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Energy Efficiency and Fluctuations in CO_2 Emissions

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Abstract

CO_2 emissions are commonly perceived to rise and fall with aggregate output. Yet many factors, including energy-efficiency improvements, emissions coefficient variations and shifts to cleaner energy, can break the positive emissions-output relationship. To evaluate the importance of such factors, we uncover shocks that by construction reduce emissions without lowering output. These novel shocks explain a substantial fraction of emissions fluctuations. After extensively examining their impacts on macroeconomic and environmental indicators, we interpret these shocks as changes in the energy efficiency of consumer products. Our results imply that models omitting energy efficiency likely overestimate the trade-off between environmental protection and economic performance.

Topics: Climate change, Econometric and statistical methods, Business fluctuations and cycles

JEL codes: E32, Q43, Q50, Q55

1 Introduction

There is a growing recognition that the design and effectiveness of regulations aimed at mitigating carbon dioxide emissions[1] are intertwined with business cycles. Scientific understanding of this research area comes from environmental dynamic stochastic general equilibrium models (E-DSGE models).[2] Existing E-DSGE models embed the trade-off between environmental protection and economic growth since in these models emissions rise and fall with aggregate output. Yet many factors, such as energy-efficiency changes, variations in emissions coefficients, or shifts to cleaner energy sources, can potentially break this trade-off. If such factors are empirically relevant for explaining emissions fluctuations, then the costs of mitigating emissions are overestimated by the existing literature.

Our study is the first to evaluate the empirical implications of factors that can affect emissions without causing a trade-off between the environment and the economy. To this end, we devised a conceptually straightforward approach based on the joint behavior of total emissions and GDP. We assume that there are two types of uncorrelated disturbances, each generating a distinct correlation pattern between emissions and GDP. The first type, the *positive correlation* (PC) shock, by construction makes emissions rise and fall with output, thereby creating an environment-economy trade-off. This type of shock conforms with the procyclicality of emissions, first documented by Doda (2014), and shares the characteristics of conventional macroeconomic shocks that are used in E-DSGE models. The second type, the *negative correlation* (NC) shock, is our primary interest. We impose that NC shocks move emissions and GDP in opposite directions and, hence, avoid the trade-off. Understanding the historical relevance, economic meaning, and impacts of the novel NC shock is at the core of our paper.

We identify the two types of disturbances via sign restrictions in a vector autoregression (VAR) using a Bayesian estimation method with informative priors (Baumeister and Hamilton, 2015). Our identification approach is based on general statistical assumptions rather than on theory-driven restrictions. This approach has the flexibility to accommodate multiple factors that share the same properties as NC shocks and en-

[1]We refer to carbon dioxide emissions interchangeably as “CO_2 emissions” or “emissions.”

[2]See the surveys by Fischer and Heutel (2013) and Annicchiarico et al. (2021).

ables the overall evaluation of these factors under a minimal set of restrictions. We find that both types of shocks have long-lasting effects on emissions and GDP as the signs of their effects extend beyond the impact period. NC shocks also account for a large share of emissions fluctuations even though no prior expectation was set regarding their importance.[3] While our identification approach does not allow us to assign a direct economic interpretation to NC shocks, we pursue multiple strategies to examine their possible drivers.

Our analysis suggests that NC shocks mostly reflect changes in the energy efficiency of consumer products. To start, a positive NC shock lowers energy intensity and emissions in the residential and commercial sectors. Its impacts on a number of U.S. macroeconomic and environmental indicators conform to the predicted effects of a structural energy-efficiency shock to consumer durable goods in a multi-sector E-DSGE model. We provide evidence that energy-efficiency gains in the residential sector have been substantive but uneven over time. As asserted by Newell et al. (2006), the overall success of technological inventions in reducing energy use and emissions depends on consumer decisions to adopt and utilize energy-efficient products. The historical NC shock series is positively correlated with pro-environmental attitudes (an aggregate proxy for consumer energy conservation behaviors). It is also positively related to energy and environmental regulations, in line with the Porter hypothesis that regulation can spur technological innovation (Porter 1991). Our interpretation of NC shocks as changes in the energy efficiency of consumer products is robust to examinations of weather extremes, changes in emissions coefficients, and shifts to cleaner energy sources.[4]

It has been well-known since Weitzman (1974) that uncertainty can break the equivalence of price and quantity regulations. The E-DSGE literature has brought a new dimension to environmental economics by focusing on uncertainties affecting macroeconomic conditions. In general equilibrium, different uncertainties, or shocks, create distinct incentives for consumers and firms and affect market outcomes and policies. Kelly (2005) shows that the welfare rankings of quantity and price regulations in a static model depend on the types of economic shocks. Dissou and Karnizova (2016) reach

[3]E.g., these shocks explain about 50% of the long-run variation in the emissions growth rate.

[4]Our approach is similar to the analysis of the term spread in Kurmann and Otrok (2013). These authors also first identify a statistical series driving the spread and then develop its economic interpretation by comparing the impulse responses it generates with those from structural models.

a similar conclusion regarding the ranking of environmental regulations in a calibrated multi-sector E-DSGE model. Annicchiarico et al. (2021) discuss key policy implications from a series of recent papers on the relationship between business cycles and environmental policy. Taken together, these studies make it clear that the design and implementation of a successful environmental policy must account for a comprehensive set of shocks that affect emissions.

The E-DSGE literature to date has focused on conventional shocks as sources of macroeconomic uncertainties. These include shocks to aggregate or sectoral productivity, monetary policy and public spending.[5] In theory, such conventional shocks change emissions in accordance with aggregate output. Despite their prominence in explaining U.S. business cycles, conventional shocks play a surprisingly limited role in accounting for historical emissions fluctuations (Khan et al., 2019).[6]

We provide new empirical evidence on the drivers of U.S. emissions fluctuations, thereby contributing to the literature on environmental policy and business cycles. The NC shocks we identify explain a significant share of emissions fluctuations. Similar to the effects of conventional macroeconomic shocks, they induce the procyclicality of the key macroeconomic indicators. Yet NC shocks are unique in their prediction that a positive realization of this shock simultaneously increases aggregate output but reduces the use and price of energy. Most importantly, our findings imply that emissions may be reduced without hindering economic activity. These results raise the need for extending the set of disturbances considered in the E-DSGE literature to include NC-type shocks, such as structural energy-efficiency shocks.

Our findings have strong implications for the structure of E-DSGE models. In existing models, a policymaker must choose between mitigating emissions and stabilizing output not only because of the nature of macroeconomic shocks but also because of the modeling assumptions. For example, it is common to model emissions as a by-product of output, following long-run integrated assessment models (e.g., Nordhaus, 2013). This assumption rules out NC shocks by construction and becomes problematic in light of our results. In practice, most anthropogenic CO_2 emissions come from fossil

[5]See Annicchiarico et al. (2021) and the references therein.

[6]Khan et al. (2019) conclude that “close to two thirds of the variation in emissions appears to be due to a structural shock not yet identified in the literature.” We conjecture that energy-efficiency shocks may be behind this mysterious structural shock.

fuel combustion. Linking emissions to energy consumption would improve our theoretical understanding of the possible pathways to decoupling emissions from economic activity. In addition, modeling the behaviors of different energy users would help identify a range of effective emissions mitigation policies. We find, for example, that the decline in total emissions after a positive NC shock is mainly driven by the responses of the residential and commercial sectors.

Finally, our paper speaks to the debate on the role of energy efficiency and conservation in climate change mitigation. Energy efficiency and conservation feature prominently in international and national strategies to combat climate change (e.g., IEA, 2021; IPCC, 2018). Empirical evidence from specific technological innovations (e.g., Gillingham and Stock, 2018), regulatory changes in energy-efficiency standards and voluntary labels (e.g., Gillingham et al., 2006; Labandeira et al., 2020), and behavioral interventions (e.g., Allcott and Mullainathan, 2010; McAndrew et al., 2021) suggest that energy-efficiency improvements and changes in energy conservation can successfully reduce energy use and emissions for specific groups of users. What remains uncertain is whether technological innovations and changes in consumer behaviors can significantly affect emissions at the aggregate level and, if so, for how long. One concern is that emissions may decline only in the short run because of the so-called rebound effects (e.g., Stern, 2020). Our findings of persistent declines in total emissions and energy consumption after a positive NC shock suggest otherwise.[7] Moreover, we document a positive relationship between a historical NC shock series and U.S. public concerns about climate change and regulations about energy use and the environment. These results provide indirect support for the view that policies targeting energy efficiency and conservation can have meaningful impacts even at the aggregate level.

The rest of our paper is organized as follows. Section 2 analyzes emissions fluctuations using a VAR model with sign restrictions. Section 3 focuses on emissions and energy consumption from end-use sectors. Section 4 explores energy efficiency as a possible driver of NC shocks. Section 5 examines extreme weather, changes in emissions coefficients, and shifts to cleaner energy. Section 6 concludes.

[7] Related to the debate, Bruns et al. (2021) use machine-learning techniques to estimate a shock with the maximum impact effect on energy consumption, which is later interpreted as an energy-efficiency shock. They find that a decline in energy consumption would regress in four years.

2 A VAR perspective on emissions fluctuations

2.1 CO_2 emissions and output data

Our key series comprises total CO_2 emissions obtained from the U.S. Energy Information Administration (EIA). Knowing how emissions are measured in practice helps better understand the results of our paper. The EIA's bottom-up approach starts with energy-consumption series disaggregated by fuel types and energy-use sectors (EIA, 2011). British thermal units (Btu) of heat for each fuel product are multiplied by product-specific CO_2 emissions coefficients and then summed up across fuels and sectors to produce the totals. We de-seasonalize monthly emissions, using the X-12 ARIMA seasonal adjustment package, and take quarterly averages. Aggregate output is the real GDP obtained from FRED, the database of the Federal Reserve Bank of St. Louis. Emissions and GDP are divided by the U.S. resident population. All of the data used in our paper are freely accessible and detailed in the online appendix. Our sample runs from 1973:Q1 to 2019:Q4.

Standard unit root and cointegration tests indicate that per capita emissions and GDP are integrated of order one but not cointegrated. Our baseline VAR model thus includes the growth rates[8] of these series, which are shown in Figure 1.[9] The scatter plot in Figure 1 reveals that emissions and output move in different directions, surprisingly rather often (about 45% of all quarters) and contrary to common belief.

