncertainty in the emissions intensity of substitute supply). If we instead assume that market leakage is driven by similarly emissions-intensive production from other Canadian oil sands, the estimated emissions reductions are about 20 percent smaller: 280 kgCO_2e/boe (95 percent range: 90 to 460 kgCO_2e/boe). For reference, the emissions intensity of oil sands is about 650 kgCO_2e/boe, suggesting net emissions reductions on the order of about half of the gross life-cycle GHG emissions of the curtailed barrel. While the above results reflect a 100-year GWP, the emissions reductions under a 20-year GWP, which gives more emphasis to methane emissions, would be larger.

In general, our central estimates imply that a barrel of curtailed oil leads to net emissions reductions regardless of the type or location of the curtailed barrel. The 95 percent uncertainty ranges nonetheless show that in some niche cases, there is a small chance that curtailment of relatively clean supply could increase emissions if substitute production comes from relatively emissions-intensive sources. However, these scenarios generally involve less plausible substitution patterns, such as an assumption that curtailment of light oil production is replaced solely by oil sands production, rather than other light oil sources. Our Monte Carlo analysis finds net emissions reductions with a high

[4] All emissions intensity values in this paper represent life-cycle emissions, including Scope 1, 2, and 3 emissions, and all values are rounded to the nearest 10 kgCO_2e/boe to avoid conveying an excessive sense of precision.

degree of certainty when the curtailed sources of supply are highly emissions-intensive oil like or heavy oils in general (99.6 percent) or Canadian oil sands in particular (99.95 percent).

2. Derivation of the Emissions Impacts of Supply-side Interventions

The economics of leakage can be derived using the standard economic tools of supply and demand. We focus on the market for crude oil, a globally priced commodity. We start by assuming there are N consumers and suppliers of crude oil, indexed by i, and denoting the quantity of crude oil supplied from supplier i as $q_{i,S}(p)$, which is a function of the price of oil denoted p. Similarly, we denote the quantity of crude oil demanded as $q_{i,D}(p)$, which is similarly a function of the price. Regardless of market structure,[5] for the market to clear it must be the case that total supply equals total demand:[6]

$$\sum_{i=1}^{N} q_{i,S}(p) = \sum_{i=1}^{N} q_{i,D}(p). \tag{1}$$

The equilibrium price of oil is the value that brings supply and demand into alignment. Next, we augment equation (1) with a retirement of $\tilde{q}$ barrels of in-the-money[7] supply from some region.

$$-\tilde{q} + \sum_{i=1}^{N} q_{i,S}(p) = \sum_{i=1}^{N} q_{i,D}(p) \tag{2}$$

The left-hand side of equation (2) is global supply, net of the retirement, denoted $Q_S = -\tilde{q} + \sum_i q_{i,S}$.The right-hand side is global demand, denoted $Q_D = \sum_i q_{i,D}$. Equation (1) can be thought of as a special case of this equation, but with no curtailed production ($\tilde{q} = 0$). The effect on the price of oil from the marginal curtailed barrel can be solved for analytically by differentiating equation (2) with respect to $\tilde{q}$:

---

[5] Alternative models that have been used by economists to study the oil markets include perfect competition, monopoly/oligopoly, and the dominant firm/competitive fringe model. We make no assumption here about which of those models is most appropriate for understanding oil markets; we instead make the far more general assumption that supply and demand curves are differentiable with slopes of the appropriate signs.

[6] More specifically, supply and demand must equate over a long enough time horizon. In practice, supply and demand can be out of balance in a given year due to inventories, which can be built up and drawn down over time. The appendix considers a generalization of this model to include T periods, finding analogous results to that of the static model.

[7] We assume throughout that the curtailed supply is in the money, meaning it has marginal costs below the market price. If it were out of the money, the retirement would have happened anyway, meaning the reduced supply is not additional and the emissions impacts are trivially zero. While this is an uninteresting case from the perspective of this model, the additionality assumption is vital to credibly claiming emissions impacts in practice.

$$-1 + \sum_{i=1}^{N} q'_{i,S}(p)\frac{dp}{d\tilde{q}} = \sum_{i=1}^{N} q'_{i,D}(p)\frac{dp}{d\tilde{q}}$$

Solving for the price effect, $dp/d\tilde{q}$, yields

$$\frac{dp}{d\tilde{q}} = \frac{1}{\sum_{i=1}^{N} q'_{i,S}(p) - q'_{i,D}(p)}$$

Because supply curves slope upward, $q'_{i,S}(p) > 0$, and demand curves slope downward, $q'_{i,D}(p) < 0$, the effect of curtailed production pushes up the price of oil: $dp/d\tilde{q} > 0$. The impact on production in each region is given by the product of this price increase and the slope of the region's supply curve. Without loss of generality, we assume the curtailed supply comes from region 1, implying the following expressions for the change in each region's production:

$$\frac{dq_{i,S}}{d\tilde{q}} = -1 + q'_{i,S}(p)\frac{dp}{d\tilde{q}} \quad for\ i = 1$$

$$\frac{dq_{i,S}}{d\tilde{q}} = q'_{i,S}(p)\frac{dp}{d\tilde{q}} \quad for\ i \neq 1$$

Summing across regions and substituting the formula for impact on the oil price,

$$\frac{dp}{d\tilde{q}} = \frac{1}{\sum_{i=1}^{N} q'_{i,S}(p) - q'_{i,D}(p)}$$

gives the effects on global supply and demand,

$$\frac{dQ_S}{d\tilde{q}} = \frac{dQ_D}{d\tilde{q}} = \frac{\sum_{i=1}^{N} q'_{i,D}(p)}{\sum_{i=1}^{N} q'_{i,S}(p) - q'_{i,D}(p)} < 0 \qquad (3)$$

The numerator is negative (demand curves slope downward), and the denominator is positive (supply curves slope upward), meaning the overall effect of the curtailed production on global oil consumption is negative. Moreover, the effect depends on the slopes of regional supply and demand.

This equation can be further simplified to be a simple function of supply and demand elasticities. First, denote region i's supply and demand elasticities as η_i and ε_i defined in the standard way:

$$\eta_i = q'_{i,S}(p)\frac{p}{q_{i,S}} \Rightarrow q'_{i,S}(p) = \eta_i \frac{q_{i,S}}{p}$$

$$\varepsilon_i = q'_{i,D}(p)\frac{p}{q_{i,D}} \Rightarrow q'_{i,D}(p) = \varepsilon_i \frac{q_{i,D}}{p}.$$

It is worth pointing out that in the notation we have suppressed the elasticity's functional dependence on price (which could be written $\eta_i(p)$ and $\varepsilon_i(p)$). Practically speaking, such elasticities may vary along different points of the supply curve. The elasticities η_i and ϵ_i should be interpreted as the elasticities at the prevailing equilibrium price. For instance, a source of supply that is entirely inframarginal at the equilibrium price p will have no price responsiveness at p ($q'_{i,S}(p) = 0$) and, thus, have an effective elasticity of zero $\eta_i = 0$.

Plugging these two definitional equations into equation (3) and further multiplying and dividing by total global supply and demand (which are the same, $Q_S = -\tilde{q} + \sum_{i=1}^{N} q_{i,S}(p) = \sum_{i=1}^{N} q_{i,D}(p) = Q_D = Q$) yields

$$\frac{dQ_D}{d\tilde{q}} = \frac{\sum_i w_{i,D}\varepsilon_i}{\sum_i w_{i,S}\eta_i - \sum_i w_{i,D}\varepsilon_i} = \frac{\overline{\varepsilon}}{\overline{\eta} - \overline{\varepsilon}} < 0 \qquad (4)$$

where $w_{i,D} = q_{i,D}/Q$ and $w_{i,S} = q_{i,S}/Q$ are weights representing region i's share of global demand and supply, and $\overline{\varepsilon}$ and $\overline{\eta}$ are the global weighted averages of the marginal demand and supply elasticities at the equilibrium price. Because as noted above these represent an aggregation of the elasticities at the prevailing equilibrium price, they are not weighted averages of supply (or demand) elasticities across the *overall* supply (or demand) curves. Rather, in the case of supply, for example, $\overline{\eta}$ reflects the response of global supply in elasticity terms at the equilibrium price point. Thus, an entirely inframarginal source of supply, for example, would contribute a zero to the $\overline{\eta}$ average.

Intuitively, the term $1/(\overline{\eta} - \overline{\varepsilon})$ in equation (4) represents the effect of curtailed supply on prices, which is largest when supply and demand are inelastic (small values of $\overline{\eta}$ and $\overline{\varepsilon}$). To derive the effect on consumption, this price impact is multiplied by the curvature of the demand curve, $\overline{\varepsilon}$. Note that the ratio $\overline{\varepsilon}/(\overline{\eta} - \overline{\varepsilon})$ is somewhere between zero and -1, indicating that only a portion of the one barrel of reduced supply is absorbed by lower demand. The remainder is made up as leakage through the supply response. That is, the change in global consumption per barrel curtailed is simply equal to the direct effect (minus one barrel) offset by the leakage (plus L barrels):

$$\frac{dQ_D}{d\tilde{q}} = -1 + L$$

We can use this to solve for L algebraically as

$$L = \frac{\overline{\eta}}{\overline{\eta} - \overline{\varepsilon}}. \qquad (5)$$

Equation (5) implies that leakage is between zero and one, given the required signs of the elasticities. It is zero when $\overline{\eta} = 0$ (perfectly inelastic supply) or $\overline{\varepsilon} \to -\infty$ (perfectly elastic demand), and it is one when $\overline{\eta} \to \infty$ (perfectly elastic supply) or $\overline{\varepsilon} = 0$ (perfectly inelastic demand), although neither situation is plausible. When the elasticities are of about the same magnitude, leakage is about 50 percent. When supply is more elastic than demand, the market leakage rate is greater than 50 percent.

The analysis has thus far been limited to impacts on supply and demand of oil, without consideration of GHG emissions. We denote the emissions intensity of the curtailed oil as $e_{\tilde{q}}$ and that of oil produced in region i as e_i (e.g., in life-cycle tons of CO_2e per barrel of oil).[8] Then the impact of an incremental barrel of curtailed supply on global life-cycle emissions from oil, defined as $E = \sum_i E_i = -e_{\tilde{q}}\tilde{q} + \sum_i e_i q_{i,S}(p)$, is given by:

$$\frac{dE}{d\tilde{q}} = -e_{\tilde{q}} + \sum_i e_i q'_{i,S}(p)\frac{dp}{d\tilde{q}}. \tag{6}$$

This reflects the reduced life-cycle emissions from the curtailed source, $e_{\tilde{q}}$, offset by the emissions, e_i, associated with the increased quantity supplied from each of the $i = 1, \dots, N$ regions, $q'_{i,S}(p)$, induced by the change in the price of oil, $dp/d\tilde{q}$. Further, equation (6) can be simplified to be written as a function of three parameters,

$$\frac{dE}{d\tilde{q}} = -e_{\tilde{q}} + \overline{e}L, \tag{7}$$

where $\overline{e}$ is the globally weighted average emissions intensity of marginal supply.[9] The weights are the relative contributions of each producing region to marginal supply—that is, the relative slopes of their supply curves, as follows:[10]

$$\overline{e} = \frac{1}{\sum_{i=1}^{N} q'_{i,S}(p)} \sum_i e_i q'_{i,S}(p) \tag{8}$$

Equation (7) is the key equation for estimating the emissions reductions achieved per barrel of oil curtailed. Its key inputs are

1. $e_{\tilde{q}}$: the emissions intensity of the curtailed oil supply,
2. $\overline{e}$: the weighted average emissions intensity of marginal oil supply, and
3. L: the market leakage rate of oil.

---

[8] The e_i term represents full life-cycle emissions, including Scope 1, 2, and 3 emissions. The emissions intensity of oil varies primarily to upstream and midstream sources of emissions, not downstream combustion emissions. This could change if carbon capture technology is deployed at scale for oil use. We view this as unlikely in the foreseeable future, as carbon capture technology has primarily focused on abating emissions from coal and gas at power plants, rather than from oil emissions, such as those from vehicles.

[9] Equation (7) can also be written equivalently as $\frac{dE}{d\tilde{q}} = -e_{\tilde{q}}(1-L) + \left(\overline{e} - e_{\tilde{q}}\right)L$. This form of the equation separates the emissions reduction owing to reduced oil consumption net of leakage, $-e_{\tilde{q}}(1-L)$, and the relative emissions intensity of the replaced barrels of consumption $\left(\overline{e} - e_{\tilde{q}}\right)L$.

[10] We can see this is the correct value because plugging this expression into the previous equation yields the definition of the emissions impact: $\frac{dE}{d\tilde{q}} = -e_{\tilde{q}} + \sum_i e_i q'_{i,S}(p)\frac{dp}{d\tilde{q}}$, noting that $L = \sum_{i=1}^{N} q'_{i,S}(p)\frac{dp}{d\tilde{q}}$.

