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Asymmetric business cycle changes in US carbon emissions and oil market shocks

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Abstract
Previous research shows that, in the USA, the elasticity of carbon emissions with respect to GDP is greater when GDP declines than when GDP increases. Using monthly US data, we examine each individual recession since 1973. We find asymmetric changes in carbon emissions in the 1973–1975, 1980, 1990–1991, and 2020 recessions but not in the 1981–1982, 2001, or 2008–2009 recessions. The former four recessions are associated with negative oil market shocks. In the first three, there was a supply shock and in 2020, a demand shock. Changes in oil consumption that are not explained by changes in GDP explain these asymmetries. Furthermore, the asymmetries are due to emissions in the transport and industrial sectors, which are the main consumers of oil. We conclude that emissions behaved similarly in 2020 to the way they did in recessions associated with oil supply shocks, but, actually, this pattern is not inherent to the business cycle itself.

Keywords COVID-19 · Climate change · Economic growth · Recessions

JEL Classification Q43 · Q54

1 Introduction

Economic growth is seen as one of the main long-run drivers of carbon dioxide and other greenhouse gas emissions (Barrett et al. 2014). However, there is relatively little research on how greenhouse gas emissions vary over the course of the business cycle. Business cycle fluctuations in emissions could have important effects on projected emissions paths used to estimate both future greenhouse gas concentrations and the cost of climate policies (Sheldon 2017). They also need to be taken into account when attempting to determine when emissions have peaked or will peak. Finally, understanding these short-run

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fluctuations may give us theoretical insight into the relationship between emissions and economic activity.

Sheldon (2017) found that, in the USA, the elasticity of GDP with respect to emissions was greater when GDP declined than when it increased.[1] However, she did not investigate the reason for this asymmetry. In this article, we investigate whether oil market shocks, which have been associated with some, but not all, recessions in the USA, may be responsible. We find that the elasticity of carbon emissions with respect to GDP is greater in recessions associated with either negative oil supply shocks or the negative oil demand shock caused by the COVID-19 pandemic. We conclude that the asymmetry is mostly due to reductions in oil consumption associated with these shocks and is not inherent to the business cycle itself. This means that changes in emissions will not be asymmetric in all future recessions, which has implications for projecting future emissions and determining whether emissions have peaked.

The 2020 COVID-19 driven recession saw a sharp drop in carbon dioxide emissions, as transportation and some other energy uses were curtailed, providing new data to test the asymmetry hypothesis. On the other hand, this was an unusual recession, as it was driven by a pandemic. 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 response would again be asymmetric. Le Quéré et al. (2021) argued that "the pervasive disruptions from the COVID-19 pandemic have radically altered the trajectory of global CO_2 emissions" (197) and suggested that there was a window of opportunity to continue the slowing of emissions growth that they had seen since 2015. The second main contribution of our research is to extend the data used in previous research to cover this most recent recession. We find that emissions changed similarly to the way they did in those previous recessions associated with oil supply shocks. This leads us to suggest that the pandemic recession will not be likely to mark a break in existing trends, though our empirical analysis only examines the USA.

We follow a similar approach to Sheldon (2017) but use US monthly GDP (Brave et al. 2019) and carbon emissions data from January 1973 to December 2020 instead of quarterly data for an earlier period. We examine the behavior of carbon emissions in each individual US recession since 1973. We find that carbon emissions respond asymmetrically to changes in GDP in the 1973–1975, 1980, 1990–1991, and 2020 recessions but not in the 1981–1982, 2001, or 2008–2009 recessions. The 1973–1975, 1980, and 1990–1991 recessions are associated with negative oil supply shocks, while the 2020 recession is associated with a negative oil demand shock. In both cases, oil consumption fell sharply. By contrast, in the 1981–1982, 2001, and 2008–2009 recessions, carbon emissions fell by the amount that would be expected from a symmetric model. We also find that the asymmetries are due to emissions in the transport and industrial sectors, which are the main consumers of oil. Finally, only emissions from oil combustion behave asymmetrically.

The following section provides a review of the previous relevant research. The third section presents a brief history of oil price shocks and US recessions. Section 4 presents our

[1] The term elasticity does not necessarily imply a causal relationship. It can simply express the typical percentage change in one variable when another changes by 1%. Though, we do think that a causal interpretation is largely warranted — that if there were exogenous shocks to GDP, carbon emissions would respond in a similar way to that estimated here — the exact value of the causal relationship could differ from the elasticities that we estimate as explained in Sect. 4.1.

methods and Section 5 our data and the results. Section 5.2 summarizes our findings and provides key conclusions.

2 Literature review

Using annual data for 160 countries for the period from 1960 to 2008, York (2012) reported that the GDP elasticity of carbon emissions 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 because reductions in the use of durable assets accumulated in booms might be relatively small in contractions. But, using data on 189 countries between 1961 and 2010, Burke et al. (2015) concluded that there was no strong evidence that emissions behaved differently during years with economic growth compared to years with falling GDP. However, they found that there is significant evidence of asymmetry over longer periods. 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. On the other hand, 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 they rose in all US expansions since 1973. Inspecting their Table 5, we also see that the ratio of the percentage change per annum in CO_2 emissions to the percentage change in GDP was greater in all contractions than in any expansion. We could explain this if changes in CO_2 emissions are explained by a time effect and a growth effect:

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

where $\Delta \ln C_t$ and $\Delta \ln G_t$ denote the first differences of the logs of carbon emissions and GDP. Because the dependent variable is in first differences, β_0 is the time effect in this regression, as it indicates the rate at which carbon emissions change in the absence of economic growth. If $\beta_0 < 0$, 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 that expands on (1) using quarterly US data. She found that the GDP elasticity of carbon emissions was greater in quarters with declining GDP than in quarters with rising GDP. Specifically, she found that a one percent increase in GDP was associated with a 0.2% increase in emissions, while a 1% decrease in GDP results in a 1.8% fall in emissions. She argued that this means that emissions will rise more slowly in the future than predicted by a symmetric model.

