# 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 $\beta_{\text{COVID}}$ 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 $\beta_{\text{COVID}}$ 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):

$$q_{\text{fuel},t} = \delta_t + \varepsilon_t \qquad \text{for fuel} = \{\text{gasoline, kerosene}\} \qquad (1)$$

$$= \beta_1 hdd_t + \beta_2 cdd_t + \varepsilon_t \qquad \text{for fuel} = \{\text{res.+com., industrial, total}\} \qquad (2)$$

$$= \beta_1 hdd_t + \beta_2 cdd_t + \beta_3 q_{solar,t} + \beta_4 q_{wind,t} + \varepsilon_t \qquad \text{for fuel} = \{\text{coal, gas, nuclear, hydro}\} \qquad (3)$$

$$= \beta_1 hdd_t + \beta_2 cdd_t + \varepsilon_t \qquad \text{for fuel} = \{\text{electricity demand}\} \qquad (4)$$

where $q_{\text{fuel},it}$ is the fuel consumption at week or day t, while $\delta_t$ 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, $\beta_{COVID}$ 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 $MtCO_2$) 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.

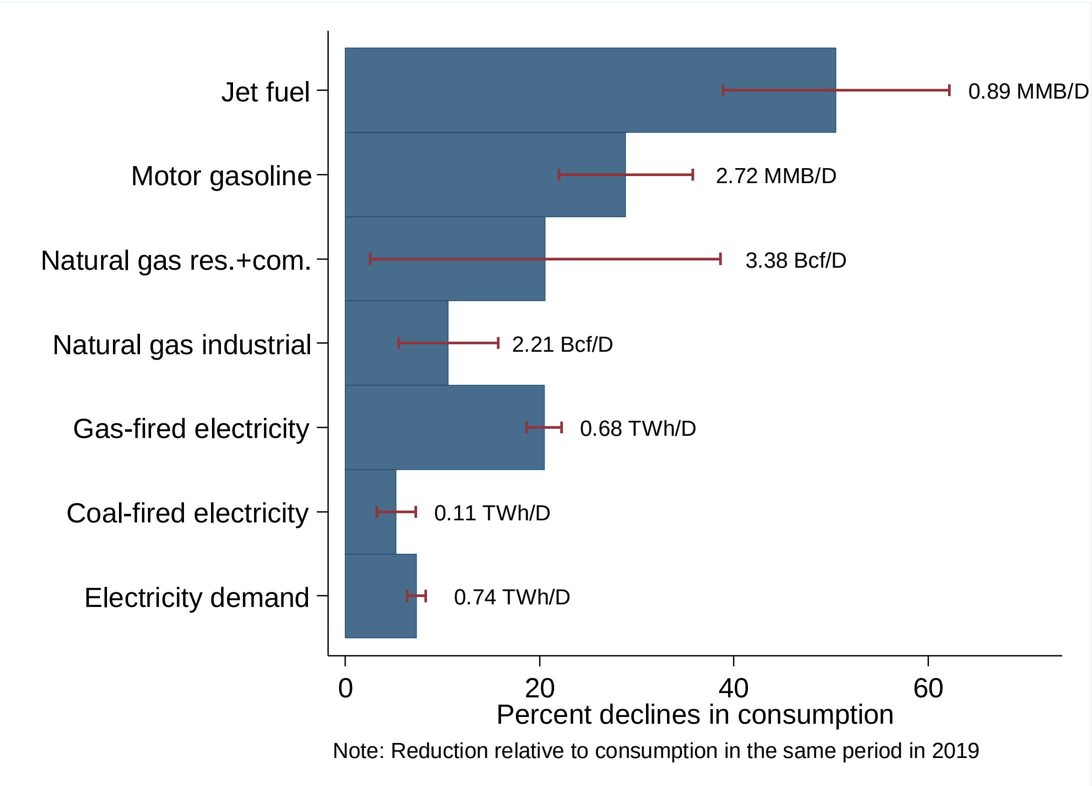



Figure 1: Percent and absolute decline in consumption by primary energy source (error bars show 99% confidence intervals).

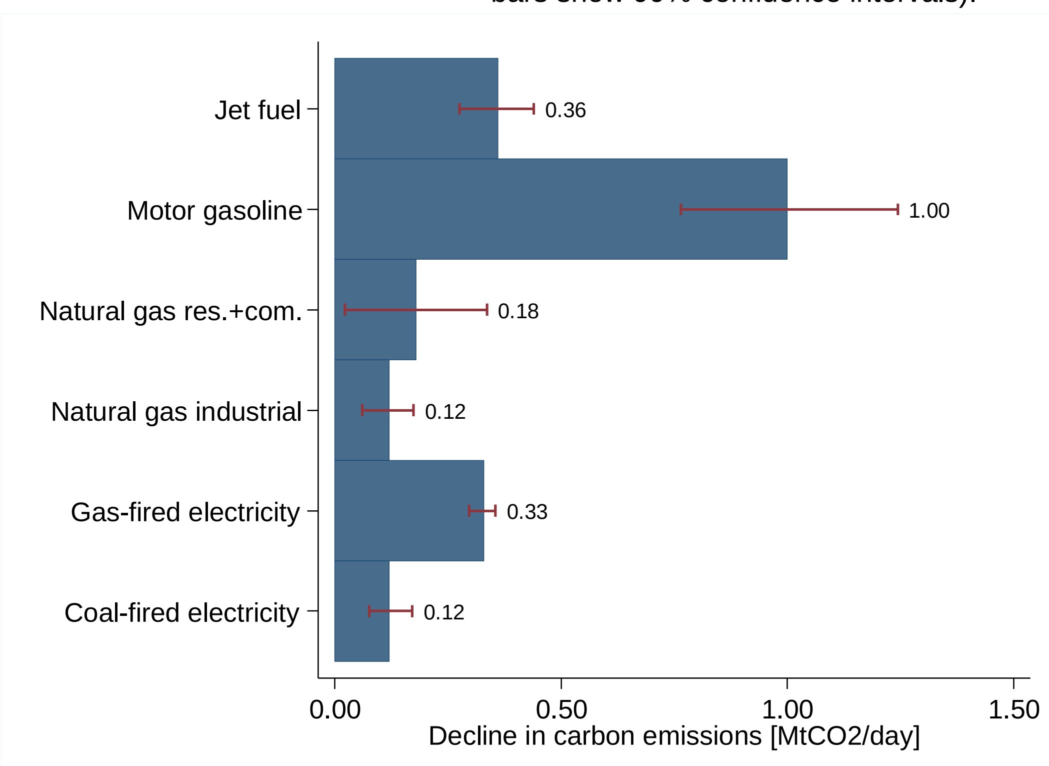



Figure 2: Absolute decline of carbon emissions by primary energy source (error bars show 99% confidence intervals)

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

| Carbon | MtCO2/ 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%<br>-5.8% | / | -5% | -2% | -8% | / | Global | IEA (2020e): Q1<br>Liu et al. (2020): Q1 |
| -11.2% | -.83 | -26%[2] | -1%[3] | -1%[1] | -2.5% | U.S. | This study: 2020 |
| -7.5% | / | -9.3% | -5.8% | -20% | -4.5% | U.S. | EIA (2020e): 2020 |
| -8% | -7.1 | -9% | < -2% | -8% | -5% | Global | IEA (2020e): 2020 |
| -5.5% | -5.5 | -9.4% | / | / | / | Global | CarbonBrief (2020b): 2020 |

[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.

