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Online Appendix to "Energy Efficiency and Fluctuations in CO_2 Emissions"[1]

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Abstract

This appendix provides additional information and analyses for "Energy Efficiency and Fluctuations in CO2 Emissions." Section 1 explains data sources and transformations. Section 2 covers a variety of robustness checks conducted for our baseline VAR results. Section 3 reports the results related to the analysis of emissions and energy consumption of major energy-use sectors. Specifically, section 3.1 demonstrates the impact of VAR estimation and model uncertainty on the inference from distributed lag models (DLMs). Section 3.2 reports the responses of energy consumption by sector to a negative correlation (NC) shock. Section 4 lays out a full description of the multi-sector dynamic stochastic general equilibrium model with pollution (E-DSGE model), which is used in our main text. Finally, section 5 includes additional results on the implications of weather extremes for our interpretation of NC shocks as changes in the energy efficiency of consumer products.

Key words: CO_2 emissions, energy efficiency, E-DSGE, sign restrictions

JEL classification: E32, Q43, Q50, Q55

1 Data Description

This section describes the variables used in our analysis along with the data sources and transformations. The variables are grouped by the sections of our paper.

1.1 VAR with Total Emissions and GDP

The baseline VAR includes growth rates of per capita total CO_2 emissions and GDP for the period from 1973:Q1 to 2019:Q4. We define the growth rate as 100 times the difference of the natural logarithms between the two consecutive quarters.

- **Total CO_2 emissions**: Energy Information Administration (EIA), total energy CO_2 emissions from energy consumption (million metric tons of carbon dioxide). Retrieved from Table 11.1 Carbon Dioxide Emissions From Energy Consumption by Source in the *Monthly Energy Review* (MER) publication of the EIA on October 28, 2020.. We de-seasonalize monthly emissions using X-12 ARIMA, and take quarterly averages.

  Online link: https://www.eia.gov/totalenergy/data/monthly/.

- **Real GDP**: U.S. Bureau of Economic Analysis (BEA), real gross domestic product (billions of chained 2012 dollars, seasonally adjusted annual rate, quarterly). Retrieved from FRED, the database of the Federal Reserve Bank of St. Louis, (label GDPC1) on October 28, 2020.

  Online link: https://fred.stlouisfed.org/series/GDPC1.

- **U.S. resident population**: U.S. Census Bureau, Population Division, U.S. resident population (thousands of persons, non-seasonally adjusted, quarterly average of the monthly data). Retrieved from HAVER (label POPR@USECON) on October 28, 2020.

- **Annual series**: The annual VAR is used for sensitivity analysis. The annual values of real GDP and resident population are set to annual averages of quarterly series. Annual CO_2 emissions are from Table 1.7 Primary Energy Consumption, Energy Expenditures, and Carbon Dioxide Emissions Indicators in the MER. The estimation sample is from 1949 to 2019.

1.2 Sector-level Analysis of Emissions and Energy Consumption

The sector-level series of emissions and energy consumption are from the EIA. The series used in the paper have the release date of November 24, 2020. There are five primary energy-use sectors: residential (homes and apartments), commercial (offices, stores, restaurants and other public gathering places), industrial (facilities and equipment used for manufacturing, agriculture, mining, and construction), transportation (travel and movements of goods), and electric power. All series in this category are published at the monthly frequency. We de-seasonalize the monthly series using X-12 ARIMA, and calculate per capita quarterly averages. Distributed lag models are estimated using the sample from 1974:Q2 to 2019:Q4, to match the sample of the posterior median estimates of the historical NC and PC shock series.

- **Emissions by sector**: Tables 11.2 - 11.6 in the MER from the EIA (million metric tons of carbon dioxide).

- **Primary energy consumption by sector**: Table 2.1 in the MER from the EIA (trillion Btu). This is direct use of fossil fuels, nuclear energy and renewables in each sector.

- **Total energy consumption by sector**: Table 2.1 in the MER from the EIA (trillion Btu). This is the sum of the primary energy use, purchased electricity, and energy losses.

1.3 Comparing Predictions from the E-DSGE Model to U.S. Data

- **Price of fossil fuels**: Cost of fossil fuel receipts at electric generating plants (dollars per million Btu, including Taxes, monthly). Table 9.9 in the MER from the EIA. We take quarterly averages of the monthly series.

- **Consumer price index of durable goods**: BEA, personal consumption expenditures on durable goods (index 2012=100, seasonally adjusted, quarterly). Table 1.1.4. Price Indexes for Gross Domestic Product (label DDURRG). Retrieved on October 29, 2020.

- **Real cost of fossil fuels**: We convert the cost of fossil fuel receipts into real terms using the BEA price index for consumer durables as a deflator, consistently with the choice of the numeraire in the E-DSGE model.

- **Aggregate consumption**: BEA, personal consumption expenditures (quantity index, 2012=100, seasonally adjusted, quarterly). Table 1.1.3. Real Gross Domestic Product, Quantity Indexes (label DPCERA). Retrieved on October 29, 2020. We convert the BEA series into per capita using the U.S. resident population.

- **Consumer durables**: BEA, personal consumption expenditures on durable goods (quantity index 2012=100, seasonally adjusted, quarterly). Table 1.1.3. Real Gross Domestic Product, Quantity Indexes (label DDURRA). Retrieved on October 29, 2020. We convert the BEA series into per capita using the U.S. resident population.

- **Aggregate investment**: BEA, Gross private domestic fixed investment (quantity index 2012=100, seasonally adjusted, quarterly). Table 1.1.3. Real Gross Domestic Product, Quantity Indexes (label A007RA). Retrieved on October 29, 2020. We convert the BEA series into per capita using the U.S. resident population.

- **Average work hours**: U.S. Bureau of Labor Statistics, Business Sector: Average weekly hours (index 2012=100, seasonally adjusted, quarterly).

  Retrieved from FRED (label PRS84006023).

  Online link: https://fred.stlouisfed.org/series/PRS84006023.

1.4 Data Used in Explorations of the Energy-Efficiency Interpretation

- **Energy Intensity Indicators**: Department of Energy, Office of Energy Efficiency and Renewable Energy, measures of energy intensity by end-use sectors (index, 1985 = 1.0, annual). The methodology for constructing these measures is described in Belzer (2014). We use the “source energy use” intensity indicators, from 1974 until 2011 (the last observation year).

The average growth rates the EI indicators were negative in each of the four end-use sectors, indicating energy-efficiency improvements over time.