2.2 A bivariate VAR model with sign restrictions

A bivariate VAR parsimoniously describes the joint dynamics between output ($\mathtt{gdp}_t$) and emissions ($\mathtt{em}_t$). We postulate two orthogonal shocks $\varepsilon_t^{\mathrm{pc}}$ and $\varepsilon_t^{\mathrm{nc}}$ in a structural VAR

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \varepsilon_t, \tag{1}$$

where $\mathbf{y}_t$=$[\Delta\mathtt{gdp}_t, \Delta\mathtt{em}_t]'$, $\mathbf{x}'_{t-1} = (\mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-m}, 1)'$, $m = 4$ and $\varepsilon_t = [\varepsilon_t^{\mathrm{pc}}, \varepsilon_t^{\mathrm{nc}}]'$. The ε_t shocks follow the normal distribution $N(\mathbf{0}, \mathbf{D})$ with a diagonal variance matrix $\mathbf{D}$.

[8] Growth rates are calculated as 100 times their first-differenced natural logs.

[9] Our inference related to historical shock estimates is robust to estimating a VAR using the log-levels or cyclical components of the HP-filtered data (section 2, online appendix).

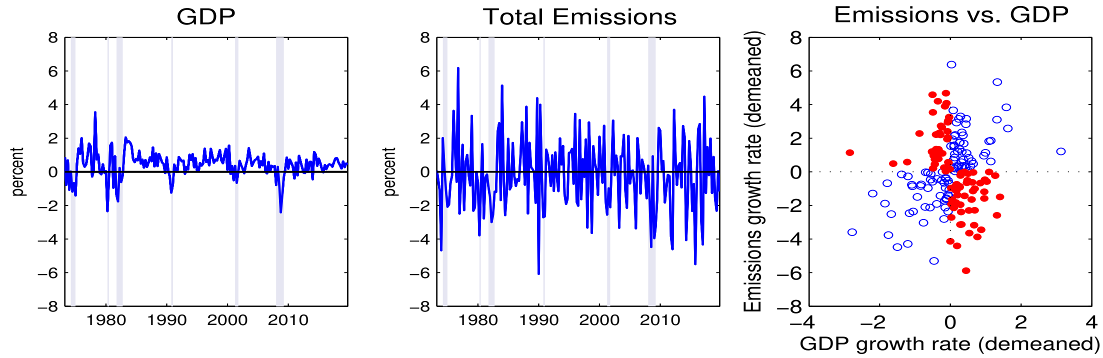


Figure 1: Real GDP and total CO_2 emissions (per capita growth rates)

Note: Red squares are the periods when emissions and output growth rates take opposite signs. Blue circles are the periods when the signs are the same. Shaded areas are the NBER recessions.

We impose the following structure on matrix $\mathbf{A}$ and its inverse

$$\mathbf{A} = \begin{bmatrix} a_n & 1 \\ a_p & -1 \end{bmatrix} \text{ and } \mathbf{A}^{-1} = \frac{1}{a_p + a_n} \begin{bmatrix} 1 & 1 \\ a_p & -a_n \end{bmatrix}. \tag{2}$$

Shocks $\varepsilon_t^{\text{pc}}$ and $\varepsilon_t^{\text{nc}}$ are identified by sign restrictions that are applied only to the impact period. We assume that a positive PC shock, $\varepsilon_t^{\text{pc}}$, increases both output and emissions, while a positive NC shock, $\varepsilon_t^{\text{nc}}$, increases output but decreases emissions. The key restrictions are $a_p \geq 0$ and $a_n \geq 0$. The parameters a_p and a_n govern the short-run income elasticity of emissions, conditional on a particular shock,

$$\left.\frac{\partial \mathtt{em}_t}{\partial \mathtt{gdp}_t}\right|_{\varepsilon_t^{\text{pc}}} = a_p \text{ and } \left.\frac{\partial \mathtt{em}_t}{\partial \mathtt{gdp}_t}\right|_{\varepsilon_t^{\text{nc}}} = -a_n. \tag{3}$$

Our identification approach provides a possible statistical orthogonalization of the error vector $\mathbf{u}_t$ in the reduced-form VAR

$$\mathbf{y}_t = \mathbf{\Phi}\mathbf{x}_{t-1} + \mathbf{u}_t, \tag{4}$$

where $\mathbf{\Phi} = \mathbf{A}^{-1}\mathbf{B}$, $\mathbf{u}_t = \mathbf{A}^{-1}\varepsilon_t$ and $E\left(\mathbf{u}_t\mathbf{u}_t'\right) = \mathbf{\Omega} = \mathbf{A}^{-1}\mathbf{D}(\mathbf{A}^{-1})'$. While our identification approach does not assign prior economic interpretation to ε_t, we pursue multiple strategies to establish the meaning of $\varepsilon_t^{\text{nc}}$ in later sections.

We implement the sign restrictions using a Bayesian estimation algorithm with informative priors proposed by Baumeister and Hamilton (2015). The algorithm explicitly acknowledges the impact of priors on posterior inference and, hence, improves the statistical treatment of the joint uncertainty about the structural parameters. We model the priors for a_p and a_n as two independent Student t distributions with three degrees of freedom, truncated to be positive, following Baumeister and Hamilton (2015). The location and scale parameters c and σ determine the shape of a truncated Student t distribution. Our choice of these parameters for a_p and a_n is guided by the existing estimates of the income elasticity of emissions. Appendix A explains how we set (c_p, σ_p) = $(1.50, 0.85)$ and (c_n, σ_n) = $(1.75, 0.7)$. Under this parameterization, a_p and a_n take values between 0.15 and 2.5 with 80% probability. We use natural conjugate priors for $\mathbf{B}$ and $\mathbf{D}$. The setup of the priors as well as the implementation of the estimation algorithm are identical to the steps described in section 5.4 in Baumeister and Hamilton (2015).

Our inference is based on the last $N = 10^5$ of the total $3 \times 10^7 + N$ draws from the joint posterior distribution $p\left(\mathbf{A}, \mathbf{D}, \mathbf{B} | \mathbf{Y}_T\right)$.[10] We focus on the pointwise posterior medians of the impulse responses and their posterior credibility sets. These objects are statistically optimal under the Bayesian absolute loss function in a VAR model with informative priors (Baumeister and Hamilton, 2018). Similarly, the posterior median estimates of the historical shock series are statistically coherent summary statistics of sign-identified s hocks.[11] In sections 3 to 5 of the paper we will use these estimates to investigate the possible economic meanings of NC shocks.

2.3 Results from the VAR model

Figure 2 plots the prior and posterior densities for parameters a_p and a_n. The data are informative about the conditional emissions-income elasticities and lead us to revise our prior beliefs towards the higher values. The median parameter estimates are $\hat{a}_p$=3.106 and $\hat{a}_n$=2.696. We next discuss the impulse responses, the forecast error variance decomposition and the historical series of the PC and NC shocks.

[10] When conducting tests suggested by Geweke (1992) and examining the series of the parameter draws and posterior densities we detect no convergence problems with the Metropolis-Hastings sampler.

[11] Our inference is robust to the use of pointwise posterior mean estimates, which are statistically optimal under the Bayesian quadratic loss function (Baumeister and Hamilton, 2018).

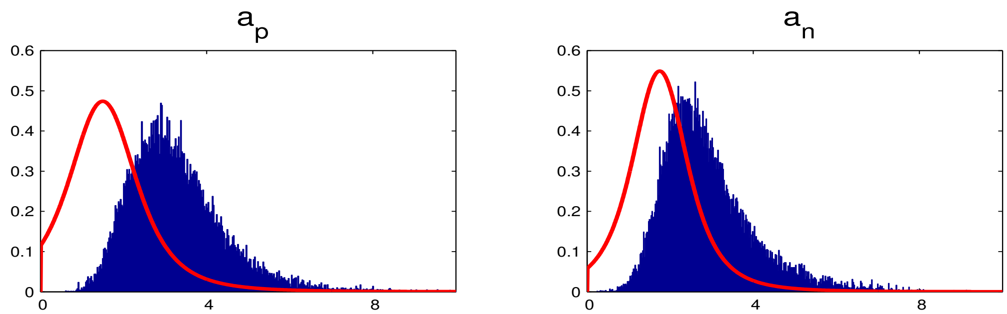


Figure 2: Prior and posterior distributions of the coefficients in matrix $\mathbf{A}$
Note: Red curves represent prior densities. Blue bars are posterior density histograms.

How do emissions and GDP respond to PC and NC shocks? Figure 3-a displays the cumulative posterior impulse response functions (IRFs) of output and emissions to positive PC and NC shocks, along with the 68% and 95% posterior credibility sets. Stock and Watson (2016) recommend normalizing structural responses on an economic variable of interest. We set the shock size to $\hat{a}_p^{(l)} + \hat{a}_n^{(l)}$ to increase GDP by one percent for each posterior draw $l = 1, ..., N$. The resulting impact responses of emissions across the draws are equal to the conditional emissions-income elasticities and are directly linked to the histograms in Figure 2.[12]

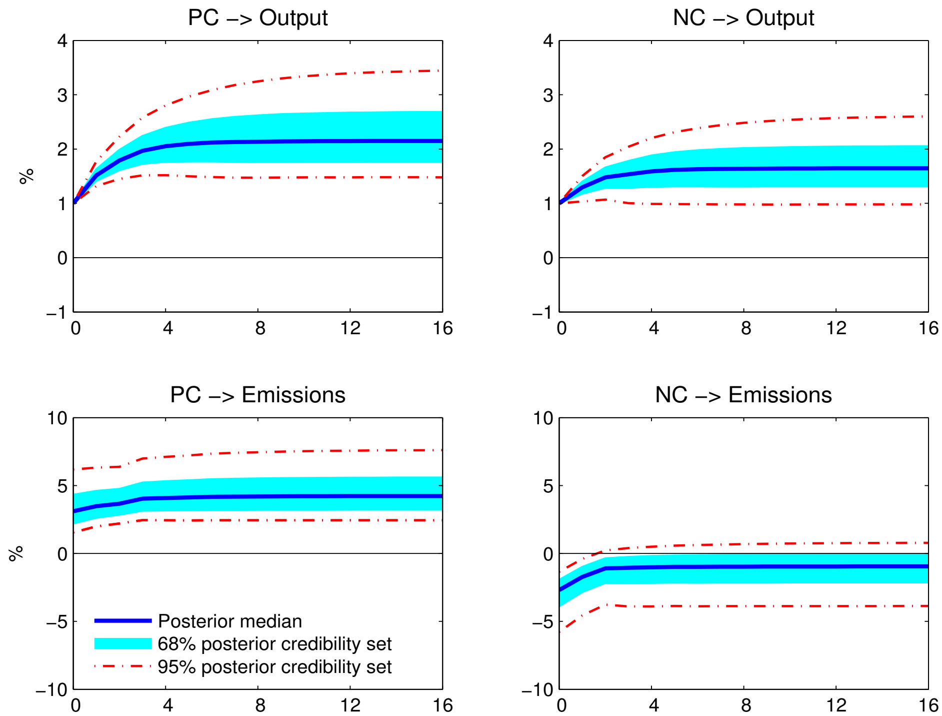
The effects of both shocks are persistent, as shown in Figure 3-a. The IRF signs extend beyond the impact quarter, the only period restricted by our identification. In all forecast horizons, output increases after both shocks and emissions increase after a positive PC shock. The paths of the emissions that occur after a positive NC shock are estimated with slightly lower confidence. Still, the median responses remain negative in all forecast horizons, along with the 68% posterior credibility set.