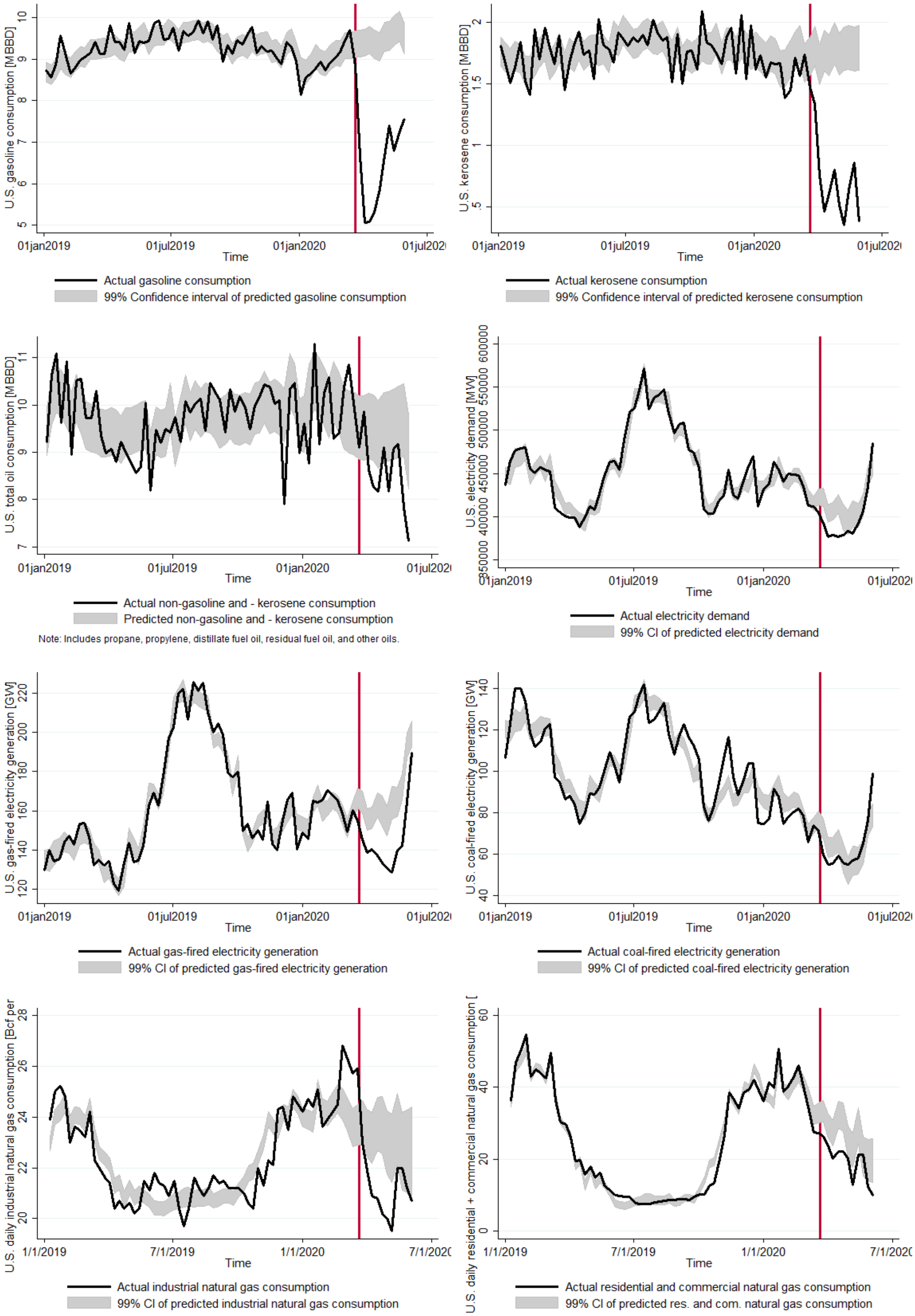



Figure 3: Comparing actual energy consumption and electricity generation with the 99% confidence interval of expected consumption in our model.

## 2 Decreased $CO_2$, $NO_x$, $SO_2$, 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 $SO_2$, 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 $CO_2$, $SO_x$ 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.

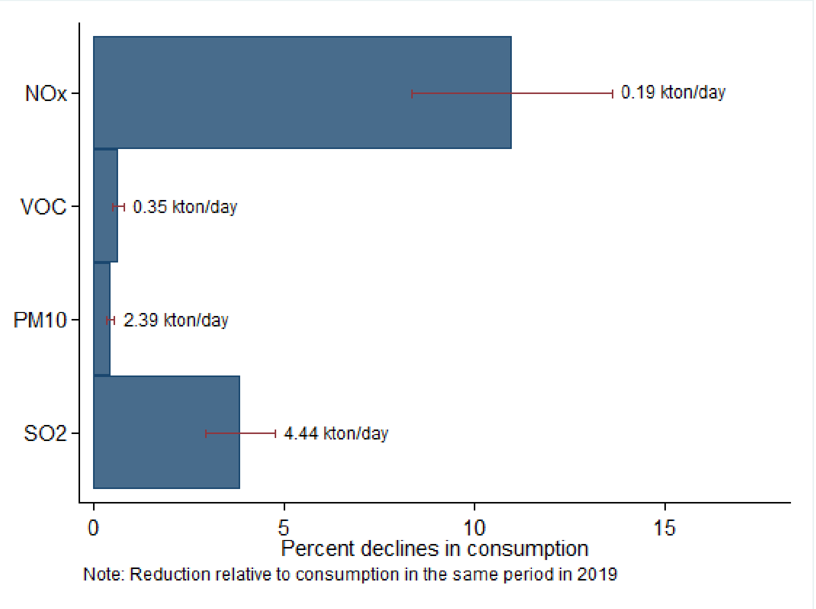



Figure 4: Estimated percentage decrease of daily local pollution emissions (error bars show 99% confidence intervals).