Online link: https://www.energy.gov/eere/analysis/energy-intensity-indicators-indicators-data.

- **Climate Change Worry Index**: Gallup, the percent of the respondents in Gallup surveys who answered "great deal" or "fair amount" to the question "I'm going to read you a list of environmental problems. As I read each one, please tell me if you personally worry about this problem a great deal, a fair amount, only a little, or not at all. ... how much do you worry about global warming or climate change?" This is the longest public opinion data on climate change, which started in 1989. The polls were conducted in March, with exceptions of four polls in April of 1990, 1991, 1999, 2000 and one in October 1997. No data is available from 1992 to 1996 and for 1998. The polling was done twice in 1999.

  Online link: https://news.gallup.com/poll/1615/Environment.aspx.

- **U.S. Environmental Policy Stringency Index**: OECD, a broad measure of environmental policy related to climate and air pollution, covering the period from 1990 to 2015. Details of the index and its properties are described in Botta and Kozluk (2014).

  Online link: http://oe.cd/OQ.

- **Energy Prices** We have used a range of energy prices to evaluate if NC shocks can be predicted by the past energy prices. The monthly series are converted into quarterly averages.

  - **Price of fossil fuels**: described above, in section 1.3.
  - **RAC**: EAI, Refiner Acquisition Cost of crude oil, composite (dollars per barrel). Table 9.1 in the MER.
  - **WTI crude oil price**: FRED, spot crude oil price: West Texas Intermediate (dollars per barrel). Online link:https://fred.stlouisfed.org/series/WTISPLC.
  - **CPI Fuel Oil and Other Fuels**: FRED, Consumer Price Index for all urban consumers: Fuel Oil and Other Fuels in U.S. City Average (index 1982-1984=100, seasonally adjusted). Online link: https://fred.stlouisfed.org/series/CUSR0000SEHE.
  - **CPI Electricity**: FRED, Consumer Price Index for all urban consumers: Electricity in U.S. City Average (index 1982-1984=100, seasonally adjusted). Online link: https://fred.stlouisfed.org/series/CUSR0000SEHF01.
  - **PCE Energy goods and services**: BEA, Table 2.3.4. Price Indexes for Personal Consumption Expenditures by Major Type of Product.
  - **PCE Gasoline and other energy goods**: BEA, Table 2.3.4. Price Indexes for Personal Consumption Expenditures by Major Type of Product.
  - **PPI Fuels and Related Products and Power**: FRED, Producer Price Index by commodity: Fuels and Related Products and Power (index 1982=100, not seasonally adjusted). Online link: https://fred.stlouisfed.org/series/PPIENG.
  - **PPI Industrial Electric Power**: FRED, Producer Price Index by commodity, Fuels and Related Products and Power: Industrial Electric Power (index 1982=100, seasonally adjusted). Online link: https://fred.stlouisfed.org/series/WPS0543.

1.5 Other Explanations for NC shocks

- **Weather indicators**: The National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental information, Climate at a Glance: National Time Series. Meteorological data exhibit strong seasonality and monthly-specific trends. A nine-point binomial filter is a statistical technique that is commonly used in climate analysis to estimate the underlying trends (e.g. Aubury and Luk, 1996). We apply this technique to month-specific observations, compute deviations of a weather-related series from the estimated trend, and then aggregate the transformed monthly series into quarterly averages. The list below specifies the original data units.

  Online link: https://www.ncdc.noaa.gov/cag/national/time-series.

  - **Average temperature**: contiguous U.S. average temperature, Fahrenheit.
  - **Heating degree days** (HDD): a quantitative index which reflects heating energy requirements (i.e. demand for energy to heat houses and businesses or to grow crops). It is defined as 65-MT=HDD, where 65 is the base temperature and MT is Mean Temperature (average of high and low). If MT is equal to or greater than 65 degrees F, HDD=0. Units: Fahrenheit degree-days.
  - **Cooling degree days** (CDD): a quantitative index which reflects cooling energy requirements (i.e. demand for energy to cool houses and businesses or to grow crops). It is defined as MT-65=CDD. If MT is equal to or less than 65 degrees F, CDD=0.

    Units: Fahrenheit degree-days.
  - **Residential energy demand temperature index** (REDTI): This series is calculated on a seasonal basis, using the sum of population weighted HDD's and CDD's (base 65). The index is scaled from 0 to 100. An index of 100 is assigned to the year with the greatest population weighted degree day average while the year with the smallest degree day average receives an index of 0.
  - **Precipitation**: contiguous U.S. precipitation. Units: inches.

- **CO_2 emissions coefficients**: EIA, historical values for 35 energy product categories (million metric tons CO_2 per quadrillion Btu, annual). Available from 1973 to 2017.

  Online link: http://www.eia.gov/environment/archive/1605/ggrpt/excel/CO2_coeffs_09_v2.xls.

- **Emissions by source**: EIA, separate series of CO_2 emissions from (i) coal, including coal coke net imports; (ii) natural gas, excluding supplemental gaseous fuels and (iii) petroleum, excluding biofuel; (million metric tons of carbon dioxide). Table 11.1 in the MER from the EIA. We take quarterly averages of the monthly series after their de-seasonalization via X-12 ARIMA. We convert the BEA series into per capita using the U.S. resident population.

2 Robustness of the Baseline VAR Results

Our baseline VAR model includes four lags of per capita growth rates of total emissions and GDP, and uses truncated Student t distributions for the key parameters a_p and a_n. This section demonstrates that our results are robust to a number of alternative assumptions. We focus on comparing the posterior median estimates of historical NC shocks of our baseline VAR and historical NC shock estimates of alternative setups. We chose this evaluation criterion due to the vital role the historical shock estimates play in the "intepretive" part of our paper.

Alternative priors We use the lognormal priors for a_p and a_n in place of the truncated Student t distributions. We set the location parameters to $\log(1.56)$ and $\log(1.75)$, and calibrate the scale parameters to 0.55 and 0.43, which results in the 80% probability that the corresponding parameters fall in the region $(0.15, 2.5)$, as was the case in our baseline setting. Our results are not sensitive to the new prior density. The data remain informative about our parameters of interest. That is, the resulting posterior histograms are almost identical to the benchmark. The estimated median NC shocks trace the benchmark series, with the correlation coefficient of 0.9998.