The ratio of emissions to GDP is known as the emissions intensity. Figure 3-b shows a persistent decline in emissions intensity (in logs) after a positive NC shock, even though our identification restrains the sign to being negative only in the impact period.[13] By contrast, emissions intensity increases after a PC shock. These IRF differences give the first indication that NC shocks may differ from conventional macroeconomic shocks.

[12]This link gives our normalization an advantage over the alternative of reporting impulse responses to a unit shock, which is more difficult to understand intuitively in our setup.

[13]We derive the IRFs of the energy intensity for each posterior parameter draw as differences between the corresponding emissions and the GDP responses, in logs.

(a) GDP and emissions



(b) Emissions intensity

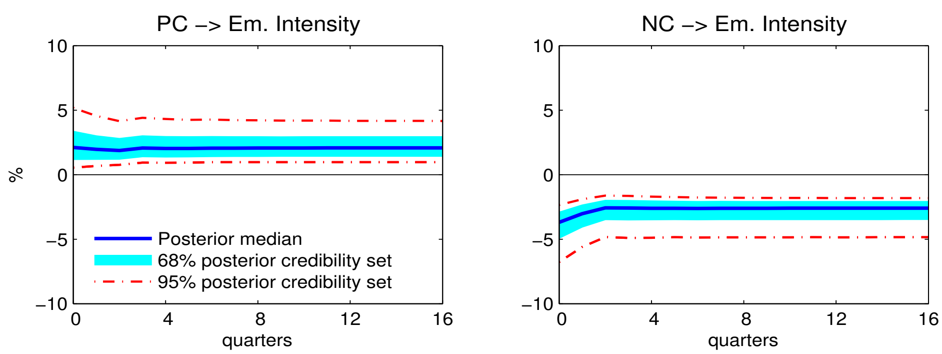


Figure 3: Cumulative responses of GDP, total emissions and energy intensity (VAR)

Note: Solid lines represent posterior median cumulative responses. Shaded regions and dashed-dotted lines denote 68% and 95% posterior credibility sets. The size of each shock is normalized to increase GDP by one percent for every posterior parameter draw.

Since emissions come from fossil fuel combustion, a decline in energy intensity may reflect factors such as energy-efficiency changes or shifts to cleaner energy so urces. We explore these interpretations in sections 4 and 5.

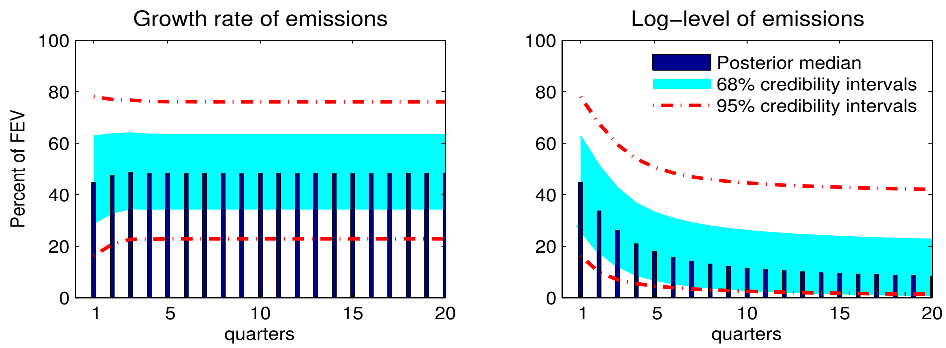


Figure 4: Percent of forecast error variance of emissions attributed to NC shocks

Note: Bars represent the Bayesian posterior median estimates of NC shocks' contributions to the forecast error variance of the growth rate and log-level of emissions, computed for the baseline VAR model. Shaded regions and dashed-dotted lines denote 68% and 95% posterior credibility intervals.

The relative importance of PC and NC shocks The forecast error variance decomposition (FEVD) helps assess the relative importance of the sign-identified shocks. Figure 4 reports the contribution of NC shocks to the mean-squared forecast errors of the emissions. The chart on the left-hand side of the figure shows that these shocks account for about half of the unpredictable movements in the growth rate of emissions. For the log-level, the median contribution of NC shocks to the FEVD remains above 20% within the first year after the shock. While this contribution declines over time, even the shock's minimum value of 8.4% surpasses the maximum contributions of neutral technology shocks, reported by Khan et al. (2019), and exceeds those of government spending and monetary policy shocks by a factor of ten (*ibid.*). These results, however, are subject to a fairly large degree of estimation uncertainty.

Historical shock realizations Figure 5 plots the posterior median estimates of the historical PC and NC shock series, starting in 1974:Q2. The red circles mark the quarters for which all estimated shock values within the 95% posterior confidence intervals have the same signs. As shown by the multiplicity of such quarters, these shocks are estimated with high confidence. All NBER recessions contain large (exceeding one standard deviation) negative realizations of the PC shocks. By contrast, the historical NC shock series does not follow a clear cyclical pattern. A possible interpretation of these results is that the PC shocks reflect conventional macroeconomic shocks, while the NC shocks have emissions-specific determinants.

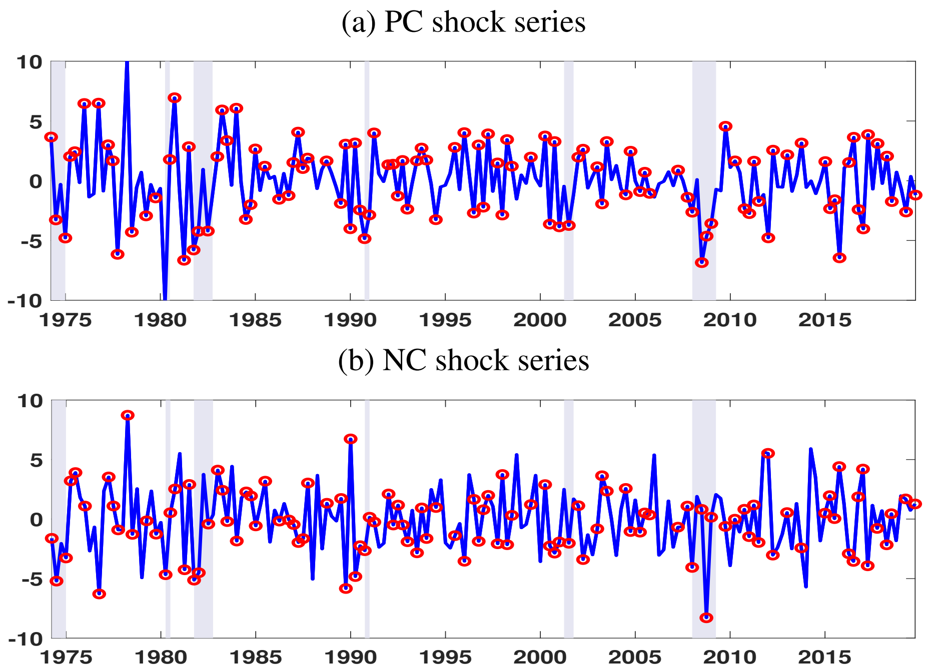


Figure 5: Historical estimates of the sign-identified VAR shocks

Note: Solid lines are the Bayesian posterior median estimates of the historical PC and NC shock series. The red circles denote quarters during which all PC and NC shock estimates in the 95% posterior confidence intervals have the same signs. Shaded areas are the NBER recessions.

Robustness We ran a battery of robustness checks, focusing on comparing the posterior median estimates of the historical NC shock series from our baseline and alternative VAR setups. We tried different priors, used the posterior mean estimates of the NC shocks in place of the medians, added extra lags to the VAR, extended the sample period to 2020:Q2, and used the data in the log-levels and the cyclical deviations from the Hodrick-Prescott trend (instead of the growth rates). We also estimated a VAR model using annual series from 1949 to 2019.

Our baseline results appear to be very robust. In fact, most correlation coefficients between the baseline and the alternative shock estimates range from 0.90 to 0.99. The only exception is the correlation coefficient of 0.62 between the annual averages of the baseline and the posterior median from the VAR with the annual data. More details about the robustness analysis are given in section 2 of the online appendix.

3 Insights from the energy-use sectors

This section extends our analysis to different energy users. We use distributed lags models to estimate how the end-use sectors defined as such by the EIA respond to PC and NC shocks. Our key finding is that the NC shocks are mostly linked to the residential and commercial sectors. This result helps us establish the meaning of these NC shocks.

3.1 Inference with distributed lags models

Distributed lags models (DLMs) provide a uniform way to estimate the responses of many variables to PC and NC shocks without adjusting the minimal set of VAR restrictions that identifies these shocks. Each DLM projects the growth rate of a variable of interest, Δz_t, on the current and past realizations of the historical shocks from the baseline VAR model (1) and includes a constant, as in

$$\Delta z_t = \alpha_z + \sum_{j=0}^{12} \beta_{zj} \hat{\varepsilon}^{\text{nc}}_{t-j} + \sum_{j=0}^{12} \gamma_{zj} \hat{\varepsilon}^{\text{pc}}_{t-j} + e_{zt}. \tag{5}$$

The regression coefficient $\beta_j (\gamma_j)$ defines the response of Δz_t observed j quarters after a unitary NC (PC) shock. The cumulative response of z_t at the horizon h is the sum of these regression coefficients from the impact period t to $t + h$. We compute standard errors using a block bootstrap, thereby correcting for possible serial correlation in the error term e_{zt}. All of the reported results are based on 20,000 replications and a block size four. The maximum horizon of 12 quarters is guided by the likelihood ratio and the F-test results. A similar two-step procedure is used by Kilian (2009) to estimate the effects of VAR-identified oil price shocks on the U.S. economy.