All three input variables are inherently uncertain. The leakage rate, L, depends on relative elasticities of global supply and demand in the oil market.[11] The emissions intensity of curtailed supply is probably easiest value to estimate, but is still subject to uncertainty due to imperfect measurement of GHG emissions, in particular upstream methane emissions from oil and gas infrastructure. The emissions intensity of marginal oil supply, $\overline{e}$, is perhaps the most difficult to estimate with high precision because doing so entails not only having emissions intensity values for all sources of marginal supply, but also having estimates of source-specific supply elasticities. An additional difficulty is estimating supply elasticities ex ante, before undeveloped fields come online. In the subsequent sections, we discuss practical approaches to choosing parameter values for elasticities and emissions intensity values in equations (7) and (8).

2.1. Substitution to Other Forms of Energy

The emissions impact of curtailed oil demand given by equation (7) represents reductions in emissions associated with oil consumption. For this to represent a complete accounting of global emissions, the reduction in oil consumption must represent full fossil fuel demand destruction (such as improved fuel economy or reduced vehicle miles traveled) in addition to substitution to alternative fuel sources (such as EVs) that may entail their own emissions. Because oil is primarily used as a transportation fuel, few alternatives have existed historically, meaning that in the past, price-induced changes in oil consumption largely reflect true demand destruction, indicating emissions estimates calculated using equation (7) based on historical parameters are indeed appropriate. However, if the elasticities used to calibrate equation (7) begin to reflect future changes in the availability of oil substitutes with non-zero emissions, such as EVs, then equation (7) could fail to account for the emissions intensity of those substitutes.

As a thought experiment, suppose widespread adoption of EVs makes oil demand perfectly elastic ($\varepsilon \to -\infty$), implying zero leakage ($L = 0$). In this case equation (7) reduces to $-e_{\tilde{q}}$, meaning one-for-one reduction in oil consumption from the curtailed supply. But this fails to account for the emissions from the electricity powering those vehicles, so the emissions reductions from equation (7) are correspondingly overstated.

More generally, a barrel of curtailed supply leads to $(1 - L)$ barrels of reduced oil consumption. Denote s as the share of that reduction that is true fossil fuel demand destruction, but $(1 - s)$ is substituted to other fuel sources with emissions intensity denoted e_s, which is in units of tons of CO_2e per barrel of oil equivalent. Then, a complete accounting of total emissions would require adding $(1 - L)(1 - s)e_s$ to equation (7). That is, for each barrel of reduced consumption, represented by $(1 - L)$, an amount equal to $(1 - s)$ of that barrel is substituted to a non-zero emissions source, with corresponding emission rate e_s.

This additional term is likely to be small. In the historical experience, there have been few substitutes for oil consumption in transportation, meaning s has likely been close to one. In our empirical application, we base demand elasticities on the historical literature, meaning our leakage estimates should largely reflect true fossil fuel demand destruction. In other words, if s is close to one, then the

[11] This model is static, but in a dynamic model parallel to that of Prest (2022b), a similar result is obtained where the elasticities are long-run values (specifically, an intertemporal long-run average, see Appendix).

additional $(1-L)(1-s)e_s$ term is effectively zero and need not be considered in the calculation, which corresponds to the assumption implicit in equation (7).

However, this may change in the future—for example, with increased adoption of EVs or other substitutes for oil. Such a development would, on one hand, reduce leakage by introducing another channel by which demand can respond (larger emissions reductions due to less leakage in equation (7)), but, on the other hand, introduce emissions from substituted fuel (smaller emissions reductions).

The importance of such substitution would depend on the emissions intensity of the substitute fuel, e_s. Given that oil substitutes will almost uniformly have lower emissions intensities than oil (e.g., EVs, heat pumps), the net effect of accounting for new substitutes over time will almost surely yield greater emissions reductions than implied by equation (7) calibrated to historical data. As an example, passenger electric vehicles have a per-mile emissions intensity of roughly one-fourth of that of gasoline vehicles at the current emissions intensity of the US electric grid.[12] At the modestly higher carbon intensity of the global average grid,[13] the per-mile emissions intensity of EVs rises to about one-third of that of gasoline vehicles. This suggests a value of e_s of approximately one-third to one-fourth of the value for oil, although this value may vary across space and time, particularly if the emissions intensity of electricity is declines in the future, or if we see improvements in EV energy efficiency. This suggests this additional term is likely to be small in the near-term, at least until breakthroughs in policy, economics, or technology relevant to oil substitutes emerge in the future. On net, however, such developments would lead to greater emissions reductions than implied by (7), as the reduction in leakage would be larger than the emissions produced by EVs.

One could alternatively mitigate concerns about emissions substitution by simultaneously curtailing both the supply and demand for oil in tandem in equal measure, as discussed by Prest (2022a). While such an approach may be promising as a policy effort—for example, by increasing the stringency of fuel economy regulations—there are not obvious channels for private actors to drive reductions in oil demand for the purpose of generating offsets. Further, an accurate accounting of those effects would require matching the characteristics of the curtailed supply and demand (e.g., product-specific elasticities and emissions intensities). If those characteristics differ, one would then need to engage in a complicated accounting adjusting for those differences, which is not a straightforward task.

2.2. When Could Leakage Be Zero? The Case of Hotelling Dynamics

An economic model frequently used to study resource extraction is the Hotelling model (Hotelling 1931). In the Hotelling model, a fixed amount of an exhaustible resource is extracted over time, and the supplier seeks to optimize the timing of that extraction. In most versions of the model, all of the

[12] E.g., 110 grams of CO_2/mile for a 2023 Tesla Model 3, versus 410 grams/mile for an average new gasoline vehicle.
https://www.fueleconomy.gov/feg/Find.do?year=2023&vehicleId=46016&zipCode=20036&action=bt3

[13] The global average grid intensity is 438 gCO_2/kWh, compared to 368 gCO2 per kWh for the United States. See https://ourworldindata.org/grapher/carbon-intensity-electricity?tab=table. Even in the countries with the most carbon-intensive grids (exceeding 700 gCO_2/kWh), EVs are still approximately half as carbon intensive as gasoline vehicles on a per-mile basis.

resource is extracted eventually, implying that changes in prices can only alter the time profile of production. The model in this paper, by contrast, does not feature such classical Hotelling-style dynamics, which we argue is justified by their weak empirical support (Krautkraemer 1998; Slade and Thille 2009; Cairns and Smith 2019; Cairns, Davis, and Smith 2021). For example, Cairns and Davis (2019) argue that Hotelling-style models "yield unsound results that should not be used for policy evaluation." Nonetheless, given their long history, it is worth considering what the consequences of a Hotelling model would be for leakage.

In our model, leakage occurs because curtailed supply leads to higher oil prices, which induces more production from other sources. How does this story change if those other sources are believed to exhibit Hotelling dynamics? Since all of the depletable resource is extracted eventually in a Hotelling model, changes in prices can only alter the time profile of production. This means that price changes induced by curtailed supply may alter the timing but not the cumulative amount of production from other sources. This would imply zero leakage in the long run.[14] This extreme outcome seems unrealistic, as such a model assumes that no fossil fuels are left in the ground in the long run, despite policy and technological developments pushing against such an outcome. If sufficiently cheap alternative energy sources are eventually developed that price out reserves, some fossil fuels will be left in the ground, with their amount determined in large part by the price mechanisms included in this paper's model—that is, which determining reserves are priced out of the market.

In summary, Hotelling-style dynamics have weak empirical support, have unrealistic implications for leakage, and are unlikely to change the fundamental mechanisms in this paper's model. See section 3.2 in Prest (2022b) for a longer discussion.

3. Estimating Market Leakage

As shown above, market leakage—the share of curtailed production that is replaced by other sources of supply—is determined by the relative elasticities of supply and demand. Those elasticities are not known for certain because of epistemic uncertainty about oil markets as they exist today and because those elasticities are likely to change over time. However, reasonable ranges and central estimates of those elasticities can be assembled from quantitative modeling from the academic literature and other sources.

In this section, we first present some general principles for determining appropriate values for supply and demand elasticities. Then, we present a review of elasticity estimates from the academic literature that meet those criteria.

3.1. General Principles for Estimating Leakage Parameters

[14] Further, even if the Hotelling model were to hold and higher prices merely accelerate extraction, this still leads to leakage in the near term and the consequent undesirable near-term acceleration in global temperature rise.

Four key questions arise when considering appropriate elasticity values to use in equation (5): geographic scale, temporal scale, estimation methodology and credibility, and frequency of update. We discuss them each in turn.

Geographic scale. The market for crude oil is global in nature, meaning the relevant elasticities for equation (5) are therefore globally representative values.[15] Thus, to the extent permitted by the available evidence, analysts should endeavor to use only globally representative values. While many studies estimate elasticities for specific regions, these may not necessarily represent the global average if the region in question has more or less elastic supply or demand. This is particularly important given how the US shale boom increased price-responsiveness there (Mason and Roberts 2018; R. G. Newell, Prest, and Vissing 2019; R. G. Newell and Prest 2019; Gilbert and Roberts 2020), suggesting supply elasticities estimated for the United States likely exceed the global average and are thus inappropriate to use directly in equation (5).

Temporal scale. Supply and demand elasticities are typically differentiated between short-run and long-run values. Short-run elasticities typically refer to responses on the time horizon of a few months or less. Estimates of short-run elasticities tend to be small and often indistinguishable from zero given the lack of time for market participants to adjust behavior. Long-run elasticities naturally tend to be larger and often much larger. The static model above intentionally does not make an explicit assumption about the relevant time frame, but it can be thought of as representing a length of time over which oil demand is sufficiently fungible, in the sense that a barrel can be shifted from one point in time to another through storage. As substantial volumes of physical oil storage exist, this can be thought of as a fairly long time period. The implication is that the elasticities in equation (5) should similarly represent long-run elasticities. In addition, the key leakage result in equation (5) generalizes to a model that accounts for intertemporal dynamics, where the appropriate elasticity values are long-run weighted averages (see Appendix). For these reasons, long-run elasticities are the appropriate values to use in leakage calculations.

Estimation methodology and credibility. A wide variety of methods have been applied to estimate oil supply and demand elasticities. These include time-series econometric approaches (Kilian and Murphy 2014), microeconometric methods (Levin, Lewis, and Wolak 2017; Coglianese et al. 2017), and structural modelling (Bodenstein and Guerrieri 2011; Balke and Brown 2018). In general, the "credibility revolution" in economics over the past several decades could suggest placing greater weight on more recent studies that incorporate recent advances in econometric methods. However, doing so in a quantitative sense remains subjective. Credibility of the resulting estimates is also important, as some individual studies may produce implausible estimates, such as estimates of the incorrect sign (e.g., a downward sloping supply curve) due to idiosyncrasies in a study's assumptions, methods, or data. Since such outliers can skew the results, some degree of expert judgment is necessary to remove implausible estimates from consideration, but caution is warranted when doing so, with a general preference for a "light touch" review.

Ideally, commissions of experts would be convened to build consensus on reasonable sources of estimates, including recommendations around best practices. There is precedent for this in other

[15] That is, appropriately production-weighted average supply elasticities, or consumption-weighted demand elasticities.

settings, such as the Environmental Protection Agency's (EPA) commission on the assessment of contingent valuation methods (Cummings, Brookshire, and Schulze 1986) and by the National Academies of Sciences, Engineering, and Medicine (e.g., NASEM (2017), which we discuss in more detail below). Carbon credit registries may opt to convene their own such panels to establish guidelines for evaluating estimates. Short of this, a practical approach could entail a recurring review of the literature on elasticities of oil supply and demand, as we did in this study, to reflect new research.

Frequency of update. As above, elasticity estimates should reflect long-run values based on the best scientific understanding of the shape of future oil markets. However, that best understanding may change over time for many reasons. New research may produce better estimates of supply and demand elasticities. Developments in policy or technology may also alter the expected trajectories of those elasticities. As one simple example, policy developments may accelerate the transition to EVs, implying larger demand elasticities than previously anticipated. At the same time, an EV transition would also shift oil demand inward, likely leading to larger oil supply elasticities as market equilibrium moves to a flatter part of the supply curve (assuming the supply curve is not iso-elastic). While this thought experiment would increase both the numerator and the denominator of the leakage ratio and therefore have offsetting impacts for the leakage rate, other developments may lead to impacts that are clearly in one direction or the other. Similarly, the emissions intensity of various kinds of oil could also change over time given, e.g., the Global Methane Pledge announced in 2021,[16] or efforts by the United States and Europe to reduce methane emissions from the oil and gas system. However, there is unfortunately little quantitative basis to adequately reflect how much key elasticity values or emissions intensities are likely to change in response to future developments. As those developments evolve over time, it may become clear that the state of the market has changed. Such changes may require an updated computation of equation (7) which may lead to a change in emissions reductions, and resulting appropriate offset crediting values, relative to what is estimated in this study. Therefore, a mechanism is needed to update elasticity estimates and emissions data over time and adjust crediting accordingly.