Next, we change the values of the scale parameters in the truncated Student t prior distributions for a_p and a_n. To this end, we re-estimate the model using much larger values of σ_p and σ_n, to reflect high uncertainty around the parameters. More specifically, instead of the baseline values $(\sigma_p, \sigma_n) = (0.85, 0.7)$, we use $(1.1, 1.1)$ and $(2, 2)$. These larger scale parameters lower the probability of a_p to be in the range of $(0.15, 2.5)$ from 80% to 73% and 54%, respectively. In the case of a_n, the probabilities are further down to 68% and 51%. While the prior distributions are more dispersed, the estimated posterior median NC shock series is again nearly distinguishable from our baseline, with the pairwise correlation at 0.9993 and 0.9994 for each value of the scale parameter.

Posterior mean estimate of historical shocks The posterior median estimate of historical shocks, used in our baseline, is statistically optimal with an absolute loss function. If we instead use a quadratic loss function, the optimal object is the posterior mean, as shown in Baumeister and Hamilton (2018). When we compare the posterior mean and the posterior median estimates of the NC shocks, we find the pair-wise correlation coefficient of 0.999, revealing that the choice between the two is practically irrelevant in our specification.

Adding more lags to VAR One may question if four lags are sufficient to adequately represent the dynamics of emissions and GDP. We re-estimate our model with eight lags in the VAR while maintaining all other assumptions. Increasing the number of lags again results in small differences in the posterior histograms and the estimated shock series. The correlation coefficient between the posterior median shock estimates of this specification and our baseline remains very high, at 0.998.

Extending the sample to 2020:Q2 Growth rates of both GDP and emissions dropped to unprecedented levels in the first two quarters of 2020, due to the spread of the Covid pandemic. When we include these additional quarters, we find that the posterior median historical PC and NC shock series are almost identical to our baseline series, with the correlation coefficients of 0.968 and 0.989, respectively. Our historical decomposition analysis shows that almost all of the drops in GDP and emissions are explained by an extremely negative PC shock realization, demonstrating the negative economic impacts of the pandemic on output and emissions. Despite the robustness of the median shock estimates, we do not include the two quarters of 2020 in our baseline analysis, as they add large uncertainty to overall estimation.

Data in log-levels To account for a possible cointegration between GDP and emissions that was not detected by the standard cointegration tests, we have re-estimated the model using data in the log-levels. While this specification has an impact on the posterior distributions of a_p and a_n, the divergence in the posterior median estimates of NC shocks is very small. The correlation coefficient of the estimated NC shocks is at 0.990.

Using HP-filtered data Business cycle researchers often work with so-called "cyclical" components of economic series, which are obtained by applying a particular filter to de-trend the data. The HP-filter, originally proposed by Hodrick and Prescott (1997), remains a popular alternative, despite some of critiques raised in the literature (e.g. Hamilton, 2018). Figure 1 plots the log-levels of GDP and total emissions, and their HP-filtered trends and the cyclical components. GDP and emissions exhibit stronger correlation between the cyclical components relative to the growth rates: the corresponding correlation coefficients are 0.625 and 0.163. Nonetheless, even with the cyclical data, emissions and GDP fall on the opposite sides of their trends in about 30% of the quarters in our sample. This is illustrated in a scatter plot in the right panel of Figure 1.

A VAR with the cyclical components of GDP and emissions rules our permanent shocks by construction. Even though the suitability of such specification may not be obvious, we re-estimate our VAR model using these alternative data in line with some business cycles studies. We keep all other assumptions identical to our baseline. As expected, we obtain different shapes of impulse responses. However, the resulting posterior median estimates of PC and NC shocks are highly positively correlated with our baseline estimates. The corresponding correlation coefficients are 0.878 and 0.898 for the PC and the NC shocks, respectively.

Using annual data Our baseline model is estimated starting 1973:Q1, due to the availability of emissions series. However, the EIA also publishes annual emissions, starting from 1949. We use this series along with annual GDP and population, and re-estimate our VAR model with one lag. We then compare the resulting posterior median historical shock series to i) the annual averages of our baseline NC shock, ii) the maximum absolute values of four quarters in the same year and iii) the sum of four quarter values in a year, during 1974 to 2019. We show these estimates in Figure 2. The correlation coefficients fall in the range from 0.56 to 0.63.

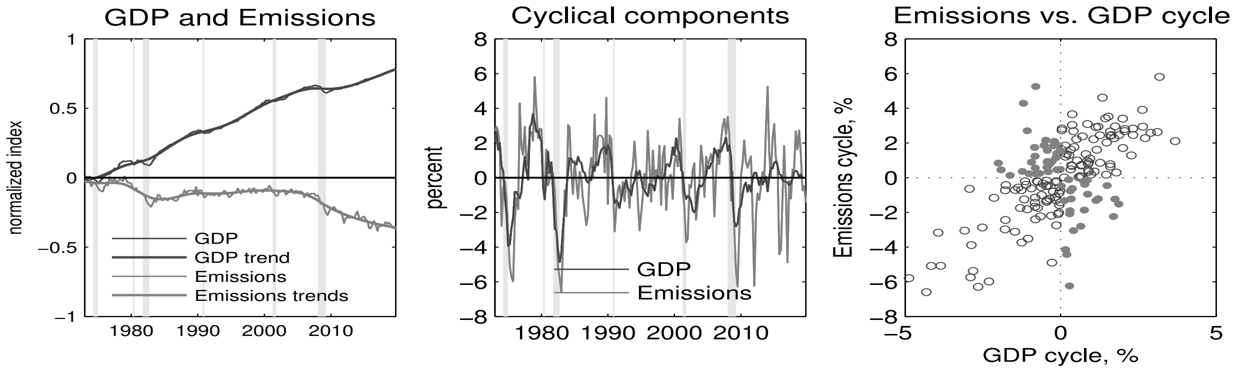


Figure 1: Trends and cycles of per capita GDP and total CO_2 emissions

Note: The series in the left panel are normalized to the 1973:Q1 values and expressed in logs. Trends and cyclical components are estimated using the HP filter with the smoothing parameter 1600. Red squares in the right panel are the periods when the cyclical components of emissions and GDP are the opposite side of their trends. Blue circles are the periods when both series are simultaneously above or below their trends. Shaded areas are the NBER recessions.