Our main DLM results are obtained with the posterior median estimates of the historical shocks (hereafter, *median shocks*). These shocks are treated as predetermined in (5), and the model is estimated using OLS. In reporting the IRFs, we set the size of each shock to 5.802, which is equal to the sum of the median estimates of $\hat{a}_p$ and $\hat{a}_n$. This approach is consistent with our normalization of the IRFs to increase GDP by one percent in the VAR. The adjusted $\bar{R}^2$ statistics for (5) can measure the quantitative contribution of the estimated shocks to explaining the variation in Δz_t.

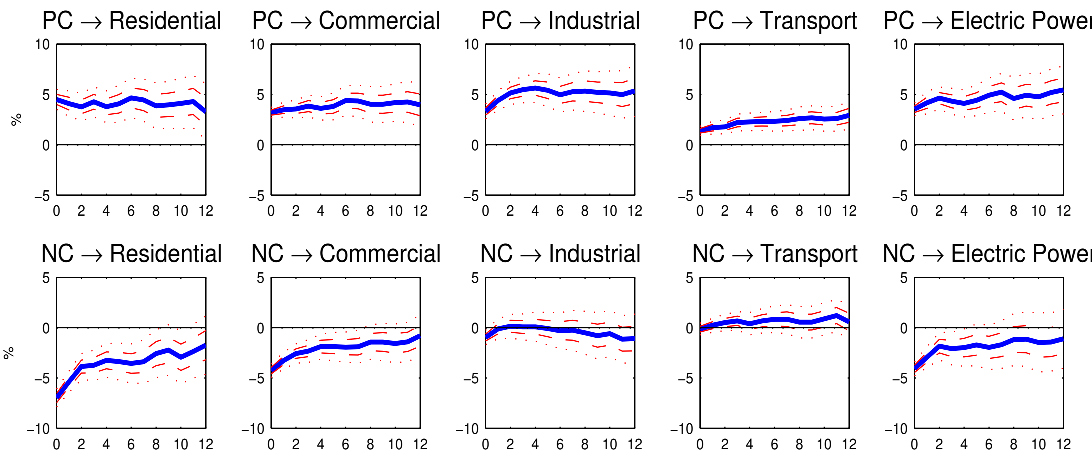


Figure 6: Responses of per capita CO_2 emissions by the end-use sectors (DLM)

Note: Solid blue lines are the cumulative responses to the median shocks, estimated using DLM (5). Dashed and dotted red lines denote one and two-standard bootstrapped error bands.

The IRF estimation with (5) is subject to three types of uncertainty: the VAR parameter estimation uncertainty, the VAR model identification uncertainty and the DLM parameter uncertainty. There is no clear guidance in the literature on how to simultaneously address these three uncertainty types. Our main DLM results incorporate the parameter uncertainty embedded in (5) but do not account for the fact that the shock estimates are generated regressors. Section 3.1 of the online appendix reports an alternative set of IRFs and confidence bands, based on the historical shocks obtained from all accepted models. That approach takes care of the VAR estimation and the model uncertainty but ignores the DLM estimation uncertainty.

3.2 Heterogeneity in responses of energy-use sectors

The EIA publishes monthly emissions and energy consumption of the residential, commercial, industrial and transportation sectors. These four end-use sectors differ substantially in their principal usage and main sources of energy (EIA, 2020). For example, homes and commercial buildings use energy for heating, cooling, lighting, and operating appliances and electronic devices. Industrial needs vary from employing energy products as direct production inputs to utilizing electricity to run machinery and equipment. In terms of energy sources, the residential and commercial sectors mainly use electricity and natural gas, while the transportation sector is a heavy user of motor gasoline. The industrial sector uses diverse energy sources. It is therefore important to establish if the responses of sectoral emissions to NC and PC shocks conform to those of total emissions. Since emissions in the four end-use sectors are derived not only from primary energy use but also from the use of purchased electricity, we also consider the electric power sector. For our analysis, we convert the monthly data to seasonally adjusted per capita quarterly averages.

Figure 6 reveals intriguing heterogeneity among end-use sectors. A PC shock behaves like an aggregate business-cycle shock, raising emissions across all sectors. By contrast, an NC shock affects each sector differently. It induces significant and prolonged emissions reductions in the residential and commercial sectors, an increase in emissions in the transportation sector and no significant emissions response in the industrial sector. Emissions in the electric power sector also decline, a response that provides additional information on how the NC shock is transmitted to energy users.

Section 3 of the online appendix includes two sets of additional results. First, accounting for the VAR estimation and model uncertainty unsurprisingly expands the range of emissions responses relative to that in Figure 6. However, the IRFs of emissions in the residential, commercial and electric power sectors remain negative for several quarters after a positive NC shock, with 95% confidence. Second, the IRFs of the total energy consumption by sector largely echo those of emissions.

Table 1 quantifies the sectoral impacts of NC and PC shocks. The NC shocks alone explain more than half of the variation in emissions growth in the residential and commercial sectors. Close to half of this contribution comes from changes in direct fossil fuel consumption. The remainder largely reflects changes in electricity use. Including both shocks in (5) raises the adjusted $\bar{R}^2$ substantially, as Table 1-b shows. Together, they explain over 80% of the growth rates in emissions in the residential and commercial sectors and over 50% in the industrial sector.

Overall, the sectoral analysis reveals that the NC shocks are mainly linked to emissions as well as energy use in the residential and commercial sectors. We argue in the next section that changes in energy efficiency, especially those related to consumer products, are likely drivers of these NC shocks.

4 NC shocks as energy-efficiency shocks

We define energy efficiency as the use of technology to manage and restrain growth in energy consumption. A product or a process is more efficient if it requires less energy to deliver the same services or provides more services for the same energy input. This section first describes an E-DSGE model where energy efficiency is determined exogenously. The main goal of the model is to derive clear predictions on how energy-efficiency shocks are transmitted to different energy users and to the whole economy. We find that the responses of U.S. variables to the estimated NC shocks conform to these predictions. We proceed by examining possible impacts of pro-environmental attitudes, regulatory changes and energy prices on NC shocks, following the interpretation of technological change in Newell et al. (2006).

4.1 Lessons about energy efficiency from the E-DSGE model

We introduce emissions into a DSGE model developed by Huynh (2016). The model includes multiple energy users, which enables us to relate the model's predictions to the sectoral responses from section 3.2. The model also features two distinct energy-efficiency shocks, affecting consumer durables and capital. The key lesson is that the effects of a positive NC shock on U.S. macroeconomic and environmental variables qualitatively match these variables' predicted paths following an improvement in the energy efficiency of the consumer durable goods in the E-DSGE model.

4.1.1 Key assumptions of the E-DSGE model

Our real business cycle model has three production sectors, perfectly competitive markets, and perfect factor mobility. Our exposition here focuses on modeling energy production and consumption, emissions and energy efficiency. Section 4 of the online appendix describes the model in detail.

Modeling energy consumption and energy efficiency Energy is used by consumers ($e_{h,t}$), energy producers ($e_{e,t}$) and producers of durable and nondurable goods ($e_{d,t}$ and $e_{n,t}$). Total energy consumed is $e_t = e_{h,t} + e_{e,t} + e_{d,t} + e_{n,t}$.

Consumers need energy to derive services from durable goods, such as appliances.

Their energy use is proportional to the service flows from durables, defined in the model as a product of the durable stock, d_t, and its rate of utilization, u_t,

$$e_{h,t} = A_{d,t} d_t u_t. \tag{6}$$

Energy intensity, $A_{d,t}$, determines the energy requirements per unit of durable service flows. For producers, energy is perfectly complementary to capital, $k_{f,t}$:

$$e_{f,t} = A_{k,t} k_{f,t},\ f \in \{e, d, n\}. \tag{7}$$

Energy intensity, $A_{k,t}$, is common across all producers, as in Huynh (2016).

The inverse of energy intensity $A_{d,t}$ ($A_{k,t}$) uniquely determines the energy efficiency of consumer durables (productive capital). As $A_{d,t}$ decreases, consumers require less energy for the same durable good services, which means the energy efficiency of the consumer durables improves. Similarly, a drop in $A_{k,t}$ corresponds to an improvement in the energy efficiency of productive capital.

Modeling production of energy and non-energy goods Energy is produced from capital, $k_{e,t}$, and labor, $h_{e,t}$. Production also depends on $Z_{e,t}$, specific to the energy sector's total factor productivity (TFP), and exhibits some wastage, σ_t:

$$y_{e,t} = Z_{e,t} (1 - \sigma_t) k_{e,t}^{\gamma_e} h_{e,t}^{1-\gamma_e},\ 0 < \gamma_e < 1, \tag{8}$$

$$\sigma_t = \frac{\omega_e}{3} \left(k_{e,t}^{\gamma_e} h_{e,t}^{1-\gamma_e} \right)^3,\ \omega_e > 0. \tag{9}$$

The convex production costs (9) help generate a low price elasticity of energy supply and prevent the energy sector from making a very rapid response to energy demand shocks. Output in the nondurable and durable goods sectors is produced according to

$$y_{f,t} = Z_t k_{f,t}^{\gamma_f} h_{f,t}^{1-\gamma_f},\ 0 < \gamma_f < 1,\ f \in \{d, n\}. \tag{10}$$

Total factor productivity Z_t is common to both sectors, following Huynh (2016).

Modeling emissions and environmental damage We model emissions as a function of energy consumption: em_t=$\kappa\ e_t$. In line with the evidence in section 5.2, the emissions coefficient $\kappa > 0$ is constant.[14] The accumulated emissions stock causes environmental damage. There is substantial uncertainty in the literature about a relevant damage function and a realistic depiction of the carbon cycle. To focus on the economic effects of energy-efficiency shocks, we model environmental damage as being a negative externality on consumer welfare. We also assume that the damage is additively separable in the utility function, as in Stern (2008) and Hassler et al. (2010). The separability assumption enables us to solve the model in a laissez-faire scenario without specifying the damage parameters and the carbon cycle.[15]

Parameter calibration and solution We solve the model in the absence of environmental regulation by log-linearizing the competitive equilibrium equations around the deterministic steady state and applying the perturbation method.