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 in the long run. However, they found that in the short run the response to changes in industrial production is symmetric.[2]

[2] 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. We think this is because transportation, which is not included in industrial production, is the most important contributor to the asymmetry.

Fig. 1 Monthly US oil prices. The nominal price is the composite refiner acquisition cost of crude oil (US EIA July 2021 Monthly Energy Review, Table 9.1). The real price is deflated by the US consumer price index (Bureau of Labor Statistics). The average annual nominal price is shown for 1973. Recessions are marked with blue shading

The cause 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, rather than the shocks themselves, caused US recessions. 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 to increasing demand — such as the increase from 2003 to 2008 — and some due to reduced supply, such as in 1979 (Baumeister and Hamilton 2019). Supply shocks lead to a reduction in global economic activity, while positive shocks to oil demand do not (Baumeister and Hamilton 2019).

3 Oil price shocks and recessions

Figure 1 presents the history of oil prices and recessions in the US since 1973. There have been three main 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

Table 1 US recessions (1973–2020)

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

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

Countries (OAPEC) decided to place an embargo on some western countries, including the USA, perceived as supporting Israel during the Yom Kippur War. The embargo lasted from October 1973 to March 1974. A recession followed in the USA from December 1973 to March 1975 (Table 1).

The second shock started in early1979 following the Iranian Revolution in January and worsened following Iraq's invasion of Iran in September 1980. A recession followed from February to July 1980. Kilian (2008) and Güntner and Henssler (2021) describe this as two separate shocks. For our purpose, the key fact is that the price of oil rose before and through the 1980 recession but peaked and began to fall before the 1981–1982 recession (Fig. 1).

There was a third spike in oil prices starting in August 1990 after Iraq invaded Kuwait, 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 USA defeated the Iraqi army and liberated Kuwait.

The 1981–1982 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 (Fig. 2).

In 2001, a recession bracketed the September 11 terrorist attack. Stock markets — especially 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 1997–1998 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.

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 increasing demand mainly fueled by the rise of China and India (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 2008–2009 recession was also partly due to the spike in the oil price.

The 2020 recession was unprecedented, as it was the result of the breakout of the COVID-19 pandemic. The global recession, and particularly restrictions on personal

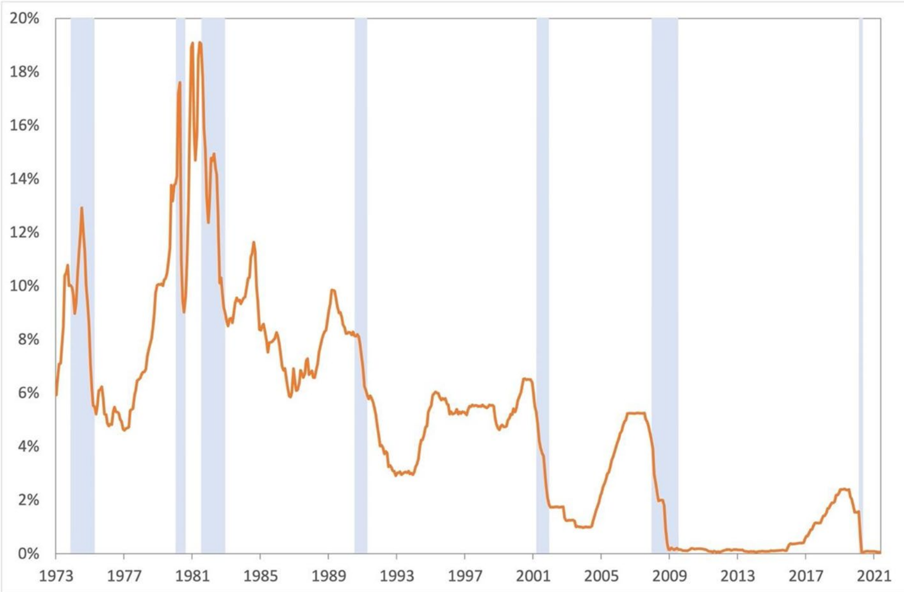

Fig. 2 Effective federal funds rate. Recessions are marked with blue shading. Source: https://fred.stlouisfed.org/series/FEDFUNDS

mobility, led to decreased 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 and Tooze 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: 1973–1975, 1980, 1990–1991, and 2020.

4 Methods

4.1 Basic specification

Our simplest model of the relationship between carbon dioxide emission changes and GDP growth is generated by adding a random error term, ϵ_t, and weather variables to (1):

$$\Delta \ln C_t = \beta_0 + \beta_1 \Delta \ln G_t + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \tag{2}$$

where H_t is heating degree days and K_t cooling degree days. The constant term, β_0, is, therefore, the mean of $\Delta \ln C_t$ when there is no economic growth (Stern et al. 2017) or climate change, and is the time effect in this regression. In contrast to Sheldon (2017), GDP is not lagged in this baseline model. Sheldon lagged GDP because she was concerned about reverse causality. However, we are only interested in the association between growth and emissions rather than in precisely measuring the causal relationship. 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.