Table 3: Assumed emission factors of considered energy sources.

| Energy source | Emission factor | Source |
|---|---|---|
| *Gasoline [kg/barrel]* | | |
| $CO_2$ | 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) |
| *Kerosene [kg/barrel]* | | |
| $CO_2$ | 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) |
| *Gas-fired electricity generation [kg/MWh]* | | |
| $CO_2$ | 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) |
| *Coal-fired electricity generation [kg/MWh]* | | |
| $CO_2$ | 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) |
| *Residential, commercial (heating) and industrial natural gas [kg/MMcf]* | | |
| $CO_2$ | 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 |

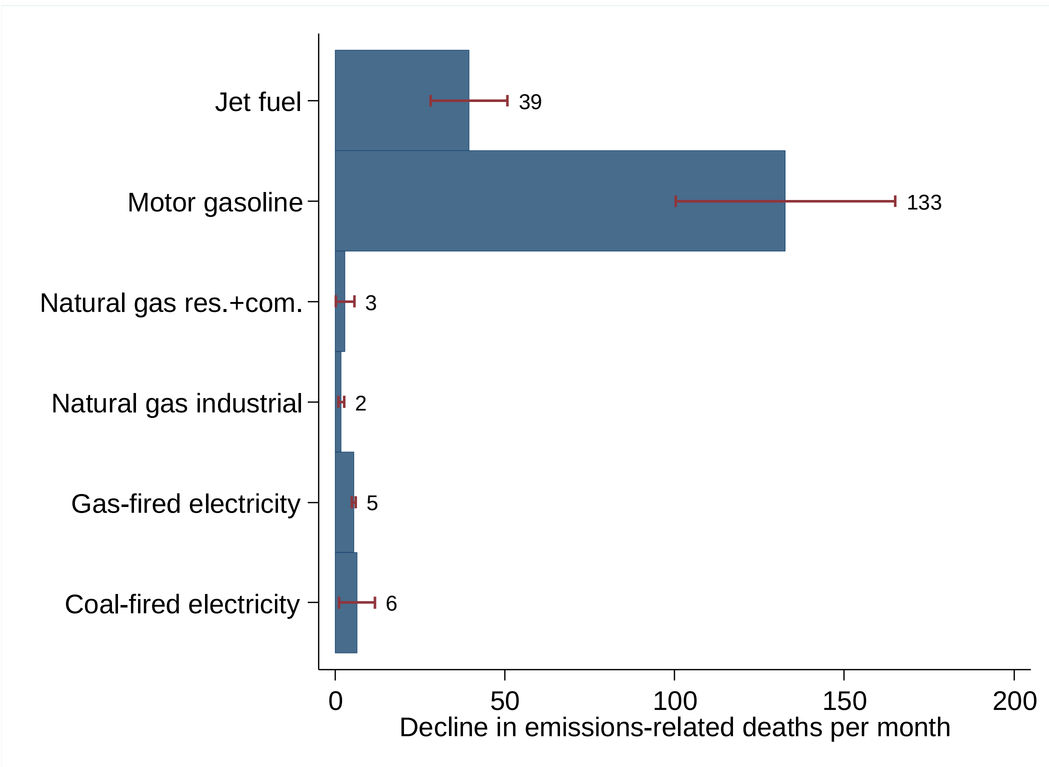



Figure 5: Avoided deaths per month because of the estimated decrease emissions of local pollutants (error bars show 99% confidence intervals).

## 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:

$$\text{stage 1: } PM2.5_{i,t} = \delta_t + \delta_i + hdd_t + cdd_t + \varepsilon_{i,t} \tag{5}$$

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

Where $\delta_t$ are day-by-month fixed effects to control for regular patterns in PM2.5 concentrations, while $\delta_i$ 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, $\beta_{COVID}$ 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 µ g/m3 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.

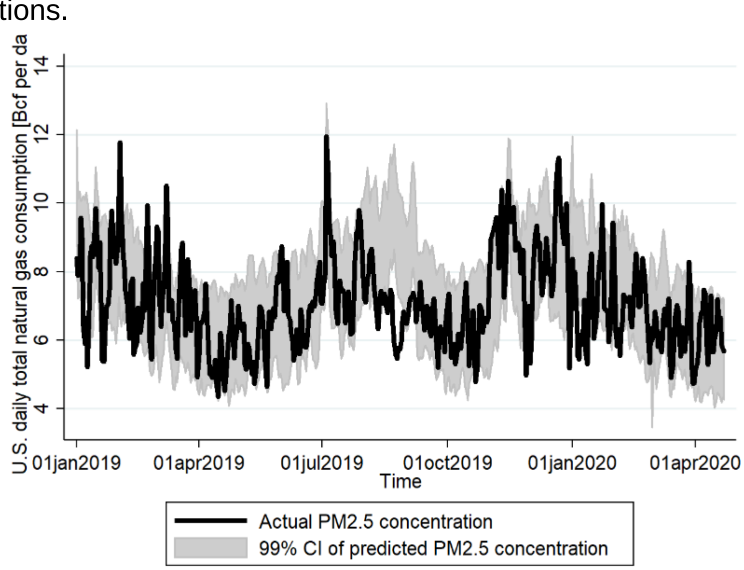



Figure 6: Actual and predicted unweighted average PM2.5 concentrations across all considered U.S. monitors in 2019-2020

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/
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-
Provided by: Massachusetts Deparment 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.

