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Asymmetric Response of Carbon Emissions to Recessions and Expansions and Oil Market Shocks

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Abstract

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Keywords

COVID-19, climate change, business cycle

JEL Classification

Q43, Q54

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1. Introduction

The 2020 COVID-19 driven recession saw a sharp drop in carbon dioxide emissions as transportation and some other energy uses were curtailed. This was an unusual recession as it was driven by a pandemic. We were curious about whether carbon emissions behaved differently in this recession than in past recessions. Previous research showed that the elasticity of carbon emissions with respect to GDP is greater when GDP declines than when it increases (Sheldon, 2017). In this paper, we examine the behavior of carbon emissions in each individual US recession since 1973 using monthly GDP (Brave *et al*., 2019) and carbon emissions data. We find that carbon emissions respond asymmetrically to changes in GDP in the 1973-5, 1980, 1990, and 2020 recessions but not in the 1981-2, 2001, or 2008-9 recessions. The 1973-5, 1980, 1990 recessions are associated with negative oil supply shocks. The 2020 recession is associated with a negative oil demand shock. In both cases, oil consumption fell sharply. By contrast, in the 1981-2, 2001, and 2008-9 recessions carbon emissions fell by the amount that would be expected given the decline in GDP.

York (2012) reported that the carbon emissions-income elasticity is higher during individual years of economic expansion than during individual years of economic contraction. He argued that this elasticity is likely to be lower during contractions, as reductions in the use of durable assets accumulated in booms might be relatively small in contractions. But, using data on 189 countries between 1961-2010, Burke *et al*. (2015) concluded that there was no strong evidence that emissions reacted differently during years with economic growth compared to years with falling GDP. However, they found that significant evidence of asymmetry emerges when effects over longer periods were considered. Economic growth tends to increase emissions not only in the same year, but also in subsequent years. Delayed effects – especially in the road transport sector – mean that emissions tend to grow more quickly after booms and more slowly after recessions. However, Doda (2013) noted significant heterogeneity in asymmetry across countries.

Shahiduzzaman and Layton (2015) point out that carbon emissions fell faster in all US recessions than in all US expansions since 1973. Inspecting their Table 5, we also see that the ratio of percentage change per annum in CO_2 emissions to percentage change in GDP was greater in all contractions than in any expansion. However, we could explain this if changes in CO_2 emissions are explained by a time effect and a growth effect:

$$\Delta\ln \boldsymbol{C_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\Delta\ln \boldsymbol{GDP_t} \tag{1}$$

where ΔlnC_t and ΔlnG_t denote the first differences of the logs of carbon emissions and GDP. Then if $\alpha < 0$, CO_2 emissions will fall faster in recessions than they rise in expansions for a given absolute percentage change in GDP even if β_1 is the same in both contractions and expansions.

Sheldon (2017) estimated an econometric model using quarterly US data. She found that the carbon emissions-income elasticity was greater in quarters with declining GDP than in quarters with rising GDP. Specifically, she found that a one percent increase in GDP results in a 0.2% increase in emissions, while a one percent decrease in GDP results in a 1.8% fall in emissions. Klarl (2020) finds similar results using monthly US data and a rolling regression method. Eng and Wong (2017) use a nonlinear autoregressive distributed lag model estimated with monthly US industrial production and CO_2 emissions data. They find that CO_2 emissions decline more rapidly in response to a given absolute percentage change in industrial production during recessions than they increase during expansions over the long run. However, they found that in the short run the response to changes in industrial production is symmetric.[1]

Carbon emissions fell sharply globally at the onset of the 2020 recession (Le Quéré *et al*., 2020) as did other pollutants (Forster *et al*., 2020). Researchers estimated emissions in near real time and tracked a very rapid rebound (Liu *et al*., 2020). Chang *et al*. (2020) predicted that at least in Taiwan the bounceback would again be asymmetric.

The causes of recessions remains a controversial topic (Kilian and Vigfusson, 2017). Most US recessions since 1973 have been associated with increases in the price of oil. But Bernanke *et al*. (1997) argued that the US Federal Reserve's response to oil price shocks caused US recessions rather than the shocks themselves. Kilian and Lewis (2011) counter that this really was only the case of the 1979 oil price shock, and it is unclear whether the Federal Reserve would have raised interest rates even in the absence of the oil price shock. Kilian (2009) and Kilian and Lewis (2011) argue that the effect of increases in the price of oil on the economy depends on the causes of those increases. Some oil price increases are primarily due

[1]We replicated Sheldon (2017) with industrial production data instead of GDP data and found that the response was symmetric. GDP and industrial production data have different short-run effects on carbon emissions.

to increasing demand – such as the increase from 2003 to 2008 – and some by reduced supply, such as in 1979 (Baumeister and Hamilton, 2019). Supply shocks lead to a reduction in global economic activity, while shocks to oil demand do not (Baumeister and Hamilton, 2019).

We follow a similar approach to Sheldon (2007) but use US monthly data from January 1973 to December 2020. In addition to testing for asymmetry regarding recessions and expansions in general, we also test whether the response of CO_2 emissions to changes in GDP is different in each individual recession. We find that the response is greater in recessions that have been closely linked to either negative oil supply shocks or to the negative oil demand shock induced by the COVID-19 pandemic. We conclude that the asymmetry is mostly due to the to the reduction in petroleum consumption.

The paper proceeds as follows. The following section provides a brief history of oil price shocks and US recessions. Section 3 presents our methods and Section 4 our data. Section 5 documents the results. Section 6 summarizes our findings and provides key conclusions.

2. Oil Price Shocks and Recessions

Figure 1 presents the history of oil prices in the US since 1973. There are normally considered to be three main negative oil supply crises in US history since 1973 (Hamilton, 2009). The first oil shock erupted in October 1973 when the Organization of Arab Petroleum Exporting Countries (OAPEC) decided to place an embargo on some western countries, including the US, perceived as supporting Israel during the Yom Kippur War. The embargo lasted from October 1973 to March 1974. A recession followed in the US from December 1973 to March 1975 (Table 1).

Figure 1 Monthly US Oil Prices

Notes: Nominal price is the refiner acquisition cost of crude oil, composite (US EIA *July 2021 Monthly Energy Review*, Table 9.1). Real price is deflated by the US consumer price index (Bureau of Labor Statistics). Average annual nominal price shown for 1973.