This raises the question of how frequently one should update the parameter values to reflect a changing evidence base and policy landscape. In some cases, there may be clear breakthroughs in policy, economics, or technology that suggest revisiting key estimates. One example in a different setting—electricity—is the 2022 passage of the Inflation Reduction Act in the United States, which prompted various modeling groups to update their models to reflect new policies.[17] Should EV adoption become considerably more enticing through, for example, lower costs to purchase and operate or improved performance, EVs will become a more viable substitute for gasoline-powered vehicles. This, in turn, would make demand for oil more elastic, but as noted previously this could also move the market to a more elastic part of the supply curve, with ambiguous implications for leakage rates. On the other hand, a revolution in industry structure, such as the shale revolution or growth of non-OPEC supply following the spikes in oil prices in the 1970s, would make supply more responsive than originally anticipated, but analogously moving the market to a more or less elastic part of the demand curve, with again ambiguous implications for leakage. Events like these would need to be

[16] https://ec.europa.eu/commission/presscorner/detail/en/statement_21_5766

[17] See, e.g., https://www.rff.org/events/rff-live/future-generation-exploring-the-new-baseline-for-electricity-in-the-presence-of-the-inflation-reduction-act/

quite large to warrant a revision of leakage estimates, and so we argue that they would be readily apparent if they come to pass.

Absent a clear change such as this, it would be sensible to establish a routine for revisiting elasticity and emissions intensity estimates on some predetermined recurring basis. There is a trade-off between updating estimates in response to every new development while also providing a predictable and thorough process for those updates. A 2017 report by the National Academies of Sciences, Engineering, and Medicine (NASEM 2017) addressed this issue in the context of recurring updates to the US government's official estimates of the social cost of greenhouse gases. While it is not a perfect parallel to the question of how often to update the parameters underlying leakage estimates, a consideration of the general principles is nonetheless instructive.

The NASEM report recommended an update cycle of approximately five years, which provides enough time for the development of evolving research, as well as a thorough synthesis of it. The proposed NASEM cycle involves three steps, the first of which involves the technical process of comprehensive updates to the modeling process that incorporates rapidly growing areas of research in climate science and impacts.[18] Due to the highly complex, multidisciplinary modeling needs underlying the social cost of carbon, that first step was envisioned to take two to three years to complete. The second step entails obtaining input and comment on the proposed estimates from scientific and technical communities and stakeholders, which would be incorporated into a finalized estimate. This step is envisioned to take six months to one year. Finally, the third step "involves a thorough independent scientific assessment of the…estimation process, in order to track and assess new scientific literature over time and make recommendations for future improvements and research."

Turning back to the considerations in updating the parameters underlying leakage estimates, a time frame of no more than five years seems similarly appropriate albeit due to two offsetting considerations. On the one hand, the NASEM's process may be overly elaborate in the context of leakage because there are fewer uncertainties and parameters involved in leakage estimation as opposed to the social cost of carbon, which depends on more complex models entailing thousands of uncertain parameters and assumptions spanning many disciplines. That consideration would suggest a simpler and perhaps more frequent update process for leakage estimation. On the other hand, part of the NASEM's motivation reflected the fact that climate impacts literature has been growing rapidly, suggesting more frequent updates are necessary to keep pace. By contrast, studies estimating supply and demand elasticities for oil have not experienced the same pace of growth, and their estimates have not changed rapidly over time, suggesting less frequent updates. On net, these two considerations suggest that an update cycle occurring no less frequently than every five years may be appropriate, although unexpected developments that alter substantially oil markets and/or emissions intensities could warrant more frequent reexaminations.

[18] NASEM envisioned that this update process would be led by an interagency working group housed in the US federal government, since the use case for the estimates was for government analyses. This logic also holds to the extent leakage estimates are similarly being used in government analyses, such as by the Department of Interior's analysis of oil and gas leasing decisions, or in regulatory offset programs.

3.2. Estimates of Demand Elasticities

There is a large literature in economics estimating elasticities of demand for oil and gasoline, but not all estimates are useful in estimating leakage. First, many studies, particularly in those using structural vector autoregression methods, focus on estimating very short-run elasticities, which are not appropriate for long-run leakage calculations. Further, many empirical estimates reflect the price elasticity of demand for gasoline, rather than for crude oil, which are related but nevertheless distinct. As noted by Hamilton (2009), because crude oil amounts to about half of the retail cost of gasoline, the price elasticity of crude oil demand should be about half as big as the elasticity for gasoline. For this reason, elasticities estimated for gasoline must be divided by two to convert to a crude oil elasticity appropriate for use in equation (5).

In light of these considerations, we conducted a review of the economic literature estimating oil or gasoline demand elasticities. We gave preference to studies that were 1) peer reviewed or otherwise from an authoritative academic source, 2) were not simply citations of other papers, and 3) presented globally representative elasticities, although we also included rigorous studies estimating elasticities for countries that are large consumers of oil, such as the United States.

This yielded more than 29 studies that provided demand elasticity estimates, from which we excluded studies that only present very short-run elasticities (typically with a time horizon of one month). From each of the remaining 24 studies, we extracted a single central estimate[19] to avoid giving greater weight to studies that report multiple values. When a range of estimates was presented, we took the average. Where appropriate, we converted gasoline elasticities to crude oil elasticities by dividing by two. In one instance, a study reported elasticities for OECD and non-OECD demand, from which we calculated a global consumption-weighted average value assuming a 53 percent OECD consumption share.[20]

From these resulting 24 estimates, we removed three implausibly small and implausibly large estimates of -0.04, -0.05, -1.21, each of which differs from the closest remaining estimate by more than a factor of two. The remaining 21 estimates are shown in Table 1 in order of publication year. These elasticities range from -0.12 (Serletis, Timilsina, and Vasetsky 2010) to -0.53 (Krupnick et al. 2017), with a simple average value of -0.33 and a standard deviation of 0.13. More than half (62 percent) of the studies have been published since 2010.

[19] In principle, we would like to incorporate not only central estimates but also uncertainty ranges through, for example, Bayesian averaging across estimates. In practice, this not possible because many studies do not report standard errors.

[20] **https://www.eia.gov/finance/markets/crudeoil/demand-oecd.php**

Table 1. Estimates of the Price Elasticity of Demand for Crude Oil

Study	Central	Peer-reviewed?
Dahl and Sterner (1991)	-0.43*	Yes
Hausman and Newey (1995)	-0.40*	Yes
Yatchew and No (2001)	-0.45*	Yes
Gately and Huntington (2002)	-0.42	Yes
Graham and Glaister (2002)	-0.39*	Yes
Cooper (2003)	-0.32	Yes
Goodwin, Dargay, and Hanly (2004)	-0.32*	Yes
Brons, Nijkamp, Pels, and Rietveld (2008)	-0.42*	Yes
Serletis, Timilsina, and Vasetsky (2010)	-0.12	Yes
Bodenstein and Guerrieri (2011)	-0.42	No (Federal Reserve discussion paper)
Dahl (2012)	-0.32*	Yes
Lin and Zeng (2013)	-0.17*	Yes
Brown, Mason, Krupnick, and Mares (2014)	-0.45	No (RFF report)
Dahl (2014)	-0.38*	No (Colorado School of Mines working paper)
Kilian and Murphy (2014)	-0.26	Yes
Levin, Lewis, and Wolak (2017)	-0.16*	Yes
Coglianese, Davis, Kilian, and Stock (2017)	-0.19*	Yes
Krupnick, Morgenstern, Balke, Brown, Herrera, and Mohan (2017)	-0.53	No (RFF report)
Balke and Brown (2018)	-0.51	Yes
Huntington (2019)	-0.15	Yes
Knittel and Tanaka (2019)	-0.19*	No (NBER working paper)
Simple average	**-0.33**	

Note: * Indicates elasticity after dividing by two to convert from gasoline to crude oil elasticities.

3.3. Estimates of Supply Elasticities

We conducted an analogous literature review to collect estimates for global oil supply elasticities. This literature is far smaller than that for demand elasticities. To avoid relying solely on a very small number of studies, which would give a false sense of confidence in the likely range of supply elasticities, we were more accommodating regarding acceptable studies for inclusion in our set (for example by including estimates based on simulation models, such as Greene and Lieby (2006)). This review resulted in nine estimates shown in Table 2, which range between 0.25 (Krichene 2002) and 0.55 (Balke and Brown 2018), with a simple average of 0.42 and a standard deviation of 0.10. As with the demand elasticities, more than half (55 percent) of these studies have been published since 2010.

Table 2. Estimates of the Price Elasticity of Supply of Crude Oil

Study	Central	Peer-reviewed?
Huntington (1994)	0.40	Yes
Brown (1998)	0.43	No (Federal Reserve Bank of Dallas report)
Krichene (2002)	0.25	Yes
Greene and Leiby (2006)	0.46	No (Oak Ridge National Lab model documentation)
Coyle, DeBacker, and Prisinzano (2012)	0.29	Yes
Brown, Mason, Krupnick, and Mares (2014)	0.40	No (RFF report)
Krupnick, Morgenstern, Balke, Brown, Herrera, and Mohan (2017)	0.51	No (RFF report)
Balke and Brown (2018)	0.55	Yes
Prest (2022b)	0.47	Yes
Simple average	**0.42**	

Using the simple average values of the above estimates for the elasticities of supply (0.42) and demand (-0.33) gives a first-order approximation of the expected market leakage rate given by equation (5):

$$L \approx \frac{0.42}{0.42 - (-0.33)} = 56\%$$

While this approximation does not reflect the full range of uncertainty in supply and demand elasticities, it remains a simple benchmark. A formal assessment of the central estimate of the leakage rate and uncertainty around it requires an explicit treatment of uncertainty in these parameter values. In our quantitative application, we undertake a Monte Carlo exercise in which we sample from the elasticities in Table 1 and Table 2, as well as uncertainty in emissions intensities of the leaked production, which we discuss next.

4. Estimates of Emissions Intensities

We draw upon data from the 2023 **Oil Climate Index plus Gas** (OCI+) data, which is a data product developed by researchers at RMI. RMI is a global think tank and the host of the OCI+, a tool comprised of underlying oil and gas GHG emissions models that have been extensively peer reviewed in the literature. The OCI+ is a bottom-up systems tool that also uses input top-down measurements (a hybrid approach) to quantify emissions from oil and gas production, processing, refining, shipping, and end uses. The OCI+ uses three underlying models to assess GHG emissions from the oil and gas value chain segments. The production model, Oil Production Greenhouse Gas Emissions Estimator (OPGEE) resides at Stanford University. The refining model, Petroleum Refinery Life-Cycle Inventory Model (PRELIM) resides at the University of Calgary. And the end use consumption model, OPEM (Oil and Gas Products Emissions Module) resides at RMI. The OCI+ and its underlying models have been peer-reviewed and internationally cited and applied in energy policy decision making for over a decade, as partially listed in the OCI+ web tool “Studies” tab.[21] For details on each model and modeling inputs and assumptions, refer to the OCI+ Methodology.[22]

The OCI+ provides annual field-level time-series estimates of life-cycle GHG emissions for 586 oil and gas fields representing two-thirds of global supply from 2015–2022. While OCI+ has detailed estimates of emissions intensities by product and stage of production (upstream, midstream, downstream), we use each field’s total life-cycle emissions intensity, which is measured in kilograms of carbon dioxide equivalent emissions per barrel oil equivalent (kgCO_2e/boe), presenting key results under both 100-year and 20-year global warming potentials (GWPs). We refer to these estimates as field-specific emissions intensity values, corresponding to e_i values in equation (8). While we will focus on 100-year GWPs for our main analysis, we also demonstrate the sensitivity of the main results to using a 20-year GWP, which gives greater emphasis to methane-intensive fields.

Equation (8) also requires information on oil production to reflect the fact that fields should be weighted in the analysis in proportion to their size. As oil supply is the focus of this paper, we focus solely on oil production as our measure of field size, rather than on oil and gas production together.[23] However, the OCI+ data only presents categorical data on field-level production, placing each field into one of five bands of crude oil production: “Very Low” (0–5 kb/d), “Low” (5–50 kb/d), “Medium” (50–250 kb/d), “High” (250–500 kb/d), or “Very High” (>500 kb/d). As we need quantitative values, we approximate field-level production as the midpoint of each bin; for the “Very High” band that has

[21] See **https://ociplus.rmi.org/about/studies**.
[22] See **https://ociplus.rmi.org/methodology**.
[23] Modeling the curtailment of gas supply raises other issues that are beyond the scope of this paper, such as the interaction between gas and coal demand.

no midpoint, we use a value of one million barrels per day (twice that band's low point). We do this calculation for each field and year, and then aggregate production and emissions to the field level across time.[24]

Figure 2 depicts the per-barrel emissions intensity estimates under a 100-year GWP, ordered from lowest to highest, versus our approximation of field-level production, with bars colored by resource type.[25] In general, fields with heavier oil tend to have higher life-cycle emissions, with the Canadian oil sands indicated on the graph as an example, averaging 650 kgCO_2e/boe, compared to the global average value of 520 kgCO_2e/boe. The Permian Basin is also indicated on the graph, with an average emissions intensity of 520 kgCO_2e/boe that is very close to the global average under the 100-year GWP. The weighted average emissions intensities for selected sets of fields are shown in Table 3; we discuss these categories in more detail in the next section.

