

Commentary

The Short-run and Long-run Effects of Covid-19 on Energy and the Environment

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We explore how the short-run effects of Covid-19 in reducing CO₂ and local air

pollutant emissions can easily be outweighed by the long-run effects of a slowing of clean energy innovation. Focusing on the United States, we show that in the short run, Covid-19 has reduced consumption of jet fuel and gasoline dramatically, by 50% and 30% respectively, while electricity demand has declined by less than 10%. CO₂ emissions have declined by 15%, while local air pollutants have also declined, saving about 200 lives per month. However, there could be a deep impact on long-run innovation in clean energy, leading to an additional 2,500 million metric tons (MMT) CO₂ cumulatively and 40 deaths per month on average from now to 2035. Even pushing back renewable electricity generation investments by one year would outweigh the emission reductions and avoided deaths from March to June of 2020. The policy response will determine how Covid-19 ultimately influences the future path of emissions.

The Covid-19 pandemic has upended the world. Any time there is a major change in economic activity, there will be implications for the environment. We take a macro-level perspective on the environmental effects of Covid-19 in both the short run and long run. In the short run, there has been an emptying of our roads, skies, factories, and commercial office buildings, reducing emissions and clearing the air, but at a dramatic cost to overall well-being and the economy. In the long run, the implications of Covid-19 are deeply uncertain. We present two illustrative thought experiments to provide insight into the long-run environmental effects of the pandemic, drawing upon evidence from previous economic shocks. These insights on long-run effects provide guidance for policy to mitigate potential long-run negative implications.

In the short run, the reduced emissions from Covid-19 are substantial, but the

health benefits from the cleaner air do not come close to outweighing the direct loss of life from the pandemic in the United States. If the threat from the pandemic subsides relatively quickly and the economy rebounds, there should be few long-run implications. However, if the struggle against Covid-19 leads to a persistent global recession, there is a real long-run threat to the adoption of clean technology, which could even outweigh any short-run “silver lining” environmental benefits due to both Covid-19 and the recession. Whether this occurs will depend on the policy response.

Our focus is on the United States, but our main findings could apply more broadly across much of the developed world, including many European countries. Fundamentally, it is the *global* response to the pandemic that will determine the long-run effects.

Short-run Effects

Covid-19 has directly led all of the world’s largest economies to come to a near-standstill, with widespread shutdowns and restrictions remaining even when shutdowns have been relaxed. Conferences, gatherings, and travel of all types have been deeply curtailed. Large swaths of the economy have been affected. One silver lining in this devastating circumstance is that it has led to reductions in emissions, including greenhouse gas emissions and local air pollutant emissions, due to the decline in the demand for energy.

We explore these reductions by comparing energy consumption in late March to June 7, 2020, after the pandemic began, to consumption before the shutdowns. We predict energy consumption during the shutdowns by controlling for the impacts of weather, renewable generation, and seasonal patterns (see [Supplemental Information](#) for details).

[Figure 1](#) displays the results. (A) shows that the largest percentage declines in energy consumption are from jet fuel and gasoline, with reductions of 50% and 30% that appear persistent (see C for overall oil consumption over time), in line with estimates of personal vehicle travel.¹ In contrast, most other categories have observed smaller reductions. Use of natural gas in residential and commercial buildings has declined by almost 20%, while overall electricity demand (and demand for coal-fired electricity) has declined by less than 10%. While commercial and industrial electricity use may have been affected by the shutdowns, some of the decline was offset by increased residential electricity demand from people staying at home, and by June, electricity consumption has largely returned to the trend (D).²

(B) illustrates the declines in CO₂ emissions corresponding to the reductions in energy use. The largest reductions are in gasoline, but the natural gas decline leads to nearly as large a reduction in CO₂ emissions as for jet fuel. These reductions imply a roughly 15% total reduction in daily CO₂ emissions, which will be the largest annual percentage decline for the United States in recorded history should this drop continue. For context, the decline in CO₂ emissions is in line with the declines laid out in the 2025 U.S. Nationally Determined Contributions under the Paris Agreement, but the sources of the decrease are entirely different than would be expected under an optimal emissions reduction strategy focusing on both behavioral and structural changes to the energy system. Other estimates tend to focus on the world rather than the United States or do not cover all fuels. While estimates for the United States cover a very wide range, our finding is similar to the 17% global decline in CO₂ emissions for the period through April 2020.³

The reductions in energy demand are also reducing emissions of local air pollutants that affect near-term human health. We calculate the reductions in SO₂, nitrogen oxides (NO_x), volatile organic compounds (VOCs), and particulate matter (PM) emissions (see [Supplemental Information](#) for details). The reductions range from 12% for NO_x to 1% for PM. We estimate that the shutdowns save about 200 lives per month, primarily driven by the lower PM emissions from transportation. Of course, these are small consolations for the over 100,000 confirmed deaths due to Covid-19 before June 2020.

Along with the reduction in driving from the shutdowns has also come a decline in traffic accidents and congestion. For example, the number of crashes over the period of March 13, 2020 to early April are less than half of the previous year, although fatal crashes did not decline by as much, perhaps due to the remaining vehicles being driven longer (see [Supplemental Information](#)).

There is also a more subtle impact due to the shutdowns: most investment in the low-carbon transition has come to a halt. Global electric vehicle sales are projected to decline by 43% in 2020⁴ due to the plummeting auto sales overall combined with low gasoline prices. New residential rooftop solar and storage installations have plummeted, as have energy efficiency audits. Even at the utility scale, renewable developments have been slowed. Overall clean energy jobs dropped by almost 600,000 by the end of April.⁵ While these are short-run impacts, they may have long-run effects.

Long-run Effects

While the short-run effects of Covid-19 are already clear, the long-run effects are highly uncertain. How the pandemic influences emissions and health outcomes in the long run depends on how long it takes to bring the pandemic under control and whether

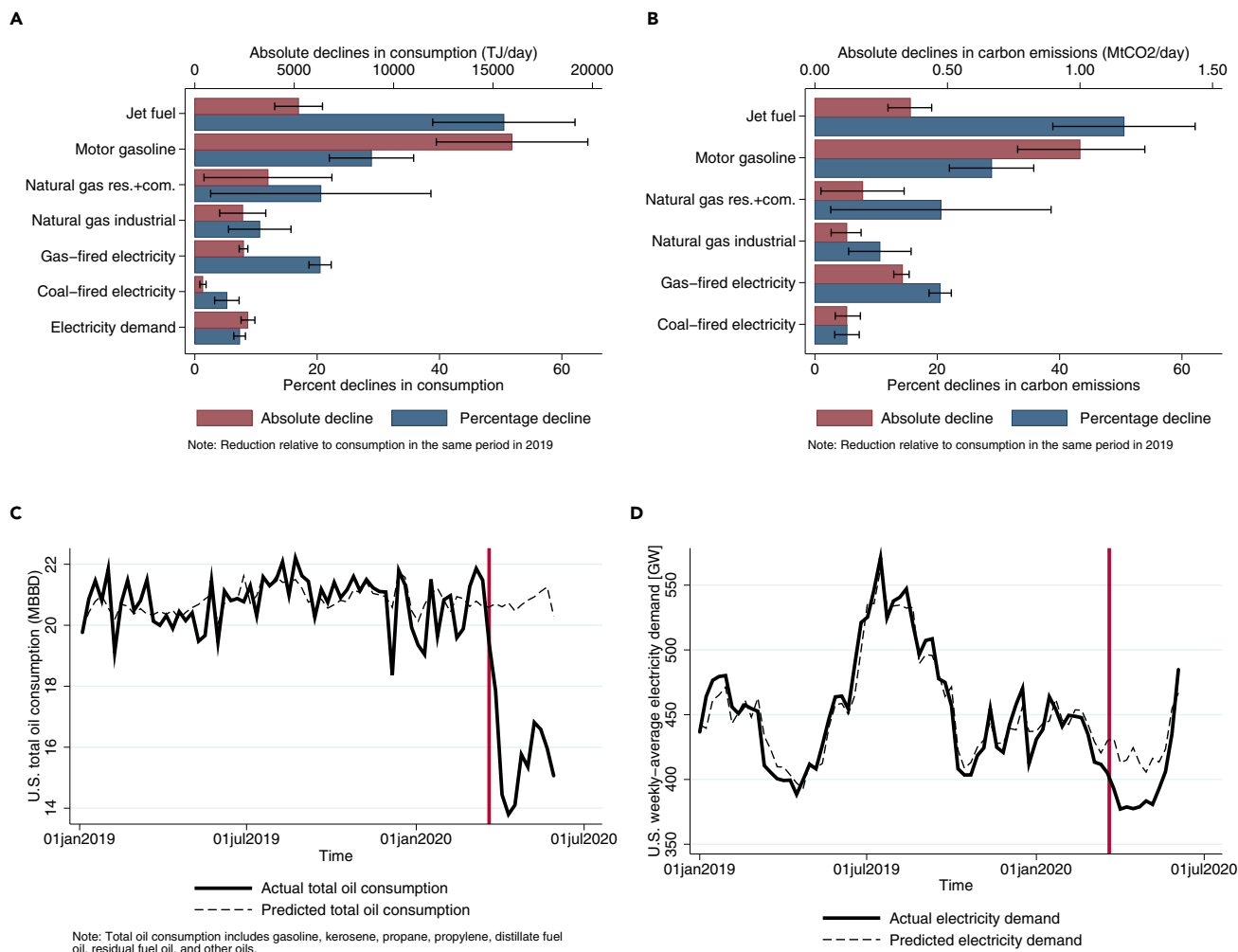


Figure 1. Declines in Energy Consumption and Emissions Due to Covid-19

Short-run reductions in energy use (terajoule [TJ]/day) and emissions (metric tons CO₂/day) due to Covid-19 in the United States. Note: 99% confidence intervals shown in (A) and (B).

the pandemic leads to a persistent economic contraction. To develop insight in the presence of such deep uncertainty, we consider two illustrative “thought experiments” that roughly bound what might happen, while emphasizing that the true outcome may fall in between these scenarios or, while unlikely, could be even more extreme than either.

The first thought experiment considers a best-case scenario where the world develops treatments and effective low-cost strategies to control Covid-19 so that the economy can be progressively reopened within a matter of several

months and entirely reopened by the end of 2020. While there would be thousands of deaths, the worst projections of millions of lives lost were averted in this scenario. Thus, Covid-19 would be a relatively short-lived shock to the world economy. Most demand for products and services will be deferred rather than destroyed, so when the entire economy is safely reopened, there will be a massive rebound in economic activity, likely even surpassing the activity prior to the outbreak.

Thus, the implications of Covid-19 will only be temporary reductions in emissions. The trends prior to the pandemic

will continue after a brief lapse, including investments in green technologies. For example, wind and solar capacity were increasing rapidly prior to Covid-19—an increase of 10.5% in 2019,⁶ and in this scenario, new installations will pick up where they left off. Energy efficiency investments will continue as if the pandemic had never happened. Overall energy-using habits will return to the preexisting trend after a rebound, leaving policymakers largely where they were prior to Covid-19, albeit with more budgetary challenges.