Table 1. US Recessions (1973-2020)

	Recession	First Month	Last Month
1	1973-5 recession	December 1973	March 1975
2	1980 recession	February 1980	July 1980
3	1981-2 recession	August 1981	November 1982
4	1990-1 recession	August 1990	March 1991
5	2001 recession	April 2001	November 2001
6	2008-9 recession	January 2008	June 2009
7	2020 recession	March 2020	April 2020

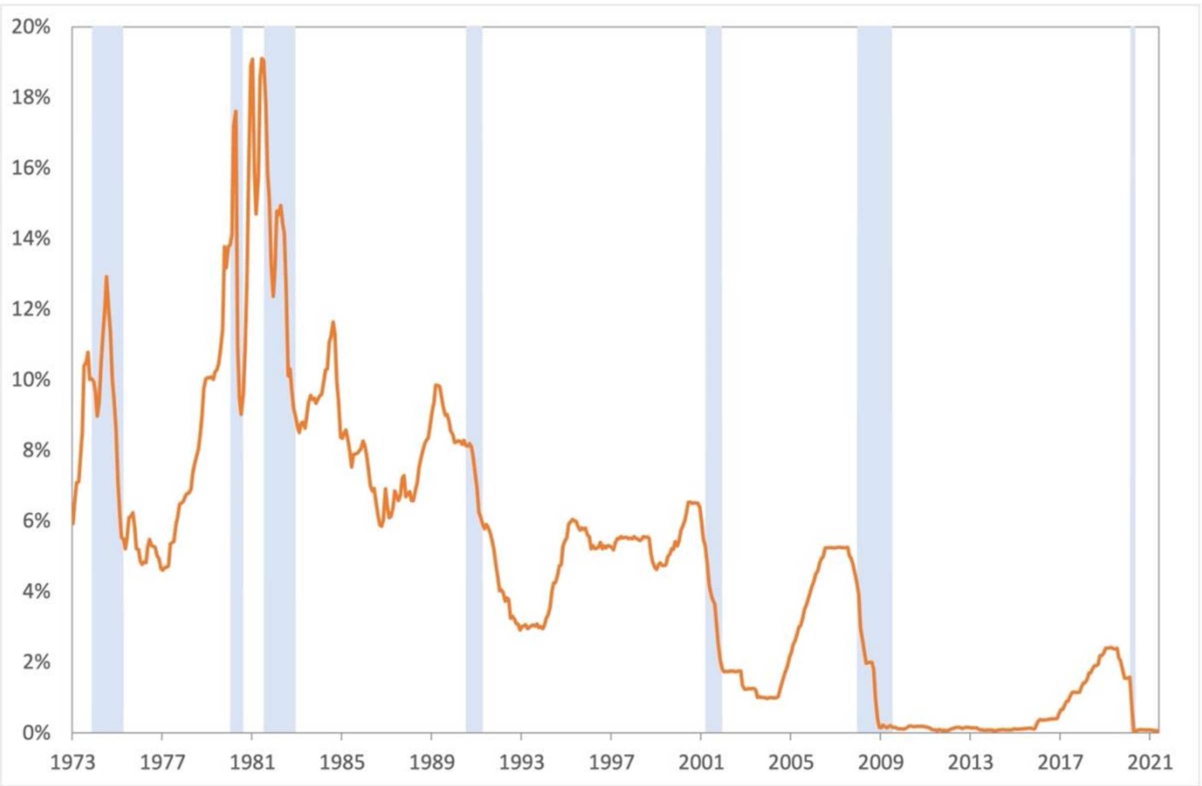
Notes: Recessions defined by the National Bureau of Economic Research (NBER). The first month of the recession is the month following the "peak month" given by the NBER.

The second shock started in early1979 following the Iranian Revolution in January and worsened following Iraq's invasion of Iran in September1980. A recession followed from February to July 1980. There was a third spike in oil prices from August 1990 after Iraq invaded Kuwait, two of the world's largest suppliers of crude oil, resulting in a shortfall of almost 9% of world oil production (Hamilton 2003). A US recession started in August 1990 and lasted till March the next year after a coalition of forces led by the US defeated the Iraqi army and liberated Kuwait.

The 1981–82 recession was primarily triggered by tight monetary policy under Federal Reserve chair Paul Volcker in response to continuously high inflation (Kilian and Lewis, 2011). The federal funds rate was raised to more than 19% in June 1981 from around 9% when Volcker took office in August 1979 (Figure 2).

In 2001, a recession bracketed the September 11 terrorist attack. Stock markets, and particularly the NASDAQ market began to fall in early 2000 in the so-called dot.com bust. These are usually seen as the causes of this recession (Bernanke 2010). The Federal Reserve raised interest rates from the beginning of 1999 to the end of 2000. The price of oil did rise from the Asian Financial Crisis in 1997-8 till late 2000 as demand bounced back. But the price of oil began to fall from September 2000. The price of oil fell particularly strongly following the attack.

Figure 2 Effective Federal Funds Rate



Notes: Recessions marked with blue shading. Source: https://fred.stlouisfed.org/series/FEDFUNDS

The price of oil rose following this recession and peaked in July 2008 at its all-time high. This increase is understood to have been driven by rising demand fueled by the rise of China and India in particular (Kilian, 2009; Hamilton, 2009). Hamilton (2009) argued that the rise in the price of oil was also partly due to stagnation of world oil production. The Great Recession in 2008 and 2009 is usually considered to have been caused by the financial crisis that started in the US housing and mortgage market. Hamilton (2009), however, argued that the 2008-9 recession was also partly due to the spike in the oil price.

The COVID-19 global recession is unprecedented as it was the result of the breakout of the Coronavirus pandemic. The global depression, and particularly restrictions on transport, led to decreasing demand for oil, triggering a sharp fall in the price of oil. The demand shock was exacerbated by the eruption of a price war between Saudi Arabia and Russia. West Texas Intermediate Crude Futures even became negative in May 2020, falling as low as -$40.32 (Mulder 2020).

In conclusion, we argue that four US recessions appear to be primarily associated with negative (reduced supply or reduced demand) shocks in the oil market: 1973-5, 1980, 1990-1, and 2020.

3. Methods

3.1. Basic specification

The simplest model of the response of carbon dioxide emission changes to GDP growth can be generated by adding a random error term, ϵ_t, and weather variables to (1):

$$\Delta\ln C_t = \beta_0 + \beta_1 \Delta\ln G_t + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \qquad (2)$$

where H_t is heating degree days and K_t cooling degree days. The constant term β_0 is, therefore, the mean of ΔlnC_t when there is no economic growth (Stern et al., 2017). In contrast to Sheldon (2017), GDP is not lagged in this baseline model. Sheldon lagged GDP because she was concerned about reverse causality. However, in this paper we are only interested in the association between growth and emissions rather than measuring a causal relationship.[2] On the other hand, Csereklyei and Stern (2015) argue that the causal effect of GDP on energy use is only a little smaller than the reduced form estimate. This argument should extend to the causal effect of GDP on carbon emissions. We also estimate models with a distributed lag specification, as described below, to test for a lagged relationship between carbon emissions and GDP.

3.2. Asymmetric specifications

We specify:

$$\Delta \ln C_t = \beta_0 + \beta_1 \Delta \ln G_t + \beta_2 D_t^- \Delta \ln G_t + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \tag{3}$$

D^- denotes the negative growth dummy that equals one when GDP growth is less than zero, and zero otherwise. The coefficient β_2 measures the difference in the elasticity of carbon emissions with respect to GDP between recession and expansion periods and so a t-test for whether this coefficient is zero is a direct test for asymmetry. β_1 is then the elasticity during expansions and $\beta_1 + \beta_2$ is the elasticity during recessions. Essentially, we are allowing for a piecewise linear response of emissions to GDP with a kink at zero GDP growth.