4.2 Asymmetric specifications

We specify:

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

where D^- denotes a dummy variable that equals one when GDP growth is negative, 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. A t test for the hypothesis that this coefficient is zero is a direct test for asymmetry. β_1 is then the elasticity during expansions and $\beta_1 + \beta_2$ the elasticity during recessions. Essentially, we are allowing for a piecewise linear relationship between emissions and GDP with a kink at zero GDP growth.

Monthly data can be somewhat noisy, as it is possible to have some months of positive growth within a recession. Therefore, we also estimate the following regression which replaces the negative economic growth dummy in (3) with a dummy variable for NBER recessions, D^R, which is equal to one if the month is included in an NBER recession and zero otherwise:

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

4.3 Recession comparison

Next, we investigate whether the 2020 recession was different to past recessions in terms of the GDP elasticity of carbon emissions:

$$\Delta lnC_t = \beta_0 + \beta_1 \Delta lnG_t + \beta_4 D_t^{past} \Delta \ln G_t + \beta_{12} D_t^{2020} \Delta \ln G_t + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \tag{5}$$

where D^{past} denotes the past recession dummy, equal to one when a month is within a recession prior to 2020 and zero otherwise. D^{2020} is equal to one when a month occurs during the 2020 recession and zero otherwise.

Since past recessions may differ in their characteristics, we also investigate 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 1973–1975 recession and zero otherwise. Similarly, $D_t^{R_2} = D_t^{1980}$ equals one for months during the 1980 recession and zero otherwise, and so forth for the remaining dummies. The months when recessions start and end are listed in Table 1.

To address the potential concern that there might be insufficient statistical power to test for asymmetry in each individual recession, we also pooled the recessions into two groups each with a common dummy variable:

$$\Delta \ln C_t = \beta_0 + \beta_1 \Delta lnG_t + \beta_S D_t^{\text{Shock}} \Delta \ln G_t + \beta_N D_t^{\text{NoShock}} \Delta \ln G_t + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \tag{7}$$

The dummy variable D_t^{Shock} equals one for the four recessions identified as being associated with oil market shocks in Section 3 and zero otherwise, and the dummy variable D_t^{NoShock} equals one for the three other recessions.

4.4 Effects of 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 to appear to be larger in recessions than expansions? We add the time series of the log of each of the three fossil fuels to the foregoing regressions for $\Delta \ln C_t$ to see whether the asymmetric effect of recessions disappears or not. If adding log oil use, $\ln P_t$, removes the asymmetry but adding the logs of the other two fossil fuels does not, 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.

4.5 Sectoral and individual fossil fuels emissions

Is asymmetry particularly pronounced in some sectors of the economy? If asymmetry is greater in sectors that predominantly use oil, 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 while still using economy-wide economic growth as the explanatory variable. We test for asymmetry in the sectoral GDP elasticity of emissions 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 as outlined in the previous subsection.

Finally, we can directly test our hypothesis that the asymmetry is related primarily to reductions in oil consumption rather than coal and natural gas, by estimating Eq. (4) while replacing the dependent variable with emissions from each of the three fossil fuels individually.

4.6 Distributed-lag model

Our primary interest is the contemporaneous relationship between carbon emissions and changes in GDP 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 estimate the dynamic relationship between CO_2 emissions and GDP, we use a distributed-lag model to compare the short- and long-run elasticities of carbon dioxide emissions with respect to GDP during recessions and expansions:

$$\Delta \ln C_t = \beta_0 + \sum_{j=0}^{m} \beta_{1,j} \Delta \ln G_{t-j} + \sum_{j=0}^{m} \beta_{3,j} D^R_{t-j} \Delta \ln G_{t-j} + \beta_H \Delta H_t + \beta_K \Delta K_t + \epsilon_t \tag{8}$$

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

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.

We also test whether the logs of CO_2 and GDP cointegrate. If they do not cointegrate, then the dynamic model in first differences is valid, and we do not need to include an error correction term. For the Johansen test, we first regressed each variable on cooling and heating degree days, while for the other two procedures we include the exogenous variables in the first stage regressions. Using the Engle and Granger (1987) approach and the augmented Dickey Fuller test with 7 lags, the test statistic is − 0.33, which clearly does not reject the null of non-cointegration. Using the Phillips and Ouliaris (1990) version of this test, we obtain a test statistic of − 2.95. The critical value at the 10% level is − 3.05, and so again we cannot reject the null. Again using 7 lags, the Johansen (1991) trace statistic is 8.06 compared to a critical value of 15.41 at the 5% level.

5 Results

5.1 Data

The Appendix presents the sources of the data. The data for our main analysis 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 US 2017). Degree days data are seasonally adjusted with the X-11 additive decomposition method. The GDP series 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 while 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.

5.2 Asymmetry of the emissions-income relationship

Columns 1 and 2 in Table 2 show that the GDP elasticity of emissions, estimated using Eq. (2), is 1.2 for the full sample, while it is only 0.8 when we exclude 2020, which suggests that the elasticity was particularly large in the 2020 recession. The time effect (i.e., the constant term) is negative and significant at the 1% level for the symmetric model but is