We view our second thought experiment as more likely. In this scenario,

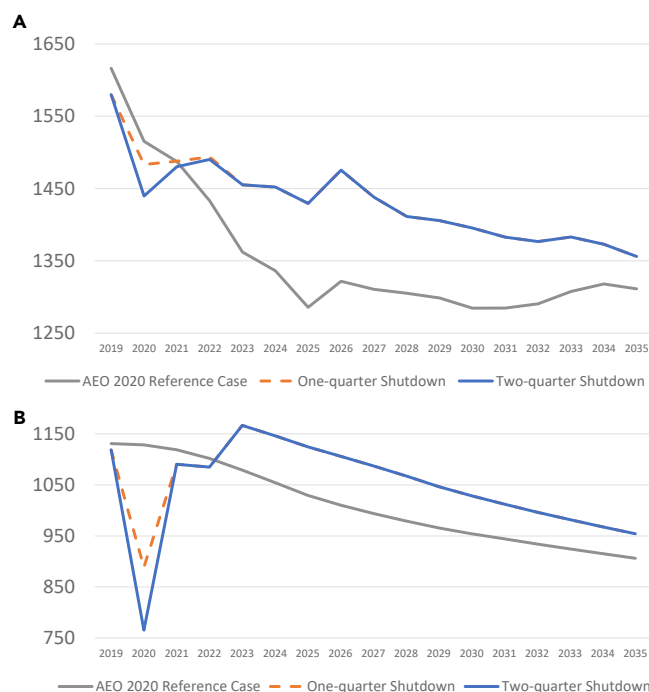


Figure 2. Illustrative Scenario of the Long-run Effects of Covid-19

Trajectory of CO₂ emissions (MtCO₂ per year) from (A) electricity generation and (B) light-duty vehicles in the United States because of short-run reductions of energy use and delayed investments in clean energy technologies and vehicle fuel economy.

the consequences of Covid-19 are far-reaching, with many more deaths, deeper disruptions to supply chains, and a persistent global recession. This could come about if there are continued flare-ups requiring backpedaling on re-opening of the economy and would be exacerbated if developing a successful vaccine in a timely manner proves impossible. In this scenario, substantial demand for goods and services will be destroyed, rather than deferred, and real production will be reduced.

In this case, there will be a direct effect and an indirect effect. The direct effect is the short-run emissions reduction due to Covid-19 and the associated recession. We can examine the effects of the Great Recession beginning in 2008 for some guidance on the effects of recession. Between 2008 and 2013, U.S. energy-related CO₂ emissions fell by nearly 10%.⁷

The indirect effect is due to changes in behavior and investment. Should shutdowns continue for an extended period of time, workers and employers may become sufficiently comfortable with remote working that even after the threat has passed, this option continues to be popular. This would reduce travel but likely increase building energy use. Home energy use would increase, while commercial building use would remain largely unchanged if office space is used in a similar manner by the remaining employees, implying a modest net effect. However, one cannot rule out more substantial changes in commercial building use if telecommuting becomes widespread. Another behavioral response might be if individuals remain fearful of taking public transportation even after the pandemic is under control and switch to driving instead. But this will likely be a modest effect in the United States, as only about 5% of commuters take public transport.⁸

The more important long-run indirect effect of Covid-19 in this case is likely to be on energy sector investment. The most marginal firms, including new firms that have yet to show a profit, are those most likely to liquidate. This could include coal mining firms due to the decreased demand for electricity and the declining profitability of coal-fired generation, but it also includes firms developing low-carbon technologies. In a recession, with financing drying up and low wholesale electricity prices due to reduced electricity demand, renewables investments will decline. This will affect rooftop solar, utility-scale solar, and energy efficiency investments.⁹ The transition to a cleaner vehicle fleet would also be affected. The short-run decline in electric vehicle sales would persist, but perhaps more importantly, cash-strapped automakers will be hard-pressed to continue investing as much in new vehicle technologies to improve efficiency, and there will be a diminished rollout of charging infrastructure.

To explore the implications of a more severe scenario, we perform an illustrative modeling exercise on how long-run emissions would be affected (see [Supplemental Information](#)). Figure 2 displays the average trajectory of CO₂ emissions from electricity generation and light-duty vehicles. For comparison, we also show what the short-run reduction would look like if it extended over either one or two quarters. We find that under plausible assumptions on how the pandemic could delay investments in clean energy technologies and vehicle fuel economy, the long-run impact on CO₂ and local air pollutant emissions could easily outweigh the short-run reductions. After netting out the short-run reduction in economic activity due to the pandemic, we calculate that delays in investments in renewables and vehicle fuel economy alone could lead to an additional 2,500 MMT of CO₂ cumulatively from 2020 to 2035. The additional

local air pollutants could lead to 40 deaths per month on average, or 7,500 deaths, from 2020 to 2035. In our simulations, we assume no *permanent* changes to consumption from the pandemic. But we calculate that if there are such changes, they would need to be large—at least 4% of total energy-related emissions—to compensate for the delayed investment. Similarly, coal retirements would have to more than double from pre-pandemic forecasts to offset the delayed renewables investment (see [Supplemental Information](#)).

Our findings suggest that even just pushing back all renewable electricity generation investments by one year would outweigh the emissions reductions and avoided deaths from March to June of 2020. However, the energy policy response to Covid-19 is the wild card that can change everything.

Implications for Policy

Even if the world does face our second thought experiment, long-run emission increases are not preordained. The government policy response is crucial.¹⁰ And there is a real reason to be concerned. Government budgets are going to be stretched thin in paying for the costs of Covid-19, making it more difficult to invest in clean energy and public transportation. Furthermore, if the economy remains in a persistent recession, there may be intense pressure to relax climate change mitigation targets. But there is also an opportunity.

Many nations around the world, including those in the EU, UK, Japan, and South Korea, are considering stimulus packages explicitly focusing on clean energy. But in the United States, it is unlikely that clean technology and infrastructure will be at the heart of any stimulus package in the near future even if that possibility cannot be ruled

out. The American Recovery and Reinvestment Act stimulus package in 2009 allocated sums toward clean energy investment, and similar investments are in the policy debate.¹¹ Even a modest allocation toward new technologies may pay dividends in the future in terms of clean air, clean jobs, and national security.¹² But simply stabilizing the economy would be valuable for putting the trends toward clean energy back on track.

At the state level, there may be more room for policy action. If financing dries up for new investment in renewables, state green banks can help bridge the gap. States can also expedite permitting, while of course retaining environmental and other safeguards. Covid-19 may also remind voters and policymakers that collective action and listening to scientists matters, leading to greater efforts on policy to reduce emissions, possibly even including carbon pricing. The research community could start new endeavors analyzing potential policy options to help bring us out of the malaise of Covid-19. These developments would be a true “silver lining” to the Covid-19 crisis.

Data and Code Availability

The data and code reported in this paper have been deposited in Github, https://github.com/MartenOvaere/energy_longruneffects_covid19_Joule.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at <https://doi.org/10.1016/j.joule.2020.06.010>.

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<https://doi.org/10.1016/j.joule.2020.06.010>

JOUL, Volume 4

Supplemental Information

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1 Decreased energy consumption

1.1 Data

Table 1 presents the time period, frequency and source of the U.S. energy consumption data used in this study. A long time series of weekly oil data is available, while data of weekly natural gas consumption and hourly electricity consumption and generation is only available from 2017 and 2019.

Table 1: Source, time period and frequency of data on U.S. energy consumption.

Energy source	Time period	Frequency	Units	Source
Petroleum and other liquids	2001-2020	Weekly	1000 B/D	(U.S. Energy Information Administration 2020d)
Natural gas	2017-2020	Weekly	Bcf/D	(U.S. Energy Information Administration 2020c)
Electricity demand	2019-2020	Hourly	MW	(U.S. Energy Information Administration 2020b)
Electricity generation	2019-2020	Hourly	MW	(U.S. Energy Information Administration 2020b)

We also use U.S. heating and cooling degree day data from U.S. National Oceanic and Atmospheric Administration (2020), to control for the effect of temperature on gas and coal consumption from heating and electricity demand. Electricity demand and generation are aggregated to daily data, while heating and cooling degree day data are aggregated to weekly data when used in the weekly oil and natural gas data.

1.2 Empirical specifications

We estimate the coefficient β_{COVID} on a COVID dummy that is equal to one on all days or weeks of data after March 25, 2020. This is the week starting on March 26 for natural gas and the week starting on March 28 for oil. We use ten weeks of post-shutdown data, until June 7, 2020.

Following Hausman and Rapson (2018), we run both a global polynomial regression and a two-step augmented local regression to estimate the effect of the COVID-19 measures on energy consumption. In the global polynomial regression, we estimate β_{COVID} in the full data sample (see second column of Table 1), while controlling for weather and seasonality. In the augmented local regression, on the other hand, we first estimate the impacts of weather, seasonality and other controls in the sample ending three weeks before the start of shutdowns, using the following empirical specifications for oil (1), natural gas (2), electricity generation (3) and electricity demand (4):

$$\begin{aligned}
 q_{\text{fuel},t} &= \delta_t + \varepsilon_t && \text{for fuel} = \{\text{gasoline, kerosene}\} && (1) \\
 &= \text{hdd}_t + \text{cdd}_t + \varepsilon_t && \text{for fuel} = \{\text{res.+com.}, \text{industrial, total}\} && (2) \\
 &= \text{hdd}_t + \text{cdd}_t + q_{\text{solar},t} + q_{\text{wind},t} + \varepsilon_t && \text{for fuel} = \{\text{coal, gas, nuclear, hydro}\} && (3) \\
 &= \text{hdd}_t + \text{cdd}_t + \varepsilon_t && \text{for fuel} = \{\text{electricity demand}\} && (4)
 \end{aligned}$$

where $q_{\text{fuel},it}$ is the fuel consumption at week or day t , while δ_t are week fixed-effects to control for regular patterns in oil consumption. Because the time period for natural gas and electricity is much shorter, we do not use fixed effects, but hdd_t and cdd_t are the number of heating and cooling degree days in day or week t , to control for the effect of temperatures on natural gas and electricity demand.

We also include daily solar and wind electricity generation, which are determined by exogenous changes in wind speed and solar irradiance.

In a second step, β_{COVID} is estimated as the difference of first-stage residuals in a narrow bandwidth around the discontinuity (March 26th, 2020). We again ignore three weeks of data before the discontinuity to mitigate concerns of behavioral change before official shutdown measures started. The global polynomial and augmented local regression lead to very similar results (see supplemental estimation file), so we present the results of the augmented local regression.

1.3 Results

Panel a of Figure 1 in the main text presents the results of the above estimation for every major energy source. Jet fuel consumption has decreased most in relative terms, while motor gasoline consumption has decreased most in absolute terms. Multiplying these estimates by carbon emission factors (see Table 2), panel b of this figure presents the decline of daily carbon emissions in million tons. Total carbon emissions decreased by around 20% for our studied energy sources, in line with the 25% decrease (200 MtCO₂) of China's carbon emissions in the first four weeks after shutdowns (CarbonBrief, 2020a).

Figure 1 and Figure 2 below present similar figures but show the absolute numbers in their original units: MMB/D, Bcf/D and TWh/D.

Table 2 compares our estimates of decreased energy consumption and associated carbon emissions with three types of recent reports. First, two recent studies look at the changes in energy consumption and emissions during shutdowns. Our short-term estimates of total carbon emissions (first row) are the most similar to Cicala et al., (2020) and Le Quéré et al., (2020). However, we estimate changes in primary energy consumption of oil and gas, and gas- and coal-fired electricity generation based on detailed U.S. data, while Le Quéré et al. (2020) estimate worldwide demand reductions using consumption proxies by sector and multiplying them by the average carbon emission intensity per sector. Cicala et al. (2020) do not estimate the effect on consumption of natural gas and coal, but their estimate of oil and electricity are very similar – although though we consider a much longer lockdown period.