Monthly data can be somewhat noisy – it is possible to have some positive months of growth within a recession. Therefore, we also estimate (3) using a dummy variable for NBER recessions, D^R:

$$\Delta \ln C_t = \beta_0 + \beta_1 \Delta \ln G_t + \beta_3 D_t^R \Delta \ln G_t + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \tag{4}$$

3.3. Recession comparison

Next, we investigate whether the 2020 pandemic recession is different from past recessions in terms of the carbon emissions-GDP elasticity:

$$\Delta ln C_t = \beta_0 + \beta_1 \Delta ln G_t + \beta_4 D_t^{past} \Delta \ln G_t + \beta_{11} D_t^{2020} \Delta \ln G_t + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \tag{5}$$

D^{past} denotes the past recession dummy, equal to one when a month is within a past recession (before the year 2020) and zero otherwise. D^{2020} is the 2020-year dummy, equal to one when a month is during the 2020 recession and zero otherwise.

[2] Using our monthly data, if we specify (2) with one lag of ΔlnG instead, its coefficient is statistically insignificantly different to zero.

Since past recessions may differ in their characteristics it is worth investigating each recession individually:

$$\Delta lnC_t = \beta_0 + \beta_1 \Delta lnG_t + \sum_{i=1}^{7} \beta_{4+i} D_t^{R_i} \Delta lnG_t + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \tag{6}$$

There are seven $D_t^{R_i}$ dummy variables, each represents a recession since 1973. $D_t^{R_1} = D_t^{1973-5}$ equals one for months during the 1973-5 recession and zero otherwise. Similarly, $D_t^{R_2} = D_t^{1980}$ equals one when or months during the 1980 recession and zero otherwise and so forth for the remaining dummies. The detailed months when recessions start and end are listed in Table 1.

3.4. Excess oil consumption and other energy use

As we argued in Section 2, four US recessions are associated with important negative shocks in the oil market. Could large falls in oil consumption associated with these shocks cause the response of emissions to changes in GDP appear to be larger in recessions than expansions? However, oil and energy use more generally typically falls in all recessions as economic activity declines. Furthermore, simply including oil consumption in the regression will explain much of the variation in carbon emissions, not just the asymmetric behavior of emissions. Therefore, we want to filter out the part of oil use that is correlated with changes in GDP. To do this, we regress changes in the log of petroleum consumption, *P*, on changes in log GDP:

$$\Delta \ln P_t = \gamma_0 + \gamma_1 \Delta lnG_t + \epsilon_t^p \tag{7}$$

We also regress changes in log natural gas, F_1, and coal, F_2, on GDP:

$$\Delta \ln F_{it} = \delta_{i0} + \delta_{i1} \Delta lnG_t + \epsilon_t^{f_i} \tag{8}$$

We then add each of the estimated residual series, $\hat{\epsilon}_t^p$, $\hat{\epsilon}_t^{f_i}$, to the foregoing regressions for ΔlnC_t to see whether the asymmetric effect of recessions disappears or not. If adding $\hat{\epsilon}_t^p$ removes the asymmetry but adding $\hat{\epsilon}_t^{f_i}$ does not, then we argue that the asymmetry is explained by the part of the decline in oil use that is greater than would be expected due to the decline in GDP alone.

3.5. Sectoral emissions and asymmetric impacts

Is asymmetry particularly pronounced in some sectors of the economy? If asymmetry is greater in sectors that predominantly use oil, in particular the transport sector, this will provide further support to the idea that asymmetry is due to changes in oil use. We apply (4) to emissions from the residential, commercial, industrial, transportation, and electric power sectors and economy-wide economic growth. We check the sectoral emissions-income asymmetry between recessions and other periods to see which sectors contribute to the overall asymmetry. We also test the effect of adding oil and other fossil fuel residuals to these regressions.

3.6. Distributed-lag model

Our primary interest is the contemporaneous correlation between carbon emissions and economic changes because it shows whether emissions fall faster relative to the fall in GDP in recessions than they rise in expansions. However, there are undoubtedly lagged effects of changes in GDP on emissions, for example due to investment in energy-using durable goods. To provide more information on how CO_2 emissions respond to changes in GDP over time, we use a distributed-lag model to compare the cumulative response of carbon dioxide emissions to changes in GDP during recessions and expansions:

$$\Delta \ln C_t = \beta_0 + \sum_{j=0}^{m} \beta_{1,j} \Delta \ln G_{t-j} + \sum_{j=0}^{m} \beta_{3,j} D_{t-j}^{R} \Delta \ln G_{t-j} + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \qquad (9)$$

The $\beta_{3,j}$ coefficients measure the difference in the elasticity of carbon emissions with respect to GDP between recession and expansion periods in period *t-j*; the coefficients $\beta_{1,j}$ are the elasticities during booms in period *t-j*. Then the long-run emissions-income elasticity during expansions is $\sum_{j=0}^{m} \beta_{1,j}$ and the difference in the long-term emissions-income elasticity between recessions and expansions is $\sum_{j=0}^{m} \beta_{3,j}$. the long-run elasticity of carbon emissions with respect to GDP during recessions is: $\sum_{j=0}^{m} (\beta_{1,j} + \beta_{3,j})$.

To specify the distributed-lag model, we use the Akaike Information Criterion (AIC) to find the optimal lag length. We use a maximum lag length of 12 months in addition to the contemporaneous terms.

4. Results

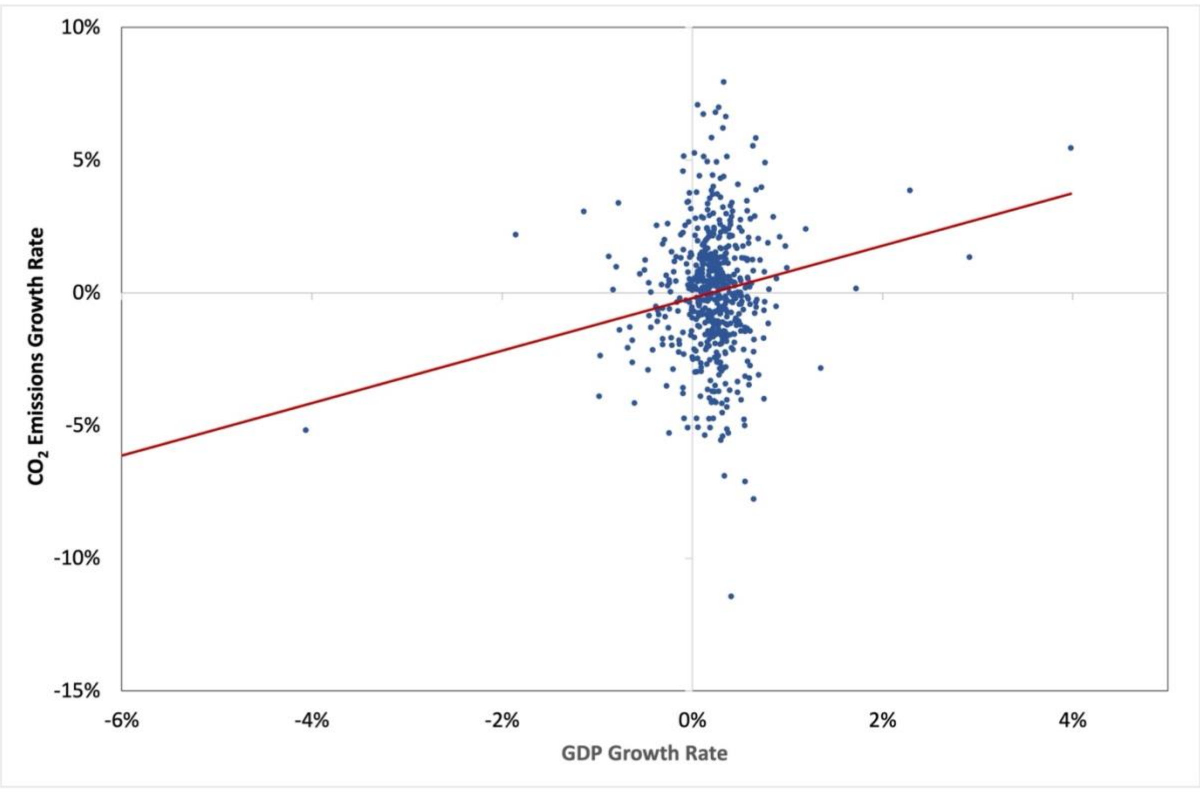
4.1. Asymmetry of the emissions-income relationship