Exogenous processes Z_t, $Z_{e,t}$, $A_{d,t}$ and $A_{k,t}$ are assumed to follow independent autoregressive processes of order one, in logs. We set all shock persistence parameters to 0.999, motivated by the empirical IRFs in Figure 3. The value of κ is inconsequential, since the dynamics of emissions and energy consumption coincide in the log-linearized model. All other parameters are directly from Huynh (2016).

4.1.2 Transmission of energy-efficiency shocks in the E-DSGE model

The IRFs of the GDP and total energy consumption from the E-DSGE model in Figure 7-a show that only the energy-efficiency shocks would be classified as NC shocks in our VAR. An energy-efficiency improvement, represented by a decline in $A_{d,t}$ or $A_{k,t}$, decreases energy and emissions but increases GDP.[16] The energy price declines after both structural energy-efficiency shocks, meaning that they both act as if they are energy-market-specific demand shocks. By contrast, TFP shocks to energy production represent energy supply shocks, while non-energy TFP shocks are aggregate demand shocks.[17] The joint analysis of the energy price, energy consumption/production and the GDP thus identifies the economic nature of the shocks in the E-DSGE model.

[14]Fischer and Springborn (2011) and Dissou and Karnizova (2016) make a similar assumption.

[15]Nordhaus (2013), Golosov et al. (2014) and Acemoglu et al. (2012) provide possible alternatives to modeling the environmental damage and the evolution of the emissions stock.

[16]Recall that the emissions deviations from the steady state mimic the energy consumption responses.

[17]An increase in $Z_{e,t}$ raises energy production but decreases the energy price. An increase in Z_t simultaneously raises aggregate output, energy production and the energy price.

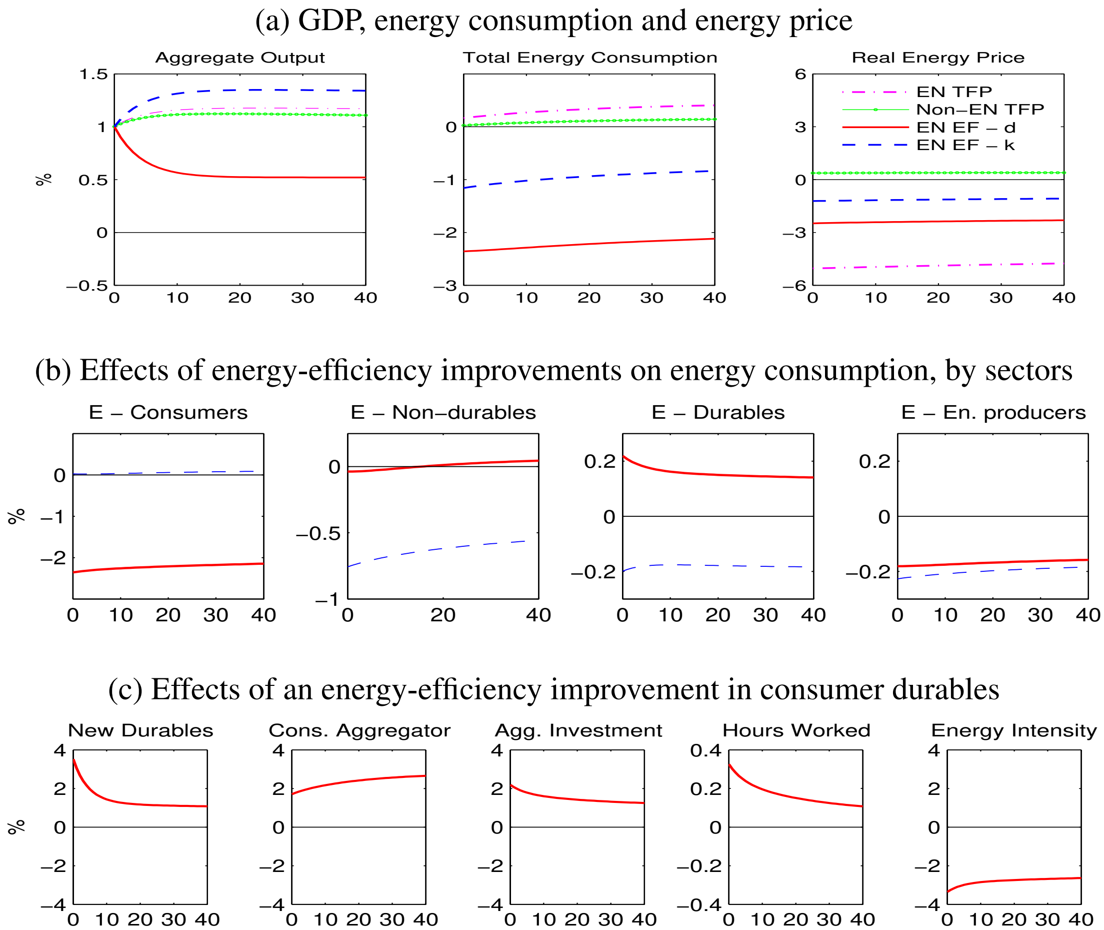


Figure 7: Impulse responses from the E-DSGE model

Note: The IRFs are in percent deviations from the deterministic steady state. Purple and green lines are the IRFs to a TFP increase in the energy sector and in the non-energy sectors. Solid red and dashed blue lines denote the responses to an increase in the energy efficiency of durable goods and capital. The shock size is normalized to increase real GDP by one percent in the E-DSGE model.

In section 3.2, a positive NC shock reduces not only total emissions but also emissions and energy consumption in the U.S. residential and commercial sectors. Figure 7-b reveals that the origin of the energy efficiency matters for explaining the sectoral responses. In the E-DSGE model, a reduction in consumers' energy use is observed only when an efficiency improvement is related to consumer durables. This shock also increases the energy consumption of non-durable and durable goods producers and decreases the energy consumption in the energy sector. Since energy-efficiency shocks to consumer durables appear to be likely drivers of the NC shocks, we next examine their effects on other variables in the E-DSGE model.

An efficiency improvement in consumer durable goods (i.e., a fall in $A_{d,t}$) decreases the consumer energy needs per service flow of durables, putting downward pressure on the energy price. Faced with lower energy costs, consumers increase their utilization[18] and new purchases of durables (Figure 7-c). These responses, however, do not fully offset the impact of higher energy efficiency, and consumer energy use falls (Figure 7-b). Lower energy spending, ceteris paribus, increases the amount of disposable income, driving up consumption demand (Figure 7-c). The energy price decline also brings a positive supply effect through lower production costs, although the increase in producers' energy demand is restrained by the existing stock of capital due to the high capital-energy complementarity. On the supply side, convex costs limit energy production adjustments. In equilibrium, total energy consumption declines and so does energy intensity (Figures 7-a and 7-c).

At the aggregate level, consumption, investment and hours worked increase in the E-DSGE model (Figure 7-c). These dynamics resemble responses to a "standard" macroeconomic shock that induces the procyclical behavior of key macroeconomic quantities. Yet, energy-efficiency shocks to consumer durables have three distinctive characteristics in the E-DSGE model. A positive shock of this kind (i) moves aggregate output and total energy consumption in opposite directions; (ii) reduces the energy price; and (iii) decreases the energy consumption of consumers.

All three distinctive characteristics of the structural shocks to the energy efficiency of consumer durables are reproduced in the responses of the actual U.S. series to NC shocks. We have already discussed GDP and consumers' energy-consumption responses. Figure 8 confirms the decline in total energy consumption and prices.[19] Figure 8 also shows that aggregate consumption and investment, new purchases of consumer durables and average work hours all increase after a positive NC shock, while energy intensity declines.[20] In sum, the IRF analysis suggests that the NC shocks appear to capture

[18]This prediction is consistent with consumer behaviors in a field experiment in Davis (2008).

[19]The energy price is measured by the EIA's cost of fossil fuel receipts at electric generating plants divided by the Bureau of Economic Analysis (BEA) price index for personal consumption expenditures on durables, in conformity with durables being the numeraire in the E-DSGE model.

[20]The consumption and investment series are from the BEA. We adjust these series by the U.S. resident population. Average weekly hours for the business sector are from FRED.

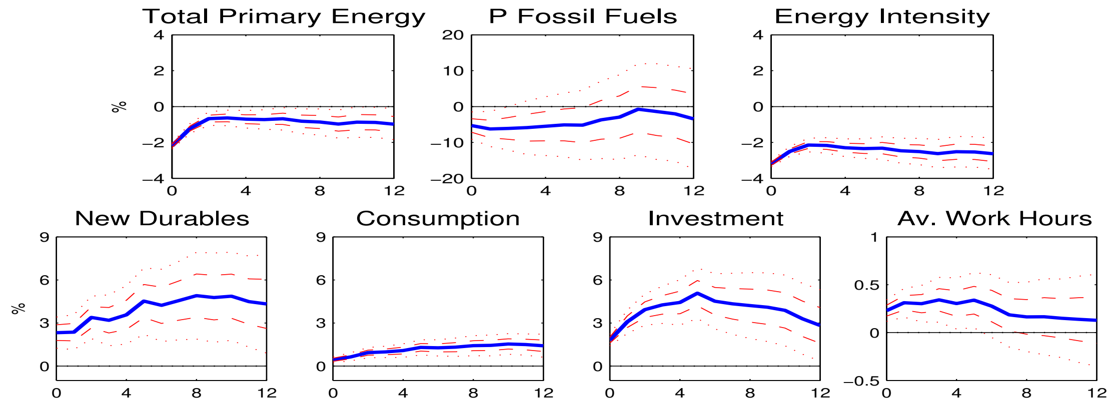


Figure 8: Responses of macroeconomic variables to positive NC shocks (DLM)

Note: Solid lines are the cumulative responses to a median NC shock, estimated using DLM (5). Dashed and dotted red lines denote one- and two-standard bootstrapped error bands.

changes in the energy efficiency of consumer products.

4.2 Further explorations of energy efficiency

This section is guided by an interpretation of energy-saving and emissions-reducing technological change proposed by Newell et al. (2006). This interpretation includes five stages: invention, innovation, diffusion, stock turnover and intensity of equipment utilization. We first present evidence that energy-efficiency gains in the residential sector have been substantive but uneven over time. We then explore possible links between the historical NC shock series and measures of energy intensity, pro-environmental attitudes, environmental and energy regulations and energy prices.