Other estimates are more different. IEA (2020e) and Liu et al. (2020) present estimates of average emission reductions over the first quarter of 2020, so their results are for a different time period and thus are difficult to compare to ours.

Our overall 2020 illustrative predictions (sixth row) are somewhat different than other studies. However, in our long-run analysis, we focus on light-duty vehicles and electricity, and assume a larger negative effect on renewable investment in our worst-case long-run scenario than in other reports. In addition, our short-term estimates and 2020 forecasts are relative to business-as-usual 2020 projections, while EIA (2020e) compares to 2019 values, which may not be an appropriate baseline. See section 5 of the SM for more information.

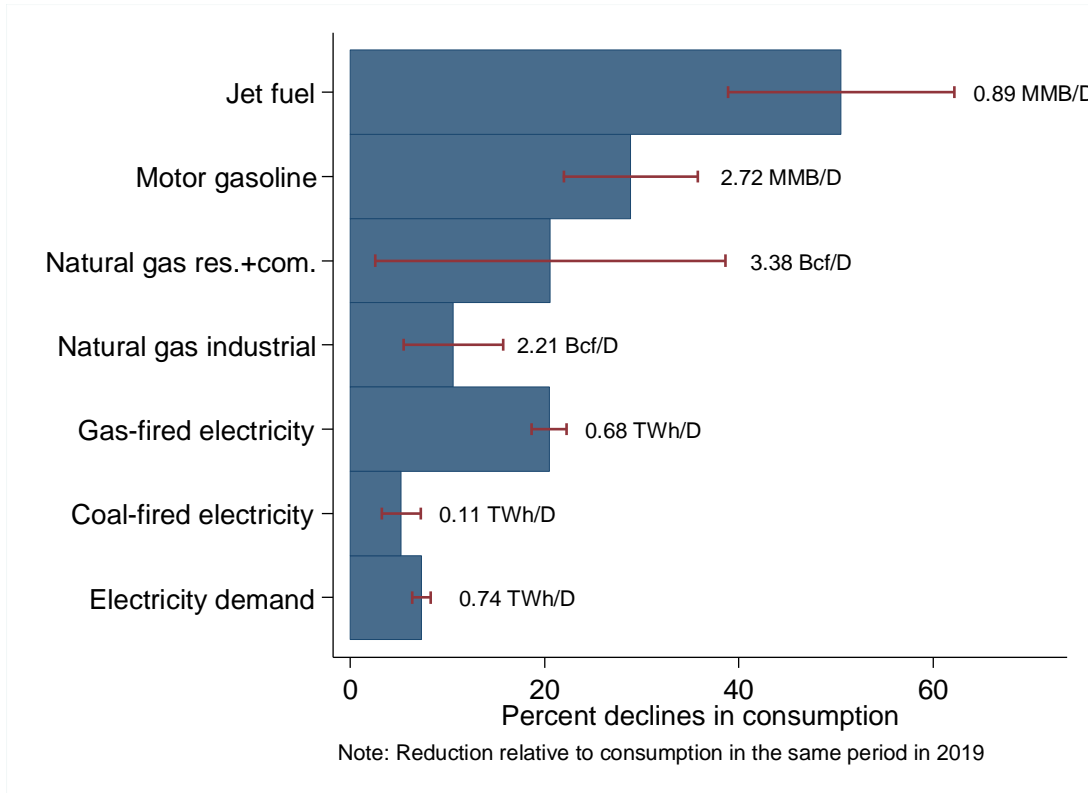


Figure 1: Percent and absolute decline in consumption by primary energy source (error bars show 99% confidence intervals).

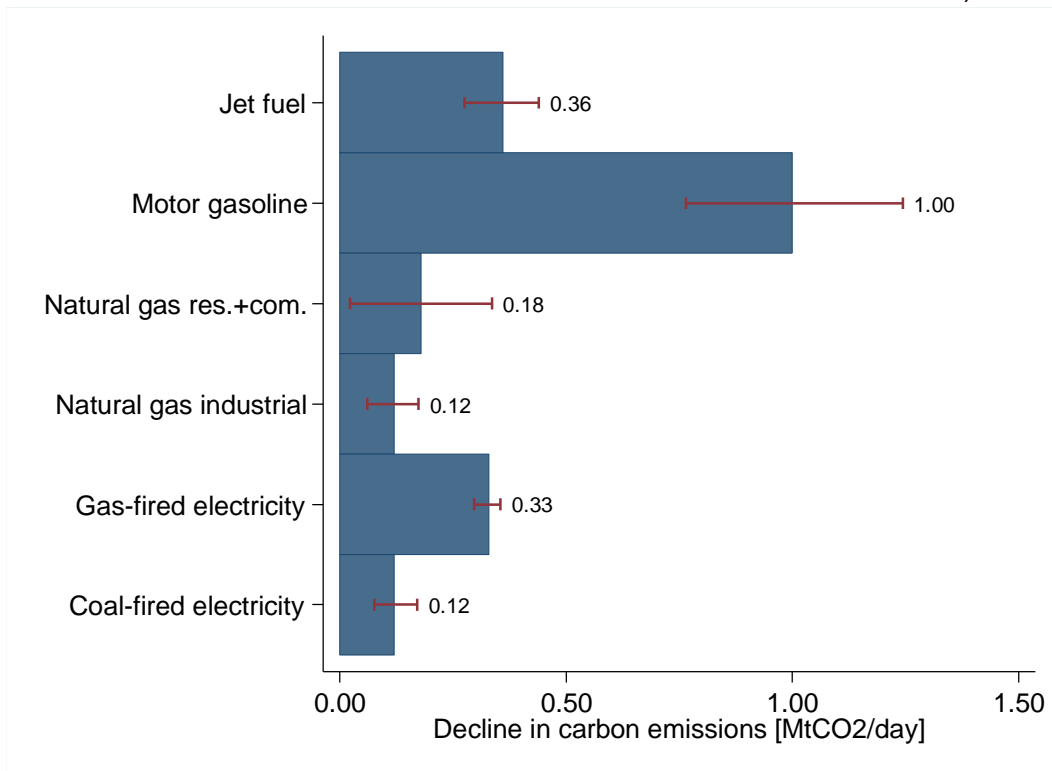


Figure 2: Absolute decline of carbon emissions by primary energy source (error bars show 99% confidence intervals)

Table 2 Forecasted decrease of carbon emissions and consumption of different energy sources

Carbon	MtCO ₂ /day	Oil	Gas	Coal	Electricity	Scope	Source
-15%	-2.11	-31%	-11%	-3% ¹	-7%	U.S.	This study: 10 weeks of shutdown, March-June
-19%	-1.53	-40%	/	/	-6%	U.S.	Cicala et al. (2020): March to mid-April
-17%	-17	/	/	/	/	Global	Le Quéré et al. (2020): March-April
-5%	/	-5%	-2%	-8%	/	Global	IEA (2020e): Q1
-5.8%							Liu et al. (2020): Q1
-11.2%	-0.83	-	-1% ³	-1% ¹	-	U.S.	This study: 2020
		26% ²			2.5%		
-7.5%	/	-	-	-20%	-	U.S.	EIA (2020e): 2020
		9.3%	5.8%		4.5%		
-8%	-7.1	-9%	< -2%	-8%	-5%	Global	IEA (2020e): 2020
-5.5%	-5.5	-	/	/	/	Global	CarbonBrief (2020b): 2020
		9.4%					

¹ From coal-fired electricity generation only.

² From light-duty vehicles only.

³ From gas-fired electricity generation only.

Figure 3 presents 2019-2020 time series of actual energy consumption and electricity generation, and compares it with the 99% confidence interval of predicted consumption, based on equations (1)-(4). The red vertical line indicates March 26th, which is the start date of shutdowns assumed in our study.

After a significant drop in gasoline and kerosene consumption around the start of the first shutdowns, gasoline consumption slowly started to increase, while kerosene consumption stayed almost flat. Consumption of other oils (propane, propylene, distillate fuel oil, residual fuel oil) has also decreased, but by much less. We also find that electricity consumption already started dropping by mid-April, which mainly led to lower gas-fired electricity generation and coal to a lesser extent. By the end of May, electricity consumption was again close to predicted levels. Industrial, residential, and commercial natural gas consumption have also decreased significantly and continue to be somewhat below predicted values.

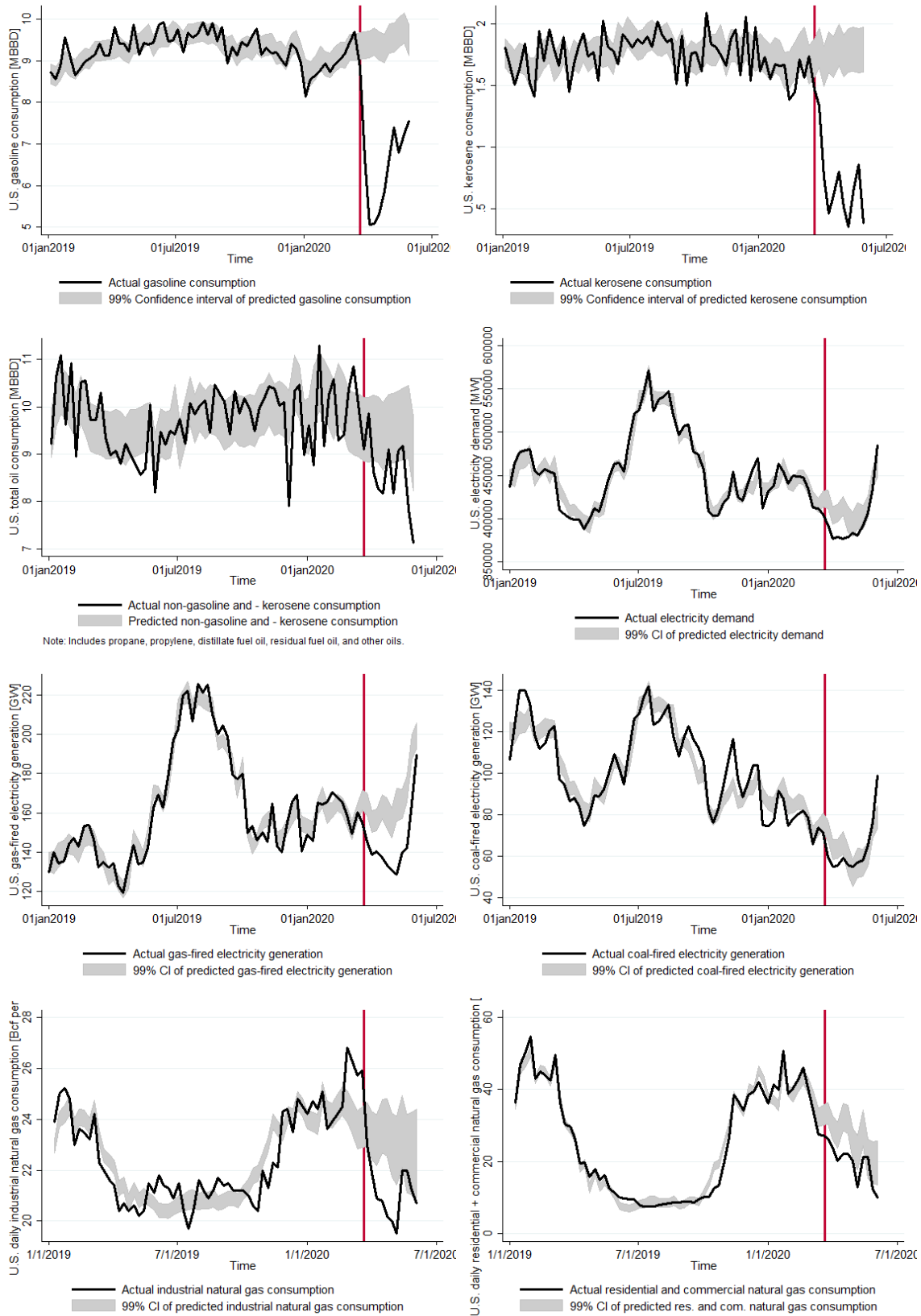


Figure 3: Comparing actual energy consumption and electricity generation with the 99% confidence interval of expected consumption in our model.