The Appendix presents the sources of the data. The data start in January 1973 and end in December 2020. We seasonally adjust the carbon dioxide emissions and energy consumption data using the X-13ARIMA-SEATS program (Census Bureau U.S. 2017). Degree days data are seasonally adjusted with the X-11-additive decomposition method. GDP is already seasonally adjusted. According to the augmented Dickey–Fuller test, the first differences of the logarithms of carbon dioxide emissions and GDP are stationary.

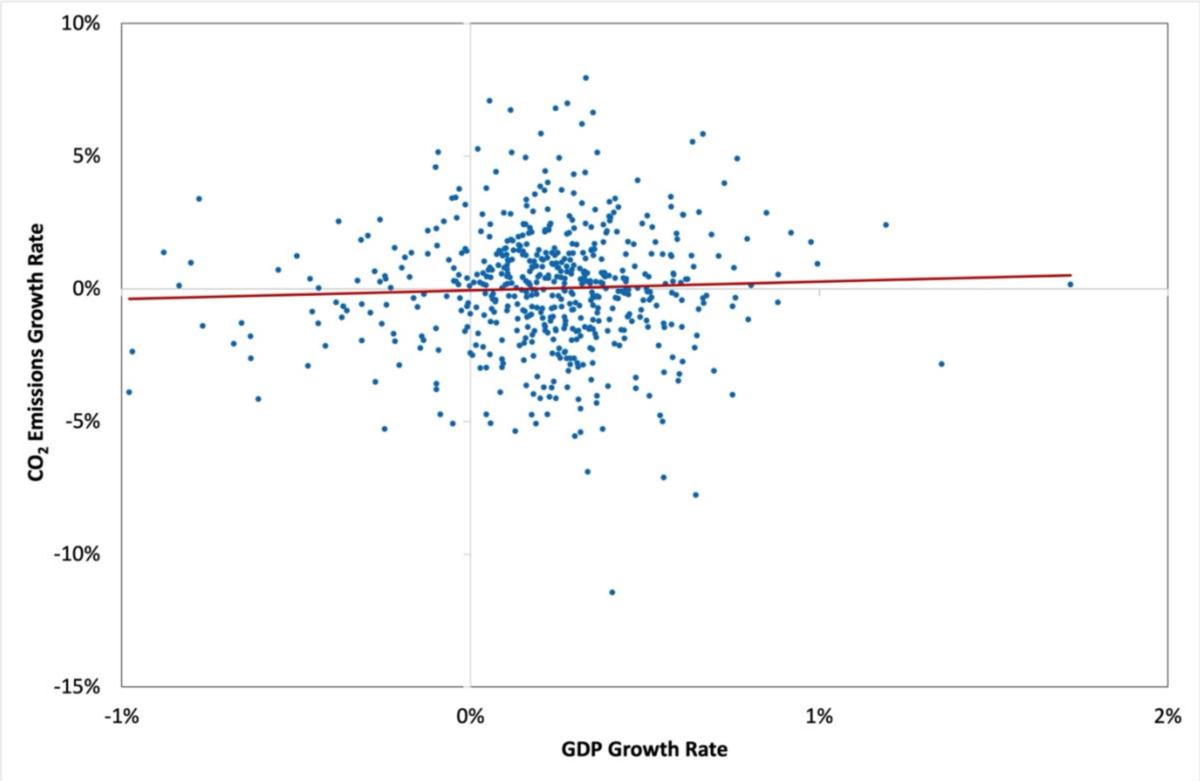
In March and April 2020, GDP fell by 3.98% and 5.91%, respectively. These extreme outliers potentially greatly affect the relationship between changes in carbon emissions and GDP. Figure 3 demonstrates the relationship between these two variables before and after 2020. Panel (A) includes all data from January 1973 to December 2020; Panel (B) includes data from January 1973 to December 2019. The slope is positive in both samples but is not as large when 2020 is excluded.

Figure 3 Monthly Carbon Dioxide Emissions and GDP Growth Rates. **A** 1973-2020, **B** 1973-2019

A



B



Columns 1-2 in Table 2 show the emissions-income elasticities using (2) for 1973-2020 and for 1973-2019, respectively. This evaluates the impact of the COVID-19 recession on the emissions-income elasticities. Column 1 shows that the emissions-income elasticity is nearly 1.2 for the full sample, while it is only 0.8 before the year 2020. The time effect is negative and significant at the 1% level in the full sample but is less statistically significantly in the other regressions in the table.

Columns 3-4 check for asymmetric effects of economic growth on carbon emissions using (3). The response is asymmetric for the full sample. The emissions-income elasticity is greater than unity and highly statistically significant when GDP growth is negative and less than one when growth is positive. Though the specifics differ, these results are broadly in line with the previous literature. However, the difference between the effects when GDP is contracting and growing is not statistically significant when the 2020 data is excluded.

In Columns 5–6 we compare recessions and expansions to identify whether the response of CO_2 emissions to growth is different during different periods using (4). The results are similar to those in Columns (3) and (4).

Table 2. Elasticities and Asymmetric Effects

Dependent variable: $\Delta\ln C_t$

Specification	(1) Elasticity 1973-2020	(2) Elasticity 1973-2019	(3) Negative changes 1973-2020	(4) Negative changes 1973-2019	(5) Recessions 1973-2020	(6) Recessions 1973-2019
$\Delta\ln G_t$	1.199***	0.775***	0.715***	0.542**	0.592***	0.681***
	(0.191)	(0.161)	(0.170)	(0.236)	(0.145)	(0.208)
$D_t^{-}\Delta\ln G_t$			0.879***	0.708		
			(0.222)	(0.526)		
$D_t^{R}\Delta\ln G_t$					1.238***	0.338
					(0.268)	(0.498)
Constant	-0.003***	-0.002***	-0.001*	-0.001	-0.001	-0.001*
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	575	563	575	563	575	563
R-squared	0.554	0.554	0.559	0.555	0.567	0.554

Notes: Variable names as in text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days also included in all regressions. *** significant at 1% , ** 5%, and * 10% significance levels.