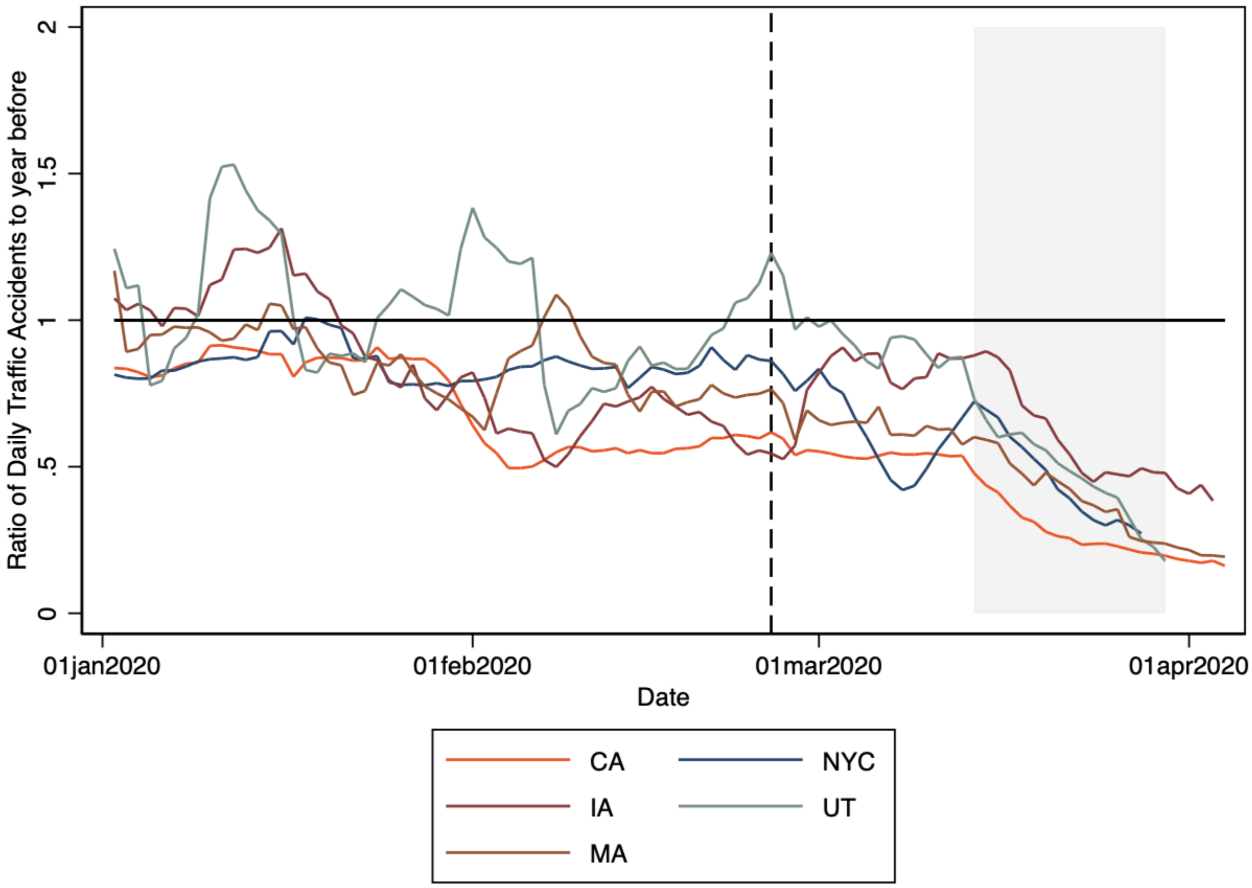



Figure 7: Seven-day moving average of the ratio of 2020 to 2019 crashes by state or region. Numbers greater than 1 indicate more crashes in 2020, while less than 1 indicate fewer crashes in 2020. The dotted line refers to February 26, while the shaded area includes all days after March 13th.

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.

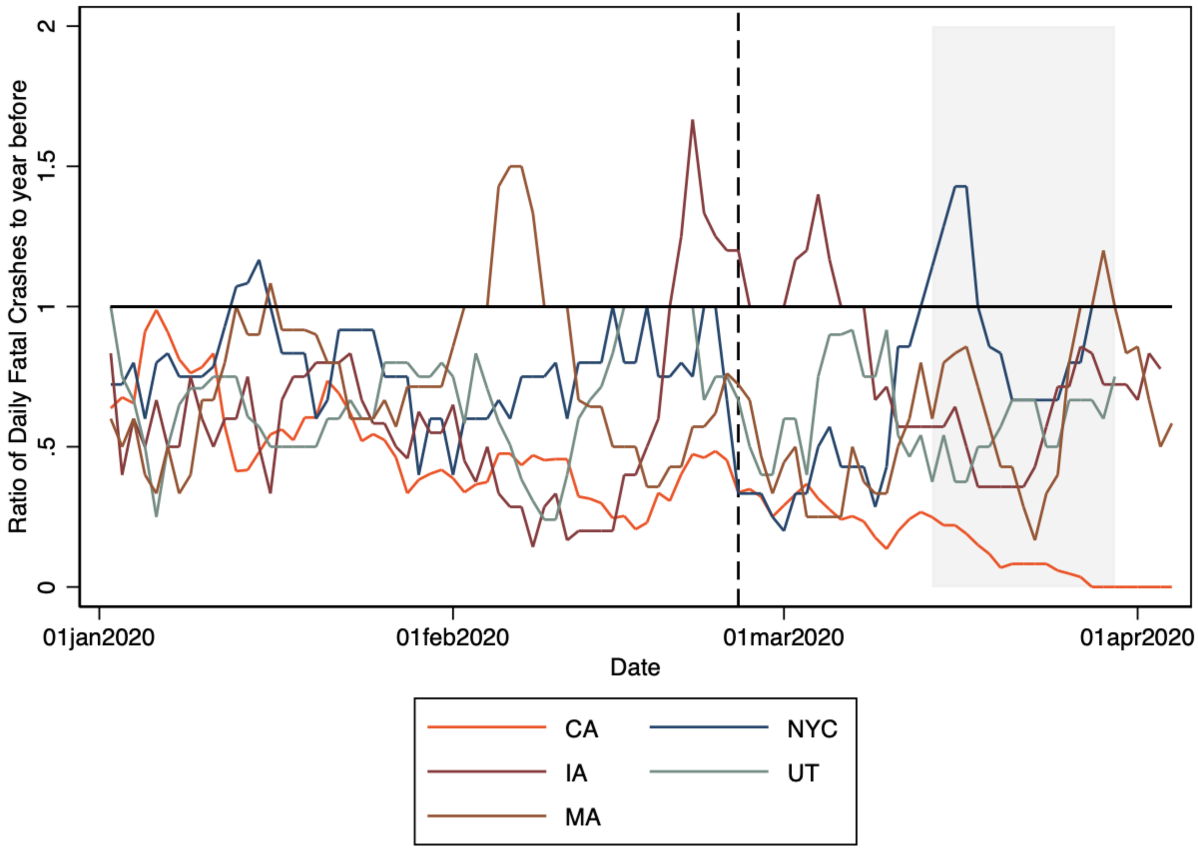



Figure 8: Seven-day moving average of the ratio of 2020 to 2019 fatal crashes by state or region. Numbers greater than 1 indicate more crashes in 2020, while less than 1 indicate fewer crashes in 2020. The dotted line refers to February 26, while the shaded area includes all days after March 13th.