2 Decreased CO₂, NO_x, SO₂, PM10 and VOC emissions and emission-related deaths

In a second step, we translate the estimated decreases of energy consumption into lower emissions of local pollutants (SO_x, NO_x, PM10 and VOC). To calculate the avoided emissions of all considered energy sources, we use the emission factors from Table 2. U.S. Environmental Protection Agency (2020b) compiles emission factors of all energy sources, but where available, we increase precision by calculating emission factors as the ratio of published total emissions and total consumption in 2018 or 2019, because emissions largely depend on the operating set point, air/fuel mixing, maintenance problems, and the control technology used. For example, local pollutant emission factors of gasoline and kerosene are calculated as the ratio of 2018 total transportation emissions (5953 kton for NO_x, 96 kton for SO₂, 431 kton for PM10, and 3230 kton for VOC.) (U.S. Environmental Protection Agency 2020a) and the 5.2 billion barrels of transportation consumption in 2018 (U.S. Energy Information Administration 2020d). Coal- and gas-fired electricity generation CO₂, SO_x and NO_x emissions are the ratio of their 2018 total emissions (U.S. Environmental Protection Agency 2020e) and total 2018 generation (968 and 1581 TWh respectively). This approach implicitly assumes that all coal- and gas-fired plants respond to lower electricity demand. If, however, less-clean plants respond more, these emission factors are an underestimation of avoided emissions. Similarly, if cleaner transportation responds more, the emission factors for gasoline are an overestimation.

PM10 and VOC emission factors of gas-fired electricity generation are assumed to equal those from EPA (2020c), while the emission factors from coal-fired electricity generation are calculated to add up to total PM10 and VOC emissions from electric fuel combustion in 2018 (182 and 38 kton) (EPA 2020a).

Figure 4 summarizes the estimated percentage decrease of daily local pollution emissions. It shows that NO_x and VOC have the largest decrease. The decrease of SO_x is limited because coal-fired electricity generation is not much impacted.

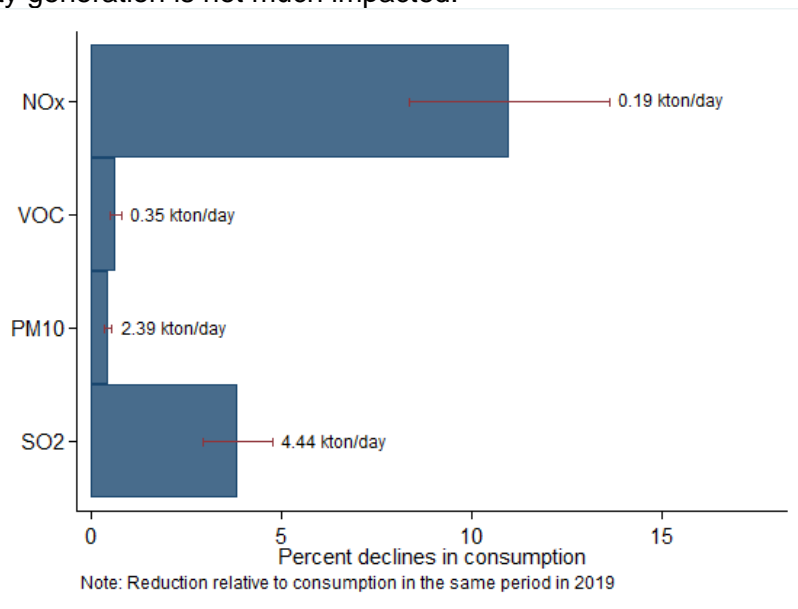


Figure 4: Estimated percentage decrease of daily local pollution emissions (error bars show 99% confidence intervals).

Table 3: Assumed emission factors of considered energy sources.

Energy source	Emission factor	Source
<i>Gasoline [kg/barrel]</i>		
CO ₂	369	(U.S. Energy Information Administration 2020a)
SO _x	0.018	(U.S. Environmental Protection Agency 2020a)
NO _x	1.145	(U.S. Environmental Protection Agency 2020a)
PM10	0.083	(U.S. Environmental Protection Agency 2020a)
VOC	0.621	(U.S. Environmental Protection Agency 2020a)
<i>Kerosene [kg/barrel]</i>		
CO ₂	402	(U.S. Energy Information Administration 2020a)
SO _x	0.018	(U.S. Environmental Protection Agency 2020a)
NO _x	1.145	(U.S. Environmental Protection Agency 2020a)
PM10	0.083	(U.S. Environmental Protection Agency 2020a)
VOC	0.621	(U.S. Environmental Protection Agency 2020a)
<i>Gas-fired electricity generation [kg/MWh]</i>		
CO ₂	480	(U.S. Environmental Protection Agency 2020e)
SO _x	0.012	(U.S. Environmental Protection Agency 2020e)
NO _x	0.118	(U.S. Environmental Protection Agency 2020e)
PM10	0.026	(U.S. Environmental Protection Agency 2020c)
VOC	0.019	(U.S. Environmental Protection Agency 2020c)
<i>Coal-fired electricity generation [kg/MWh]</i>		
CO ₂	1090	(U.S. Environmental Protection Agency 2020e)
SO _x	0.983	(U.S. Environmental Protection Agency 2020e)
NO _x	0.724	(U.S. Environmental Protection Agency 2020e)
PM10	0.115	(U.S. Environmental Protection Agency 2020a)
VOC	0.008	(U.S. Environmental Protection Agency 2020a)
<i>Residential, commercial (heating) and industrial natural gas [kg/MMcf]</i>		
CO ₂	53,120	(U.S. Energy Information Administration 2020a)
SO _x	0.27	(U.S. Environmental Protection Agency 2020c)
NO _x	23	(U.S. Environmental Protection Agency 2020c)
PM10	3.5	(U.S. Environmental Protection Agency 2020c)
VOC	2.5	(U.S. Environmental Protection Agency 2020c)

In a next step, we calculate the number of avoided deaths because of lower local pollution emissions. Using the mortality factors of table 3 (Muller 2014; Muller et al. 2011), Figure 5 presents the number of avoided deaths per month for the duration of the current shutdown measures. Our approach for U.S. total consumption and emissions implicitly assumes that emissions decrease uniformly across the U.S. This is a conservative estimate, given that the decrease of jet fuel and motor gasoline is larger in densely populated areas. To study the geographical distribution of local pollution in more detail, the next section looks at the concentration of PM2.5 across different monitors in the United States.

Table 4: Deaths per 1000 tons of pollutant emissions in the U.S. (Muller 2014; Muller et al. 2011).

Pollutant	Deaths per 1000 tons
SO _x	2.7486
NO _x	0.2912
PM10	7.9521
VOC	0.6924

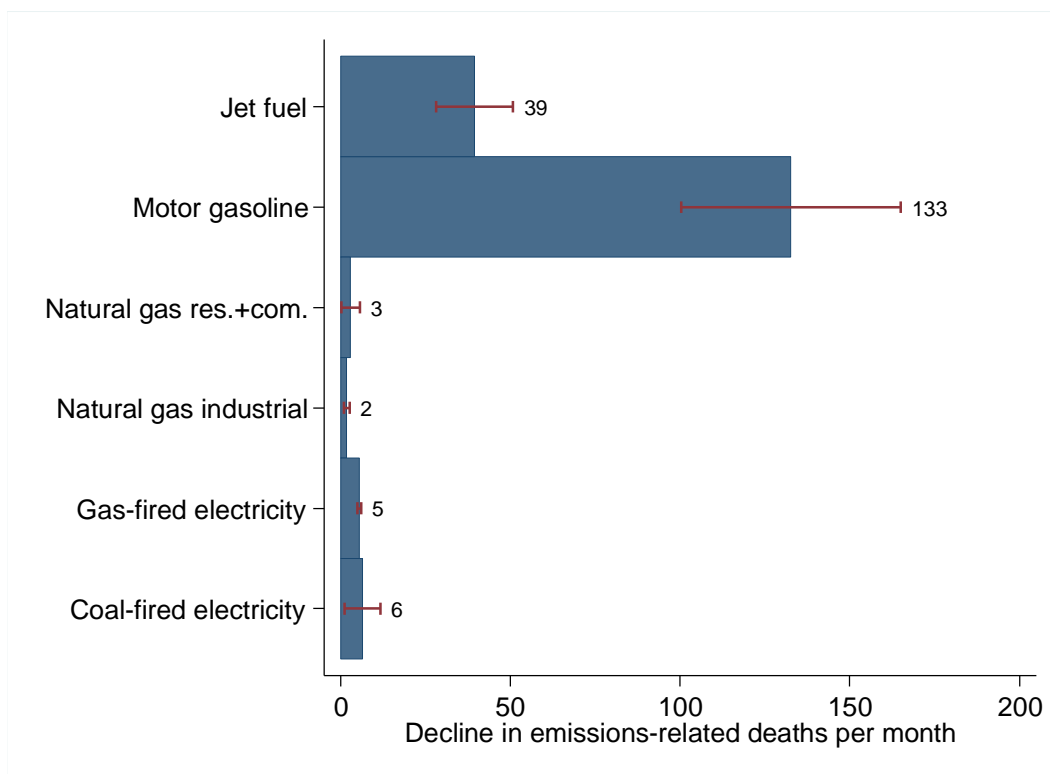


Figure 5: Avoided deaths per month because of the estimated decrease emissions of local pollutants (error bars show 99% confidence intervals).

3 Decreased PM2.5 concentrations

To study the concentration of local pollution more directly, compared to the aggregate emission in the previous section, we analyze PM2.5 concentrations using 2012-2020 data from the U.S. Environmental Protection Agency (2020d) of 785 U.S. monitors with readings in April 2020. We use these 1.8 million day-monitor observations of mean PM2.5 concentrations to estimate the effect of shutdowns on local PM2.5 concentrations. As before, we run both a global polynomial and a two-step local regression, with the following empirical specification:

$$\text{stage 1: } PM_{2.5,i,t} = \delta_t + \delta_i + hdd_t + cdd_t + \varepsilon_{i,t} \tag{5}$$

$$\text{stage 2: } \Delta \hat{PM}_{2.5,i,t} = \beta_{COVID} COVID_{i(s),t} + \text{time}_i + \varepsilon_{i,t} \tag{6}$$

Where δ_t are day-by-month fixed effects to control for regular patterns in PM2.5 concentrations, while δ_i are monitor fixed effects to control for persistent differences in PM2.5 concentrations. Because temperature affects air pollution, we also control for the number of heating or cooling degree days. In the second stage, β_{COVID} is estimated as the difference of first-stage residuals in a narrow bandwidth around the discontinuity, indicated by the $COVID_{i,t}$ dummy, which is equal to one when a stay-at-home order is effective in the state where monitor i is located (New York Times 2020).