While there is variation in the life-cycle emissions intensity, the curve in Figure 2 is fairly flat except around the highest and lowest emissions intensity fields, which highlights the value of targeting supply-side interventions towards the most emissive fields. This stability owes largely to two factors. First, the 100-year GWP puts less emphasis on methane-intensive fields than a 20-year GWP would. Second, end-use emissions—which include emissions from combustion of the final product—account for an average of 75 percent of total life-cycle emissions under a 100-year GWP,[26] and end-use emissions vary much less across fields than do production, shipping, and refining emissions. In addition, there is even further similarity in life-cycle emissions intensities within a resource type, such as light oil, which is important when considering the possibility that curtailed oil production may be substituted by oil of a similar quality.

Figure 3 shows field-level emissions intensities under a 20-year GWP, which results in more variation in emissions intensity due to the greater emphasis on methane emissions intensity, which varies much more across fields than CO_2 emissions intensity does. This brings many light oil fields (gray bars in Figure 3) that are considered low-emitting under a 100-year GWP to the higher end of the emissions intensity curve. Notably, with a 20-year GWP the Permian Basin is now among the most emissions-intensive oil play, averaging 680 kgCO_2e/boe, which is within 0.5% of the emissions intensity of Canadian oil sands, as contrasted with being about average under a 100-year GWP (see Table 3). In the next section, we combine this OCI+ data with the elasticity estimates discussed above to conduct a Monte Carlo analysis and assess emissions reductions given by equation (7).

[24] We use a simple average of field-level production over time and production-weighted average of field-level emissions intensity.

[25] For simplicity, in this figure we aggregate OCI+'s 10 resource types into four (gas and light/medium/heavy oil, where condensate is included in the light oil category).

[26] The analogous figure for a 20-year GWP is 68 percent.

Figure 2. Field-level Life-cycle GHG Emissions Intensity Estimates versus Approximate Cumulative Production, 100-Year GWP

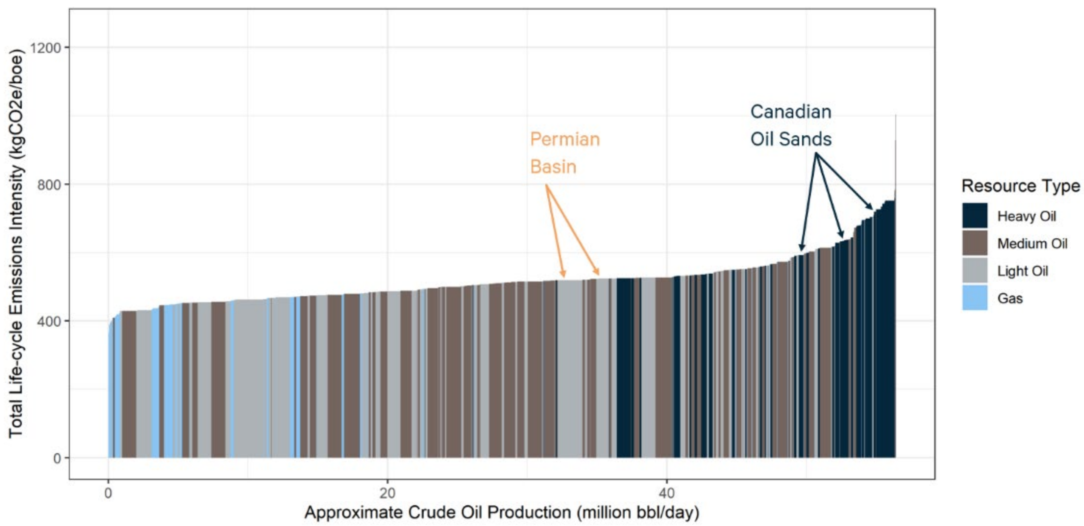


Figure 3. Field-level Life-cycle GHG Emissions Estimates versus Approximate Cumulative Production, 20-Year GWP

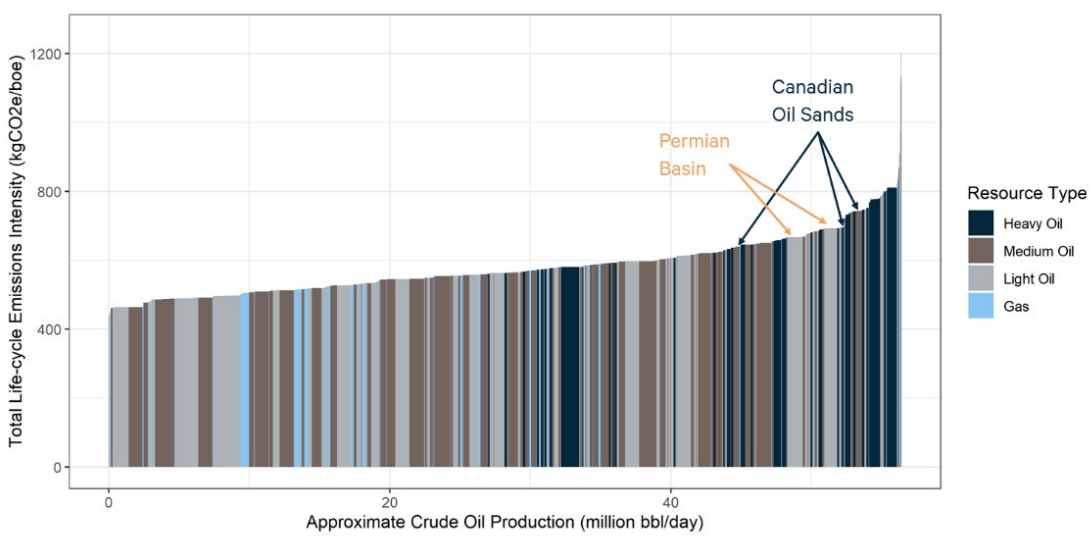


Table 3. Life-cycle Emissions Intensities of Selected Sets of Fields

	Emissions intensity ($kgCO_2e$/boe)	
Field type	**100-year GWP**	**20-year GWP**
All (market average)	520	580
Oil sands	650	690
Permian Basin	520	680
Light oil	500	570
Medium oil	510	560
Heavy oil	610	670
Sweet oil	540	600
Sour oil	520	580
Region		
OPEC	510	570
North America	540	610
Central/South America and Caribbean	570	630
Europe	480	520
North Africa	530	620
Other Africa	530	610
Middle East	490	540
Russia and Central Asia	510	580
East/Southeast Asia	560	610

Notes: All figures represent weighted averages from fields corresponding to the given category, where we use our approximations of crude oil production as weights. All emissions change values are rounded to the nearest 10 $kgCO_2e$/boe.

5. Quantitative Application

In this section, we combine the ranges of supply and demand elasticities with the OCI+ data on field-level emissions intensities to conduct a series of Monte Carlo simulations to estimate the net emissions reductions that could be achieved by curtailing oil supply and how those estimates vary by the type of oil curtailed and substituted.

The first set of inputs are distributions of supply and demand elasticities. As discussed above, the empirical research on oil price elasticities of supply and demand has produced a range of long-run estimates. To empirically explore the degree of sensitivity of emission leakage under this range of elasticity estimates and emission intensities of the potentially leaked oil, we first conduct a Monte Carlo focused on the leakage rate.

We begin by forming a distribution of market leakage rates—that is, equation (5)—by sampling from supply and demand elasticities. We create this leakage-rate distribution through two different sampling methods. In the first method, we take 10,000 draws, with replacement, from the list of demand and supply elasticities given in Table 1 and Table 2, respectively. With each draw i of an ε_i and η_i value, we form a leakage rate value, L_i, based on equation (5), resulting in 10,000 leakage rate estimates. For the second method, we specify parameterized distributions of supply and demand elasticities. Specifically, for the supply and demand elasticities, respectively, we calculate the means $(\bar{\eta}, \bar{\varepsilon})$ and standard deviations $(\sigma_\eta, \sigma_\varepsilon)$ based on the individual elasticity estimates given in Tables 1 and 2. We then assume that supply and demand elasticities are both distributed as truncated normal distributions with the respective supply and demand elasticity distributions of $TN(\bar{\eta}, \sigma_\eta, 0, \infty)$ and $TN(\bar{\varepsilon}, \sigma_\varepsilon, -\infty, 0)$, with each set of elasticities constrained to have the appropriate sign. In both approaches, we assume no correlation between supply and demand elasticities because the underlying factors driving the two are largely unrelated. Supply elasticities are driven by the cost structures of oil production, which are plausibly unrelated to the drivers of demand elasticities—behavioral responses (e.g., changes in vehicle miles driven) and the availability of substitutes (e.g., electric vehicles). Absent any basis to suggest even the sign of any correlation between these elasticities, let alone its magnitude, we treat them as uncorrelated.

Figure 4 shows histograms of the two leakage rates under the two sampling methods. The two methods lead to similar distributions of leakage rates, with almost identical means (56.9 percent versus 56.7 percent).[27] Given this similarity, we present results below based on the "sampling with replacement" of the individual elasticities approach because it more explicitly represents the elasticity literature, rather than approximates it. While Figure 4 shows market leakage, L, as in equation (5), that is only one component of the formula for emissions reductions in equation (7). The other key components are the emissions intensities of the curtailed and substitute sources.

While the curtailed source of supply is generally known, the sources of substitute supply and their emissions intensities are more uncertain. Because it is not generally feasible to empirically estimate

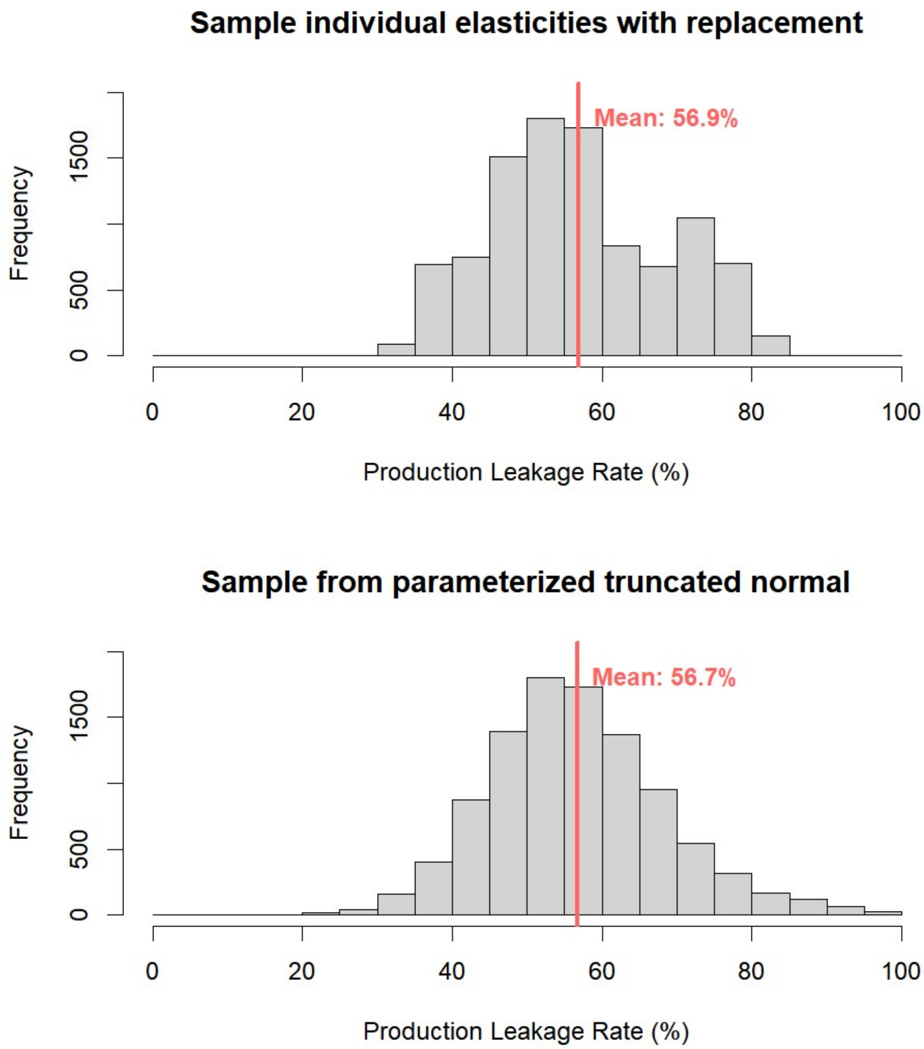
[27] The primary difference between the two approaches is that the truncated normal approach produces a fatter-tailed distribution of the leakage rate, owing to extreme draws of parameterized elasticity distributions that are outside of the range of the elasticity estimates from the literature (e.g., a demand elasticity that is effectively zero).

the sources of substitute supply (e.g., it is generally not possible to empirically estimate with historic data how much a given field X will increase production if field Y is curtailed), we focus with a neutral default assumption that substitute supply can come from any field in proportion to its production share. We refer to this as the “market average” case because, on average, this approach treats substitute supply at the production-weighted average emissions intensity. We also assess the sensitivity of this approach to alternative assumptions about potential sources of substitute supply. For example, in one case we assume that substitute supply comes solely from OPEC. These scenarios could represent a proxy for cost structures that could lead some sources of supply to be more price-responsive due to, say, varying cost structures. For example, Caldara, Cavallo, and Iacoviello (2019) find that OPEC is about twice as price-responsive than average.[28] Similarly, onshore North American supply is estimated to be more price-responsive than the global average (R. G. Newell and Prest 2019; R. G. Newell, Prest, and Vissing 2019; Prest 2022b), and many such fields also have below-average emissions intensities in the OCI+ data.