Table 3. Asymmetric Effects for Individual Recessions

Dependent variable: $\Delta\ln C_t$

Specification	(1) Past recessions	(2) Individual recessions
$\Delta\ln G_t$	0.626***	0.608***
	(0.147)	(0.147)
$D_t^{past}\Delta\ln G_t$	0.437	
	(0.448)	
$D_t^{2020}\Delta\ln G_t$	1.347***	
	(0.184)	
$D_t^{1973-75}\Delta\ln G_t$		1.663**
		(0.824)
$D_t^{1980}\Delta\ln G_t$		1.016***
		(0.328)
$D_t^{1981-82}\Delta\ln G_t$		-0.614**
		(0.294)
$D_t^{1990-91}\Delta\ln G_t$		1.944***
		(0.400)
$D_t^{2001}\Delta\ln G_t$		-1.287
		(0.951)
$D_t^{2008-09}\Delta\ln G_t$		0.079
		(0.438)
$D_t^{2020}\Delta\ln G_t$		1.367***
		(0.184)
Constant	-0.001*	-0.001
	(0.001)	(0.001)
Observations	575	575
R-squared	0.569	0.572

Notes: Variable names as in text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days also included in all regressions. *** significant at 1%, ** 5%, and * 10% significance levels.

Column 1 in Table 3 compares the difference in the elasticity in the 2020 recession compared to expansions and the difference between expansions and all other past recessions using (5). The COVID-19 recession has a pronounced asymmetric response of carbon emissions. The previous six recessions overall do not show a statistically significant asymmetric response. Two possibilities could cause this aggregate result. The first possibility is there is no asymmetric response of carbon emissions during recessions and booms. Alternatively, CO_2 emissions respond asymmetrically during some recessions while symmetrically for the rest, the effects offsetting each other.

To investigate which is the case, Column 2 identifies individual recessions and compares the response of carbon emissions in expansions to that in each of the seven individual recessions from 1973 to 2020. The results show that along with the 2020-recession, in the 1973-5 recession, 1980 recession, and 1990 recession, the responses of carbon emissions in recessions are significantly larger than in expansions. The difference is statistically significant at the 5% level for the 1973-5 recession and significant for the following recessions at the 1% level. This is interesting because these past recessions are associated with negative oil supply shocks. while the 2020 recession is associated with a negative oil demand shock because of the sudden outbreak of the pandemic. The emissions-income elasticity in the other three recessions is not significantly greater to the elasticity in general and the sign of the estimated coefficient is even negative in two of the recessions.

4.2. Impacts of oil crises

The results in Table 3 suggest that the asymmetric effect of growth on carbon emissions in some recessions compared to booms is likely associated with negative oil market shocks. In Table 4, we examine whether changes in oil use that are not explained by GDP explain this asymmetry by including the estimated residuals from (7) in the models we have estimated up to this point. As use of other energy also declines during recessions, to investigate whether this is responsible for the asymmetry, we also add the estimated residuals for coal and natural gas use from (8).

Column 1 in Table 4 is our baseline model that compares carbon emissions during recessions and booms. Columns 2-5 demonstrate how residual oil and other fossil fuel use variables (coal and natural gas) affect this relationship.

When we add $\hat{\epsilon}_t^p$ in Column 2, the coefficient for recessions becomes negative but statistically insignificant, showing that petroleum consumption changes have a significant role in creating this asymmetry. However, the results in Columns 3-5 show that the difference between recessions and booms is still highly significant when we add the other fossil fuel series. These results show that this asymmetry is not mainly due to a drop in other fossil fuels during recessions.

Table 4. Adding Fossil Fuel Residuals to the Asymmetric Model

Dependent variable: $\Delta\ln C_t$

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
$\Delta\ln G_t$	0.592***	1.234***	0.382***	0.545***	0.380***
	(0.145)	(0.131)	(0.119)	(0.135)	(0.103)
$D_t^R\Delta\ln G_t$	1.238***	-0.187	1.530***	1.133***	1.384***
	(0.268)	(0.163)	(0.238)	(0.277)	(0.247)
Oil residual		0.488***			
		(0.027)			
Coal residual			0.297***		0.241***
			(0.032)		(0.024)
Natural gas residual				0.297***	0.259***
				(0.018)	(0.016)
Constant	-0.001	-0.003***	-0.000	-0.001	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.567	0.727	0.684	0.729	0.804
Observations	575	575	575	575	575

Notes: Variable names as in text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days also included in all regressions. *** significant at 1%, ** 5%, and * 10% significance levels.

Columns 2-5 in Table 5 show the effect of including $\hat{\epsilon}_t^p$ and $\hat{\epsilon}_t^{fi}$ on the coefficients of individual recessions. When we include the oil consumption residual, the asymmetric response of carbon emissions is removed or weakened for the four recessions that show asymmetry in Column 1. This shows that asymmetric changes in petroleum consumption explains these asymmetries. The coal residual does not remove any of the asymmetries (Column 3). The natural gas residual does not remove the asymmetry of carbon emissions in the 1990-1 and the 2020 recessions though the asymmetry is no longer statistically significant for the 1973-5 and 1980 recessions (Column 4).

Figure 4 attempts to explain why this is. We used the Hodrick-Prescott filter to remove the long-run trends in the variables in order to focus on the business cycle scale fluctuations. Oil use fell sharply in December 1973 and January 1974. However, the use gas moved in tandem. In 1974 and 1975 gas use tracked the use of oil relatively closely. Throughout this period the price of natural gas rose fairly smoothly, and gas use fell. Coal use was much more stable. However, the big move down in gas use does seem to be initiated by the oil crisis as it happens at exactly the same time. In 1980, we see that oil use tracks GDP quite well, though moving more than GDP on both the up and downside. In fact, oil use was falling since early 1979 as the price of oil ramped up. Gas use spiked higher in February and March 1980. The reversal of that spike in the following months means that gas use followed the path of oil to some degree over subsequent months, but overall gas use simply fluctuates over this period. Therefore, we argue that these asymmetries are associated with large falls in oil use, which in 1973-5 was also mirrored by the change in gas use and in 1980 was accidentally mirrored in gas use for a short period.