With a monitor-specific linear trend in the second stage, we find that PM2.5 concentrations have on average decreased by around $-0.5 \mu\text{g}/\text{m}^3$ since the start of the shutdowns. This result is robust to the inclusion of different monitor and time fixed effects (like week-of-year, day-of-week month, and day). However, when the monitor-specific linear trend is removed from the estimation, the sign reverses and PM2.5 concentrations have increased since the start of the shutdowns. Therefore, we conclude that there is insufficient robust evidence (yet) that PM2.5 concentrations have significantly decreased across the U.S.

Figure 6 provides additional evidence of no significant changes in PM2.5 concentration by plotting the actual unweighted average PM2.5 concentration across all considered U.S. monitors in 2019-2020. It shows that PM2.5 concentrations have been within the interval of expected concentrations.

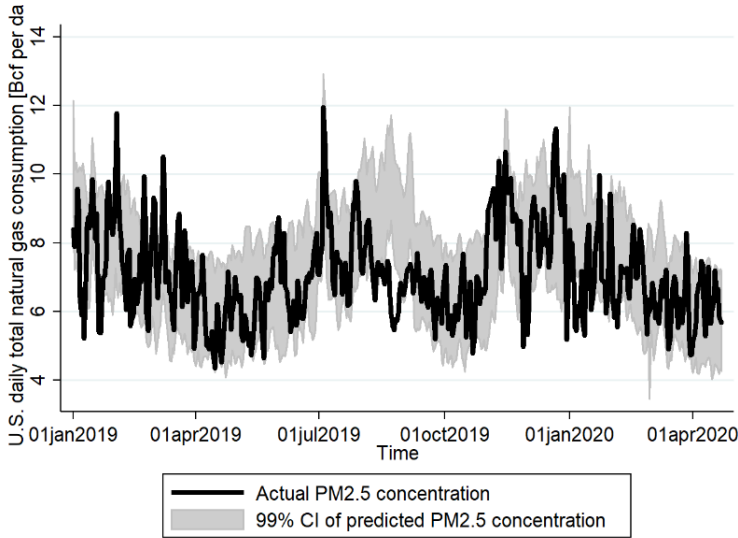


Figure 6: Actual and predicted unweighted average PM2.5 concentrations across all considered U.S. monitors in 2019-2020

U.S. Environmental Protection Agency (2020d) has data on concentrations of other local pollutants like SO₂ and NO₂, but at the time of writing this article, March and April 2020 data were not yet available. However, news articles have cited proprietary sources to suggest up to 31% decline of NO₂ in some urban areas, such as San Francisco (Wall Street Journal 2020).

4 Reductions in Vehicle Crashes

4.1 Data Sources

Along with reduced driving should come reductions in vehicle crashes. We drew upon detailed crash records from several states that have publicly available data.

The latest detailed crash records were available at the state/city level for Utah, Massachusetts, Iowa, California and New York city. This data is comprised of vehicle/person level crash entries and includes any collision that resulted in an injury, death or property value exceeding \$1000/\$1500 depending on the reporting authority.

NYC data:

Extracted from NYC Open Data portal:

<https://data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Vehicles/bm4k-52h4>

Series: Motor Vehicles Collisions – Vehicles

Data provided by: Police Department (NYPD)

Description: The Motor Vehicle Collisions vehicle table contains details on each vehicle involved in the crash. Each row represents a motor vehicle involved in a crash. It includes all crashes where there was an injury, a death or at least \$1000 worth of property damage.

Received/requested on: 04/01/2020

Timespan we use: 01/01/2019-03/28/2020

Utah:

Requested from the Department of Public Safety, State of Utah

<https://highwaysafety.utah.gov/crash-data/>

Timespan we use:

Description: The data contains details on each crash and people involved. Information is collected when a crash involves injuries, deaths or at least \$1,500 worth of property damage.

Received/requested on: 04/01/2020

Timespan we use: 01/01/2019-03/30/2020

Massachusetts:

Extracted from: MassDOT IMPACT Open Data

<https://massdot-impact-crashes-vhb.opendata.arcgis.com/datasets/2020-person-level-crash-details>

[https://massdot-impact-crashes-vhb.opendata.arcgis.com/datasets/2019-person-level-crash-details-](https://massdot-impact-crashes-vhb.opendata.arcgis.com/datasets/2019-person-level-crash-details)

Provided by: Massachusetts Department of Transportation

Description: The data contains details on each crash and people involved. Information is collected when a crash involves injuries, deaths or at least \$1,000 worth of property damage.

Received/requested on: 04/23/2020
Timespan we use: 01/01/2019-04/17/2020

Iowa:

Extracted from: ICAT – Iowa Crash Analysis Tool
<https://icat.iowadot.gov/>

Provided by: Iowa Department of Transportation

Records crashes that have resulted in an injury/fatality or the estimated property damage of the crash is equal to or greater than \$1,500.

Received/requested on: 04/22/2020

Timespan we use: 01/01/2019-04/03/2020

California:

Extracted from:

<http://iswitrs.chp.ca.gov/Reports/jsp/userLogin.jsp>

Series comes from: The Statewide Integrated Traffic Records System (SWITRS)

Provided by: California Highway patrol

Records crashes that have resulted in an injury/fatality or the estimated property damage of the crash is equal to or greater than \$1,000.

Received/requested on: 04/10/2020

Timespan we use: 01/01/2019-04/09/2020

4.2 Analysis

For initial descriptive evidence, we began by plotting the ratio of total traffic crashes in 2020 to the same time period in 2019 at the daily level. This is below in Figure 7. We observe a slight downward trend after February 26th, which is the date thought at the time to be the first Covid-19 death in the United States and a clearer downward trend after March 13th when President Trump declared a national emergency. The average pre-February 26th ratio is just below 1, while the average post-March 13th ratio is 0.41 when averaged across all of these regions.

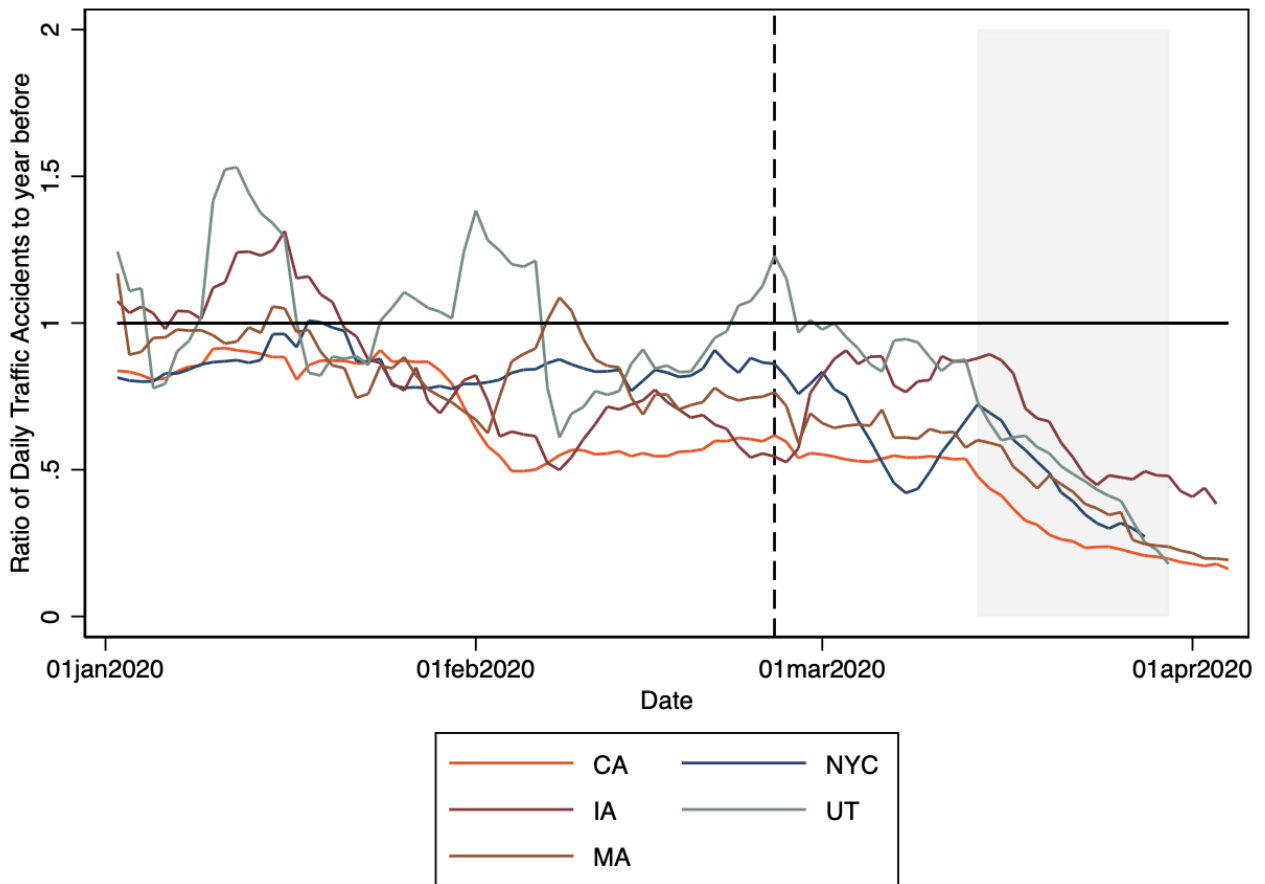


Figure 7: Seven-day moving average of the ratio of 2020 to 2019 crashes by state or region. Numbers greater than 1 indicate more crashes in 2020, while less than 1 indicate fewer crashes in 2020. The dotted line refers to February 26, while the shaded area includes all days after March 13th.

We can create a similar figure for crash fatalities. Figure 8 shows this figure, which plots the ratio of crash fatalities in 2020 to 2019. The pattern is much less clear for fatalities and it is difficult to discern a downward trend. Looking at the data, the average fatality ratio drops only very slightly between pre-February 26th and post-March 13th. This might be due to higher speeds on roadways with less congestion leading to more fatal crashes when crashes do occur.