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.

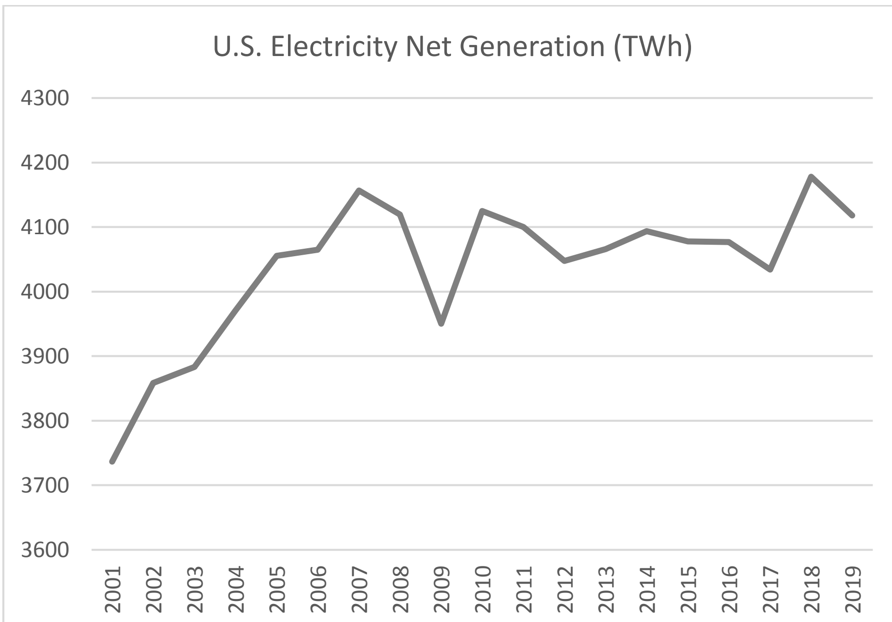
Our second thought experiment is much less optimistic. It represents a case where Covid-19 is not brought under control for at least another year, and perhaps longer. The global economy goes into a deeper recession. Government budgets at all levels are strained. Many firms go bankrupt and most of those 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.

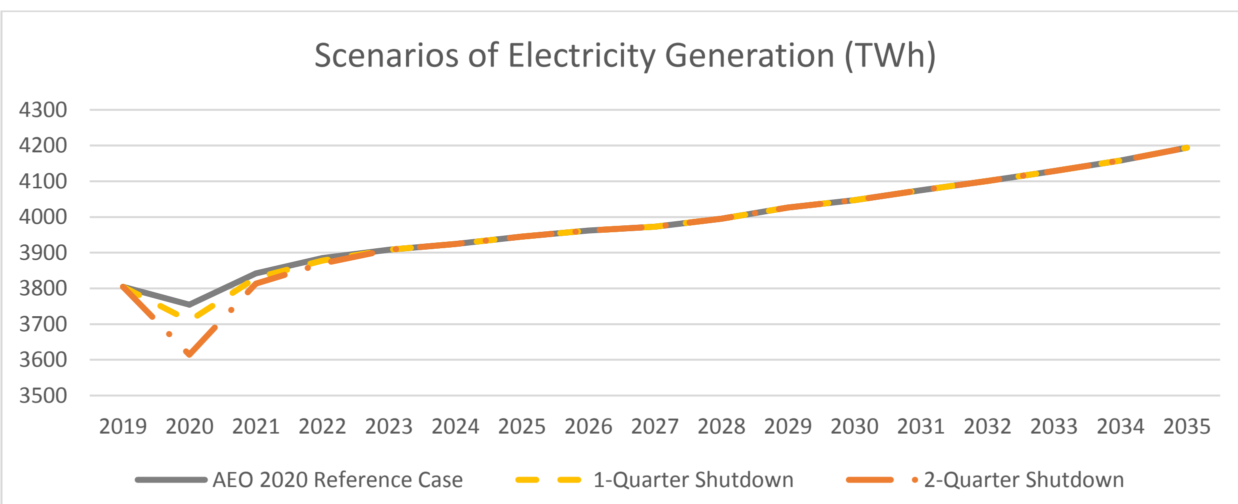
Our modeling of the second long-run scenario consists of two main components. First, energy demand will change due to the shutdown and economic recovery in the near future. Second, fuel mixes and emissions rates will change due to possible delays in renewable technology investments and product releases, 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.

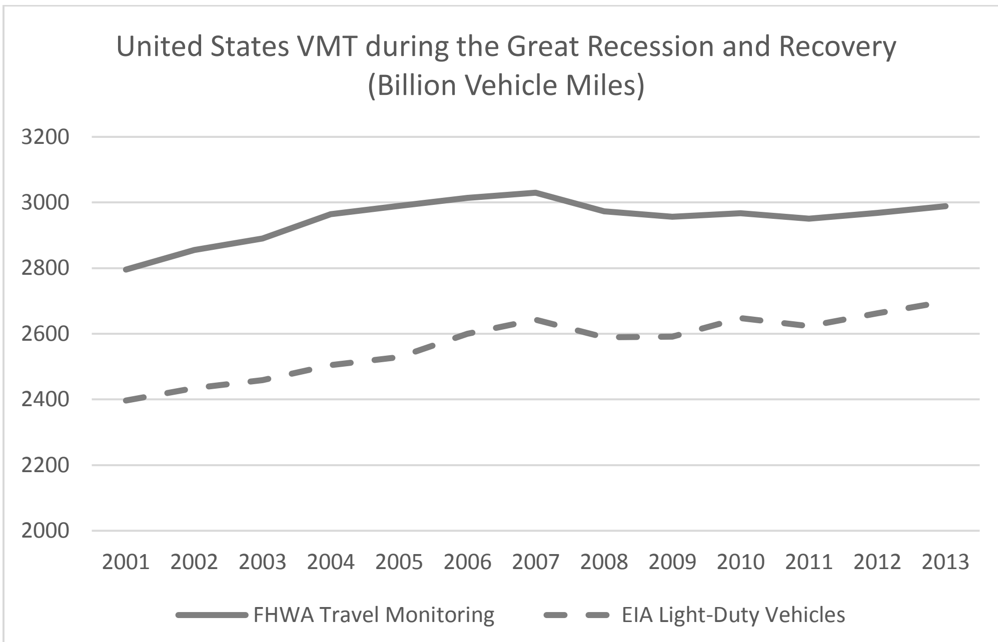



(b) Electricity generation projection used in calculations.