Table 5. Adding Fossil Fuel Residuals to the Individual Recessions Regression

Dependent variable: $\Delta \ln C_t$

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
$\Delta \ln G_t$	0.608***	1.224***	0.409***	0.579***	0.421***
	(0.147)	(0.135)	(0.119)	(0.136)	(0.101)
$D_t^{1973-75} \Delta \ln G_t$	1.663**	0.345	1.513**	0.694	0.693
	(0.824)	(0.532)	(0.699)	(0.694)	(0.572)
$D_t^{1980} \Delta \ln G_t$	1.016***	0.365	0.903***	0.313	0.309
	(0.328)	(0.287)	(0.249)	(0.328)	(0.261)
$D_t^{1981-82} \Delta \ln G_t$	-0.614**	-1.109***	-0.148	-0.659**	-0.274
	(0.294)	(0.325)	(0.238)	(0.277)	(0.233)
$D_t^{1990-91} \Delta \ln G_t$	1.944***	0.076	2.237***	1.011***	1.366***
	(0.400)	(0.708)	(0.263)	(0.312)	(0.350)
$D_t^{2001} \Delta \ln G_t$	-1.287	-1.341	-0.854	0.806	0.896
	(0.951)	(0.875)	(0.825)	(0.726)	(0.603)
$D_t^{2008-09} \Delta \ln G_t$	0.079	-0.265	0.027	0.339	0.264
	(0.438)	(0.281)	(0.443)	(0.396)	(0.407)
$D_t^{2020} \Delta \ln G_t$	1.367***	-0.162	1.688***	1.266***	1.540***
	(0.184)	(0.158)	(0.172)	(0.194)	(0.177)
Oil residual		0.486***			
		(0.028)			
Coal residual			0.298***		0.242***
			(0.032)		(0.025)
Natural gas residual				0.297***	0.260***
				(0.018)	(0.016)
Constant	-0.001	-0.003***	-0.000	-0.001*	-0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
R-squared	0.572	0.729	0.689	0.733	0.808
Observations	575	575	575	575	575

Notes: Variable names as in text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days also included in all regressions. *** significant at 1%, ** 5%, and * 10% significance levels.

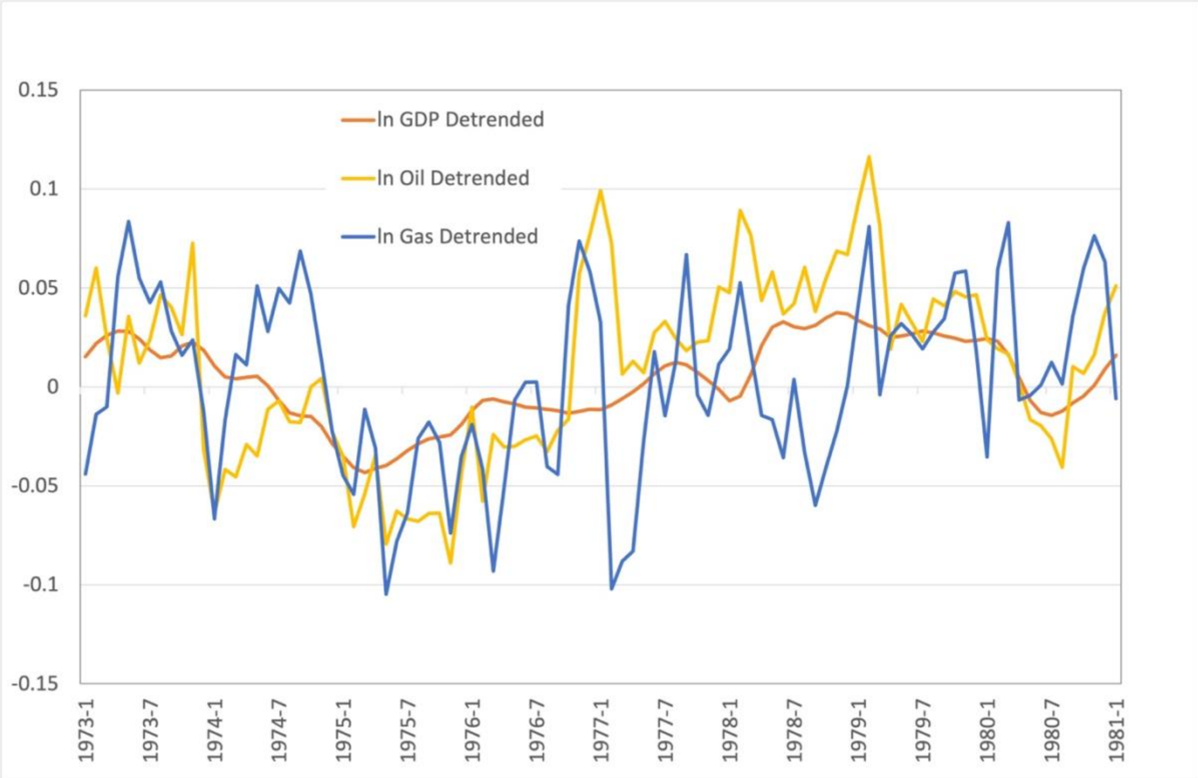


Figure 4. Detrended Logs of GDP, Oil, and Natural Gas Consumption 1973-80

4.3. Sectoral responses and the effect of controlling for excess petroleum consumption

To determine whether the asymmetric effects vary across sectors and to further understand the mechanism behind asymmetry, we apply (5) to sectoral emissions and total GDP. The results are shown in Table 6. The transportation and industrial sectors have statistically significantly different emissions changes during recessions compared to expansions, with estimates of the coefficient of $D_t^R \Delta \ln G_t$ of 1.1 and 2.8, respectively, both of which are significant at the 1% level. There is no significant asymmetry in other sectors. Therefore, aggregate asymmetry of carbon emissions to GDP primarily comes from the transportation and industrial sectors.

The transportation and industrial sectors are the two largest end-use sectors for oil consumption, accounting for approximately 94% of total petroleum consumption (66% from the transportation sector and 28% from the industrial sector) in 2020 (Energy Information Administration 2021). As only these two sectors show significant asymmetries, this further confirms that the asymmetric response of carbon emissions during recessions and booms is primarily explained by oil.

During the COVID-19 recession, transportation was very strongly affected. This explains why including or excluding the 2020 COVID-19 recession from the sample in Tables 2 and 3 changes the results. Global road transport decreased by approximately 50% compared to the 2019 mean level by the end of March 2020 (IEA, 2020).

Table 6. Sectoral Emissions-Income Asymmetry

Dependent variable: $\Delta\ln C_t$ (sectoral)

	(1) **Residential**	(2) **Commercial**	(3) **Industrial**	(4) **Transportation**	(5) **Electric Power**	(6) **Total**
$\Delta\ln G_t$	-0.127	0.144	0.664***	0.556***	0.739**	0.592***
	(0.692)	(0.429)	(0.256)	(0.161)	(0.326)	(0.145)
$D_t^R \Delta\ln G_t$	-1.106	0.244	1.073***	2.798***	0.336	1.238***
	(0.674)	(0.526)	(0.367)	(0.475)	(0.382)	(0.268)
Constant	-0.001	-0.000	-0.001	0.000	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.455	0.394	0.083	0.470	0.525	0.567
Obs.	575	575	575	575	575	575

Notes: Carbon emissions are sectoral data, GDP is at the national level. Variable names as in text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days also included in all regressions. *** significant at 1%, ** 5%, and * 10% significance levels.

Table 7 shows how adding the oil consumption residual to the sectoral emissions regressions affects the results. Column 4 shows that the asymmetric response of carbon emissions from transportation sector is removed when we add the oil residual. For the industrial sector, the asymmetry also declines when we add the oil residual. Petroleum use is the second largest energy source for the industrial sector, accounting for 42.52% in total fossil fuels used, slightly less than the share of natural gas (52.81%) (Energy Information Administration, 2021). However, the asymmetry is not totally removed. Maybe there are also other mechanisms at play in the industrial sector along the lines of those suggested by Sheldon (2017), such as scrapping of energy intensive capital during downturns. This requires further research beyond the scope of this paper.