Across our alternative scenarios, we simultaneously vary two dimensions: the oil production that is curtailed, and the source of substitute supply. In each case, we define a category of fields under consideration for curtailment and randomly sample—10,000 times with replacement—a field from that category (e.g., Canadian oil sands or Permian Basin fields), with sampling weights equal to their approximated production. We separately define a category of fields where substitute production may arise and analogously randomly sample from those fields. For each set of “curtailed sources” and “substitute sources,” this yields 10,000 estimates of curtailed emissions intensity $e_{\tilde{q}}$ and “leaked” emissions intensity e_i, in which the substitute production comes only from field i. That is, in each draw, all fields except the sampled one are dropped from equation (8), resulting in $\overline{e} = e_i$ equation (7), and similarly so for $e_{\tilde{q}}$.

[28] That study is not included in Table 2 because it only estimates short-run supply elasticities.

Figure 4. Histograms of Simulated Market Leakage Rates under Two Sampling Approaches



The assumption that all substitute supply comes from a single randomly sampled field is conservative from the standpoint of uncertainty in emissions avoided. This increases the uncertainty range of our emissions estimates relative to an alternative assumption that all fields in the "substitution sources" category contribute a small amount to the total leaked production. This alternative assumption would imply using the weighted average emissions intensity within a category for $\bar{e}$ in (7). Such an approach would yield similar central estimates but a narrower uncertainty range than those presented below. We present results using the alternative weighted-average emissions intensity approach in the Appendix, showing that the key takeaways in central estimates and share of samples yielding net emissions reductions are nonetheless similar, although the 95 percent ranges are narrower.

With 10,000 samples of emissions intensity values for both curtailed ($e_{\tilde{q}}$) and substitute supply ($\bar{e}$) in hand, we then couple them with 10,000 independent draws of the leakage rate L shown in the top panel of Figure 4 to calculate the net emissions change using equation (7). We conduct this exercise for each pair of categories of curtailed and substitute supply.

We chose our sets of "curtailed" and "substitute" sources based on a variety of factors. In the simplest case, we randomly sample one of the 586 fields in the OCI+ data, with a likelihood in proportion to its approximated crude oil production, to be the one that is curtailed or that ramps up production in response to the curtailed barrel. We call this the "market average" case because in expectation it corresponds to curtailed and substitute supply having a market-average emissions intensity.

Since the curtailed oil is a choice variable for the entity retiring oil assets, we focus on key areas under consideration such as North America, including the highly emissive Canadian oil sands and Permian Basin. We also consider broad categories of oil types—light, medium, and heavy, or sour versus sweet. This yields nine categories of sources of curtailed supply.

For possible substitute sources, we include all nine categories used for the curtailed sources, plus an additional eight regional dimensions because the marginal source of supply may depend in some manner on physical location (due to, say, to the connectedness of markets and energy infrastructure). For instance, the retirement of a field in North America may prompt more production from other North American fields as the retirement may open more pipeline or rail transportation options and perhaps more local refining capacity. We also include OPEC as a category, given its historical relevance as a swing supplier. In addition, the type of oil and its refining needs would also play a role. This could occur because refining capacity tends to be geared towards certain types of oil. Thus, the retirement of a field that produces, for example, heavy oil may induce more heavy oil production, as there would be some newly created refining capacity for that type of oil. Altogether, we run 1.53 million simulations (reflecting 10,000 draws each for nine categories of curtailed supply and 17 categories of substitute supply).

We summarize a subset of these simulations in Table 4, which presents the expected value (average) of the net change in emissions from this exercise for each of the nine categories of curtailed sources and the percent of the 10,000 draws that lead to net emission reductions. For this table, we focus on two potential sources of substitute supply: one case in which all sources are candidates for substitute supply, and another in which all substitute production must come from the same category of sources as the curtailed supply.

The primary takeaways from Table 4 are that, first, across many regions, oil types, and the GWP used, our estimates of average net emission reductions from the curtailment of a barrel of oil is generally about 40–50 percent of the emissions intensity of the retired barrel and, second, almost all of our Monte Carlo draws lead to net emission reductions.

The fact that virtually all our draws lead to emission reductions highlights the fact that while there is considerable variation in leakage parameters L and cross-field emissions intensity, the variation in the combination of those parameters rarely leads to scenarios that predict emission increases with the curtailment of a barrel, and this is relatively insensitive to what type of oil barrel is curtailed. This result is particularly striking given our conservative approach of sampling field-level emissions intensities, which likely overstates the uncertainty ranges of net emissions impacts. Finally, using a 20-year GWP leads to modestly larger CO_2e reductions, as the emissions intensity of curtailed supply is higher, but this effect is somewhat offset by more emissive substitute supply. Except for the methane-intensive Permian Basin, the net effect of these two forces is modest. For this reason, for the remainder of the paper we focus on results only using the 100-year GWP, although interested readers can see the full 20-year GWP results in the Appendix.

Table 4.Net Emissions Change per Curtailed Barrel when Substitute Production's Emissions Intensity Reflects All Fields or Same as Curtailed Source

Substitute production from:	**All sources (market average)**				**Same sources**			
	Average net emissions change (kgCO_2e/boe)		*Share of draws with emissions reductions (%)*		*Average net emissions change (kgCO_2e/boe)*		*Share of draws with emissions reductions (%)*	
Curtailed source	**100-year GWP**	**20-year GWP**	**100-year GWP**	**20-year GWP**	**100-year GWP**	**20-year GWP**	**100-year GWP**	**20-year GWP**
All (market average)	-220	-250	98.52	98.31	-220	-250	98.52	98.31
North America	-240	-280	98.94	99.05	-230	-270	97.78	98.56
Oil sands	-350	-360	99.94	99.84	-280	-300	99.90	99.95
Permian Basin	-230	-350	99.15	99.86	-230	-290	100	100
Light oil	-200	-240	98.41	98.02	-220	-250	99.49	98.52
Medium oil	-220	-230	98.67	98.06	-220	-240	99.61	99.21
Heavy oil	-320	-340	99.67	99.61	-260	-290	98.58	98.95
Sweet oil	-240	-270	99.00	98.87	-230	-260	98.97	98.33
Sour oil	-220	-240	98.53	97.97	-220	-250	98.67	98.40

Notes: All emissions change values are rounded to the nearest 10 kgCO_2e/boe.

We present a broader set of substitution sources and the resulting implications for emission reductions from the curtailment of a barrel in a certain area or oil type in Tables 5, 6, and 7, all of which use a 100-year GWP. Table 5 shows the expected value (average) of the net change in emissions from this exercise, with the curtailed sources shown in the rows and the substitute sources in columns. Importantly, our Monte Carlo exercise allows us to assess uncertainty around these central estimates by providing 95 percentile ranges, which are shown in Table 6 (for the 97.5th percentile) and Table 7 (for the 2.5th percentile). Larger negative numbers indicate larger emissions reductions, with the green shading shown in proportion to those reductions.

The cell in the first row and column shows the "market average" case (noting that the market-average emissions intensity is 520 kgCO_2e/boe, see Table 3). In this case, the central estimate for the net reduction in emissions is 220 kgCO_2e/boe (95 percent range: 30 to 450 kgCO_2e/boe), which reflects the reduced net emissions of about 43 percent of that average emissions intensity. This is consistent with a 57 percent leakage rate (i.e., one barrel retired is counteracted by a 0.57-barrel increase in supply from other producers).

Table 5. Average Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 100-Year GWP

Change in CO2e emissions per barrel curtailed (kg/boe)

Substitute Source

Curtailed Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-220	-150	-220	-230	-210	-200	-250	-220	-220	-240	-230	-200	-240	-230	-170	-210	-230
North America	-240	-170	-240	-250	-230	-210	-270	-240	-240	-260	-250	-220	-260	-250	-190	-230	-240
Oil Sands	-350	-280	-350	-360	-340	-320	-380	-350	-350	-370	-360	-330	-360	-360	-300	-340	-350
Permian Basin	-230	-150	-230	-240	-220	-200	-250	-220	-220	-250	-240	-200	-240	-230	-180	-220	-230
Light Oil	-200	-130	-200	-210	-190	-170	-230	-200	-200	-220	-210	-180	-220	-210	-150	-190	-200
Medium Oil	-220	-140	-210	-220	-200	-190	-240	-210	-210	-230	-220	-190	-230	-220	-160	-200	-220
Heavy Oil	-320	-240	-310	-320	-310	-290	-340	-310	-310	-330	-320	-290	-330	-320	-260	-310	-320
Sweet Oil	-240	-170	-240	-250	-230	-210	-270	-240	-240	-260	-250	-220	-260	-250	-190	-230	-240
Sour Oil	-220	-150	-220	-230	-210	-190	-250	-220	-220	-240	-230	-200	-240	-230	-170	-210	-220

Δ Emissions (CO2e): -150, -200, -250, -300, -350

Turning to the second row, curtailing North American oil has a slightly larger impact on emissions (240 $kgCO_2e/boe$) because North American oil production is slightly (~4 percent) more emissions-intensive than average. The curtailment of oil sands in the third row shows much larger emissions reductions of 350 $kgCO_2e/boe$ in the first column (95 percent range: 170 to 520 $kgCO_2e/boe$), owing to its high emissions intensity. However, if the curtailment of a barrel from an oil sands field prompts increases in production (leakage) from other oil sands fields, the emissions reductions are a somewhat more modest 280 $kgCO_2e/boe$ (95 percent range: 90 to 460). For reference, the emissions intensity of oil sands is about 650 $kgCO_2e/boe$, suggesting net emissions reductions of about half of the gross emissions intensity of the curtailed barrel.

Looking across the columns, we see that the net emissions reductions are largely insensitive to the source of substitute supply, except in the few cases where that substitute source has emissions intensities that are extremely high (oil sands) or extremely low (Europe). This result owes to the relative flatness of the emissions intensity curve and suggests that the default use of a "market-average" emissions intensity of substitute supply is a reasonable approximation, unless there is clear reason to think that the curtailment of a specific field is likely to drive production by a specific source or region, such as due to idiosyncratic market dynamics like pipeline constraints.

In terms of the sign of the impacts, our central estimates imply net emissions reductions across the board. While the range of magnitudes is indeed wide, there is little uncertainty in the sign of the impacts on emissions, particularly for highly emissions-intensive fields. Considering the, roughly speaking, "worst-case scenario" 97.5th percentile in Table 6, the oil sands row uniformly shows net reductions in emissions regardless of the substitute source of supply.

The worst-case scenarios do show that in some cases there is a small chance curtailment of relatively clean supply could increase emissions. This could arise if 1) curtailed supply is relatively clean, 2) the leakage rate is high (generally above 75 percent), and 3) leaked production comes from relatively emissions-intensive sources (see the cells in white and red in Table 6). However, these scenarios generally involve less plausible substitution patterns, such as an assumption that curtailment of light oil production is replaced solely by oil sands production, rather than other sources of light oil.

Our Monte Carlo analysis finds net emissions reductions with a high degree of certainty when the curtailed sources of supply are highly emissions-intensive oil like heavy oils (99.6 percent) or Canadian oil sands (99.95 percent). Across all of our 1.53 million simulations, we find net emissions reductions in 98.68 percent of cases. In the Appendix, we show a sensitivity analysis using the alternative approach of using weighted-average emissions intensity values for each category of curtailed and substitute supply instead of field-level sampling. That approach yields essentially identical central estimates and higher certainty of net emissions reductions; in that case, across all 1.53 million simulations using the 100-year GWP, we find net reductions in more than 99.9 percent of cases.