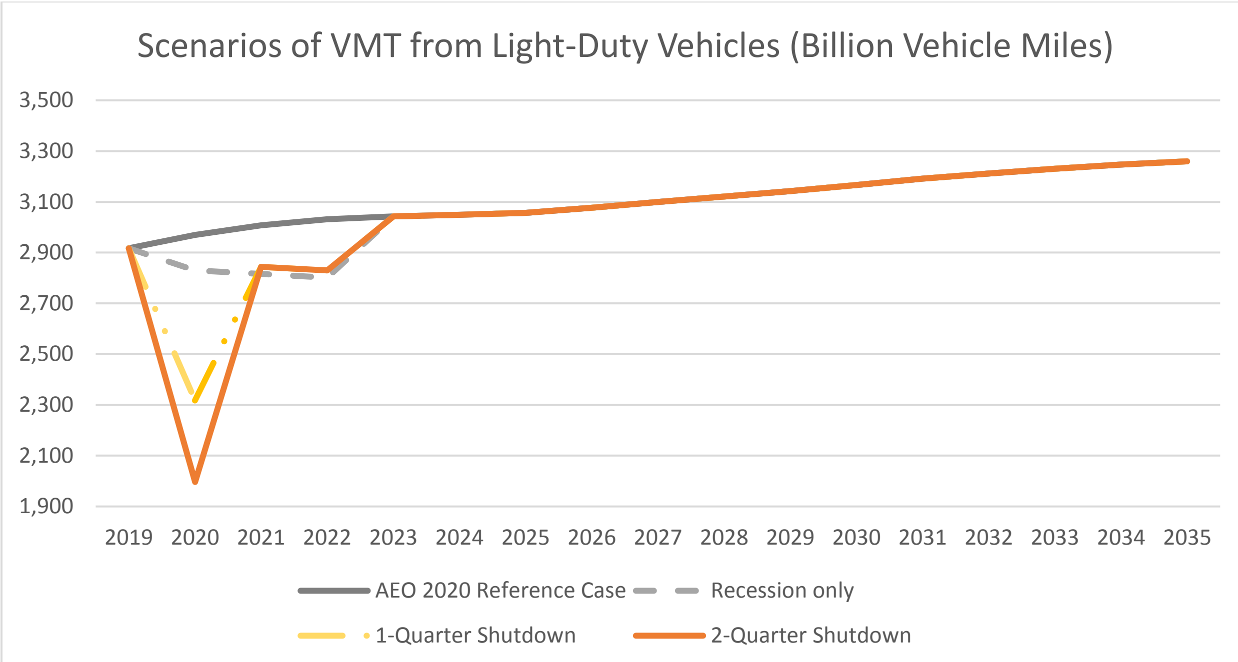
Figure 9

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.

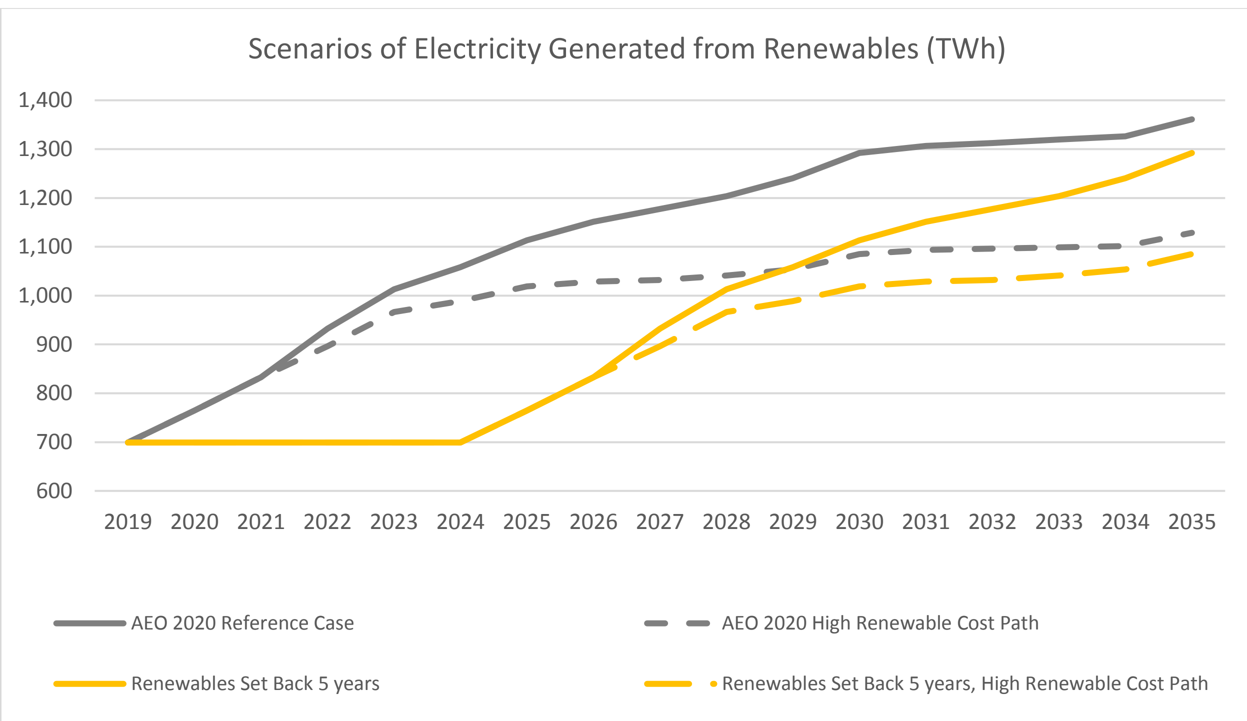
In Figure 10b, the solid gray line depicts the reference case from the 2020 AEO (EIA 2020e). The dashed line represents VMT in an economic recession similar to the Great Recession of 2008. The two lines with big dips in 2020 represent VMT from one or two quarters of shutdown as well as VMT from behavioral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