Table 7. Adding Oil Consumption Residuals to Sectoral Emissions Regressions

Dependent variable: $\Delta\ln C_t$ (sectoral)

	(1) Residential	(2) Commercial	(3) Industrial	(4) Transportation	(5) Electric
$\Delta\ln G_t$	-0.326	0.140	0.794***	1.983***	0.730**
	(0.286)	(0.204)	(0.264)	(0.016)	(0.315)
$D_t^R \Delta\ln G_t$	-1.232***	-0.028	0.786*	-0.133***	0.239
	(0.407)	(0.298)	(0.406)	(0.023)	(0.360)
Oil residual	0.416***	0.328***	0.945***	0.998***	0.050***
	(0.033)	(0.022)	(0.126)	(0.010)	(0.009)
Constant	-0.001	-0.001	-0.002*	-0.004***	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
R-squared	0.667	0.647	0.312	0.997	0.576
Obs.	575	575	575	575	575

Notes: Carbon emissions and oil residual are sectoral data, GDP is national level. Variable names as in text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days also included in all regressions. *** significant at 1%, ** 5%, and * 10% significance levels.

In Table 8, we add the sectoral residual other fossil fuels consumption variable to the sectoral regressions. This has almost no effect on the coefficients of the industrial and transportation regressions reported in Table 6. Therefore, the difference in sectoral response of carbon emissions between recessions and expansions is explained by changes in oil use rather than by changes in the use of other fossil fuels.

Table 8. Adding Other Fossil Fuels Residuals to Sectoral Emissions Regressions

Dependent variable: $\Delta\ln C_t$ (sectoral)

	(1) Residential	(2) Commercial	(3) Industrial	(4) Transportation	(5) Electric
$\Delta\ln G_t$	-1.067**	-0.206	0.599***	0.547***	0.633*
	(0.476)	(0.327)	(0.210)	(0.160)	(0.336)
$D_t^R \Delta\ln G_t$	-0.152	0.233	1.077***	2.799***	0.190
	(0.563)	(0.356)	(0.356)	(0.470)	(0.345)
Other fossil fuels residual	0.719***	0.685***	0.620***	0.031**	0.841***
	(0.037)	(0.023)	(0.050)	(0.013)	(0.047)
Constant	0.001	0.000	-0.001*	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.788	0.789	0.454	0.475	0.824
Observations	575	575	575	575	575

Notes: Carbon emissions and other fossil fuels residual are sectoral data, GDP is national level. Variable names as in text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days also included in all regressions. *** significant at 1% , ** 5%, and * 10% significance levels.

4.4. Distributed-Lag Specifications

Table 9 reports the lag length selection criteria for the symmetric and asymmetric distributed lag models. Columns 1-2 report the lag selection criteria with the symmetric model, i.e., a restricted version of Equation (9) omitting the second summation. Columns 3-4 report the lag selection criteria for the asymmetric model between recessions and contraction in Equation (9). Since the lag selection process starts with a maximum lag length of twelve, we use 563 observations for all models to make sure that the information criteria for models with different numbers of lags are comparable.

We select the optimal lag length by choosing the model with the lowest AIC (Akaike Information Criterion). For the symmetric model, both the AIC and BIC (Bayesian Information Criterion) select a lag length of two. For the asymmetric model, the AIC chooses a lag length of four while BIC prefers zero lags. In Table 10, we report results with distributed-lag specifications of both two and four lags.

Table 9. Lag Selection

Maximum lag	**(1)** **AIC** Symmetric model	**(2)** **BIC**	**(3)** **AIC** Asymmetric model	**(4)** **BIC**
Lag length=0	-3055.719	-3038.385	-3072.204	-3050.538$^{\Psi}$
Lag length =1	-3063.469	-3041.803	-3074.841	-3044.508
Lag length =2	-3071.370$^{\Psi}$	-3045.371$^{\Psi}$	-3078.025	-3039.025
Lag length =3	-3069.560	-3039.227	-3079.618	-3031.952
Lag length =4	-3068.889	-3034.222	-3081.099$^{\Psi}$	-3024.766
Lag length =5	-3067.087	-3028.088	-3077.198	-3012.199
Lag length =6	-3065.215	-3021.882	-3074.117	-3000.451
Lag length =7	-3063.215	-3015.549	-3070.161	-2987.829
Lag length =8	-3061.222	-3009.222	-3066.380	-2975.381
Lag length =9	-3059.360	-3003.028	-3063.580	-2963.915
Lag length =10	-3057.484	-2996.818	-3059.743	-2951.411
Lag length =11	-3055.490	-2990.491	-3055.817	-2938.819
Lag length =12	-3054.263	-2984.930	-3056.644	-2930.979

Note: Ψ means this lag is selected with smallest value for AIC or BIC. Symmetric model and asymmetric in this table are referring to Equation (9).

Columns 1 and 4 in Table 10 show the short-run emissions-income elasticity for the symmetric and asymmetric models. Columns 2–3 in Table 10 shows the estimates of the long-term emissions elasticity of income for the symmetric model and Columns 4-6 for the asymmetric model.

Columns 2-3 in Table 10 show that the estimate of the long-run emissions elasticity of income using 2 lags is 1.4 and using 4 is 1.5. However, the long-run elasticity is not significantly different to the short-run coefficient in Column (1).[3]

Column 5 shows the cumulative response of carbon emissions during expansions is unity while the long-term emissions-income elasticity during recessions is 1.7 using a lag length of two. With four lags the long-run elasticity still equals unity under expansions and becomes 1.4 during recessions. With two lags the difference between the elasticity during recessions and expansions is 0.7 (*p*-value for the null hypothesis that there is no difference between estimates for booms and recessions is 0.005). But with four lags the difference is only 0.4 and is not statistically significant (*p*-value for the null hypothesis that there is no difference between estimates for booms and recessions is 0.136). Still, the asymmetry is most pronounced in the very short run and becomes smaller in the longer run.

[3] The p-values for testing the null hypothesis that the sum of GDP terms equals short-run coefficient (1.2) are 0.227 and 0.166 for two and four lags, respectively.