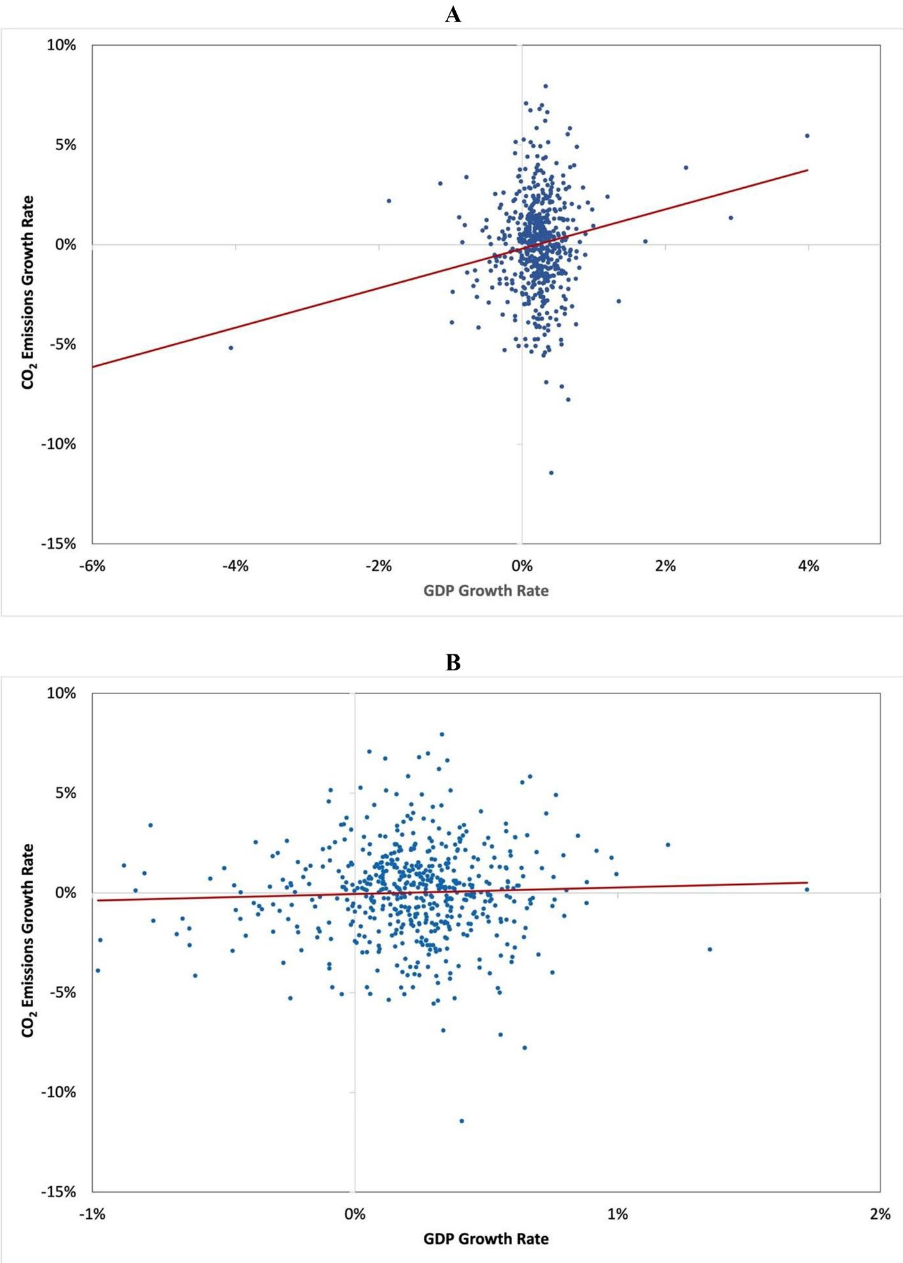

Fig. 3 Monthly carbon dioxide emissions and GDP growth rates. **A** 1973–2020, **B** 1973–2019

less statistically significantly in the other regressions in the table. A decline in emissions of 0.3% per month or 3.6% per year is very substantial. As we noted in Sect. 2, with a negative time effect, emissions will fall faster in recessions than in expansions even if $\partial \ln C/\partial \ln G$ is constant. When we allow $\partial \ln C/\partial \ln G$ to vary, the time effect is much smaller.

Table 2 Elasticities and asymmetric effects

	(1)	(2)	(3)	(4)	(5)	(6)
Specification	Elasticity 1973–2020	Elasticity 1973–2019	Negative changes 1973–2020	Negative changes 1973–2019	Recessions 1973–2020	Recessions 1973–2019
$\Delta \ln G_t$	1.199***	0.775***	0.715***	0.542**	0.592***	0.681***
	(0.191)	(0.160)	(0.169)	(0.235)	(0.144)	(0.207)
$D_t^- \Delta \ln G_t$			0.879***	0.708		
			(0.221)	(0.524)		
$D_t^R \Delta \ln G_t$					1.238***	0.338
					(0.267)	(0.496)
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

Dependent variable: $\Delta \ln C_t$. Variable names as in the 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

	(1)	(2)	(3)
Specification	Past recessions	Individual recessions	Recessions and oil market shocks
$\Delta \ln G_t$	0.626*** (0.146)	0.608*** (0.146)	0.615*** (0.144)
$D_t^{past} \Delta \ln G_t$	0.437 (0.446)		
$D_t^{2020} \Delta \ln G_t$	1.347*** (0.183)	1.367*** (0.182)	
$D_t^{1973-5} \Delta \ln G_t$		1.663** (0.816)	
$D_t^{1980} \Delta \ln G_t$		1.016*** (0.325)	
$D_t^{1981-2} \Delta \ln G_t$		−0.614** (0.292)	
$D_t^{1990-1} \Delta \ln G_t$		1.944*** (0.396)	
$D_t^{2001} \Delta \ln G_t$		−1.287 (0.942)	
$D_t^{2008-9} \Delta \ln G_t$		0.079 (0.434)	
$D_t^{\text{Shock}} \Delta \ln G_t$			1.359*** (0.182)
$D_t^{\text{NoShock}} \Delta \ln G_t$			−0.317 (0.322)
Constant	−0.001* (0.001)	−0.001 (0.001)	−0.001 (0.001)
Observations	575	575	575
R squared	0.569	0.572	0.572

Dependent variable: $\Delta \ln C_t$. Variable names as in the 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 3–4 test for an asymmetric relationship between economic growth and carbon emissions using Eq. (3). The relationship is asymmetric for the full sample. The GDP elasticity of emissions is greater than unity when GDP growth is negative and less than one when growth is positive, and the difference is highly statistically significant. 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. Again, we see that the elasticity seems to have been particularly large during the 2020 recession. In Columns 5–6, we compare recessions and expansions using Eq. (4). The results are similar to those in Columns (3) and (4), showing that we can use this approach instead of Eq. (3).