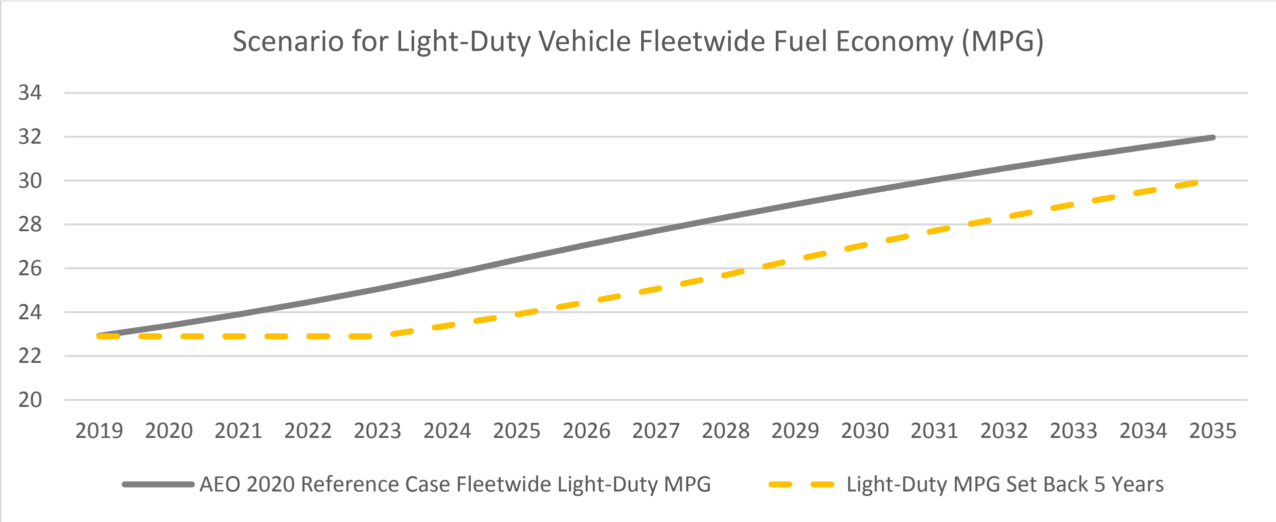
To understand how there may be persistent, lingering effects of Covid-19, we are interested in comparing the shorter-run impacts to the long-run impacts of delayed investments in renewable technology and reducing vehicle emissions.

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.

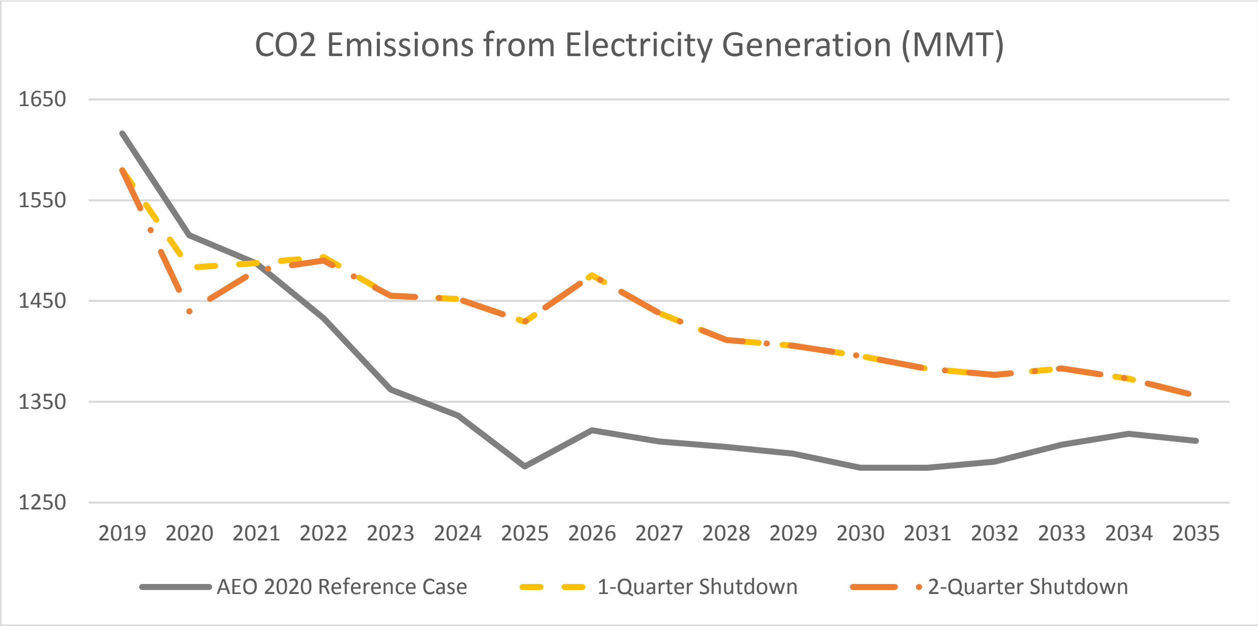



(b) The grey solid line is the reference case from the 2020 AEO. The yellow dashed line is our scenario for what might happen to fleet-wide fuel economy in the U.S. Fleet-wide fuel economy includes fuel economy of the vehicle stock, newly purchased vehicles, as well as EPA MPG-equivalents for alternative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