Table 10. Distributed Lag Results

Dependent variable: $\Delta\ln C_t$

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln G_t$	1.199***	2.251***	2.273***	0.592***	1.612***	1.724***
	(0.191)	(0.260)	(0.272)	(0.145)	(0.541)	(0.598)
$\Delta\ln G_{t-1}$		-1.662***	-1.859***		-1.485**	-2.616***
		(0.329)	(0.522)		(0.729)	(0.848)
$\Delta\ln G_{t-2}$		0.837***	1.322**		0.838*	2.906***
		(0.219)	(0.634)		(0.435)	(1.057)
$\Delta\ln G_{t-3}$			-0.559			-1.792*
			(0.499)			(0.963)
$\Delta\ln G_{t-4}$			0.313			0.810
			(0.245)			(0.494)
$D_t^R\Delta\ln G_t$				1.238***	0.734*	0.707*
				(0.268)	(0.386)	(0.413)
$D_{t-1}^R\Delta\ln G_{t-1}$					0.454	0.948**
					(0.322)	(0.437)
$D_{t-2}^R\Delta\ln G_{t-2}$					-0.494*	-1.171**
					(0.260)	(0.575)
$D_{t-3}^R\Delta\ln G_{t-3}$						0.172
						(0.239)
$D_{t-4}^R\Delta\ln G_{t-4}$						-0.264
						(0.233)
Long-run emissions-income elasticity	1.199*** (0.191)	1.425*** (0.186)	1.490*** (0.209)			
Long-run emissions-income elasticity (expansions)				0.592*** (0.145)	0.966*** (0.232)	1.031*** (0.237)
Long-run emissions-income elasticity (recessions)				1.829*** (0.195)	1.660*** (0.192)	1.424** (0.240)
Difference in emissions-income elasticity between recessions and expansions				1.238*** (0.268)	0.694*** (0.247)	0.393 (0.263)
Constant	-0.003***	-0.003***	-0.003***	-0.001	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.554	0.568	0.574	0.567	0.577	0.588
Observations	575	573	571	575	575	571

Notes: Variable names and definitions of long-run elasticities as in text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days also included in all regressions. *** significant at 1%, ** 5%, and * 10% significance levels.

5. Conclusions

We have provided new evidence on the asymmetric response of CO_2 emissions to changes in GDP during recessions and economic expansions. On average, carbon emissions change faster relative to GDP in recessions compared to in expansions. This is especially the case when we include data from 2020.

Comparing individual US recessions since 1973, during the 1973-5, 1980, 1990, and 2020 recessions, the response of carbon emissions to GDP is significantly different from that in expansions. We do not find a statistically significant asymmetric response for other recessions. The previous three recessions with asymmetric impacts (1973-5, 1980, and 1990 recessions) are associated with three negative oil supply shocks, while the 2020 recession is associated with a negative oil demand shock. Controlling for changes in oil use that are not correlated with GDP removes this asymmetric response. Controlling similarly for coal and does not. Controlling for natural gas use removes the asymmetry in 1973-5 and 1980. In 1973-5, gas use tracks oil use very closely. They both fall sharply when the oil crisis hits. In 1980, the recession was much shorter and we argue that gas and oil appear to track each other during these few months accidentally.

The response of sectoral emissions to changes in GDP vary. The transportation and industrial sectors show significantly asymmetric carbon emissions changes during economic contractions compared to expansions while the other sectors do not. These two sectors are also key oil consumers compared to other sectors, accounting for approximately 94% of total petroleum consumption in 2020. These findings strongly suggest that it is negative oil market shocks rather than recessions *per se* that result in higher emissions-income elasticities in some recessions.

There are some caveats. The asymmetry in industrial sector emissions does not appear to entirely be explained by changes in oil use that are not correlated with GDP. Further research is needed to find the mechanism responsible. However, transportation sector emissions explain the main effect. The asymmetry in the 1973-5 and 1980 recessions can also be explained by asymmetric changes in natural gas.

We also estimated a distributed lag specification. Using the optimal lag length, the difference between the elasticity in recessions and expansions is smaller but is still statistically significant. Adding further lags eliminates the asymmetry. Therefore, asymmetry is most pronounced in the short run.

Because the asymmetric response of emissions appears to be mostly due to negative oil market shocks, we should not expect all recessions to have outsize effects on emissions. Therefore, counter to Sheldon (2017), we should expect a small role for asymmetry in the future path of carbon emissions. Similarly, it might be hard to extrapolate our results to other countries. However, we would predict that asymmetry would be less important in countries where oil use and transport play a smaller role in the economy.

Appendix A. Data Sources and Variable Definitions

Carbon dioxide (CO_2) emissions: Carbon dioxide emissions from primary fuels including coal, natural gas, and petroleum (Aviation gasoline, distillate fuel oil, petroleum coke, motor gasoline etc.). Unit: Million metric tons. Source: Table 11.1 in *EIA Monthly Energy Review* (Energy Information Administration, 2020). Monthly data on energy and carbon dioxide emissions data are available at: https://www.eia.gov/totalenergy/data/monthly/index.php

Gross domestic product (GDP): Monthly GDP data are derived from the Brave-Butters-Kelley Indexes (BBKI), Federal Reserve Bank of Chicago (Brave *et.al* 2019). The source provides the monthly growth rate at an annualized rate, we divide the annualized growth rate by twelve to convert it to the real monthly rate.

Petroleum consumption: Monthly petroleum consumption data are provided by EIA. They are given as sectoral petroleum consumption (Table 3.7a Residential and commercial sectors, 3.7b Industrial sector, 3.7c Transportation and electric power sectors). Unit: Quadrillion BTU.

Primary energy consumption: Monthly primary energy data are from Table 1.1 in *EIA Monthly Energy Review*. Unit: Quadrillion BTU.

Primary energy consumption by sector: Primary energy use in residential, commercial, industrial, transportation, and electric power sectors. Unit: Trillion BTU. Source: Tables 2.1-2.6 in *EIA Monthly Energy Review*.

Sectoral CO_2 emissions: Sectoral carbon emissions by major source, including residential, commercial, industrial, transportation, electric power sectors. Unit: Million metric tons of carbon dioxide. Source: Tables 11.2-11.6 in *EIA Monthly Energy Review* .

Sectoral energy use: Sectoral energy use include coal, oil, and natural gas. The end-use of each fuel from residential, commercial, industrial, transportation, electric power sectors are used. Unit: Quadrillion BTU. Source: Tables 2.2-2.6 in *EIA Monthly Energy Review*.

Heating degree days: A day's heating degree days is measured by the number of degrees the daily average temperature is below 65 degrees Fahrenheit (°F). The monthly population-weighted heating degree days data are provided by EIA (Table 1.9 Heating degree-days by Census division).

Cooling degree days: A day's cooling degree days is measured by the number of degrees the daily average temperature is above 65 degrees Fahrenheit (°F). The monthly population-weighted cooling degree days data are provided by EIA (Table 1.10 Cooling degree-days by Census division).

D_t^-: A dummy that identifies whether GDP grows or falls in each month compared to the prior month. It equals one when economic growth is positive and equals zero when GDP falls.

D_t^R: A dummy that identifies whether a month is in recession or expansion period. It equals one when it is within an NBER recession and zero otherwise.

D_t^{past}: A dummy that identifies whether a month is in a recession prior to 2020. It equals one if the month is in recession before 2020 (1973-5, 1980, 1981, 1990, 2001, 2008-9 recessions) and equals zero otherwise. D_t^{2020} equals one if a month is in the 2020 recession and equals zero otherwise.

D^{R_i}: This represents dummies for individual recessions. Seven dummies are set to denote each of the seven recessions for the period 1973-2020. D_t^{1973-5} equals one when a month is in the 1973-5 recession and zero otherwise; D_t^{1980} equals one when it is in the 1980 recession and zero otherwise. Similarly, D_t^{1981-2}, D_t^{1990-1}, D_t^{2001}, D_t^{2008-9}, D_t^{2020} identify whether a month is during the 1981-2, 1990-1, 2008-9, and 2020 recessions or not. They equal one when a month is within individual recession and zero otherwise.

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