Column 1 in Table 3 shows the difference in the elasticity in the 2020 recession compared to expansions and the difference between expansions and all other past recessions using Eq. (5). The elasticity of carbon emissions with respect to GDP in the COVID-19 recession was greater than one and very statistically significant. The elasticity for the

Table 4 Adding fossil fuel consumption to the asymmetric model

	(1)	(2)	(3)	(4)	(5)
$\Delta \ln G_t$	0.592***	0.508***	0.298**	0.542***	0.214*
	(0.145)	(0.128)	(0.119)	(0.134)	(0.120)
$D_t^R \Delta \ln G_t$	1.238***	−0.187	1.530***	1.133***	0.048
	(0.268)	(0.162)	(0.237)	(0.276)	(0.109)
Oil consumption		0.488***			0.467***
		(0.027)			(0.014)
Coal consumption			0.297***		0.261***
			(0.032)		(0.020)
Natural gas consumption				0.297***	0.230***
				(0.017)	(0.009)
Constant	−0.001	−0.001**	−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	0.949
Observations	575	575	575	575	575

Dependent variable: $\Delta \ln C_t$. Variable names as in the 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

previous six recessions overall is not statistically significantly different from zero. There are two possible explanations for these results. The first possibility is that carbon emissions do not have an asymmetric response prior to 2020. Alternatively, CO_2 emissions respond asymmetrically during some recessions and symmetrically or even in the opposite direction in others, the effects offsetting each other.

To investigate which is the case, in Column 2, we compare the GDP elasticity 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 1973–1975 recession, 1980 recession, and 1990–1991 recession, the elasticity of carbon emissions with respect to changes in GDP was significantly larger than in expansions. The difference is statistically significant at the 5% level for the 1973–1975 recession and significant at the 1% level for the 1980 and 1990–1991 recessions. 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 GDP elasticity of emissions in the other three recessions is not significantly greater than the elasticity in expansions, and the sign of the estimated coefficient is even negative in two of the recessions (1981–1982 and 2001).

In Column 3, we pool recessions into two groups using Eq. (7). We find a highly statistically significant difference of 1.36 between the elasticity for the four recessions we associated with oil market shocks and the elasticity in expansions. The difference between the elasticity in the other three recessions and in expansions is not statistically significant.

5.3 Impacts of oil crises

The results in Table 3 suggest that the asymmetric relationship between growth and carbon emissions in some recessions compared to expansions is likely associated with negative oil

Table 5 Adding fossil fuel consumption to the individual recessions regression

	(1)	(2)	(3)	(4)	(5)
$\Delta \ln G_t$	0.608***	0.501***	0.325***	0.576***	0.233**
	(0.147)	(0.133)	(0.118)	(0.135)	(0.116)
$D_t^{1973-5} \Delta \ln G_t$	1.663**	0.345	1.513**	0.694	−0.486*
	(0.824)	(0.526)	(0.692)	(0.686)	(0.265)
$D_t^{1980} \Delta \ln G_t$	1.016***	0.365	0.903***	0.313	−0.254
	(0.328)	(0.284)	(0.246)	(0.324)	(0.194)
$D_t^{1981-2} \Delta \ln G_t$	−0.614**	−1.109***	−0.148	−0.659**	−0.714***
	(0.294)	(0.322)	(0.235)	(0.273)	(0.188)
$D_t^{1990-1} \Delta \ln G_t$	1.944***	0.076	2.237***	1.011***	−0.314
	(0.400)	(0.701)	(0.260)	(0.308)	(0.312)
$D_t^{2001} \Delta \ln G_t$	−1.287	−1.341	−0.853	0.806	0.671
	(0.951)	(0.866)	(0.816)	(0.718)	(0.490)
$D_t^{2008-9} \Delta \ln G_t$	0.079	−0.265	0.027	0.339	−0.092
	(0.438)	(0.278)	(0.438)	(0.391)	(0.187)
$D_t^{2020} \Delta \ln G_t$	1.367***	−0.162	1.688***	1.266***	0.106
	(0.184)	(0.156)	(0.170)	(0.192)	(0.145)
Oil consumption		0.486***			0.465***
		(0.028)			(0.014)
Coal consumption			0.298***		0.261***
			(0.032)		(0.020)
Natural gas consumption				0.297***	0.231***
				(0.018)	(0.009)
Constant	−0.001	−0.001**	−0.000	−0.001**	−0.001*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
R-squared	0.572	0.729	0.689	0.733	0.950
Observations	575	575	575	575	575

Dependent variable: $\Delta \ln C_t$. Variable names as in the 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

market shocks. In Table 4, we examine whether changes in oil use explain this asymmetry by including log oil consumption in the models we have estimated up to this point. As the use of other energy also declines during recessions, we also test whether log coal and natural gas use are responsible for the asymmetry.