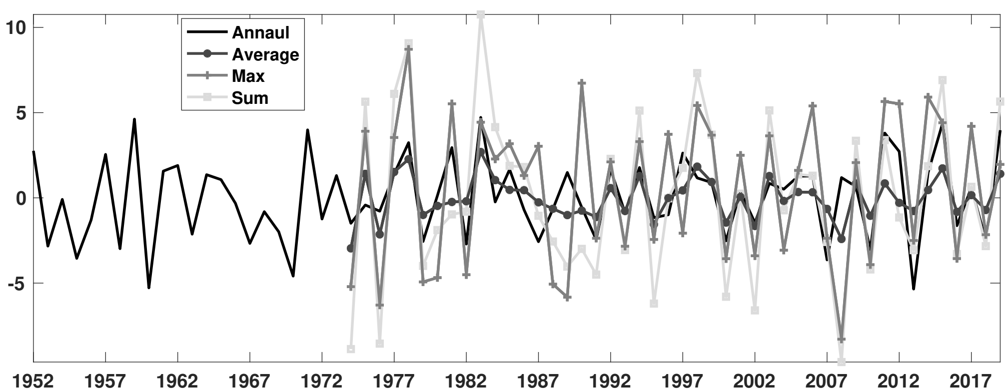


Figure 2: Historical NC shocks using annual data

Note: This figure plots the posterior median estimates of historical NC shocks using annual data (black). This series is compared to the annual averages (blue), the maximum of absolute values in a year (red), and the sum of four quarterly values (green) of our baseline quarterly shock estimates.

3 Additional Analysis of Energy-Use Sectors

This section includes two sets of results. First, we demonstrate the impact of VAR estimation and model uncertainty on the inference from distributed lag models (DLMs), defined section 2.1 of the main text. Then we report impulse responses of energy consumption from the DLM approach.

3.1 Accounting for VAR Estimation and Model Uncertainty in DLMs

In the main text, we use the posterior median estimates of historical realizations of the NC shocks to estimate impulse responses of emissions by sectors with DLMs. This approach does not account for the fact that the posterior median is a generated regressor. We proceed differently here. Specifically, we estimate a DLM for each of the $N = 10^5$ structural VAR models, using a VAR-specific historical NC shock estimate. Then we compute the implied impulse responses based on the DLM regression coefficients. We sort the impulse responses for each horizon, and plot the median responses along with 68% and 95% bands in Figure 3. These impulse responses capture the VAR model and estimation uncertainty but do not account for the parameter uncertainty in the DLMs.

Unsurprisingly, the accepted range of responses in Figure 3 increases substantially relative to the range reported in Figure 5 in the main text. Still, the responses of emissions in the residential, the commercial and the electric power sectors remain negative for several quarters after both shocks with the 95$\%$ confidence.

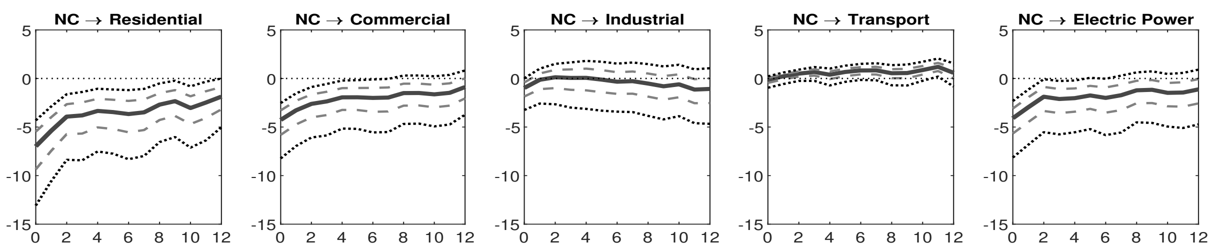


Figure 3: Impact of VAR estimation and model uncertainty on IRFs of emissions

Note: This figure reports the cumulative responses of per capita emissions from total energy consumption, by energy-use sectors. Solid blue lines connects the median responses in each horizon, obtained from a large number of DLMs, each corresponding to a distinct structural VAR model $l = 1, ..., N$. Dashed and dotted lines represent the 68% and 95% values, respectively. The size of the shocks is set to $\hat{a}_p^{(l)} + \hat{a}_n^{(l)}$ to increase GDP by one percent in each structural VAR model $l = 1, ...N$.

3.2 Responses of Energy Consumption by Sector

We have shown in the main text of our paper how CO_2 emissions by sector respond to the estimated PC and NC shocks. Empirical CO_2 emissions series are constructed from total energy consumption. The latter includes the use of primary energy (fossil fuels, nuclear energy and renewables), purchased electricity, and energy losses. Figure 4 demonstrates that the responses of per capita total energy consumption, by sectors, to both PC and NC shocks resemble those of the emissions (Figure 5 in the main text). The key result is that the reduction in the total energy use to a positive NC shock is mainly driven by a decline in the energy use in the residential and commercial sectors, in line with the responses of the sector-level emissions.

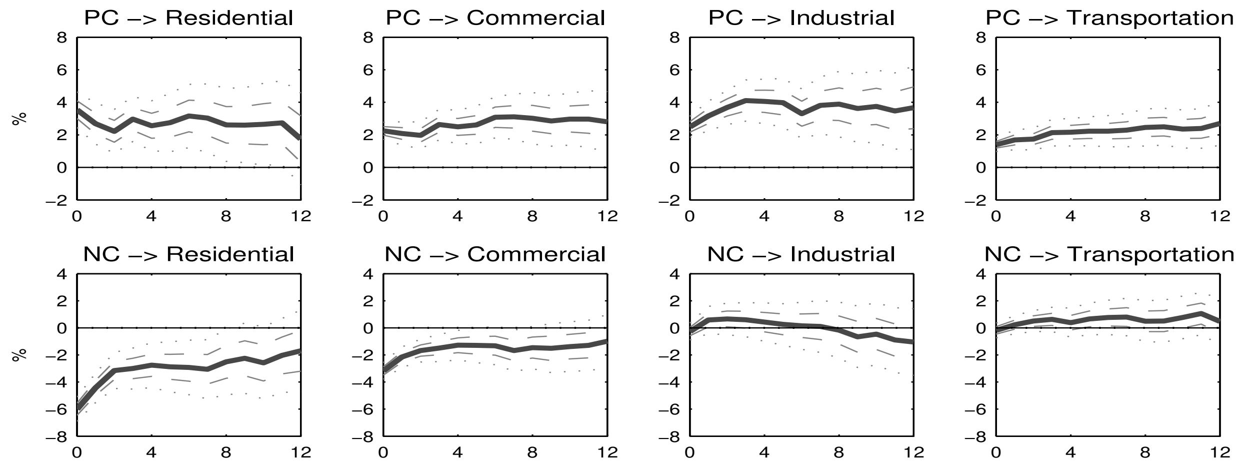


Figure 4: Responses of per capita total energy consumption by sector (DLM)

Note: Solid lines are the cumulative responses to the median shocks based the DLM described by equation (5) in the main text. The size of the shocks is normalized to increase GDP by one percent in the baseline VAR. Dashed and dotted red lines denote one and two-standard error bootstrap confidence bands.