4.2.1 Technological change and market incentives

In Newell et al. (2006), technological change starts with *invention*–the creation of a new product or process to reduce the energy use for the same service–and *innovation*, which is its commercialization. Multiple technological breakthroughs have already reduced energy and emissions in the residential sector (e.g., loose-fiber insulation, low-emissivity window coatings, electric heat pump water heaters) or have shown a potential do so (e.g., magnetic refrigeration, insulating window films).[21] LED (light-emitting diodes) is the recent success story. The energy efficiency of lighting is measured by the amount of light in lumens per unit of energy used in watts. The average efficacy of LEDs has improved by 6-8 lm/W each year since 2010 (IEA, 2020). Current LED efficacies are at least twice as high as those of compact fluorescent lamps and halogens. According to the EIA, a complete switch to LEDs in the U.S. over 2013-2033 would decrease electricity consumption for lighting by almost 50% and avoid 1,800 million metric tons of CO_2 emissions.[22]

As available commercial products are adopted by consumers (*diffusion*), models that are more energy efficient will replace less-efficient ones, thereby increasing the average energy efficiency of the existing stock of models (*stock turnover*). At the level of major consumer products (heating and cooling equipment, water heaters, refrigerators, lighting, and appliances), average energy efficiency has improved over time, albeit at a varying pace. While energy-efficiency measures for these products are not readily available, examples of time-series estimates can be found in the literature.[23] A changing mix of product characteristics of all existing models and diffusion choices can explain these variations and even a decline in the energy-efficiency measures that are aggregated across product models (Newell et al., 1999).

Surprisingly, technological innovation setbacks are possible. For instance, the U.S. market witnessed two failed attempts to commercialize heat pump water heaters in the 1950s and early 1980s before they were relaunched successfully in 2009 (Willem et al., 2017). The latest models are at least twice as energy efficient as conventional electric water heaters, yet their market penetration remains low, possibly due to consumer preferences or lack of awareness.

The success of technology in reducing emissions depends not only on the energy efficiency of the existing stock of equipment but also on its *utilization intensity*. This final stage highlights the behavior of technology users (Newell et al., 2006). If the

[21] E.g., https://www.energy.gov/energysaver.

[22] https://www.energy.gov/articles/top-8-things-you-didn-t-know-about-leds.

[23] See, for example, Figure 2 in Nadel (2002) for energy intensity measures of U.S. refrigerators, central air conditioners and gas furnaces; Figure 5 in Brucal and Roberts (2019) for the average energy consumption of clothes washers, and Figure II in Newell et al. (1999) for changes in the energy efficiency of room and central air conditioners and gas water heaters.

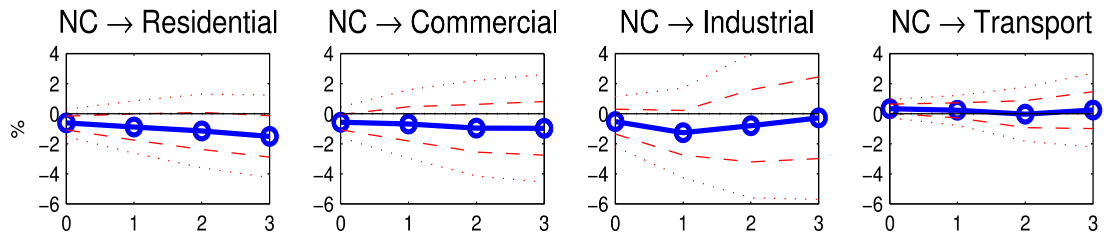


Figure 9: Responses of annual energy intensity indicators (DLM)

Note: Solid lines are the cumulative responses based on a DLM with the annual averages of the quarterly median NC shocks. The model includes three lags and contemporaneous shock values and a constant. Dashed and dotted lines are one- and two-standard block bootstrapped error bands. The sizes of the shocks are normalized to increase GDP by one percent.

utilization of energy-using services grows or more energy-intensive products are favored by users, then the total energy use can increase rather than decrease after an energy-efficiency improvement. However, the existing evidence on this rebound effect at the aggregate level is mixed (e.g., Stern, 2020).

Energy efficiency is often measured using energy intensity, or the quantity of energy per unit of output or activity. In our E-DSGE model, a unique correspondence exists between energy intensity and energy efficiency. More generally, higher efficiency is expected to reduce energy intensity. We find a persistent decline in the ratio of total energy consumption to GDP, the most common measure of energy intensity, after a positive NC shock (Figure 8). The energy-to-GDP ratio, however, will reflect not only energy efficiency but also behavioral and structural factors, such as changes in the industrial structure, energy mix, weather or demographics. The U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy corrects for such factors to provide energy intensity indicators (EIIs) that measure energy efficiency as accurately as possible. The annual EIIs from 1974 to 2011 are published for the end-use sectors. The residential sector EII manifests that the energy efficiency in this sector improved by 1.05% per year, on average. Figure 9 reports the estimated responses of the EIIs to a positive NC shock. Although the estimates are not very precise, we find that the residential sector EIIs decline. These results re-enforce our interpretation of NC shocks as being changes in the energy efficiency of consumer products.

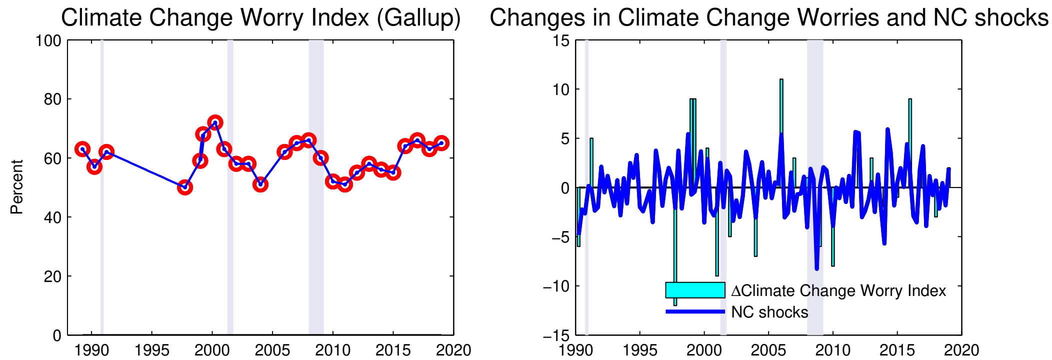


Figure 10: U.S. public attitudes towards climate change and NC shocks

Note The circles represent the percent of the respondents in Gallup surveys who answered "a great deal" or "a 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?" The right-hand panel plots changes in the index from the previous survey, along with the median NC shocks.

4.2.2 Energy conservation and NC shocks

Energy conservation includes one-time investment behaviors that enhance the efficiency performance of a product or a process as well as repetitive behaviors that reduce energy use, such as car-pooling or air-drying clothes. Most empirical evidence on energy conservation comes from controlled or quasi-controlled energy-efficiency interventions aimed at reducing financial and informational barriers faced by c onsumers. Systematic reviews by Abrahamse et al. (2005), Allcott and Mullainathan (2010) and McAndrew et al. (2021) identify large differences in intervention types as well as in targeted and measured outcomes. While the overall evidence is mixed, some interventions have been very successful in reducing energy consumption and emissions in a cost-effective way (e.g., Allcott, 2011; Delmas and Lessem, 2014).[24]

To explore a possible link between energy conservation and NC shocks, we use a measure of U.S. public opinion on climate change from Gallup. Two observations motivate our approach. First, multiple psychological theories rationalize that there is a relationship between attitudes and behaviors.[25] Empirical studies find that attitudes that are more pro-environmental help reduce energy consumption (e.g., Heberlein and War-

[24] Carbon abatement costs of these interventions are often negative (Gillingham and Stock, 2018).

[25] E.g., theories of social norms (Allcott, 2011; Delmas and Lessem, 2014), of cognitive dissonance (Festinger, 1962), of self-perception (Bem, 1972), and of planned behavior (Ajzen, 1991).

riner, 1983; Sapci and Considine, 2014; Bruderer Enzler et al., 2019) and increase the self-reported frequency of energy-conservation behaviors (e.g., Pothitou et al., 2016). Second, countries with higher levels of concern about climate change tend to have lower per capita CO_2 emissions (Stokes et al., 2015).

Gallup has been polling Americans about how much they personally worry about global warming and climate change since 1989. The Climate Change Worry Index (CCWI), displayed in Figure 10, reports the percentage of respondents who stated that they worried "a great deal" or "a fair amount." The change in the index from the previous poll is positively related to the historical NC shock series (Figure 10). The correlation coefficient between the two series is 0.521 (s.e. 0.115) in the quarters during which the polls were conducted. By contrast, this statistic for the historical PC shock series is 0.002 (s.e. 0.189).

Previous research finds that pro-environmental views tend to be procyclical (e.g., Kahn and Kotchen, 2010; Brulle et al., 2012) but also linked to other factors unrelated to economic activity. Elite cues, media coverage of climate change and advocacy by pro-environmental groups and their opponents (e.g., corporations and industry trade associations) are deemed to play significant roles in shaping aggregate opinion trends, while extreme weather events and scientific information dissemination have limited impacts (e.g., Brulle et al., 2012; Daniels et al., 2012).

To further investigate the relationship between NC shocks and climate change worries, we compute the historical decomposition of emissions for two periods (Figure 11-a). The first period (1997:Q4-2000:Q2) includes the peak in public climate change worries. CO_2 emissions grew by 1.57% during this time. The U.S. economy was booming and the PC shocks made a positive contribution of 3.94%. However, the NC shocks had a number of sizable positive realizations, in line with rising pro-environmental attitudes, and offset the positive contributions of the PC shocks on emissions by -2.45%. The second period (2007:Q4-2009:Q2) corresponds to the decline in the CCWI during the Great Recession. Emissions plunged by -11.16%. The recessionary impact of the negative PC shocks contributed more than the actual drop, dragging emissions down by -12.00%. However, the NC shocks pushed emissions up by 0.81%, consistent with the decline in the CCWI.