Table 6. 97.5th Percentile of Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 100-Year GWP

Change in CO2e emissions per barrel curtailed (kg/boe)

Substitute Source

Curtailed Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-30	50	-60	-50	0	20	-80	-40	-40	-80	-60	0	-60	-60	50	-20	-40
North America	-40	40	-70	-60	-10	20	-90	-50	-50	-80	-70	0	-80	-60	40	-30	-50
Oil Sands	-170	-90	-200	-190	-130	-110	-220	-180	-170	-210	-200	-130	-200	-190	-90	-160	-170
Permian Basin	-70	20	-110	-90	-20	10	-130	-80	-90	-120	-110	-30	-110	-100	20	-60	-70
Light Oil	-20	60	-50	-40	10	40	-80	-30	-40	-70	-60	20	-60	-50	60	-10	-30
Medium Oil	-30	50	-70	-60	0	30	-90	-40	-50	-80	-70	0	-70	-60	50	-20	-40
Heavy Oil	-110	-20	-130	-130	-80	-60	-160	-110	-120	-150	-140	-70	-140	-130	-30	-90	-110
Sweet Oil	-50	40	-80	-70	-20	10	-100	-50	-60	-90	-80	-10	-80	-70	30	-40	-50
Sour Oil	-30	50	-60	-50	0	30	-80	-40	-40	-80	-60	0	-70	-60	50	-20	-40

Δ Emissions (CO2e): 50, 0, -50, -100, -150, -200

Table 7. 2.5th Percentile of Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 100-Year GWP

Change in CO2e emissions per barrel curtailed (kg/boe)

Substitute Source

Curtailed Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-450	-380	-440	-450	-440	-430	-470	-440	-440	-460	-450	-430	-460	-450	-410	-440	-450
North America	-480	-420	-470	-480	-480	-460	-500	-480	-470	-490	-480	-460	-490	-480	-440	-470	-480
Oil Sands	-520	-460	-510	-520	-510	-500	-530	-510	-510	-520	-520	-500	-520	-520	-480	-510	-520
Permian Basin	-350	-300	-330	-350	-340	-330	-360	-340	-340	-350	-340	-340	-350	-340	-320	-340	-350
Light Oil	-360	-310	-350	-370	-360	-340	-380	-350	-350	-370	-360	-350	-370	-360	-330	-350	-360
Medium Oil	-380	-320	-360	-380	-370	-360	-390	-370	-370	-380	-380	-360	-380	-380	-340	-370	-370
Heavy Oil	-520	-460	-510	-520	-520	-500	-540	-510	-510	-530	-520	-510	-530	-520	-490	-510	-520
Sweet Oil	-440	-380	-420	-440	-430	-420	-450	-430	-430	-440	-440	-420	-440	-430	-390	-420	-430
Sour Oil	-460	-390	-450	-460	-450	-430	-480	-450	-450	-470	-460	-440	-460	-460	-420	-450	-460

Δ Emissions (CO2e): -300, -350, -400, -450, -500

6. Conclusion

Supply-side interventions that retire highly emitting fossil fuel assets have received increased attention from policymakers and private actors alike. Yet concerns about leakage of production to other sources of supply have raised questions about how much emissions reductions they can achieve. In this paper, we estimate the effects of these supply-side interventions on global emissions, accounting for both market leakage as well as the relative emissions intensity of different sources of supply. We account for uncertainty in such leakage rates and the emissions intensities of the curtailed and substitute sources of supply through a Monte Carlo analysis, drawing on key supply and demand elasticities from the economics literature and emissions intensity estimates from the state-of-the-art OCI+ dataset on 586 oil and gas fields around the world.

We find that the emissions reductions from supply-side interventions are on the order of 40–50 percent of the gross emissions of each barrel curtailed, depending on the relative emissions intensity of the curtailed and substitute sources of supply. While the precise magnitude of the emissions reductions achieved span a considerable range, in general, our results imply that supply-side interventions are highly likely to reduce greenhouse gas emissions on net, with 98.68 percent of the scenarios we consider yielding net reductions.

Further, targeting supply-side interventions at highly emissions-intensive heavy oils is likely to have greater impact on emissions. For example, curtailing Canadian oil sands, which have an average intensity of 650 $kgCO_2e$/boe, is expected to yield emissions reductions of 350 $kgCO_2e$/boe (95 percent range: 170 to 520 $kgCO_2e$/boe) if leakage comes from production with market-average emissions intensity. However, if leaked production from the curtailment of oil sands is primarily in the form of more production in other oil sands fields, the emissions reductions are somewhat smaller: 280 $kgCO_2e$/boe (95% range: 90 to 460 $kgCO_2e$/boe). These central values suggest net emissions reductions roughly one-half as large as the emissions intensity of the curtailed source of supply, a result which varies depending on the sources of curtailed and substitute supply.

7. References

Asheim, Geir B., Taran Fæhn, Karine Nyborg, Mads Greaker, Cathrine Hagem, Bård Harstad, Michael O. Hoel, Diderik Lund, and Knut E. Rosendahl. 2019. "The Case for a Supply-Side Climate Treaty." *Science* 365 (6451): 325–27. **https://doi.org/10.1126/science.aax5011**.

Balke, Nathan S., and Stephen P. A. Brown. 2018. "Oil Supply Shocks and the US Economy: An Estimated DSGE Model." *Energy Policy* 116 (May): 357–72. **https://doi.org/10.1016/j.enpol.2018.02.027**.

Bodenstein, Martin, and Luca Guerrieri. 2011. "Oil Efficiency, Demand, and Prices: A Tale of Ups and Downs," October. **https://www.federalreserve.gov/econres/ifdp/oil-efficiency-demand-and-prices-a-tale-of-ups-and-downs.htm**.

Brons, Martijn, Peter Nijkamp, Eric Pels, and Piet Rietveld. 2008. "A Meta-Analysis of the Price Elasticity of Gasoline Demand. A SUR Approach." *Energy Economics* 30 (5): 2105–22. **https://doi.org/10.1016/j.eneco.2007.08.004**.

Brown, Stephen P A. 1998. "Global Warming Policy: Some Economic Implications." Economic Review, Fourth Quarter. Federal Reserve Bank of Dallas.

Brown, Stephen P A, Charles Mason, Alan Krupnick, and Jan Mares. 2014. "Crude Behavior: How Lifting the Export Ban Reduces Gasoline Prices in the United States." Issue Brief. Resources for the Future. **https://www.rff.org/publications/issue-briefs/crude-behavior-how-lifting-the-export-ban-reduces-gasoline-prices-in-the-united-states/**.

Cairns, Robert D., Graham A. Davis, and James L. Smith. 2021. "Letter to the Editor on Belfiori (EEEP Vol. 10(1)): Fossil Fuel Subsidies, the Green Paradox and the Fiscal Paradox." *Economics of Energy & Environmental Policy* 10 (1). **https://www.proquest.com/openview/21726c77481ec8ceca3d5e7aa4083533/1?pq-origsite=gscholar&cbl=2069346**.

Cairns, Robert D., and James L. Smith. 2019. "The Green Paradox, A Hotelling Cul de Sac." *Economics of Energy & Environmental Policy* 8 (2). **https://doi.org/10.5547/2160-5890.8.2.rcai**.

Caldara, Dario, Michele Cavallo, and Matteo Iacoviello. 2019. "Oil Price Elasticities and Oil Price Fluctuations." *Journal of Monetary Economics* 103 (May): 1–20. **https://doi.org/10.1016/j.jmoneco.2018.08.004**.

Coglianese, John, Lucas W. Davis, Lutz Kilian, and James H. Stock. 2017. "Anticipation, Tax Avoidance, and the Price Elasticity of Gasoline Demand." *Journal of Applied Econometrics* 32 (1): 1–15. **https://doi.org/10.1002/jae.2500**.

Cooper, John C.B. 2003. "Price Elasticity of Demand for Crude Oil: Estimates for 23 Countries." *OPEC Review* 27 (1): 1–8. **https://doi.org/10.1111/1468-0076.00121**.

Coyle, David, Jason DeBacker, and Richard Prisinzano. 2012. "Estimating the Supply and Demand of Gasoline Using Tax Data." *Energy Economics* 34 (1): 195–200. **https://doi.org/10.1016/j.eneco.2011.07.011**.

Cummings, Ronald G., David S. Brookshire, and William D. Schulze. 1986. *Valuing Environmental Goods: An Assessment of the Contingent Valuation Method*. Rowman & Allanheld.

Dahl, Carol A. 2012. "Measuring Global Gasoline and Diesel Price and Income Elasticities." *Energy Policy*, Modeling Transport (Energy) Demand and Policies, 41 (February): 2–13. **https://doi.org/10.1016/j.enpol.2010.11.055**.

———. 2014. “What Do We Know about Gasoline Demand Elasticities?” Colorado School of Mines Working Papers, November. **https://ideas.repec.org//p/mns/wpaper/wp201411.html**.

Dahl, Carol, and Thomas Sterner. 1991. “Analysing Gasoline Demand Elasticities: A Survey.” *Energy Economics* 13 (3): 203–10. **https://doi.org/10.1016/0140-9883(91)90021-Q**.

Erickson, Peter, Michael Lazarus, and Georgia Piggot. 2018. “Limiting Fossil Fuel Production as the next Big Step in Climate Policy.” *Nature Climate Change* 8 (12): 1037–43. **https://doi.org/10.1038/s41558-018-0337-0**.

Gately, Dermot, and Hiliard G. Huntington. 2002. “The Asymmetric Effects of Changes in Price and Income on Energy and Oil Demand.” *The Energy Journal* 23 (1). **https://doi.org/10.5547/ISSN0195-6574-EJ-Vol23-No1-2**.

Gilbert, Ben, and Gavin Roberts. 2020. “Drill-Bit Parity: Supply-Side Links in Oil and Gas Markets.” *Journal of the Association of Environmental and Resource Economists* 7 (4): 619–58. **https://doi.org/10.1086/708160**.

Goodwin, Phil, Joyce Dargay, and Mark Hanly. 2004. “Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review.” *Transport Reviews* 24 (3): 275–92. **https://doi.org/10.1080/0144164042000181725**.

Gordon, Deborah. 2021. *No Standard Oil: Managing Abundant Petroleum in a Warming World*. Oxford University Press.

———. 2023. “We Need to Talk About Methane.” In *The Fletcher Forum of World Affairs*, 47:5–10. The Fletcher School of Law and Diplomacy.

Gordon, Deborah, Eugene Perk Han Tan, and Jeffrey Feldman. 2016. “Changing Oils, Changing Management.” *Journal of Industrial Ecology* 20 (4): 673–75.

Graham, Daniel J., and Stephen Glaister. 2002. “The Demand for Automobile Fuel: A Survey of Elasticities.” *Journal of Transport Economics and Policy* 36 (1): 1–25.

Greene, David L., and Paul Newsome Leiby. 2006. “The Oil Security Metrics Model: A Tool for Evaluating the Prospective Oil Security Benefits of DOE’s Energy Efficiency and Renewable Energy R&D Programs.” ORNL/TM-2006/505. Oak Ridge National Lab. **https://doi.org/10.2172/930748**.

Hamilton, James D. 2009. “Causes and Consequences of the Oil Shock of 2007–08.” *Brookings Papers on Economic Activity* 2009: 215–61.

Handler, Brad, and Morgan Bazilian. 2021. “Exploring Carbon Retirement Portfolios.” *Payne Commentary Series,* Colorado School of Mines, July. **https://repository.mines.edu/handle/11124/14109**.

Harstad, Bård. 2012. “Buy Coal! A Case for Supply-Side Environmental Policy.” *Journal of Political Economy* 120 (1): 77–115. **https://doi.org/10.1086/665405**.

Hausman, Jerry A., and Whitney K. Newey. 1995. “Nonparametric Estimation of Exact Consumers Surplus and Deadweight Loss.” *Econometrica* 63 (6): 1445–76. **https://doi.org/10.2307/2171777**.

Hotelling, Harold. 1931. “The Economics of Exhaustible Resources.” *Journal of Political Economy* 39 (2): 137–75.

Huntington, Hillard G. 1994. “Oil Price Forecasting in the 1980s: What Went Wrong?” *The Energy Journal* 15 (2). **https://doi.org/10.5547/ISSN0195-6574-EJ-Vol15-No2-1**.

Huntington, Hillard G., James J. Barrios, and Vipin Arora. 2019. “Review of Key International Demand Elasticities for Major Industrializing Economies.” *Energy Policy* 133 (October): 110878. **https://doi.org/10.1016/j.enpol.2019.110878**.

Jing, Liang, Hassan M. El-Houjeiri, Jean-Christophe Monfort, Adam R. Brandt, Mohammad S. Masnadi, Deborah Gordon, and Joule A. Bergerson. 2020. "Carbon Intensity of Global Crude Oil Refining and Mitigation Potential." *Nature Climate Change* 10 (6): 526–32. **https://doi.org/10.1038/s41558-020-0775-3**.

Kilian, Lutz, and Daniel P. Murphy. 2014. "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil." *Journal of Applied Econometrics* 29 (3): 454–78. **https://doi.org/10.1002/jae.2322**.

Knittel, Christopher, and Shinsuke Tanaka. 2019. "Driving Behavior and the Price of Gasoline: Evidence from Fueling-Level Micro Data." w26488. National Bureau of Economic Research. **https://doi.org/10.3386/w26488**.