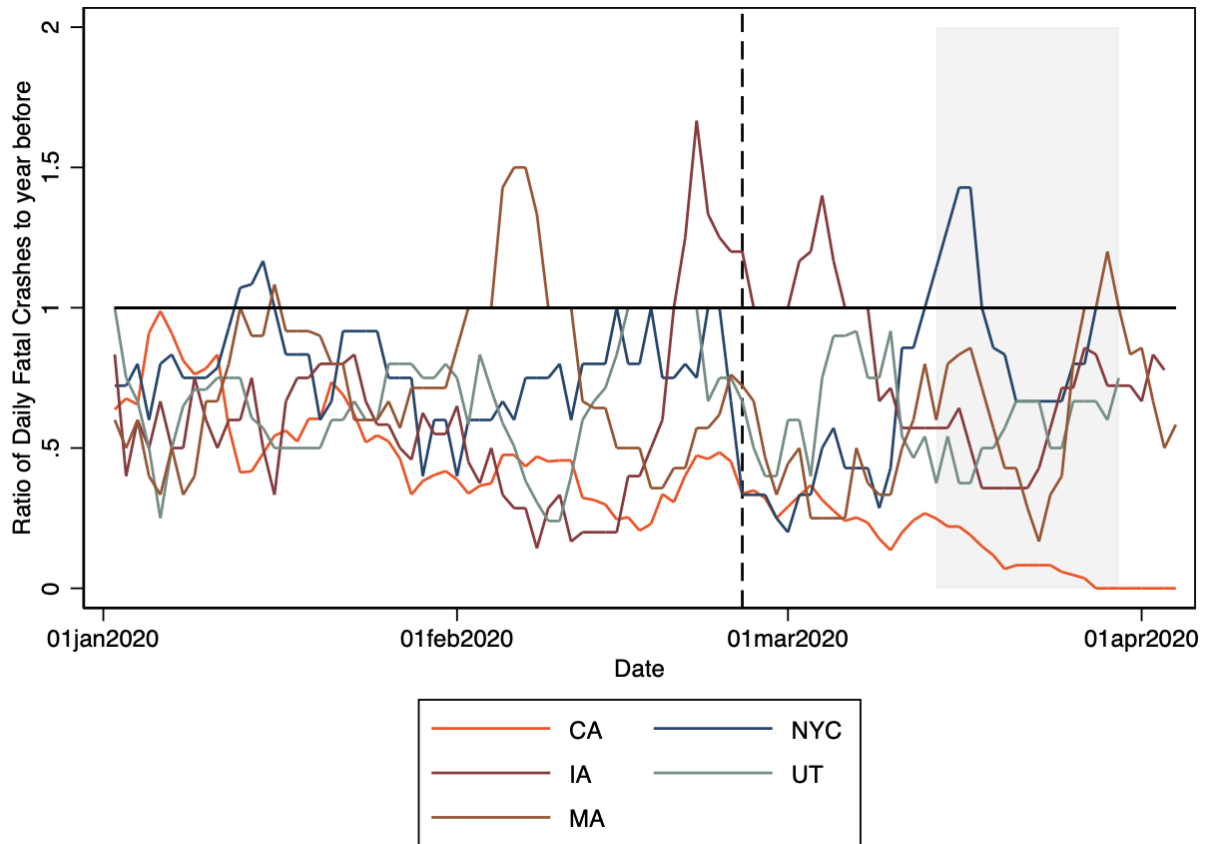


Figure 8: Seven-day moving average of the ratio of 2020 to 2019 fatal crashes by state or region. Numbers greater than 1 indicate more crashes in 2020, while less than 1 indicate fewer crashes in 2020. The dotted line refers to February 26, while the shaded area includes all days after March 13th.

We also run a set of regressions to explore the effects further using difference-in-difference or regression discontinuity designs, and find similar results – a clear effect on overall traffic crashes, but little or no effect on fatalities, depending on the specification (results are available from the authors upon request).

5 Long-run Impacts

We develop two illustrative thought experiments to provide insight into the potential long-run impacts of Covid-19. Our philosophy in this exercise is not to exactly forecast any outcome or provide probabilities on what the outcomes might be, but rather to provide a deeper understanding of the implications of possible scenarios of what might happen. We focus on only two scenarios for greater simplicity and transparency.

Our first (optimistic) thought experiment is simple: Covid-19 is brought under control quickly with treatments and/or a vaccine, and a strong economic recovery quickly comes about. This economic recovery could happen as early as the fall of 2020. This scenario does not require much modeling, as it is clear that the impacts on long run technology development will be minimal, and while there may be budgetary impacts on firms and governments, these are not so arduous as to dramatically change the flows of capital towards clean technology.

Our second thought experiment is much less optimistic. It represents a case where Covid-19 is not brought under control for at least another year, and perhaps longer. The global economy goes into a deeper recession. Government budgets at all levels are strained. Many firms go bankrupt and most of those that do not are just focusing on survival, and thus are short on cash to invest in new technologies. This thought experiment might be thought of as a plausible lower-bound on what might happen, although we would like to emphasize that even worse outcomes are still possible. We view this scenario as useful for allowing us to make some illustrative quantitative estimates of what the possible implications might be, recognizing that the exact numbers are not predictions, but rather projections of a possible world intended for insight into the factors at play.

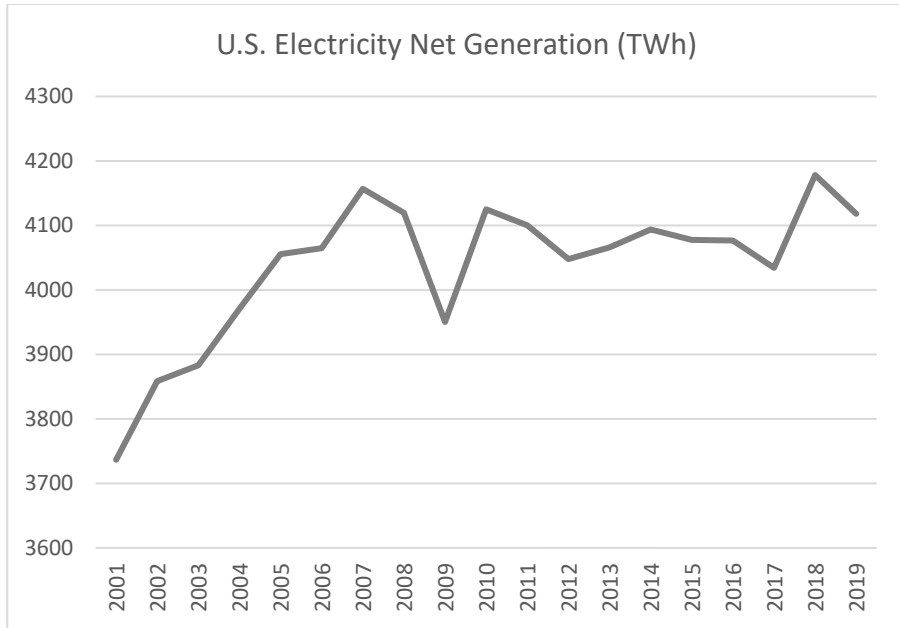
Note that we do not explicitly model policy interventions in either scenario, but rather assume that policy roughly follows the pre-Covid-19 trends. Explicitly modeling the policy responses and how they affect energy use and emissions is outside the scope of this commentary, but is a valuable pathway for future research.

Our modeling of the second long-run scenario consists of two main components. First, energy demand will change due to the shutdown and economic recovery in the near future. Second, fuel mixes and emissions rates will change due to possible delays in renewable technology investments and product releases, which has longer-run implications. We combine our assumptions on energy demand and emissions rates to construct potential long-run impacts on emissions. Our calculations of emissions impacts are relative to the projections in the 2020 Annual Energy Outlook (AEO) Reference Case (EIA 2020e). We recognize that there are likely to be other impacts but we view these as the largest two impacts, and thus we focus on them for our illustrative estimates. One of the more notable other possible impacts could be an accelerating of coal plant retirements, leading to a counteracting emissions decrease. This could be due to permanently lower consumption due to the pandemic. At the end of Section 5.3, we will discuss how large the emission-reducing forces would have to be to compensate for the emissions increases we model.

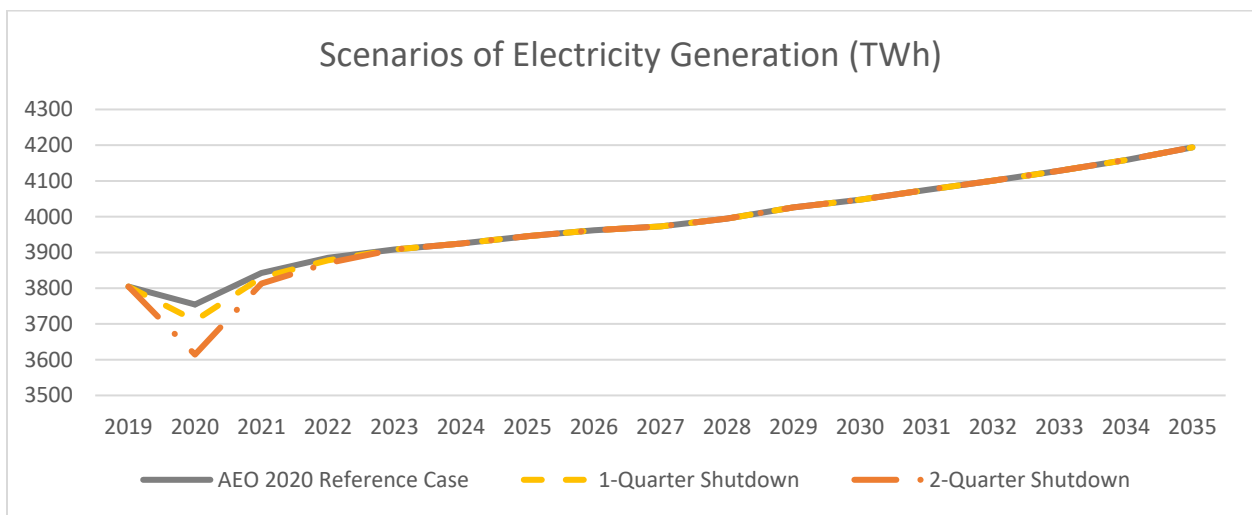
5.1 Short-run Change in Energy Demand: Electricity generation and light-duty vehicle miles traveled

For impacts of the shutdown, we use our estimates on electricity generation, which found that electricity declined less than 10% due to the shutdown (Section 1 of the SI). Our scenario considers a strict shutdown lasting one to two quarters. We use historical data during and after

the 2008 Great Recession to help guide our construction of electricity generation scenarios during the post-shutdown economic recovery. Electricity generation dropped in 2009 and grew in 2010 by about 4% each (Figure 6a, EIA 2020f). In the current pandemic, the slowdown in production and other economic activity hit much sooner than in the Great Recession that began with a financial crisis, so we assign the largest decline in electricity generation to 2020, followed by a similarly-sized rebound. We assume that electricity generation returns to the original trends by 2023. Figure 9b depicts the Reference case from the 2020 AEO (EIA 2020e) in the solid line, one-quarter shutdown in the dashed line, and a two-quarter shutdown in the dash-dotted line.



(a) Historical U.S. electricity generation in terawatt hours, all sectors. Data source: EIA 2020f.

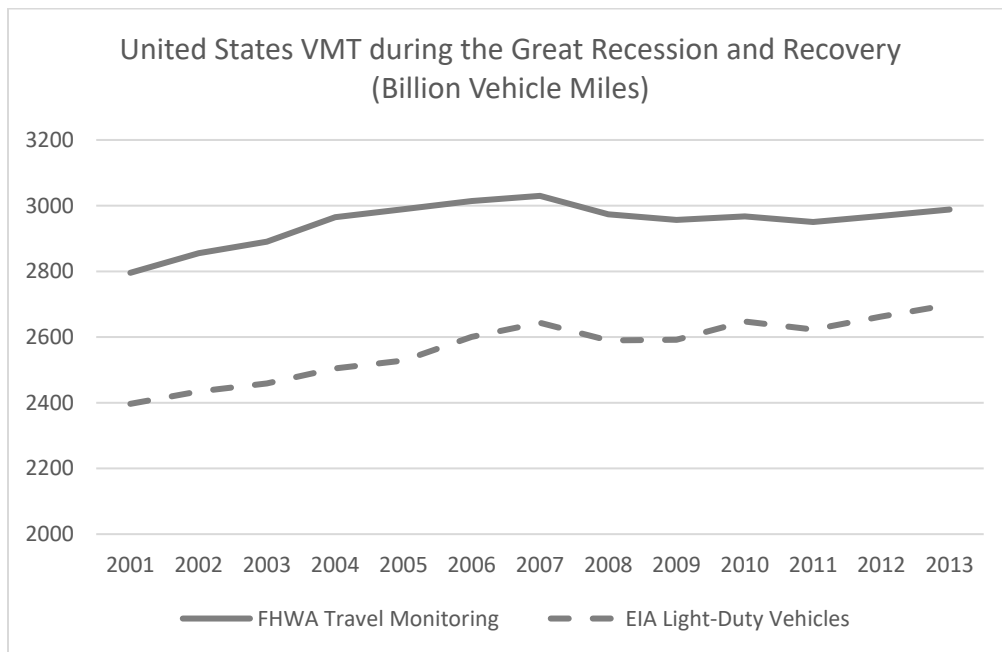


(b) Electricity generation projection used in calculations.