(a) Periods related to changes in public attitudes toward climate change

(b) Periods related to regulatory changes

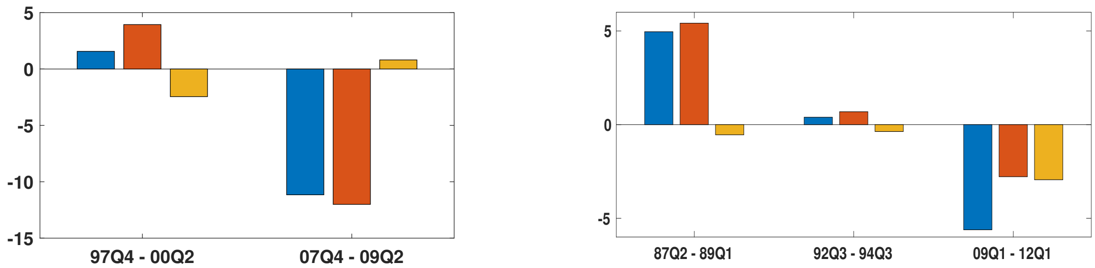


Figure 11: Historical decomposition of emissions (in percent)

Note: Blue bars denote actual emissions changes. Red and yellow bars are the posterior median estimates of the historical contribution of the PC and NC shocks to emissions changes, computed following Baumeister and Hamilton (2018).

4.2.3 Government regulation and NC shocks

Porter (1991) put forward a hypothesis that environmental regulation can spur technological innovation, increase competitiveness and even offset regulation compliance costs. Acemoglu et al. (2012) formalize the Porter hypothesis in a general equilibrium model with directed (endogenous) technological change. They show that environmental goals can be achieved "without sacrificing (much or any) long-run growth," through the use of carbon taxes and research subsidies (p. 133). Several studies find positive effects of stricter regulations on patents (e.g., Girod et al., 2017; Martínez-Zarzoso et al., 2019), on the number of commercial models (e.g., Brucal and Roberts, 2019) and on average energy efficiency (e.g., Newell et al., 1999). Comprehensive reviews by Gillingham et al. (2006) and Labandeira et al. (2020) find energy-efficiency policies to be effective in reducing energy use and emissions. The results are particularly strong for appliance standards and utility-based demand-side management programs in the U.S. residential sector. Furthermore, energy-efficiency standards do not appear to cause significant adverse effects on manufacturers (e.g., Jaffe et al., 1995; Nadel, 2002; Brucal and Roberts, 2019). In sum, regulatory changes may reduce emissions without tempering economic growth.

We assess the link between regulation and NC shocks in two ways. To start, Figure 11-b reports the historical decomposition of emissions around three milestone federal

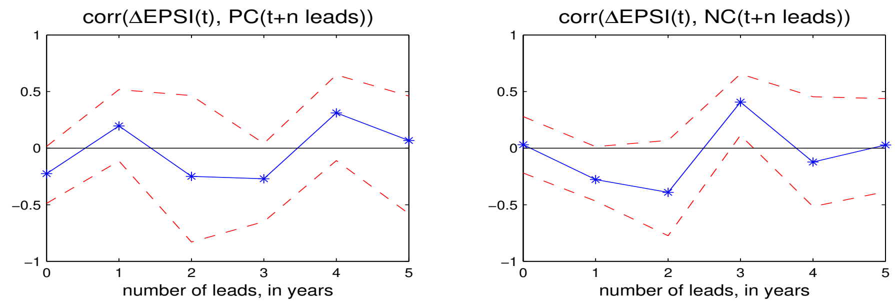


Figure 12: Environmental Policy Stringency Index, PC and NC shocks

Note: This figure reports cross-correlations between the changes in the OECD Environmental Policy Stringency Index and the annual averages of the quarterly median PC and NC shocks. The dashed lines are the 95% bootstrapped confidence bands, based on 10,000 draws.

regulations. The National Appliance Energy Conservation Act of 1987 established national mandatory minimum efficiency standards for 15 categories of household appliances. The Energy Policy Act of 1992 extended the product coverage. The American Recovery and Reinvestment Act of 2009 was implemented in the midst of the Great Recession and included a number of energy-related provisions.

Regarding the first two acts, for the historical decomposition of emissions, we selected eight quarters from the regulation implementation dates. The positive NC shocks after each regulation reduce emissions by -0.54% and -0.37%, respectively, partly offsetting the contributions from the PC shocks.

Under the American Recovery and Reinvestment Act of 2009, the Department of Energy invested more than $US 31 billion through the Act in projects aimed at creating new power sources and enhancing energy efficiency for homeowners and businesses. Most funding was dispersed between 2009:Q1 and 2012:Q1,[26] so we use this time period for our historical decomposition. The third set of bars in Figure 11 (b) shows that the NC shocks explain about half of the sizable -5.61% drop in emissions.

The second exercise involves the OECD Environmental Policy Stringency Index (EPSI) for the U.S. economy (1990-2015).[27] The EPSI is a broad measure of environmental policy that goes beyond any single regulation and integrates market- and non-market-based environmental policy instruments. Albrizio et al. (2017) and Martínez-Zarzoso et al. (2019) find that more-stringent policies, corresponding to higher values

[26] See https://www.energy.gov/downloads/successes-recovery-act-january-2012 for more details.

[27] Retrieved from http://oe.cd/OQ. Accessed May 15, 2021.

on the EPSI, promote R&D activities, increase the number of patents and stimulate productivity growth in OECD countries. Figure 12 reports the correlations of the changes in the EPSI with the leads of the historical PC and NC shock series. More-stringent regulations are negatively related to the PC shocks contemporaneously, pointing to possible immediate economic costs. However, the EPSI changes are also positively correlated with the three-years-ahead values of the NC shocks. This positive sign is consistent with the Porter hypothesis that regulation can induce technological change if the NC shocks reflect changes in energy efficiency.

4.2.4 Energy prices and NC shocks

It has been argued that rising energy prices could induce technological change (e.g., Newell et al., 2006). Our baseline VAR does not include energy prices. To check for the possible effects of past energy prices on the historical NC shock series, we estimate a number of linear projections. We examine multiple energy prices in nominal and real terms, restrict price changes to only price increases, compute non-linear net-price increases, use different subsamples and also vary the number of lags. In no specification do past energy prices affect NC shocks in a statistically significant way.

We showed in section 4.1.2 that positive NC shocks decrease the real price of fossil fuels, in line with the predicted effects of a positive energy-efficiency shock in the E-DSGE model. Our results suggest that, to the extent the NC shocks capture changes in energy efficiency, these changes are not induced by energy prices. Consistent with our results, Newell et al. (1999) find that a large fraction of the efficiency improvements in consumer durables is unrelated to energy price changes.

5 Other possible drivers of NC shocks

This section explores three possible drivers of NC shocks: (i) extreme weather, (ii) changes in CO_2 emissions coefficients, and (iii) shifts from dirtier to cleaner energy sources. We find some support for the first alternative. However, correcting for weather changes retains the importance of energy efficiency.

5.1 Weather extremes

Weather extremes can have strong impacts on energy consumption, emissions and economic activity (e.g., Dell et al., 2014). Energy demand for heating and cooling surges in very cold winters and hot summers; hence, emissions surge during these periods. At the same time, output can decrease through multiple channels, including infrastructure damage and falls in labor productivity. The National Oceanic and Atmospheric Administration (NOAA), which has kept track of billion-dollar U.S. weather and climate disasters since 1980, attributes 26 disaster events to freezes and winter storms and 11 to heat waves and droughts. NC shocks may thus reflect weather extremes.

To study this possibility, we start with the national average temperature from the NOAA. We compute the quarterly means of the deviations from the month-specific trends. We also construct three series of extreme temperatures, breaking down a year into heating and cooling seasons. The *cold* (*warm) heating season* variable is defined by the temperature values in quarters 1 and 4 when the mean temperature is more than one standard deviation below (above) the average, and by zeros otherwise. Similarly, the non-zero values of a *hot cooling season* variable are set to temperatures that exceed one standard deviation above the means in quarters 2 and 3.[28]

Table 2 shows the complexity of the weather effects on the economy, as the average temperature is significantly correlated with both historical shock series. For NC shocks, the correlations are the strongest during heating seasons. The correlation signs are intuitive. In a cold heating season, when low temperatures drive up energy demand and emissions, a negative NC shock is likely to occur. A positive NC shock in a warm heating season implies that milder weather tends to lower energy demand and emissions while extending seasonal work and raising economic activity.

We re-estimate the IRFs of emissions using a version of (5) augmented with the current and lagged values of the average temperature, the Residential Energy Demand Temperature Index and precipitation.[29] Controlling for weather indicators increases the initial response of residential sector emissions to an NC shock from -6.77% to -4.75%.

[28]The online appendix expands on the weather data construction, reports the IRFs obtained with weather controls and includes the correlation and adjusted $\bar{R}^2$ tables discussed in the text.

[29]All weather indicators are based on the monthly series from the NOAA. Our model includes two lags, but increasing the number of lags further has minimal effects on the estimates.

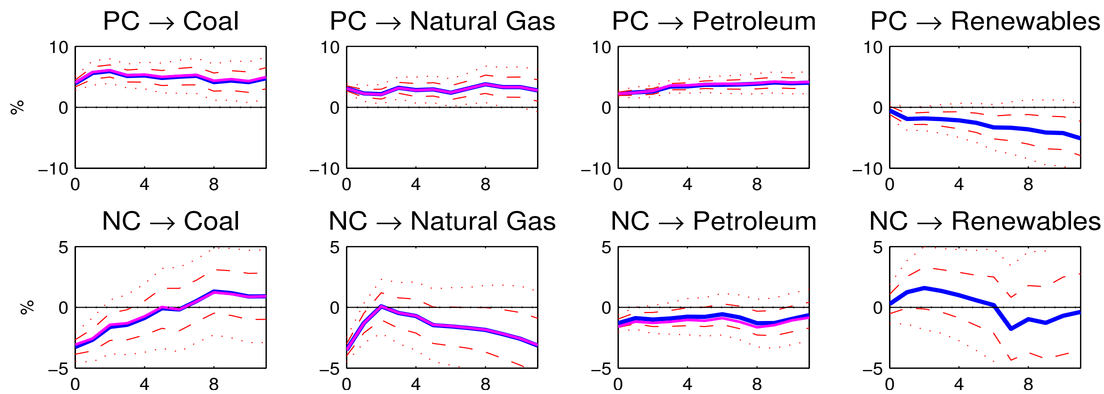


Figure 13: IRFs of emissions and energy consumption by energy source (DLM)

Note: Cumulative responses of per capita total energy consumption (thick blue lines) and total emissions (thin magenta lines) are obtained from the DLM (5). Dashed and dotted lines are block-bootstrapped one- and two-standard errors bands.