Column 1 in Table 4 (identical to Column 5 in Table 2) is our baseline model that compares carbon emissions during recessions and expansions. Columns 2–5 demonstrate how oil and other fossil fuel use variables affect this relationship. 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 and 4 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 mainly due to a decline in oil consumption rather than a decline in the use of other fossil fuels during recessions.

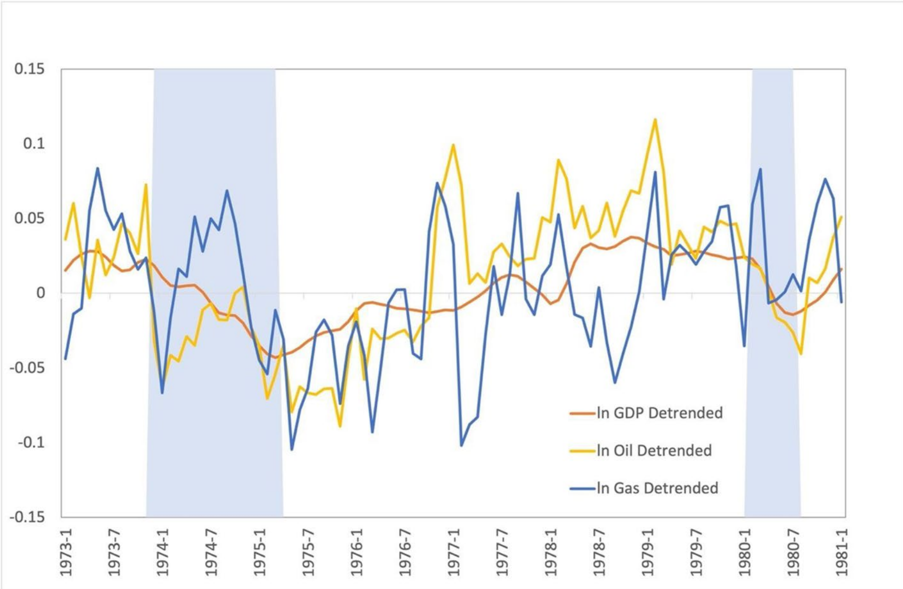

Fig. 4 Detrended logs of GDP, oil, and natural gas consumption 1973–1980. Recessions are marked with blue shading

In Table 5, we investigate the effect of oil and other fossil fuel use in each individual recession. When we include oil consumption, the asymmetric relationship between emissions and growth is removed or weakened for the four recessions that show asymmetry in Column 1. This shows that asymmetric changes in petroleum consumption explain these asymmetries. The coal residual does not remove any of the asymmetries (Column 3). The natural gas residual does not remove the asymmetry in the 1990–1991 and the 2020 recessions, though the asymmetry is no longer statistically significant for the 1973–1975 and 1980 recessions (Column 4). Column (5) includes all fossil fuel use variables. These results are similar to those in Column (2) where we only included the oil residual. As expected, the R-squared for this regression is close to unity, as we are explaining changes in carbon emissions with changes in all three fossil fuels.

Figure 4 shows why natural gas consumption can explain the asymmetries in the 1973–1975 and 1980 recessions. We use the Hodrick-Prescott filter to remove the long-run trends in the variables in order to focus on the business cycle scale fluctuations.[3] Oil use fell sharply in December 1973 and January 1974. However, gas use moved in tandem with oil use. In the remainder of 1974 and in 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. In fact, oil use was falling since early 1979 as the price of oil ramped up. Gas use spiked higher in February and March

[3] We do not use these detrended variables in any of the econometric analysis. Hamilton (2018) suggests to instead estimate the trend component by regressing y_{t+h} on the four most recent values of y at time t, where $h = 24$ for monthly data. Because our data start in January 1973, and we want to investigate the oil price shock in that year that would not work in our case.

Table 6 Sectoral emissions-income asymmetry

	(1)	(2)	(3)	(4)	(5)	(6)
	Residential	Commercial	Industrial	Transportation	Electric Power	Total
$\Delta \ln G_t$	−0.127	0.144	0.664***	0.556***	0.739**	0.592***
	(0.689)	(0.427)	(0.254)	(0.160)	(0.324)	(0.144)
$D_t^R \Delta \ln G_t$	−1.106	0.244	1.073***	2.798***	0.336	1.238***
	(0.671)	(0.523)	(0.365)	(0.473)	(0.381)	(0.267)
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

Dependent variable: $\Delta \ln C_t$ (sectoral). Carbon emissions are sectoral data, GDP is at the national level. Variable names as in the 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

1980. The reversal of that spike in the following months means that gas use followed the path of oil to some degree over the subsequent recession months, but gas use simply fluctuates over the broader period around the recession. Therefore, we argue that these asymmetries are primarily associated with large falls in oil use, which in 1973–1975 was also mirrored by the change in gas use and in 1980 was accidentally mirrored by gas use for a short period.

5.4 Sectoral analysis

To investigate whether the asymmetric effects vary across sectors and to further understand the mechanism behind asymmetry, we apply Eq. (4) to sectoral emissions and total GDP. The results are shown in Table 6. The transportation and industrial sectors have statistically significantly greater emissions changes during recessions compared to expansions. There is no significant asymmetry in other sectors. Therefore, the aggregate asymmetry 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 2020). As only these two sectors show significant asymmetries, this further confirms that the asymmetric relationship between carbon emissions and GDP 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 (International Energy Agency 2020).