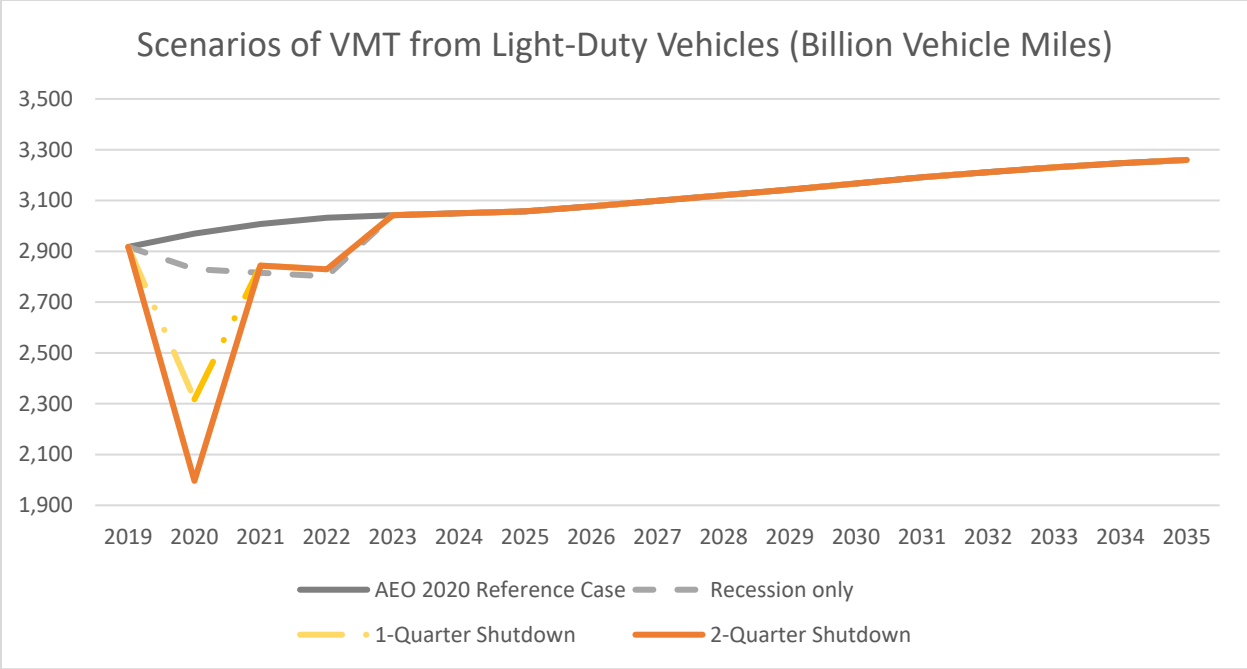
Figure 9

For transportation, we focus on emissions from light-duty vehicles. Given that data on vehicle miles traveled (VMT) are not yet available from the Federal Highway Administration (FHWA), we turn to cellphone data provided by Apple Mobility Trends and Streetlight Data Inc. (See References for access information). Our scenarios consider a strict shutdown lasting one to two quarters.

We again look to historical data on the Great Recession to guide our assumptions on what may happen to energy demand in transportation after the shutdown has been lifted and the economic recovery begins. Historical data on VMT in the U.S. (Figure 10a, FHWA 2020 and EIA 2020f) show that after about a 2% decline in 2008, VMT fluctuated with small increases and decreases during the recovery years afterwards.



(a) Historical U.S. vehicle miles traveled in billions of vehicle miles. Data from the FHWA are for all traffic, while data from the EIA are for light-duty vehicles only (FHWA 2020, EIA 2014). Both data series show about a 2% drop in VMT in 2008.



(b) Light-duty VMT projection used in our calculations.
Figure 10

Driving behavior change may persist after shutdowns are lifted. People may drive less if they work from home a few more days per week than before. However, people may drive more if they are concerned about contagion on public transit or other shared forms of transit. To take into account these two opposing effects on VMT, we assign 1/3 of the person-miles from public/shared transit to light-duty vehicle VMT through the end of 2022. Using data from the 2017 National Household Travel Survey (NHTS) and a summary report based on the NHTS, 1/3 of person-miles from public transit aligns with about 1% of light-duty VMT (FHWA 2017a, b). We assume work habits and public/shared transit ridership return to their original trend lines eventually, after vaccines become available and due to pressures from traffic congestion or financial constraints. Note that even though public/shared transit ridership is very low compared to light-duty VMT from a national perspective, such ridership tends to be concentrated in densely populated urban areas. Therefore, local policymakers in urban areas that already experience traffic congestion may be especially concerned about a shift from public/shared transit to private vehicles.

In Figure 10b, the solid gray line depicts the reference case from the 2020 AEO (EIA 2020e). The dashed line represents VMT in an economic recession similar to the Great Recession of 2008. The two lines with big dips in 2020 represent VMT from one or two quarters of shutdown as well as VMT from behavioral changes. The VMT for all scenarios returns to the 2020 AEO reference case (EIA 2020e) from 2023 onwards.

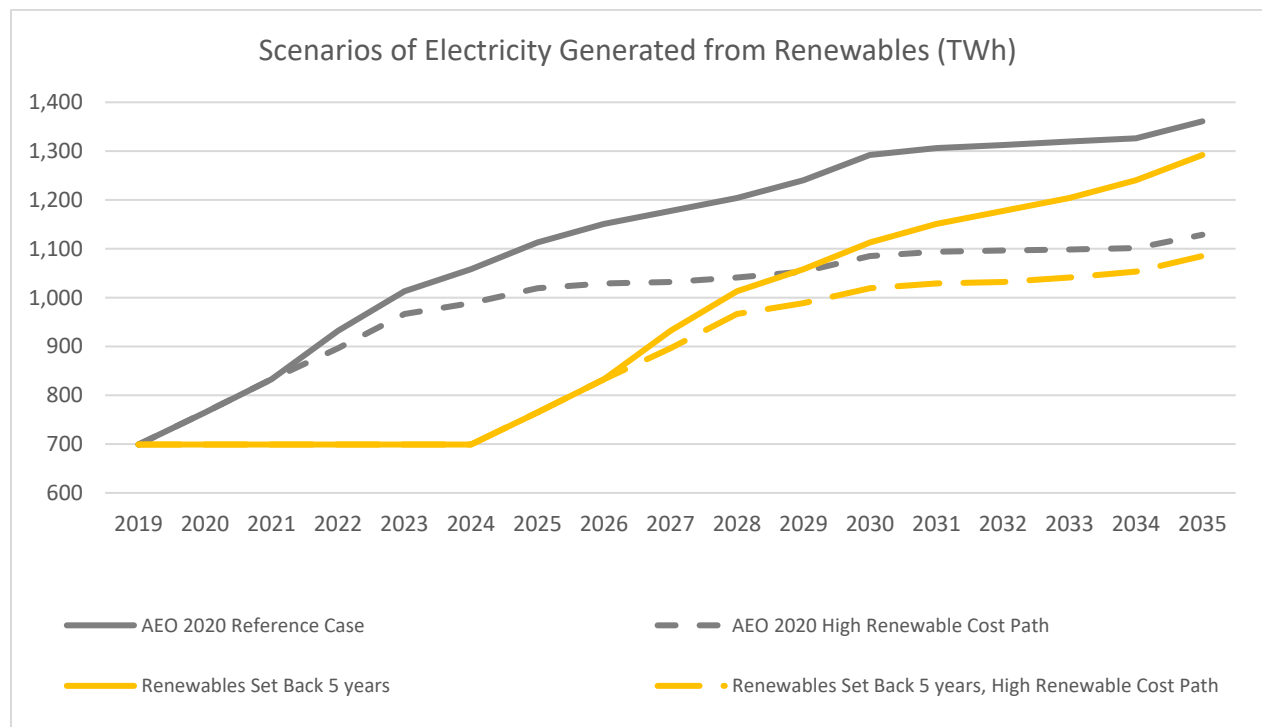
5.2 Long-run changes in investment and regulation

To understand how there may be persistent, lingering effects of Covid-19, we are interested in comparing the shorter-run impacts to the long-run impacts of delayed investments in renewable technology and reducing vehicle emissions.

Construction of new solar and wind generation capacity has halted or significantly slowed during

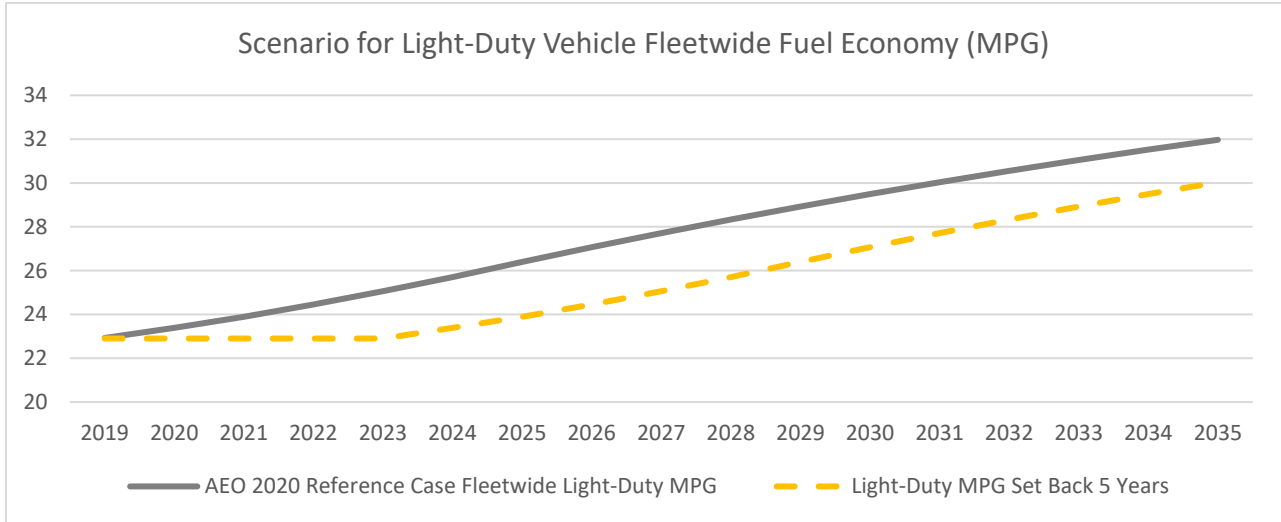
the shutdown, depending on physical-distancing guidelines in each city or state. However, even after the shutdowns are lifted in the U.S., global supply chains may be slower to recover (EIA 2020g). State and local government budgets for renewable technology projects may no longer be available. Improvements to the technology from innovation, R&D, and learning-by-doing may also be impacted in the long run. Therefore, we consider two potential scenarios in the long run. The first is to push back new renewable generation capacity in the 2020 AEO (EIA 2020e) reference case to a later year. The second is to push back new renewable generation capacity as well as to put renewables on a higher-cost path. Fortunately, there is a high-cost path in a 2020 AEO (EIA 2020e) side case that we leverage (Figure 11a). Our final emissions estimates will average across these cases.