4 Detailed Description of the E-DSGE Model

This section provides a detailed description of the dynamic stochastic general equilibrium model with emissions (E-DSGE model) used in section 3.1 of our paper. We extend the model of Huynh (2016) to include emissions from energy consumption. The notation and parameterization closely follows Huynh (2016), with some minor exceptions.

4.1 Modeling Emissions and Environmental Damages

As explained in section 3.1.1 of our paper, a single energy type is used by consumers ($e_{h,t}$), energy producers ($e_{e,t}$) and by producers of durable and nondurable goods ($e_{d,t}$ and $e_{n,t}$). We model carbon emissions as proportional to the total use of energy: $em_t = \kappa e_t$, with $e_t = e_{h,t} + e_{e,t} + e_{d,t} + e_{n,t}$. The emissions intensity coefficient κ is constant, and one unit of energy emits the same amount of CO_2 irrespective of whatever it is used by consumers or producers. In this model, emissions vary due to energy use decisions of different agents. Our modeling choice is close to Fischer and Springborn (2011) and Dissou and Karnizova (2016). This modeling strategy enables us to link the model predictions with the impulse responses of sectoral emissions in the U.S. data.

CO_2 emissions in our model generate a negative externality. The current period emissions accumulate over time and create economic damages. Golosov et al. (2014) describe a possible way of modeling how stock of emissions S_t evolves over time,

$$S_t = \sum_{j=0}^{t+T} (1 - \chi_j)\, em_{t-j}.$$

The value $\chi_j \in [0, 1]$ for all j. It governs the persistence of current emissions contributions. In particular, a fraction $(1 - \chi_j)$ of carbon will be left the atmosphere j periods in the the future.[1]

Similar to Hassler et al. (2010), we model environmental damages through their negative impact on the consumer's welfare. Specifically, the stock of emissions S_t creates disutility $-\eta\Psi(S_t)$, $\eta > 0$, $\Psi' > 0$. Since we study the model in the absence of environmental regulation, the values of damage parameters and the exact formulation of S_t are inconsequential.

4.2 Consumers

The representative consumer has the expected lifetime utility

$$U = E_0 \sum_{t=-0}^{\infty} \beta^t \left[\varphi \ln c_t + (1 - \varphi) \ln (1 - h_t) - \eta\Psi(S_t)\right]. \tag{1}$$

The discount factor $\beta \in (0, 1)$ and $\varphi > 0$. The composite consumption good c_t combines non-durable goods n_t, the stock of durables d_t and the utilization rate of the durables stock u_t in a constant elasticity of substitution (CES) aggregator with the elasticity of substitution $1/(1 - \rho)$

$$c_t = \left[\phi^{1-\rho} (u_t d_t)^\rho + (1 - \phi)^{1-\rho} n_t^\rho\right]^{1/\rho}. \tag{2}$$

Here $\phi \in (0, 1)$ represents the share of the durables usage in the consumer's consumption bundle. The use of durables requires energy. The total energy used by the consumers is proportional to the service flows from the stock of durables

$$e_{h,t} = A_{d,t} u_t d_t, \tag{3}$$

$$A_{d,t} = a \exp(X_{d,t}),\ a > 0. \tag{4}$$

Energy intensity $A_{d,t}$ is modelled to be constant in Huynh (2016)'s baseline specification. That is, it is assumed that $\exp(X_{d,t}) \equiv 1$. However, section 4.3 of Huynh (2016)'s paper reports impulse responses to a one-time increase in the value of a. We assume that $X_{d,t}$ follows an autoregressive (AR) process of order one, as stated in the law of motion (23).

The consumer receives the wage rate w_t per unit of labor supplied, and earns the rental rate

[1] See Heutel (2012) for an alternative modeling of the emissions stock.

r_t per unit of capital owned. The consumer's investment decisions for $i_{d,t}$ and $i_{k,t}$ determine the evolution of the stocks of durables and capital,

$$d_{t+1} = i_{d,t} + (1 - \delta_{d,t})\, d_t + \frac{\omega_d}{2} \left(\frac{d_{t+1} - d_t}{d_t} \right)^2, \ \omega_d > 0, \tag{5}$$

$$k_{t+1} = i_{k,t} + (1 - \delta_k)\, k_t + \frac{\omega_k}{2} \left(\frac{k_{t+1} - k_t}{k_t} \right)^2, \ \omega_k > 0. \tag{6}$$

The assumption of the quadratic adjustment costs follows the calibration of Huynh (2016). The depreciation rate of durables $\delta_{d,t}$ varies with the intensity of their utilization,

$$\delta_{d,t} = \frac{a_1}{a_2 + 1} u_t^{a_2+1}, \ \ a_1 > 0, \ a_2 > 0. \tag{7}$$

Following Huynh (2016), the rate of capital depreciation δ_k is constant.

The consumer faces the budget constraint

$$p_{e,t} e_{h,t} + p_{n,t} n_t + i_{d,t} + i_{k,t} = w_t h_t + r_t k_t, \tag{8}$$

where $p_{e,t}$ and $p_{n,t}$ are the prices of energy and nondurables, expressed in units of the consumer durable goods. Stated differently, the common price of durables and capital is taken as the numeraire and normalized to one.