Table 7 shows how adding log oil consumption to the sectoral emissions regressions in Table 6 affects the results. Column 4 shows that transportation sector carbon emissions are no longer asymmetric when we add oil consumption. For the industrial sector, the asymmetry also declines when we add oil use. Petroleum is the industrial sector's second largest

Table 7 Adding oil consumption to sectoral emissions regressions

	(1)	(2)	(3)	(4)	(5)
	Residential	Commercial	Industrial	Transportation	Electric
$\Delta \ln G_t$	0.242	0.334	0.123	0.0133	0.794**
	(0.289)	(0.207)	(0.274)	(0.015)	(0.311)
$D_t^R \Delta \ln G_t$	−1.232***	−0.028	0.786*	−0.133***	0.239
	(0.405)	(0.297)	(0.404)	(0.023)	(0.359)
Oil consumption	0.416***	0.328***	0.945***	0.998***	0.050***
	(0.033)	(0.022)	(0.125)	(0.010)	(0.009)
Constant	−0.001	−0.001	−0.000	−0.000	−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

Dependent variable: $\Delta \ln C_t$ (sectoral). Carbon emissions and oil residual variables use 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 8 Adding other fossil fuels consumption to sectoral emissions regressions

	(1)	(2)	(3)	(4)	(5)
	Residential	Commercial	Industrial	Transportation	Electric
$\Delta \ln G_t$	−0.106	−0.130	0.258	0.549***	0.280
	(0.488)	(0.325)	(0.213)	(0.159)	(0.331)
$D_t^R \Delta \ln G_t$	−0.152	0.233	1.077***	2.799***	0.190
	(0.561)	(0.355)	(0.354)	(0.467)	(0.343)
Other fossil fuels consumption	0.719***	0.685***	0.620***	0.031**	0.841***
	(0.036)	(0.023)	(0.050)	(0.013)	(0.047)
Constant	−0.001	−0.000	−0.000	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

Dependent variable: $\Delta \ln C_t$ (sectoral). GDP is at the national level, other variables use sectoral data. Variable names as in the 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% levels

energy source, accounting for 42% of total fossil fuels used, while natural gas accounts for 53% (Energy Information Administration 2020). 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 article.

In Table 8, we add the log of other fossil fuel (coal and gas combined) consumption to the sectoral regressions. This has almost no effect on the coefficients of the industrial

Table 9 Emissions from individual fossil fuels

	(1)	(2)	(3)	(4)
Emissions source	Total CO_2 emissions	CO_2 emissions from oil	CO_2 emissions from coal	CO_2 emissions from gas
$\Delta \ln G_t$	0.592***	0.155	1.060**	0.152
	(0.144)	(0.252)	(0.452)	(0.217)
$D_t^R \Delta \ln G_t$	1.238***	3.356***	− 1.035**	0.384
	(0.267)	(0.582)	(0.453)	(0.285)
Constant	− 0.001	0.001	− 0.003**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
R squared	0.567	0.344	0.366	0.402
Observations	575	575	575	575

Dependent variable: $\Delta \ln C_t$. 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

and transportation regressions reported in Table 6. Therefore, the difference in the sectoral response of carbon emissions to recessions and expansions is explained by changes in oil use rather than by changes in the use of other fossil fuels.

We also regress changes in emissions from each individual fossil fuel on economic growth as shown in Table 9. Column (1) is the same as in Table 4. Economic growth has an asymmetric effect on emissions from oil (column 2) but not from gas (column 4), while the elasticity of coal emissions with respect to GDP is smaller in recessions than in expansions (column 3).

5.5 Distributed-lag specifications

For the symmetric model, both the Akaike information criterion (AIC) and Bayesian information criterion (BIC) select an optimal lag length of two. For the asymmetric model, the AIC chooses a lag length of four, while the BIC prefers zero lags. In Table 10, we report results with distributed-lag specifications of both two and four lags. Columns 1 and 4 show the short-run GDP elasticity of emissions for the symmetric and asymmetric models, repeating information presented in previous tables. Columns 2–3 in Table 10 show the estimates of the long-run 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 lags is 1.5.

Column 5 shows that using a lag length of two the long-run elasticity of carbon emissions with respect to GDP during expansions is unity, while the long-term GDP elasticity of emissions during recessions is 1.7. With four lags, the long-run elasticity still equals unity in 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

Table 10 Distributed lag results

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln G_t$	1.199***	2.251***	2.273***	0.592***	1.612***	1.724***
	(0.191)	(0.259)	(0.270)	(0.144)	(0.536)	(0.591)
$\Delta \ln G_{t-1}$		− 1.662***	− 1.859***		− 1.485**	− 2.616***
		(0.327)	(0.518)		(0.724)	(0.838)
$\Delta \ln G_{t-2}$		0.837***	1.322**		0.838*	2.906***
		(0.218)	(0.630)		(0.431)	(1.045)
$\Delta \ln G_{t-3}$			− 0.559			− 1.792*
			(0.496)			(0.952)
$\Delta \ln G_{t-4}$			0.313			0.810
			(0.243)			(0.488)
$D_t^R \Delta \ln G_t$				1.238***	0.734*	0.707*
				(0.267)	(0.383)	(0.408)
$D_{t-1}^R \Delta \ln G_{t-1}$					0.454	0.948**
					(0.320)	(0.432)
$D_{t-2}^R \Delta \ln G_{t-2}$					− 0.494*	− 1.171**
					(0.258)	(0.568)
$D_{t-3}^R \Delta \ln G_{t-3}$						0.172
						(0.236)
$D_{t-4}^R \Delta \ln G_{t-4}$						− 0.264
						(0.230)
Long-run elasticity	1.199*** (0.191)	1.425*** (0.185)	1.490*** (0.207)			
Long-run elasticity: expansions				0.592*** (0.144)	0.966*** (0.230)	1.031*** (0.234)
Long-run elasticity: recessions				1.829*** (0.194)	1.660*** (0.190)	1.424** (0.237)
Difference in elasticity between recessions and expansions				1.238*** (0.267)	0.694*** (0.245)	0.393 (0.260)
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

Dependent variable: $\Delta \ln C_t$. Variable names and definitions of the long-run elasticities as in the text. Newey–West standard errors with 12 lags in parentheses. First differences of heating degree days and cooling degree days are also included in all regressions. ***Significant at 1%, **5%, and *10% significance levels

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). These results show that the asymmetry is most pronounced in the very short run and becomes smaller in the longer run.