Krautkraemer, Jeffrey A. 1998. "Nonrenewable Resource Scarcity." *Journal of Economic Literature* 36 (4): 2065–2107.

Krichene, Noureddine. 2002. "World Crude Oil and Natural Gas: A Demand and Supply Model." *Energy Economics* 24 (6): 557–76. **https://doi.org/10.1016/S0140-9883(02)00061-0**.

Krupnick, Alan, Richard Morgenstern, Nathan Balke, Stephen P A Brown, and Ana María Herrera. 2017. "Oil Supply Shocks, US Gross Domestic Product, and the Oil Security Premium." Report. Resources for the Future.

Lazarus, Michael, and Harro van Asselt. 2018. "Fossil Fuel Supply and Climate Policy: Exploring the Road Less Taken." *Climatic Change* 150 (1): 1–13. **https://doi.org/10.1007/s10584-018-2266-3**.

Levin, Laurence, Matthew S. Lewis, and Frank A. Wolak. 2017. "High Frequency Evidence on the Demand for Gasoline." *American Economic Journal: Economic Policy* 9 (3): 314–47. **https://doi.org/10.1257/pol.20140093**.

Lin, C.-Y. Cynthia, and Jieyin (Jean) Zeng. 2013. "The Elasticity of Demand for Gasoline in China." *Energy Policy* 59 (August): 189–97. **https://doi.org/10.1016/j.enpol.2013.03.020**.

Masnadi, Mohammad S., Hassan M. El-Houjeiri, Dominik Schunack, Yunpo Li, Jacob G. Englander, Alhassan Badahdah, Jean-Christophe Monfort, et al. 2018. "Global Carbon Intensity of Crude Oil Production." *Science* 361 (6405): 851–53. **https://doi.org/10.1126/science.aar6859**.

Mason, Charles F., and Gavin Roberts. 2018. "Price Elasticity of Supply and Productivity: An Analysis of Natural Gas Wells in Wyoming." *The Energy Journal* 39 (01). **https://doi.org/10.5547/01956574.39.SI1.cmas**.

National Academies of Sciences, Engineering, and Medicine. 2017. *Valuing Climate Changes: Updating Estimation of the Social Cost of Carbon Dioxide*. Washington, DC: National Academies Press. **https://doi.org/10.17226/24651**.

National Academies of Sciences, Engineering, and Medicine. 2017. *Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide*. Washington, DC: National Academies Press.

Newell, Peter, and Andrew Simms. 2020. "Towards a Fossil Fuel Non-Proliferation Treaty." *Climate Policy* 20 (8): 1043–54. **https://doi.org/10.1080/14693062.2019.1636759**.

Newell, Richard G., and Brian C. Prest. 2019. "The Unconventional Oil Supply Boom: Aggregate Price Response from Microdata." *The Energy Journal* 40 (3). **https://doi.org/10.5547/01956574.40.3.rnew**.

Newell, Richard G., Brian C. Prest, and Ashley B. Vissing. 2019. "Trophy Hunting versus Manufacturing Energy: The Price Responsiveness of Shale Gas." *Journal of the Association of Environmental and Resource Economists* 6 (2): 391–431. **https://doi.org/10.1086/701531**.

Ploeg, Frederick van der, and Armon Rezai. 2020. "Stranded Assets in the Transition to a Carbon-Free Economy." *Annual Review of Resource Economics* 12 (1): 281–98. **https://doi.org/10.1146/annurev-resource-110519-040938**.

Prest, Brian C. 2021. "Supply-Side Reforms to Oil and Gas Production on Federal Lands: Modeling the Implications for Climate Emissions, Revenues, and Production Shifts." Resources for the Future. **https://www.rff.org/publications/working-papers/supply-side-reforms-oil-and-gas-production-federal-lands/**.

———. 2022a. "Partners, Not Rivals: The Power of Parallel Supply-Side and Demand-Side Climate Policy." Resources for the Future. **https://www.rff.org/publications/reports/partners-not-rivals-the-power-of-parallel-supply-side-and-demand-side-climate-policy/**.

———. 2022b. "Supply-Side Reforms to Oil and Gas Production on Federal Lands: Modeling the Implications for CO2 Emissions, Federal Revenues, and Leakage." *Journal of the Association of Environmental and Resource Economists* 9 (4): 681–720. **https://doi.org/10.1086/718963**.

Prest, Brian C., and James H. Stock. 2021. "Climate Royalty Surcharges." Working Paper. Working Paper Series. National Bureau of Economic Research. **https://doi.org/10.3386/w28564**.

RMI. 2022. "Oil Climate Index plus Gas v.1.0." Oil Climate Index plus Gas. 2022. **https://ociplus.rmi.org/**.

Serletis, Apostolos, Govinda R. Timilsina, and Olexandr Vasetsky. 2010. "Interfuel Substitution in the United States." *Energy Economics* 32 (3): 737–45. **https://doi.org/10.1016/j.eneco.2010.01.013**.

Slade, Margaret E., and Henry Thille. 2009. "Whither Hotelling: Tests of the Theory of Exhaustible Resources." *Annual Review of Resource Economics* 1 (1): 239–60. **https://doi.org/10.1146/annurev.resource.050708.144223**.

Yatchew, Adonis, and Joungyeo Angela No. 2001. "Household Gasoline Demand in Canada." *Econometrica* 69 (6): 1697–1709.

Appendix

A.1. Sensitivity Approach to Emissions Intensity Calculation

This appendix presents a sensitivity analysis under the alternative assumption that all fields within a given category contribute to curtailed or substitute supply in proportion to their production, rather than the field-specific sampling of emissions intensity used in our main results. This sensitivity analysis focuses on the 100-year GWP to correspond with the tables in the main results. This effectively replaces the field-specific distribution of emissions intensities with their production-weighted average. The results are shown in Tables A1–A4, which are analogous to Tables 4–7 in the main text.

Comparing the average net emissions changes Table A1 to Table 4 and Table A2 to Table 5, this alternative assumption has essentially no effect on the average estimates, which only differ very slightly due to randomness in the Monte Carlo sampling. But by restricting the uncertainty range in emissions intensity, it reduces the spread in net emissions impacts, which is now nearly entirely driven by uncertainty in the leakage rate. This yields narrower uncertainty ranges in Tables A3 and A4 as compared to Tables 6 and 7 and higher certainty of emissions reductions. Among the curtailed sources considered in Table A1, we do not find even a single draw featuring net emission increases. Across our 1.53 million simulations using the 100-year GWP, we find less than 0.1 percent of draws yielding net emissions increases. These draws represent cases with high draws of the leakage rate (uniformly over 77 percent) and assume that low emissive curtailed categories (primarily light oil) are substituted by highly emissive ones to very high ones (primarily oil sands), which seems like a relatively implausible assumption.

Table A1. Net Emissions Change per Curtailed Barrel when Substitute Production's Emissions Intensity Reflects All Fields or Same as Curtailed Source, Not Sampling from Field-level Emissions Intensities

Substitute production from:	**All sources (market average)**				**Same sources**			
	Average net emissions change (kgCO$_2$e/boe)		*Share of draws with emissions reductions (%)*		*Average net emissions change (kgCO$_2$e/boe)*		*Share of draws with emissions reductions (%)*	
Curtailed source	**100-year GWP**	**20-year GWP**	**100-year GWP**	**20-year GWP**	**100-year GWP**	**20-year GWP**	**100-year GWP**	**20-year GWP**
All (market average)	-220	-250	100	100	-220	-250	100	100
North America	-240	-280	100	100	-230	-260	100	100
Oil sands	-350	-360	100	100	-280	-300	100	100
Permian Basin	-230	-350	100	100	-230	-290	100	100
Light oil	-200	-240	100	100	-210	-240	100	100
Medium oil	-220	-230	100	100	-220	-240	100	100
Heavy oil	-320	-340	100	100	-260	-290	100	100
Sweet oil	-240	-270	100	100	-230	-260	100	100
Sour oil	-220	-250	100	100	-220	-250	100	100

Table A2. Average Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 100-Year GWP, Not Sampling Intensities

Change in CO2e emissions per barrel curtailed (kg/boe)

Substitute Source

Curtailed Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-220	-150	-220	-230	-210	-190	-250	-220	-220	-240	-230	-200	-230	-230	-170	-210	-220
North America	-240	-170	-240	-250	-230	-210	-270	-240	-240	-260	-250	-220	-260	-250	-190	-230	-240
Oil Sands	-350	-280	-350	-360	-340	-320	-380	-350	-350	-370	-360	-330	-360	-360	-300	-340	-350
Permian Basin	-230	-160	-230	-240	-220	-200	-250	-220	-220	-250	-230	-200	-240	-230	-180	-220	-230
Light Oil	-200	-130	-200	-210	-190	-170	-230	-200	-200	-220	-210	-180	-210	-210	-150	-190	-200
Medium Oil	-220	-140	-210	-220	-200	-190	-240	-210	-210	-230	-220	-190	-230	-220	-160	-210	-220
Heavy Oil	-320	-240	-310	-320	-300	-290	-340	-310	-310	-330	-320	-290	-330	-320	-260	-310	-320
Sweet Oil	-240	-170	-240	-250	-230	-210	-270	-240	-240	-260	-250	-220	-260	-250	-190	-230	-240
Sour Oil	-220	-150	-220	-230	-210	-190	-250	-220	-220	-240	-230	-200	-230	-230	-170	-210	-220

Δ Emissions (CO2e): -150, -200, -250, -300, -350

Table A3. 97.5th Percentile of Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 100-Year GWP, Not Sampling Intensities

Change in CO2e emissions per barrel curtailed (kg/boe)

Substitute Source

Curtailed Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-110	-10	-110	-120	-90	-70	-140	-100	-100	-130	-120	-80	-130	-110	-40	-90	-110
North America	-130	-30	-130	-140	-110	-90	-170	-120	-120	-160	-140	-100	-150	-140	-60	-120	-130
Oil Sands	-240	-140	-240	-250	-220	-200	-270	-230	-230	-260	-250	-210	-260	-240	-170	-220	-240
Permian Basin	-120	-10	-110	-120	-100	-70	-150	-110	-110	-140	-120	-80	-130	-120	-40	-100	-120
Light Oil	-90	10	-90	-100	-70	-50	-120	-80	-80	-110	-100	-60	-110	-90	-20	-70	-90
Medium Oil	-100	0	-100	-110	-90	-60	-140	-90	-90	-130	-110	-70	-120	-110	-30	-90	-100
Heavy Oil	-200	-100	-200	-210	-190	-160	-240	-190	-190	-230	-210	-170	-220	-210	-130	-190	-200
Sweet Oil	-130	-30	-130	-140	-110	-90	-160	-120	-120	-160	-140	-100	-150	-140	-60	-110	-130
Sour Oil	-110	-10	-110	-120	-90	-70	-140	-100	-100	-130	-120	-80	-130	-120	-40	-90	-110

Δ Emissions (CO2e): 0, -100, -200

Table A4. 2.5th Percentile of Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 100-Year GWP, Not Sampling Intensities

Change in CO2e emissions per barrel curtailed (kg/boe)

Substitute Source

Curtailed Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-330	-280	-330	-330	-320	-310	-350	-330	-330	-340	-330	-310	-340	-330	-300	-320	-330
North America	-350	-310	-350	-360	-340	-330	-370	-350	-350	-360	-360	-340	-360	-350	-320	-340	-350
Oil Sands	-460	-410	-460	-460	-450	-440	-480	-460	-450	-470	-460	-440	-470	-460	-430	-450	-460
Permian Basin	-340	-290	-330	-340	-330	-320	-350	-330	-330	-350	-340	-320	-340	-340	-300	-330	-340
Light Oil	-310	-260	-310	-310	-300	-290	-330	-310	-310	-320	-310	-290	-320	-310	-280	-300	-310
Medium Oil	-320	-280	-320	-330	-320	-310	-340	-320	-320	-340	-330	-310	-330	-330	-290	-320	-320
Heavy Oil	-420	-380	-420	-430	-420	-410	-440	-420	-420	-440	-430	-410	-430	-430	-390	-420	-420
Sweet Oil	-350	-300	-350	-360	-340	-330	-370	-350	-350	-360	-350	-340	-360	-350	-320	-340	-350
Sour Oil	-330	-280	-330	-330	-320	-310	-350	-330	-330	-340	-330	-310	-340	-330	-300	-320	-330

Δ Emissions (CO2e): -300, -350, -400, -450

A.2. Detailed Results under a 20-Year GWP

Table A5. Average Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 20-Year GWP

Change in CO2e emissions per barrel curtailed (kg/boe)