However, the overall pattern of the IRFs of emissions remains the same and the adjusted $\bar{R}^2$ for emissions and total energy consumption show little change (section 5, online appendix). We hence conclude that our interpretation of NC shocks as capturing energy-efficiency changes is robust to weather variations.

5.2 Changes in the CO_2 emissions coefficients

The EIA uses CO_2 emissions coefficients in estimating emissions. Reflecting chemical compositions, these coefficients range from 53 million metric tons of CO_2 emissions per quadrillion Btu for pipeline gas to 114 for coal coke. A decline in the emissions coefficients will reduce total emissions for a given level of energy use and aggregate output. Hence, changes in the coefficients could be possible drivers of NC shocks.

The published CO_2 emissions coefficients, however, vary surprisingly little over time. These coefficients are constant for 24 of 35 products for the entire period since 1973 and for all energy products before 1980 and after 2010. Furthermore, the emissions coefficients for eight products actually increase over time.

Motor gasoline and jet fuel are two products with frequent revisions in the emissions coefficients between 1980 and 2010; in 2019, they accounted for 22% and 5%, respectively, of total CO_2 emissions. These revisions were due to the phasing out of leaded

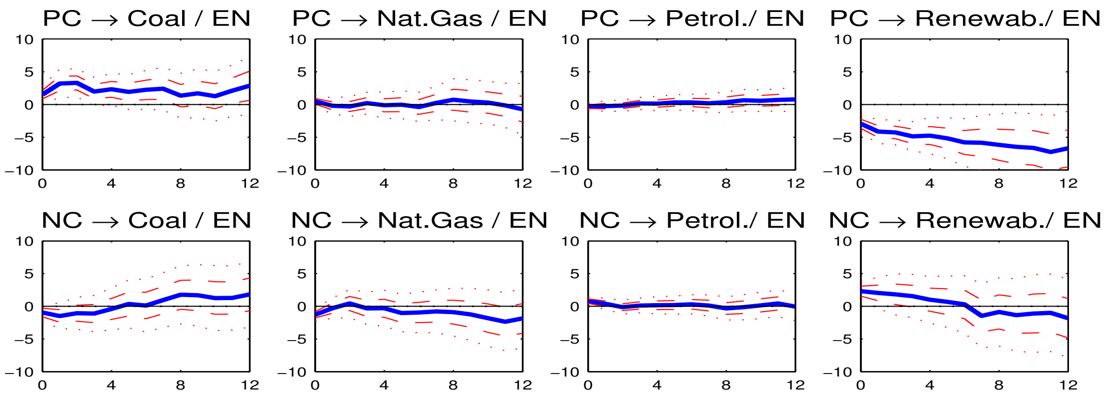


Figure 14: Impulse responses of energy shares (DLM)

Note: EN denotes total primary energy consumption. Solid lines are cumulative responses from (5). Dashed and dotted lines are block-bootstrapped one- and two-standard errors bands.

gasoline, varying aromatic hydrocarbons, the development of fuel additives and shifting from naphtha- to kerosene-based jet fuel (EIA, 2011). However, emissions from motor gasoline and jet fuel rise after positive NC shocks (available on request). As these responses go against the decline in total CO_2 emissions in the baseline VAR, changes in the emissions coefficients of such products cannot explain the NC shocks.

Another perspective on the role of emissions coefficients comes from comparing the IRFs of emissions and energy consumption from the main energy sources. The minimal differences between the two types of IRFs in Figure 13 imply that even at the level of major fossil fuels, the ratio of emissions to energy consumption (*aka* the emissions coefficient) exhibits little variation. Therefore, we rule out the possibility of emissions coefficients being important drivers of NC shocks.

5.3 Substitution to cleaner energy sources

Shifts to less-polluting energy sources may reduce emissions without causing declines in total energy consumption and output. Reductions in the use of coal, the most polluting fossil fuel, have already made large contributions to U.S. emissions mitigation. In the 2007-2019 period alone, CO_2 emissions from coal declined by a billion metric tons (EIA, 2020). The EIA (2020) also estimates that changes in the electricity generation fuel mix reduced CO_2 emissions in the residential and commercial sectors by 99 million metric tons in 2019. The empirical impacts of decarbonization on aggregate economic activity are less known.

We estimate cumulative IRFs of per capita coal, natural gas, petroleum and renewables consumption (Figure 13) and their shares in total primary energy consumption (Figure 14). Consumption of all fossil fuels drops for a few quarters after a positive NC shock, while the responses of renewables are not significant. The energy shares remain fairly constant except in the very short run. Together, the IRFs reject changes in the energy mix as being likely drivers of NC shocks. Rather, they point to a reduction in the overall energy demand, consistent with the responses of total energy consumption and the energy price, as shown in Figure 8.

A strikingly different IRF pattern is generated by a positive PC shock. We observe a sustained increase in all three fossil fuels and a persistent decline in renewables. The PC shock triggers a significant reallocation of energy consumption between coal and renewables. Recall that a positive PC shock is normalized to increase emissions and output. The linearity of (5) implies that a decrease in emissions corresponds to a negative PC shock and that the responses to a negative shock will take the opposite sign to those reported in Figures 13 and 14. Our results thus may be interpreted to suggest that a reduction in emissions through switching to less-polluting energy sources may also lower aggregate output.

6 Concluding remarks

Our research was largely motivated by the trade-off between protecting the environment and maintaining economic performance embedded in the literature on business cycles and environmental policy. We identified novel NC shocks, which by construction avoided this trade-off by inducing the opposite effects on GDP and emissions. Our identification was based on statistical restrictions and it imposed no priors about the importance of NC shocks. Nonetheless, the NC shocks explained a large share of the variations in emissions. They also shared the characteristics of a structural shock to energy efficiency, which increased aggregate output but decreased energy consumption and prices. The sector-level analysis of emissions revealed that the NC shocks had the strongest relationship with the residential sector.

Our results imply that structural models that omit NC-type disturbances, such as energy-efficiency shocks, likely overestimate the cost of emissions mitigation. Since these shocks have different impacts on emissions and GDP, optimal policy responses to NC shocks would also likely be different from those to conventional macroeconomic shocks. Further research is needed to evaluate this conjecture.

Our results also call for explicit and detailed modeling of the choices of different energy users, especially of consumers. This approach would help devise effective policies to tackle emissions that originate from different sectors. The residential sector is the most responsive to energy policies (e.g., Labandeira et al., 2020) and the costs of behavioral interventions are low (e.g., Gillingham and Stock, 2018). Mandatory energy-efficiency standards or voluntary labeling programs, such as ENERGY STAR, are theoretically suboptimal to carbon pricing. However, these policies are generally more politically accepted. We share the views expressed by Annicchiarico et al. (2021) that incorporating non-pricing mechanisms, such as energy-efficiency standards, into E-DSGE models would be a fruitful research area.

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Tables

Table 1: Adjusted $\bar{R}^2$ statistics from DLMs for energy consumption and emissions

	Direct fossil fuel consumption	Total energy consumption	Total energy CO_2 emissions
(a) DLM with NC shocks only			
Residential	0.241	0.550	0.579
Commercial	0.300	0.488	0.534
Industrial	0.028	0.039	0.050
Transportation	0.064	0.064	0.068
Electric Power	0.449		
(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		

Table 2: Posterior median PC and NC shocks and temperature indicators

	PC shocks		NC shocks	
Weather indicator	corr.	std.error	corr.	std.error
Average temperature °F	-0.131	(0.080)	0.321	(0.075)
Cold heating season	-0.089	(0.079)	0.301	(0.068)
Warm heating season	-0.092	(0.085)	0.280	(0.076)
Hot cooling season	0.058	(0.080)	-0.019	(0.074)

Note: Standard errors are based on bootstrap sampling with replacement. Correlation coefficients for the heating and cooling seasons are computed using only the values for those seasons.

A Selection of prior distributions for a_p and a_n

The priors for a_p and a_n are two independent Student t distributions, with v degrees of freedom, truncated to be positive. The prior density takes the form

$$p(\mathbf{A}) = \left\{ \begin{array}{ll} \frac{f(a_p;c_p,\sigma_p,v)}{1-F(0;c_p,\sigma_p,v)} \frac{f(a_n;c_n,\sigma_n,v)}{1-F(0;c_n,\sigma_n,v)} & \text{if } a_p \geqslant 0,\ a_n \geqslant 0, \\ 0 & \text{otherwise,} \end{array} \right\},$$

where $f(x;c,\sigma,v)$ is the density for a Student t variable with a location parameter c, a scale parameter σ, and a degree of freedom v, evaluated at x,

$$f(x;c,\sigma,v) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\sigma\Gamma(v/2)} \left(1 + \frac{(x-c)^2}{\sigma^2 v}\right)^{-(v+1)/2}$$

The cumulative distribution function is $F(x;c,\sigma,v) = \int_{-\infty}^{x} f(z;c,\sigma,v)\,dz$.

We set $v = 3$, as it guarantees the existence of finite means and variances of the posterior distributions. The choice of c and σ is related to the estimates of the income elasticity of emissions. Many published estimates are between 0.4 and 1.0, although values as low as -0.5 and as high 3 have been reported in the literature (e.g., Liddle, 2015, and references therein). However, empirical studies are not consistent with respect to the types of measures used, data frequency, time horizons of the elasticities, data sets, estimation methods, treatment of nonstationarity, heterogeneity and income endogeneity, nor are they consistent on the inclusion of additional control variables. Selecting a particular estimate for our study is not trivial since previous studies typically do not differentiate the sources of the GDP movements. Exceptionally, Burke et al. (2015) instrument external shocks to the GDP of a country by using the GDP growth of its export partners. Their instrumental variable strategy increases the estimated emissions-income elasticity from 0.52 (s.e. 0.07) to 0.86 (s.e 0.26).

To overcome the lack of conditional emissions-income-elasticity estimates, we select the mode parameters to partly reflect the scale of the data. We estimate an OLS regression of the growth rate of emissions on the growth rate of GDP and a constant for the periods of positive comovement, using the data shown by the blue circles in Figure 1. The results imply $c_p = 1.50$. Repeating the exercise for the periods of negative comovement (the red circles in Figure 1), we obtain $c_n = 1.75$. In comparison, the OLS estimate for a similar regression using the data for the whole sample is 0.49. We calibrate the scale parameters to $\sigma_p = 0.85$ and $\sigma_n = 0.7$ so that a_p and a_n take the values between 0.15 and 2.5 with an 80% probability.