6 Conclusions

We have presented new evidence on the asymmetric relationship between CO_2 emissions and changes in GDP during recessions and economic expansions. On average, carbon emissions change faster relative to GDP in recessions than in expansions. However, comparing individual US recessions since 1973, during the 1973–1975, 1980, 1990–1991, and 2020 recessions, the elasticity of carbon emissions with respect to GDP is significantly different from that in expansions, while we do not find a statistically significant asymmetric relationship for other recessions. The earlier three recessions with asymmetric effects (1973–1975, 1980, and 1990–1991 recessions) are associated with negative oil supply shocks, while the 2020 recession is associated with a negative oil demand shock. Controlling for changes in oil use removes this asymmetry. Controlling similarly for coal does not. Controlling for natural gas use removes the asymmetry in 1973–1975 and 1980. In 1973–1975, 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 accidentally appear to track each other during these few months.

The changes in sectoral emissions in association with 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. We also show that only emissions from oil use have a larger elasticity with respect to GDP in recessions than in expansions. These findings suggest that it is negative oil market shocks rather than recessions per se that result in higher GDP elasticities of emissions in some recessions. However, the asymmetry in industrial sector emissions does not appear to be entirely explained by changes in oil use that are not correlated with GDP. Further research is needed to find the mechanism responsible. As mentioned above, perhaps this is due to scrapping of less efficient physical assets in recessions. Additionally, elevated oil prices may prompt private households and transport companies to transition from older vehicles to more energy-efficient models.

We also estimate a distributed lag specification. With two lags, the difference between the elasticity in recessions and expansions is smaller but is still statistically significant, while adding further lags results in a statistically insignificant asymmetry. Therefore, asymmetry is most pronounced in the short run.

Kilian (2009) decomposed changes in the global price of oil and oil production, and a measure of global economic activity into the contributions of demand, supply, and oil market specific shocks. If this model were expanded to include a US oil consumption variable and take into account the debate on such models (Baumeister and Hamilton 2019; Kilian 2022), the effect of such shocks in generating asymmetric changes in carbon dioxide emissions could be investigated. However, such a study is beyond the scope of the current paper.

Because the asymmetric changes in emissions are mostly associated with negative oil market shocks, we should not expect all future recessions to have outsize effects on emissions. We predict that asymmetry would be less important in countries where oil use and transport play a smaller role in the economy than they do in the USA. Sheldon (2017) used a simulation to show that asymmetric business cycle fluctuations in emissions could significantly reduce projected emissions used to estimate both future greenhouse gas concentrations and the cost of climate policies. Counter to Sheldon (2017), we expect a small and decreasing role for asymmetry in the long-run path of carbon emissions relevant to climate change unless there are major oil market shocks in the future. If transportation shifts to electric power, oil shocks should become quickly less important in predicting the path of carbon emissions. On the other hand, in the near term, understanding how emissions change with the business cycle and oil market shocks should be important in explaining the short-term trend in carbon emissions and determining when and whether emissions have peaked. Carbon emissions appear to have already peaked in the USA, but our research should be extended to other countries for this purpose. The steep fall in carbon emissions during the COVID-19 pandemic turned out to not be the global peak in carbon emissions despite talk of "growing back greener" (Taherzadeh 2021). The sharp reduction in emissions in 2020 was merely due to reduced transportation during the pandemic rather than a fundamental shift to a greener economy. Similarly, Chen et al.'s (2022) projection that China's emissions would peak before 2026 now seems less likely to be realized, as emissions are currently rising faster in China than immediately before the pandemic (Ahmed and Stern 2023).

Appendix

Data Sources.

Main Regressions

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), which were published by the Federal Reserve Bank of Chicago (Brave et al. 2019):

https://www.chicagofed.org/publications/bbki/index.

The series has been continued by the Indiana Business Research Center at the Kelley School of Business at Indiana University:

https://fred.stlouisfed.org/series/BBKQLEIX

The estimates are based on a factor analysis of quarterly GDP growth a panel of 490 monthly measures. 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 the 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 in EIA Monthly Energy Review). Unit: Quadrillion BTU.

Natural gas consumption: Monthly natural gas consumption data are provided by the EIA. They are given as sectoral natural gas consumption (Table 4.3 Consumption by sector in EIA Monthly Energy Review). Unit: Quadrillion BTU.

Coal consumption: Monthly coal consumption data are provided by the EIA. They are given as sectoral coal consumption (Table 6.2 Consumption by sector in EIA Monthly Energy Review). Unit: Quadrillion BTU.

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.

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 1.10 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 1.11 Cooling degree-days by Census division).

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Author contributions Both authors contributed to the study conception and design. Data collection and analysis were performed by XJ. Both authors wrote and commented on previous versions of the manuscript. Both authors read and approved the final manuscript.

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Data availability This study uses publicly available data as described in the Appendix. The dataset and code used to estimate the study are available at http://www.sterndavid.com/Data and on Figshare https://doi.org/10.6084/m9.figshare.24311755.

Declarations

Competing interests The authors declare no competing interests.

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