Substitute Source

Curtailed Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-250	-190	-200	-260	-230	-220	-290	-230	-240	-280	-260	-230	-260	-260	-200	-240	-250
North America	-280	-220	-230	-290	-270	-250	-320	-260	-270	-310	-290	-270	-290	-290	-240	-270	-290
Oil Sands	-360	-300	-310	-370	-340	-330	-400	-340	-350	-390	-370	-340	-370	-370	-310	-350	-360
Permian Basin	-350	-280	-290	-360	-330	-320	-380	-330	-330	-370	-350	-330	-350	-360	-300	-330	-350
Light Oil	-240	-170	-180	-250	-220	-210	-270	-220	-220	-260	-240	-220	-250	-250	-190	-220	-240
Medium Oil	-230	-170	-180	-240	-210	-200	-270	-210	-220	-260	-240	-210	-240	-240	-180	-220	-240
Heavy Oil	-340	-270	-280	-340	-320	-310	-370	-310	-320	-360	-340	-320	-340	-350	-290	-320	-340
Sweet Oil	-270	-210	-220	-280	-250	-240	-310	-250	-260	-300	-280	-250	-280	-280	-220	-260	-280
Sour Oil	-250	-180	-190	-250	-230	-220	-280	-220	-230	-270	-250	-230	-250	-260	-200	-230	-250

Δ Emissions (CO2e): -200, -250, -300, -350

Table A6. 97.5th Percentile of Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 20-Year GWP

Change in CO_2e emissions per barrel curtailed (kg/boe)

Curtailed Source \ Substitute Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-20	30	20	-40	0	30	-100	0	-10	-80	-50	0	-40	-50	40	-10	-30
North America	-60	10	-10	-70	-20	0	-130	-30	-50	-100	-70	-40	-60	-80	10	-40	-60
Oil Sands	-160	-100	-120	-170	-130	-100	-230	-130	-150	-210	-170	-140	-170	-190	-90	-140	-160
Permian Basin	-160	-100	-140	-170	-130	-90	-240	-140	-150	-210	-180	-140	-170	-190	-90	-140	-160
Light Oil	-10	50	20	-20	10	40	-90	10	0	-60	-40	10	-20	-40	50	10	-20
Medium Oil	-20	40	20	-30	10	40	-90	0	-10	-70	-40	0	-30	-50	50	0	-20
Heavy Oil	-100	-40	-60	-120	-80	-50	-180	-80	-100	-150	-120	-90	-110	-130	-40	-90	-110
Sweet Oil	-40	20	0	-60	-20	10	-110	-20	-20	-90	-60	-20	-60	-70	20	-20	-50
Sour Oil	-20	40	20	-30	10	40	-90	10	0	-70	-40	0	-30	-50	50	0	-20

Δ Emissions (CO_2e): 50, 0, -50, -100, -150, -200

Table A7. 2.5th Percentile of Net Emissions Impacts of One Barrel of Curtailed Supply, by Curtailed Sources (rows) and Substitute Sources (columns), 20-Year GWP

Change in CO_2e emissions per barrel curtailed (kg/boe)

Curtailed Source \ Substitute Source	Market Average	Oil Sands	Permian Basin	OPEC	North America	Central/South America and Caribbean	Europe	North Africa	Other Africa	Middle East	Russia and Central Asia	East/Southeast Asia	Light Oil	Medium Oil	Heavy Oil	Sweet Oil	Sour Oil
Market Average	-500	-440	-440	-510	-490	-480	-520	-480	-480	-520	-500	-480	-510	-510	-460	-490	-510
North America	-510	-460	-450	-510	-500	-490	-530	-500	-490	-520	-510	-490	-520	-510	-470	-500	-510
Oil Sands	-540	-490	-490	-550	-520	-520	-560	-520	-520	-550	-540	-530	-540	-540	-500	-530	-540
Permian Basin	-490	-440	-440	-490	-480	-470	-500	-470	-470	-490	-480	-470	-490	-490	-460	-480	-490
Light Oil	-470	-420	-420	-480	-460	-450	-490	-450	-460	-480	-470	-450	-480	-470	-430	-460	-470
Medium Oil	-430	-370	-380	-430	-410	-410	-450	-410	-410	-440	-430	-410	-430	-430	-390	-420	-430
Heavy Oil	-560	-500	-500	-560	-540	-540	-580	-540	-540	-570	-550	-540	-560	-560	-520	-550	-560
Sweet Oil	-520	-460	-460	-520	-500	-490	-540	-490	-490	-530	-510	-490	-520	-520	-470	-500	-520
Sour Oil	-490	-440	-440	-490	-480	-470	-520	-470	-480	-510	-490	-470	-490	-500	-450	-480	-490

Δ Emissions (CO_2e): -400, -450, -500, -550

A.3. The Effect of Dynamics

The model considered in this study is static, but more generally oil is a storable commodity, which introduces relevant intertemporal dynamics. This is important when considering whether to use short-run or long-run values for the key inputs into equations (7) and (8), including supply and demand elasticities and the emissions intensities of marginal supply. Extending the model to be dynamic reveals a conceptually similar result to those found in the main equations and demonstrates that the relevant input parameters should be based on long-run values. Long-run elasticities tend to be larger than short-run ones, which has ambiguous effects on the leakage rate. However, it may be reasonable to expect the long-run marginal source of supply to be cleaner than the short-run value, given international goals to cut methane emissions over time.

In this appendix, we derive results analogous to equations (7) and (8) but in the framework of a dynamic model, where supply and demand are now additionally indexed by time, t. Now, assuming oil can be stored for future use through inventories, the market-clearing condition is that the sum of intertemporal supply and demand, including the barrel withheld today (now indexed by $t = 1$), balance:

$$-\tilde{q}_1 + \sum_{i=1}^{N}\sum_{t=1}^{T} q_{i,t,S}(p_t) = \sum_{i=1}^{N}\sum_{t=1}^{T} q_{i,t,D}(p_t).$$

Differentiating the market clearing condition with respect to $\tilde{q}$:

$$-1 + \sum_{i=1}^{N}\sum_{t=1}^{T} q'_{i,t,S}(p_t)\frac{dp_t}{d\tilde{q}} = \sum_{i=1}^{N}\sum_{t=1}^{T} q'_{i,t,D}(p)\frac{dp_t}{d\tilde{q}}$$

Solving for the price effect, $dp_t/d\tilde{q}$, yields

$$\frac{dp_t}{d\tilde{q}} = \frac{1}{\sum_{i=1}^{N}\sum_{t=1}^{T} q'_{i,t,S}(p_t) - q'_{i,t,D}(p)}$$

This is exactly the same form as the price effect in the main case, except that the values that matter are the sum of marginal supply and demand across both region and time. The effect on total global supply and demand in year t, $Q_{t,S} = \sum_{i=1}^{N} q'_{i,t,S}(p)$ and $Q_{t,S} = \sum_{i=1}^{N} q'_{i,t,S}(p)$, are

$$\frac{dQ_{t,S}}{d\tilde{q}} = \frac{\sum_{i=1}^{N} q'_{i,t,S}(p_t)}{\sum_{i=1}^{N}\sum_{t=1}^{T} q'_{i,t,S}(p_t) - q'_{i,t,D}(p)}$$

$$\frac{dQ_{t,D}}{d\tilde{q}} = \frac{\sum_{i=1}^{N} q'_{i,t,D}(p)}{\sum_{i=1}^{N}\sum_{t=1}^{T} q'_{i,t,S}(p_t) - q'_{i,t,D}(p)}$$

Note that now the impacts on global supply and demand are the same in the long run, but they need not be the same in any given year. Just as in the static model, the impact on supply and regional demand need not be the same for every individual region.

However, the cumulative effect on global oil consumption is given by the sum of annual consumption over time,

$$\frac{dQ_D}{d\tilde{q}} = \sum_{t=1}^{T} \frac{dQ_{t,D}}{d\tilde{q}} = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} q'_{i,t,D}(p_t)}{\sum_{i=1}^{N} \sum_{t=1}^{T} q'_{i,t,S}(p_t) - q'_{i,t,D}(p_t)}$$

As in the static model, this equation can be further simplified to be a function of supply and demand elasticities. First, denote region i's supply and demand time-t elasticities as $\eta_{i,t}$ and $\varepsilon_{i,t}$:

$$\eta_{i,t} = q'_{i,t,S}(p_t) \frac{p_t}{q_{i,t,S}} \Rightarrow q'_{i,t,S}(p_t) = \eta_{i,t} \frac{q_{i,t,S}}{p_t}$$

$$\varepsilon_{i,t} = q'_{i,t,D}(p_t) \frac{p_t}{q_{i,t,D}} \Rightarrow q'_{i,t,D}(p_t) = \varepsilon_{i,t} \frac{q_{i,t,D}}{p_t}$$

Plugging these two into the previous equation and further multiplying and dividing by total global supply and demand (which are the same, $Q_S = -\tilde{q} + \sum_{i,t} q_{i,t,S}(p_t) = \sum_{i,t} q_{i,t,D}(p_t) = Q_D = Q$) yields

$$\frac{dQ_D}{d\tilde{q}} = \frac{\sum_{t=1}^{T} p_t^{-1} \sum_{i=1}^{N} w_{i,t,D}\varepsilon_{i,t}}{\sum_{t=1}^{T} p_t^{-1} \sum_{i=1}^{N} w_{i,t,S}\eta_{i,t} - w_{i,t,D}\varepsilon_{i,t}}$$

where $w_{i,t,D} = q_{i,t,D}/Q_D$ and $w_{i,S} = q_{i,t,S}/Q_S$ are weights representing the share of cumulative demand and supply coming from region i in year t. If the price follows a no-arbitrage condition and rises annually at the rate of interest, denoted r (which is also consistent with a Hotelling price path), as in $p_t = p_1(1+r)^{t-1}$, then the p_t^{-1} terms are all replaced by $(1+r)^{-(t-1)}$, as follows:

$$\frac{dQ_D}{d\tilde{q}} = \frac{\sum_{t=1}^{T} (1+r)^{-(t-1)} \sum_{i=1}^{N} w_{i,t,D}\varepsilon_{i,t}}{\sum_{t=1}^{T} (1+r)^{-(t-1)} \sum_{i=1}^{N} w_{i,t,S}\eta_{i,t} - w_{i,t,D}\varepsilon_{i,t}}$$

This is conceptually analogous to equation (4) but instead of production-weighted average elasticities, they are temporally discounted production-weighted average elasticities. As the discount rate approaches zero, this collapses to using intertemporally and regionally averaged elasticity values, as in

$$\frac{dQ_D}{d\tilde{q}} = \frac{\overline{\varepsilon}}{\overline{\eta} - \overline{\varepsilon}}$$

where now $\overline{\varepsilon} = \sum_{t=1}^{T} \sum_{i=1}^{N} w_{i,t,D}\varepsilon_i$ and $\overline{\eta} = \sum_{t=1}^{T} \sum_{i=1}^{N} w_{i,t,S}\eta_i$. This is the same result as in the static model, which holds when $r = 0$ or $T = 1$ (in which the dynamic model collapses to the static one). When $r > 0$, we should place somewhat greater weight on near-term supply and demand elasticities.

Note also that we can write this as a within-year regional weighted average, which is then weighted by year t's contribution to total supply and demand over time.

$$\frac{dQ_D}{d\tilde{q}} = \frac{\sum_{t=1}^{T}(1+r)^{-(t-1)} \frac{Q_{t,D}}{Q_D} \sum_{i=1}^{N} \frac{q_{i,t,D}}{Q_{t,D}} \varepsilon_i}{\sum_{t=1}^{T}(1+r)^{-(t-1)} \left[\frac{Q_{t,S}}{Q_S} \sum_{i=1}^{N} \frac{q_{i,t,S}}{Q_{t,S}} \eta_i - \frac{Q_{t,D}}{Q_D} \sum_{i=1}^{N} \frac{q_{i,t,D}}{Q_{t,D}} \varepsilon_i\right]}$$

Denoting the emissions intensity of region i's oil in period t as $e_{i,t}$, cumulative global emissions are given by

$$E = -e_{\tilde{q}} + \sum_{i,t} e_{i,t} q_{i,t,S}(p).$$

The impact of curtailed production on overall emissions are then

$$\frac{dE}{d\tilde{q}} = -e_{\tilde{q}} + \sum_{i,t} e_{i,t} q'_{i,t,S}(p_t) \frac{dp_t}{d\tilde{q}}.$$

This can be re-written in an analogous form to equation (7) as

$$\frac{dE}{d\tilde{q}} = -e_{\tilde{q}} + \overline{e}L,$$

Where now the weighted average emissions intensity and leakage rate values reflect their intertemporal analogues:

$$\overline{e} = \frac{1}{\sum_{i,t} q'_{i,t,S}(p_t) \frac{dp_t}{d\tilde{q}}} \sum_{i,t} e_{i,t} q'_{i,t,S}(p_t) \frac{dp_t}{d\tilde{q}}$$

and

$$L = \sum_{i,t} q'_{i,t,S}(p_t) \frac{dp_t}{d\tilde{q}}.$$

These results thus mirror the one-period case in the main text, indicating that the results from the simple one-period model nonetheless extend to a T-period case.