The future of improvements in vehicle technology also looks uncertain. Multiple car manufacturers, such as Ford, GMC, and Rivian, have announced delays in releasing new electric models without specifying a new date (Howard 2020, Foldy 2020). Many state and local government plans to invest in electric vehicle charging infrastructure are in limbo as budgets have been decimated. Lastly, people may drive more as well as buy less fuel-efficient vehicles due to historically low gas prices. At this time, it is unclear whether Corporate Average Fuel Economy standards (CAFE) will be relaxed (either in terms of whether the recently finalized 2020-2026 Trump Administration SAFE rule will hold up in court or whether the standards will be adjusted further in later years due to the pandemic). Similarly, it is unclear whether the Zero-Emissions Vehicle (ZEV) mandates will be adjusted. Given this uncertainty, we consider an illustrative scenario where investment is pushed back and regulation is not as forceful, so that the overall fuel economy trajectory of the U.S. light-duty vehicle fleet is pushed back by five years (Figure 11b).



(a) Grey solid line represents the amount of electricity generated from renewable sources in the U.S. in the AEO 2020 reference case. The grey dashed line represents the scenario

where renewables take a high-cost path, which dampens investments. The yellow solid and long-dashed lines are our scenarios for renewable generation, pushed back by five years and either resuming the AEO reference case or taking the high-cost path, respectively.



(b) The grey solid line is the reference case from the 2020 AEO. The yellow dashed line is our scenario for what might happen to fleet-wide fuel economy in the U.S. Fleet-wide fuel economy includes fuel economy of the vehicle stock, newly purchased vehicles, as well as EPA MPG-equivalents for alternative fuel vehicles.

Figure 11

5.3 Results: Comparing changes in short-run consumption to long-run investment and regulation

Annual emissions from electricity and light-duty vehicles in our scenarios have similar patterns (Figure 2 in the main text and replicated below as Figure 12 for easy reference). Emissions during a one- and two-quarter shutdown are lower than the 2020 AEO reference case (EIA 2020e) and the percentage decrease of light-duty vehicle emissions during the early years of the Great Recession (gray dashed line in panel b). However, after quantities return to the original trend, annual emissions are higher because of delays in renewable technology investment or fuel economy improvements. The results in this section use the same emissions factors and mortality factors as in Section 1 and 2 of the SM.

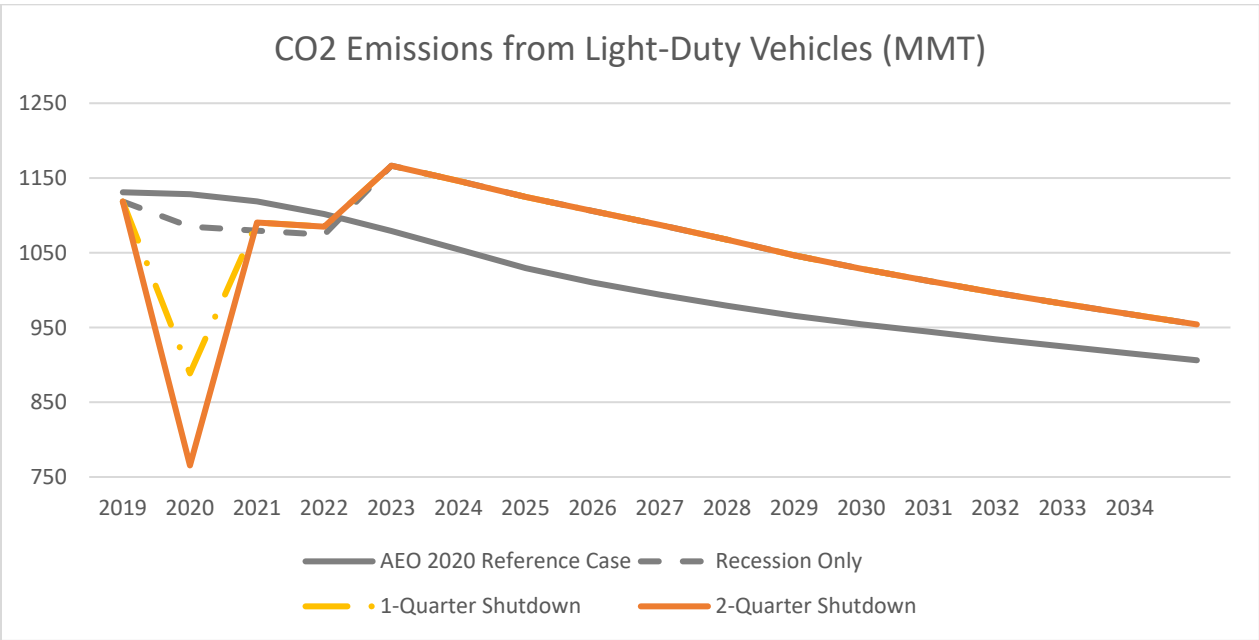
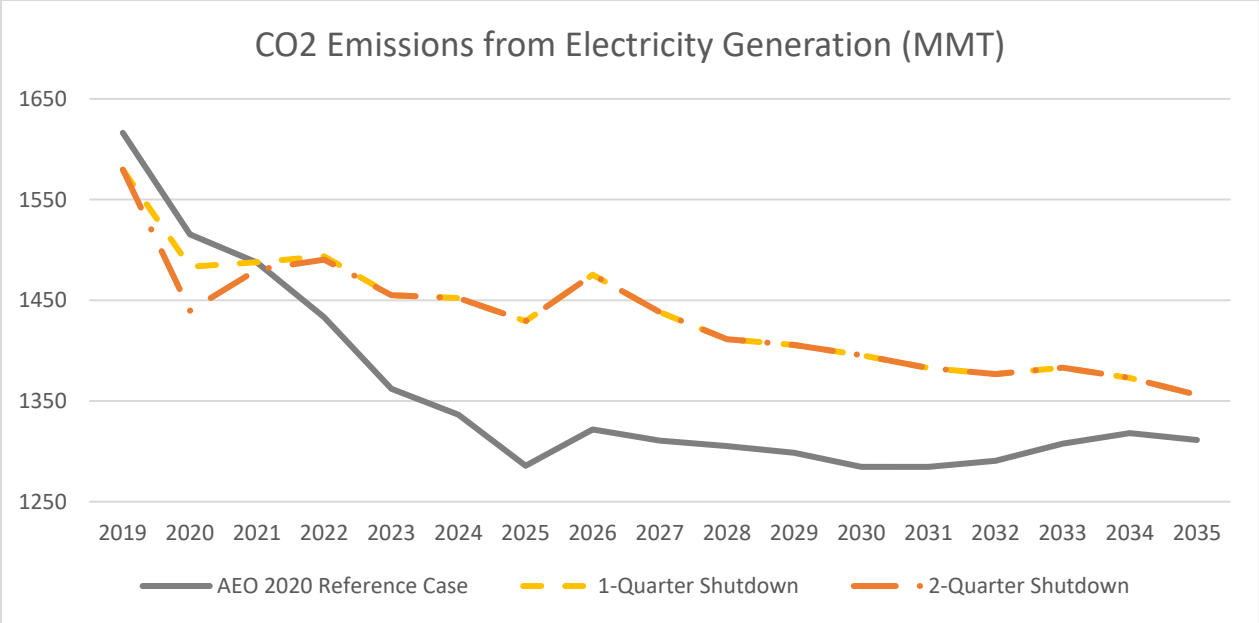


Figure 12 Emissions Scenarios

As we can see in Figure 12, emissions in the medium run from electricity in our scenarios are higher than the projections from the 2020 AEO reference case. Delays in the building of renewable generation capacity that was expected to come online from 2020 through 2023 outweigh the short-run reduction in electricity demand from the pandemic shutdown and an economic recession. Our calculations show that a delay by one year of anticipated renewable generation capacity investment (83 more deaths, 35 MMT CO₂ more) would outweigh the emissions reductions from a one-quarter shutdown (56 fewer deaths, 24 MMT less CO₂), for a net impact of 27 more deaths from local pollution and 11 MMT more CO₂ emitted.

In the next few years, emissions from light-duty vehicles decrease relative to the 2020 AEO reference case (EIA 2020e) because of the dramatic reductions in VMT during the shutdowns and declines during an economic recession. However, in the long run, emissions are higher relative to the reference case because of delays in fuel economy improvements and alternative fuel vehicle adoption in the scenario that we consider.

For each year of each scenario, we take the new quantities of energy demanded (Figures 9b and 10b) and calculate emissions based on the new fuel mix or fuel economy in our hypothetical long-run scenarios (Figure 11) and the emissions factors in Table 3. We can then report the CO2 emissions and translate the local pollutants to mortality impacts using the mortality factors in Table 4. We find that emissions from electricity generation and light-duty vehicles would increase over the period 2020-2035 compared to the reference case. Carbon dioxide emissions would increase by about 2600 MMT, and total deaths due to local pollution would increase by about 7400.

Table 5: Emissions outcomes from calculations based on scenarios of energy demand and investment described in Sections 5.1 and 5.2.

Electricity			
Difference Relative to 2020 AEO Reference Case	2020-2035	2020-2023	2024-2035
NOx (ktons)	878	153	725
SO2 (ktons)	938	164	774
PM10 (ktons)	153	27	126
VOC (ktons)	40	7	33
Total Deaths	4075	712	3362
Monthly Average Deaths	21.2	3.7	17.5
CO2 Emissions (MMT)	1841	319	1522
Light-Duty Vehicles			
Difference Relative to 2020 AEO Reference Case	2020-2035	2020-2023	2024-2035
NOx (ktons)	2552	-654	3206
SO2 (ktons)	40	-10	50
PM10 (ktons)	186	-46	232
VOC (ktons)	1384	-355	1739
Total Deaths	3383	-841	4125
Monthly Average Deaths	17.1	-17.5	28.6
CO ₂ Emissions (MMT)	823	-211	1034

The emissions outcomes for the different pollutants are included in Table 4 and in Table 5, we break out the change in carbon dioxide emissions and deaths from the reference case into those from consumption (short-run) and investment (long-run). To offset the additional CO₂ emissions from delayed investments in electricity generation and light-duty vehicles, energy-related emissions would have to permanently decrease by at least 4%.

In the electricity sector, we would need to enter 2024 with twice as much coal capacity retired than in the 2020 AEO reference case (which already includes continued coal plant retirements) to offset the delay in renewables investment in our scenario. We view this as somewhat unlikely,

although we would not be surprised if there is some increase in retirements. For further context, the additional CO₂ emissions from delayed renewables investments over 2024-35 are equivalent to replacing about 41 GW of coal generation with gas-fired plants over the same period (at the average capacity factor of 62.6% projected by the 2020 AEO reference case (EIA 2020e) over 2024-35). This is substantially greater than the coal plant retirements scheduled for 2020 pre-Covid, which amount to 5.8 GW according to the U.S. Energy Information Administration (<https://www.eia.gov/todayinenergy/detail.php?id=42495>).

Table 6: Carbon dioxide emissions and mortality impacts broken out by consumption change only, investment change only (renewable generation capacity or fuel economy improvements), and combined net effect. Because of division by fuel economy, the combined scenario for light-duty vehicles is not a linear sum of the consumption-change-only and investment-change-only columns. All numbers are relative to the reference case.

	Carbon emissions (CO ₂ MMT)			Deaths		
	consumption	investment	combined	consumption	investment	combined
Electricity						
2020-35	-66	1907	1841	-154	4229	4075
2020-23	-66	385	319	-154	867	712
2024-35	0	1521	1521	0	3362	3362
Light-Duty Vehicles						
2020-35	-439	1275	823	-1749	5087	3283
2020-23	-439	241	-211	-1749	962	-841
2024-35	0	1034	1034	0	4125	4125

In future work, investigating the potential impact of policy responses, like stimulus investments, will be important.

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