The consumer chooses $\{c_t, n_t, u_t, d_{t+1}, \delta_t, h_t, e_{h,t}, i_{d,t}, i_{k,t}, k_{t+1}\}$ to maximize the lifetime utility (1) subject to (2), (3), (5), (6), (7), and (8). The first order necessary conditions include the transversality conditions for the stocks of durable and capital goods, the budget constraint (8), the accumulation equations (5) and (6), the definitions of consumption aggregator (2), the energy choice (3) and the depreciation rate (7), plus the intratemporal trade-off between the non-durable consumption and leisure,

$$(1 - \phi)^{1-\rho} \frac{\varphi}{1 - \varphi} (1 - h_t)\, c_t^{-\rho} n_t^{\rho - 1} = \frac{p_{n,t}}{w_t}, \tag{9}$$

the intratemporal trade-off between the non-durable consumption and durable goods utilization,

$$\left(\frac{1 - \phi}{\phi} \right)^{1-\rho} \left(\frac{n_t}{u_t d_t} \right)^{\rho - 1} = \frac{p_{n,t}}{A_{d,t} p_{e,t} + a_1 u_t^{a_2}} \tag{10}$$

the intertemporal Euler equation for consumer durables

$$\begin{aligned}\frac{MU_{n,t}}{p_{n,t}}\left(1+\frac{\partial g_{d,t}}{\partial d_{t+1}}\right) &= \beta E_t MU_{d,t+1} \\ &+\beta E_t \frac{MU_{n,t+1}}{p_{n,t+1}}\left(-p_{e,t+1}A_{d,t+1}u_{t+1}+1-\delta_{d,t+1}-\frac{\partial g_{d,t+1}}{\partial d_{t+1}}\right) \quad (11)\end{aligned}$$

with $g_{d,t} = \frac{\omega_d}{2}\left(\frac{d_{t+1}}{d_t}-1\right)^2$, $\frac{\partial g_{d,t}}{\partial d_{t+1}} = \frac{\omega_d}{d_t}\left(\frac{d_{t+1}}{d_t}-1\right)$, $\frac{\partial g_{d,t}}{\partial d_t} = -\omega_d\left(\frac{d_{t+1}}{d_t}-1\right)\frac{d_{t+1}}{d_t^2}$, and the intertemporal Euler equation for capital,

$$\frac{MU_{n,t}}{p_{n,t}}\left[1+\frac{\omega_k}{k_t}\left(\frac{k_{t+1}}{k_t}-1\right)\right] = \beta E_t\frac{MU_{n,t+1}}{p_{n,t+1}}\left[r_{t+1}+1-\delta_k+\omega_k\frac{k_{t+2}}{k_{t+1}^2}\left(\frac{k_{t+2}}{k_{t+1}}-1\right)\right] \quad (12)$$

In the expressions above, the marginal utilities correspond to the following expressions:

$$\begin{aligned}MU_{n,t} &\equiv \frac{\partial U}{\partial n_t} = \varphi\left(1-\phi\right)^{1-\rho}c_t^{-\rho}n_t^{\rho-1} \\ MU_{d,t} &\equiv \frac{\partial U}{\partial d_t} = \varphi\phi^{1-\rho}c_t^{-\rho}d_t^{\rho-1}u_t^{\rho} \\ MU_{u,t} &\equiv \frac{\partial U}{\partial u_t} = \varphi\phi^{1-\rho}c_t^{-\rho}d_t^{\rho}u_t^{\rho-1} \\ MU_{h,t} &\equiv \frac{\partial U}{\partial h_t} = \left(1-\varphi\right)\frac{1}{1-h_t}\end{aligned}$$

4.3 Producers

There are three perfectly competitive sectors: durables, non-durables and energy sectors. The representative firm in each sector maximizes profits by choosing capital $k_{f,t}$, labor $h_{f,t}$ and energy $e_{f,t}$, $f \in \{e,d,n\}$. All three input factors are perfectly mobile across the sectors.

The use of capital in each sector requires energy. In particular, each sector's energy consumption is given by

$$e_{f,t} = A_{k,t}k_{f,t},\ f\in\{e,d,n\},\ b>0, \quad (13)$$

where $A_{k,t} = b\exp\left(X_{k,t}\right)$. Similarly to the case of consumers, energy intensity $A_{k,t}$ is modelled to be constant in Huynh (2016)'s baseline specification. That is, it is assumed that $\exp\left(X_{k,t}\right) \equiv 1$. However, section 4.3 of Huynh (2016)'s paper reports impulse responses to a one-time increase in the value of b. We assume that $X_{k,t}$ follows an autoregressive (AR) process of order one, as stated in (24). The variable $k_{f,t}$ denotes the sectoral stock of capital. This specification implies perfect complementarity between capital and energy. It also implies that energy costs increase the marginal cost of capital.

4.3.1 Non-durable and durable goods producers

The nondurable and durable goods are produced according to the following production function

$$y_{i,t} = Z_t k_{i,t}^{\gamma_i} h_{i,t}^{1-\gamma_i},\ \gamma_i \in (0,1)\,, \tag{14}$$

with $y_{i,t}$ denoting output of sector $i \in \{d,n\}$. Z_t is the non-energy total factor productivity (TFP). In Huynh (2016)'s notation, $Z_t = \exp(A_t)$.

The first order necessary conditions of the sector $i \in \{d,n\}$ include include (13), (14) and

$$MPL_{i,t} = \frac{w_t}{p_{i,t}} \text{ or } (1-\gamma_i)\, Z_t k_{i,t}^{\gamma_i} h_{i,t}^{-\gamma_i} = \frac{w_t}{p_{i,t}} \tag{15}$$

$$MPK_{i,t} = \frac{r_t + A_{k,t} p_{e,t}}{p_{i,t}} \text{ or } \gamma_i Z_t k_{i,t}^{\gamma_i - 1} h_{i,t}^{1-\gamma_i} = \frac{r_t + A_{k,t} p_{e,t}}{p_{i,t}} \tag{16}$$

The price of the durable goods is the numeraire (i.e. $p_{d,t} = 1$) and the price of non-durable goods $p_{n,t}$ is expressed in terms of consumer durables.