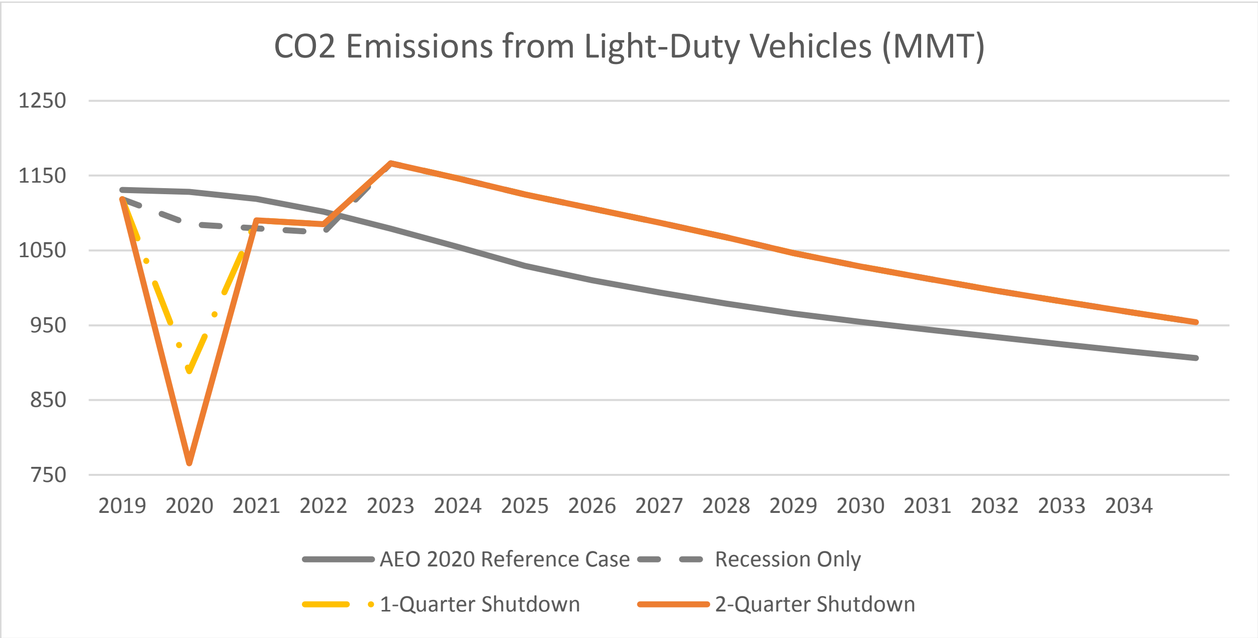




Figure 12 Emissions Scenarios

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 $CO_2$ more) would outweigh the emissions reductions from a one-quarter shutdown (56 fewer deaths, 24 MMT less $CO_2$), for a net impact of 27 more deaths from local pollution and 11 MMT more $CO_2$ 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<br>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<br>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 $CO_2$ 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 $CO_2$ 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 Adminstration (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.

## References


Apple Mobility Trends (2020). Available at https://www.apple.com/covid19/mobility.

Cicala, Steve, Stephen P Holland, Erin T Mansur, Nicholas Z Muller, and Andrew J Yates. 2020. Expected Health Effects of Reduced Air Pollution from COVID-19 Social Distancing.

Federal Highway Administration. (2017a). 2017 National Household Travel Survey, U.S. Department of Transportation, Washington, DC. Available online: https://nhts.ornl.gov.

Federal Highway Administration. (2017b). Summary of Travel Trends, 2017 National Household Travel Survey, U.S. Department of Transportation, Washington, DC. Available online: https://nhts.ornl.gov/assets/2017_nhts_summary_travel_trends.pdf.

Federal Highway Administration. (2020). Traffic Volume Trends. Available online: https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm.

Foldy, B. (2020). Electric-Truck Startup Rivian Delays Launch of Its First Pickup [online]. Wall Street Journal. Available online: https://www.wsj.com/livecoverage/coronavirus-2020-04-07/card/VDaqRCoYvJv3qraFmJfQ. Accessed 30 April 2020.

Hausman, C. and Rapson, D. (2018). Regression Discontinuity in Time: Considerations for Empirical Applications. *Annual Review of Resource Economics*.

Howard, P. W. (2020). Report: Ford Mustang Mach-E delayed, company notifies customers in Norway [online]. Detroit Free Press. Available online: https://www.freep.com/story/money/cars/ford/2020/04/27/ford-europe-mustang-mach-e-launch/3032970001/. Accessed 30 April 2020.

Wall Street Journal (2020). Coronavirus Offers a Clear View of What Causes Air Pollution [online]. Wall Street Journal. Available at: https://www.wsj.com/articles/coronavirus-offers-a-clear-view-of-what-causes-air-pollution-11588498200?

Le Quéré, C., Jackson, R.B., Jones, M.W. et al. Temporary reduction in daily global CO2 emissions during the COVID-19 forced confinement. Nat. Clim. Chang. (2020). https://doi.org/10.1038/s41558-020-0797-x

Liu, Zhu, Zhu Deng, Philippe Ciais, Ruixue Lei, Steven J Davis, Sha Feng, Bo Zheng, et al. COVID-19 Causes Record Decline in Global CO2 Emissions.

Muller, B. N. Z., Mendelsohn, R., and Nordhaus, W. (2011). Environmental Accounting for Pollution in the United States Economy. *American Economic Review*, 101(August):1649–1675.

Muller, N. Z. (2014). Boosting GDP growth by accounting for the environment. *Nature*, 345(6199):0–2.

New York Times (2020). Which States and Cities Have Told Residents to Stay at Home. Available at https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at- home-order.html.

U.S. Energy Information Administration (2014). Annual Energy Outlook Issues in Focus: Light-duty vehicle energy demand: demographics and travel behavior. Available online: https://www.eia.gov/outlooks/archive/aeo14/veh_demand.php.

U.S. Energy Information Administration (2020a). Carbon Dioxide Emissions Coefficients. Available at https://www.eia.gov/environment/emissions/co2_vol_mass.php.

U.S. Energy Information Administration (2020b). U.S. Electric System Operating Data. Available at https://www.eia.gov/opendata/qb.php?category=2123635.

U.S. Energy Information Administration (2020c). U.S. Natural Gas Weekly Update. Available at https://www.eia.gov/naturalgas/weekly/#tabs-supply-2.

U.S. Energy Information Administration (2020d). U.S. Weekly petroleum and other liquids supplied. Available at https://www.eia.gov/dnav/pet/pet_cons_wpsup_k_w.htm.

U.S. Energy Information Administration (2020e). Annual Energy Outlook. Available online: https://www.eia.gov/outlooks/aeo/.

U.S. Energy Information Administration (2020f). Electricity Data Browser - U.S. Net generation for all sectors, monthly. Available online: https://www.eia.gov/electricity/data/browser/.

U.S. Energy Information Administration (2020g). Short-Term Energy Outlook. Available online: https://www.eia.gov/outlooks/steo/pdf/steo_full.pdf

U.S. Environmental Protection Agency (2020a). Air Pollutant Emissions Trends Data. Available at https://www.epa.gov/air-emissions-inventories/air-pollutant- emissions-trends-data.

U.S. Environmental Protection Agency (2020b). AP-42: Compilation of Air Emissions Factors. Available at https://www.epa.gov/air-emissions-factors-and- quantification/ap-42-compilation-air-emissions-factors.

U.S. Environmental Protection Agency (2020c). AP 42, Fifth Edition, Volume I Chapter 1: External Combustion Sources. Available at https://www3.epa.gov/ttn/chief/ap42/ch01/.

U.S. Environmental Protection Agency (2020d). Outdoor Air Quality Data. Available at https://www.epa.gov/outdoor-air-quality-data/download-daily-data.

U.S. Environmental Protection Agency (2020e). Power Plant Data Highlights. Available at https://www.epa.gov/airmarkets/power-plant-data-highlights.

U.S. National Oceanic and Atmospheric Administration (2020). Degree days. Available at ftp://ftp.cpc.ncep.noaa.gov/htdocs/degree_days/weighted/daily_data/.

Streetlight Data Inc. (2020). Companion data to StreetLight VMT Monitor Map. Available by request at https://learn.streetlightdata.com/vmt-data-counties.