4.3.2 Energy producers

Production of energy exhibits some wastage and inefficiencies in the production process. These inefficiencies become larger as the energy sector expands. Specifically, energy $y_{e,t}$ is produced according to

$$y_{e,t} = Z_{e,t}\,(1-\sigma_t)\, k_{e,t}^{\gamma_e} h_{e,t}^{1-\gamma_e}, \tag{17}$$

where $Z_{e,t} = \exp(A_{e,t})$ and

$$\sigma_t = \frac{\omega_e}{3}\left(k_{e,t}^{\gamma_e} h_{e,t}^{1-\gamma_e}\right)^3,\ \omega_e > 0. \tag{18}$$

Convex production costs in the form of (18) provide a mechanism to generate a low price elasticity of energy supply and prevent a very rapid response of the energy sector to energy market demand shocks. The first order necessary conditions of the sector $i \in \{d,n\}$ include (13), (17), (18) and

$$MPL_{e,t} = \frac{w_t}{p_{e,t}} \text{ or } Z_{e,t}\left[(1-\gamma_e)(1-\sigma_t)\left(\frac{k_{e,t}}{h_{e,t}}\right)^{\gamma_e} - \frac{\partial \sigma_t}{\partial h_{e,t}} k_{e,t}^{\gamma_e} h_{e,t}^{1-\gamma_e}\right] = \frac{w_t}{p_{e,t}} \tag{19}$$

$$MPK_{i,t} = \frac{r_t + A_{k,t} p_{e,t}}{p_{i,t}} \text{ or }$$

$$Z_{e,t}\left[\gamma_e (1-\sigma_t)\left(\frac{k_{e,t}}{h_{e,t}}\right)^{\gamma_e - 1} - \frac{\partial \sigma_t}{\partial k_{e,t}} k_{e,t}^{\gamma_e} h_{e,t}^{1-\gamma_e}\right] = \frac{r_t + A_{k,t} p_{e,t}}{p_{e,t}} \tag{20}$$

Here

$$\frac{\partial \sigma_t}{\partial h_{e,t}} = 3\left(1-\gamma_e\right)\frac{\sigma_t}{h_{e,t}}, \text{ and } \frac{\partial \sigma_t}{\partial k_{e,t}} = 3\gamma_e \frac{\sigma_t}{k_{e,t}}.$$

4.4 Stochastic processes

The four stochastic shocks are assumed to be independent to each other. Further, we assume that each shock follows a stationary autoregressive process of order one.

$$Z_t = \rho_z Z_{t-1} + \varepsilon_{z,t},\ \varepsilon_{z,t} \sim^{i.i.d.} N\left(0, \sigma_z^2\right) \tag{21}$$

$$Z_{e,t} = \rho_e Z_{e,t-1} + \varepsilon_{e,t},\ \varepsilon_{e,t} \sim^{i.i.d.} N\left(0, \sigma_e^2\right) \tag{22}$$

$$X_{d,t} = \rho_d X_{t-1} + \varepsilon_{d,t},\ \varepsilon_{d,t} \sim^{i.i.d.} N\left(0, \sigma_d^2\right) \tag{23}$$

$$X_{k.t} = \rho_k Z_{t-1} + \varepsilon_{k,t},\ \varepsilon_{d,t} \sim^{i.i.d.} N\left(0, \sigma_k^2\right) \tag{24}$$

All innovations ε_t are uncorrelated at all lags and leads.

4.5 Equilibrium

In a competitive equilibrium, the producers maximize profits, the consumers solve the utility maximization problems and prices adjust to clear the markets. The market clearing conditions are

The market for capital	k_t	$=$	$k_{d,t} + k_{n,t} + k_{e,t}$	(25)
The market for labor	h_t	$=$	$h_{d,t} + h_{n,t} + h_{e,t}$	(26)
The market for durables goods	$y_{d,t}$	$=$	$i_{d,t} + i_{k,t}$	(27)
The market for non-durable goods	$y_{n,t}$	$=$	n_t	(28)
The market for energy	$y_{e,t}$	$=$	$e_{h,t} + e_{n,t} + e_{d,t} + e_{e,t}$	(29)

In a multi-sector model, value-added aggregate output must be derived by aggregating output produced by different sectors and excluding energy used in production:

$$p_t y_t = y_{d,t} + p_{n,t} y_{n,t} + p_{e,t} e_{h,t}, \tag{30}$$

where the aggregate price index is $p_t = \left[\phi(1 + A_{d,t} p_{e,t})^{\frac{\rho}{\rho-1}} + (1-\phi) p_{n,t})^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}}$.

4.6 Model calibration and solution

The model is solved by log-linearizing the equilibrium equations around the deterministic steady state using the perturbation method. We take the model parameters from Huynh (2016) and refer the reader to that paper for the explanation of the calibration strategy. On the consumer side, the discount factor $\beta = 0.99$, the share of consumption value in the consumer utility $\varphi = 0.34$, the share of durables usage in the consumption aggregate $\phi = 0.2$, the capital depreciation rate $\delta_k = 0.015$, the parameters in the depreciate rate and the adjustment cost functions $a_1 = 0.145$, $a_2 = 0.165$, $\omega_d = 0.4$, and $\omega_k = 0.05$. On the production side, $\gamma_d = 0.34$, $\gamma_n = 0.38$, $\gamma_e = 0.552$, and $\omega_e = 9.36$. The values $a = 0.085$ and $b = 0.0086$ are chosen to match the empirical ratios of energy use by consumers and producers to real GDP. The persistence of all stochastic shocks is set to ρ_i =0.999 for all four macroeconomic shocks $i \in \{z, e, d, k\}$.

We focus on the model's predictions for macroeconomic and energy use indicators in a *laissez-faire* scenario. Since we are not computing optimal policy, we can bypass making a stance on the parameters describing the damage function and the stock of emissions for two reasons. First, the dynamics of emissions in the log-linearized model coincide with the dynamics of total energy because emissions are proportional to the energy use. Second, the separability structure of the preferences means that the consumer's decisions are not directly affected by the stock of emissions.

5 Additional Results on Effects of Weather Extremes

We demonstrate in the main text that the NC shocks have the strongest impact on emissions and energy consumption in the residential and commercial sectors. According to the EIA, space heating and cooling account for more than half of total energy use by the residential sector, and more than a third by the commercial sector EIA (2012, 2015). Since most of these energy needs are met by the use of fossil fuels (directly through the use of natural gas or indirectly with the use of electricity), seasonal changes in energy demand for heating and cooling will lead to emissions fluctuations. In this section, we evaluate the sensitivity of our results to controlling for weather variations.

Energy demand for heating and cooling surges in very cold winters and very hot summers. While the spells extreme temperatures are often short-lived, they can still have sizable impacts on emissions. For example, EIA (2020) lists a "polar vortex" as the key driver of CO_2 emissions in 2014. At the same time, extreme cold or extreme hot weather conditions can have multiple negative impacts on economic activity, ranging from direct crop and infrastructure damages, travel and work disruptions to indirect impacts on labor productivity. More formally, the NOAA keeps track of billion-dollar weather and climate disasters. Since 1980, 26 disaster events in the U.S. were caused by a freeze or a winter storm.

Very cold winters and very hot summers thus may be the times when emissions rise while output falls. To investigate this possibility, we use several U.S. national weather indicators: the national average temperature, the heating degree days, the cooling degree days, the residential energy demand temperature index and precipitation. Quayle and Diaz (1980) and Heim Jr et al.

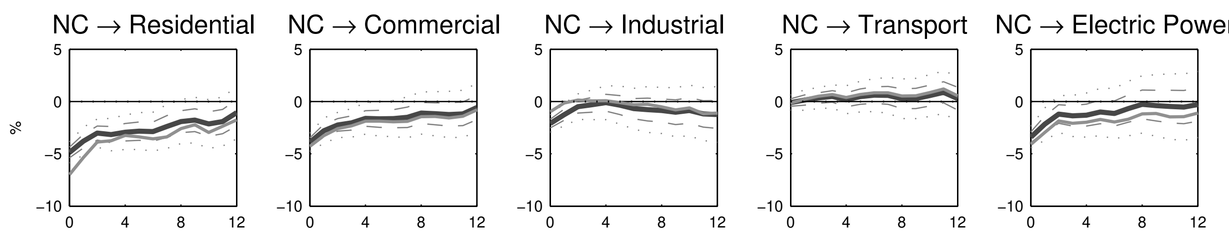
Table 1: Posterior median PC and NC shocks and weather indicators

	PC shocks		NC shocks	
Weather indicator	corr.	std.error	corr.	std.error
Average temperature °F	-0.131	(0.080)	0.321	(0.075)
Heating degree days	0.242	(0.077)	-0.424	(0.070)
Cooling degree days	0.149	(0.063)	-0.097	(0.055)
REDTI	0.352	(0.061)	-0.393	(0.062)
Precipitation	-0.208	(0.084)	0.166	(0.081)

Note: Meteorological series are set to the quarterly averages of monthly percentage deviations from the month-specific trends, constructed with the 9-point binomial filter. Standard errors are based on bootstrap sampling with replacement.

(2003) show that the REDTI is strongly positively related to household energy demand. The degree of humidity affects perceived temperatures, and hence influence human tolerance to heat and cold. As mentioned in the main text, we also construct three indicators of extreme temperatures, breaking down the year into the heating and cooling seasons.

(a) CO_2 emissions from total energy consumption (per capita)



(b) Total energy consumption (per capita)

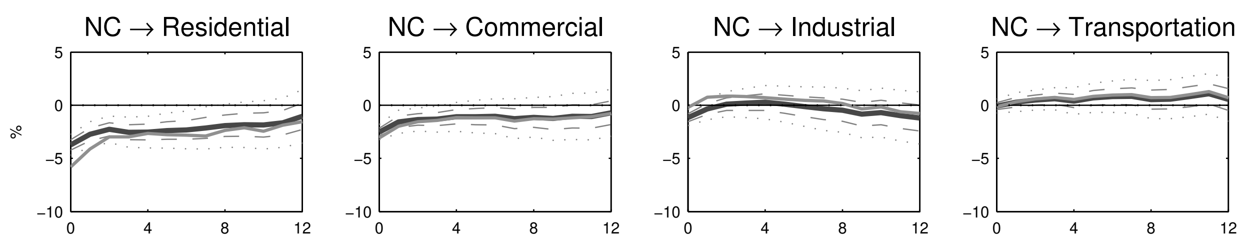


Figure 5: Impact of weather indicators on responses to NC shocks (DLM)

Note: Solid blue lines are the cumulative responses estimated from the distributed lags models augmented with weather indicators. Dashed and dotted red lines denote one and two-standard error bootstrap confidence bands. Thin solid magenta line reproduced the responses from the benchmark DLM defined by equation (5) in the main text of our paper.

Table 1 reports the correlation coefficients between the weather indicators and the posterior median estimates of the PC and NC shocks. We obtain the expected correlation signs for the NC shocks. By our normalization, a positive value of the NC shock increases output but reduces emissions. Increased demand for heating in a colder winter, as measured by higher values of the HDD or REDTI indices, increases emissions. Thus, these indicators are negatively correlated with the NC shocks. If extreme temperature changes drive the NC shocks, then we should find negative realizations of these shocks during very cold winters and very hot summers. It is also possible that milder than usual winters can be associated with positive realizations of the NC shocks. Warmer conditions in the heating season will put a downward pressure on the energy demand (i.e. lower emissions) and can extend seasonal work, such as construction, thereby increasing the economic activity. In both cases, we should expect a positive correlation between the NC shocks and the extreme temperature series. We re-estimate the DLMs adding the weather indicators as extra regressors. Our set of the weather controls includes the average temperature, the REDTI and the precipitation series. We include their contemporaneous values and the two lags.[2]

Table 2: Adjusted $\bar{R}^2$ from DLM for energy consumption and emissions with weather indicators

	Direct fossil fuel consumption	Total energy consumption	Total energy CO_2 emissions
(a) DLM with NC shocks, PC shocks and weather indicators			
Residential	0.613	0.803	0.837
Commercial	0.637	0.740	0.815
Industrial	0.357	0.453	0.556
Transportation	0.286	0.293	0.274
Electric Power	0.674		
(b) DLM with NC and PC shocks			
Residential	0.365	0.770	0.819
Commercial	0.489	0.723	0.808
Industrial	0.311	0.423	0.514
Transportation	0.286	0.290	0.277
Electric Power	0.674		

Note: All models include a constant. The NC and the PC shocks are included with the current values and 12 lags. The weather indicators are included with the current values and two lags. Panel (b) is a reproduction of panel (b) of Table 4 of the paper for convenience.

Consistent with previous research, we find that seasonal variations in weather matter for the residential sector. Specifically, the impact effect of a positive NC shock size on the residential sector emissions increases from -6.77% to -4.75% when the weather controls are included in the DLM. Table 2 reports that the adjusted $\bar{R}^2$ for direct fossil fuel consumption almost doubles for the residential sector and increases substantially for the commercial sector. However, a comparison of the statistics in panels (a) and (b) reveals that the adjusted $\bar{R}^2$ for total energy consumption and

[2]Increasing the number of lags further has minimal effect on the estimates. Our inference regarding the responses is also robust to using the year-over-year growth rates of the weather indicators instead of deviations from the trend.

total CO_2 it generates in each of the four end-use sectors change little. Figure 5 shows that the overall pattern of the impulse responses of emissions and energy consumption also remains the same. We hence conclude that our interpretation of the NC shocks as capturing energy-efficiency changes is robust to weather extremes.

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