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# Estimating and forecasting the impact of nonrenewable energy prices on US renewable energy consumption☆

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ABSTRACT

This paper measures the impact of nonrenewable energy prices on renewable energy consumption in the U.S. We do so using monthly data for the period 1973:1–2018:12, and a series of recursively identified VAR models with nonrenewable energy prices ordered ahead of renewable energy consumption measures in each of the VAR models. We also investigate whether information on nonrenewable energy prices can be used to improve forecasts of renewable energy consumption. Our general findings are as follows (i) Shocks to nonrenewable energy prices have positive and statistically significant impacts on renewable energy consumption. (ii) Allowing for nonlinearities/asymmetries in nonrenewable energy prices lead to more statistical significance in the responses of the various renewable energy consumption measures (iii) The percentage of the variation in renewable energy consumption that is explained by nonrenewable energy prices is quantitatively small. (iv) In many cases, models with nonrenewable energy prices improve the forecast performance of simple AR models.

## 1. Introduction

Renewable energy is probably one of the most significant solutions to the global environmental crisis. Consuming more renewable energy helps reduce environmental degradation, amends the already existing damages (Kečeк et al., 2019; Alvarado et al., 2019) and has positive impacts on economic growth (see e.g. Wang et al. (2011), Dogan et al. (2020), Zafar et al. (2019) and Atems and Hotaling (2018)).[1]

Therefore, scientists and policymakers in the US and across the globe are studying the factors that can increase the consumption of clean sources of energy. Some of these factors include government programs (such as rebates, subsidies, or taxes credits), as well as the creation of renewable certificates (Apergis and Payne, 2010; Kaygusuz, 2007). A paper by Carfora and Scandurra (2019) revealed that climate fund incentives lead to lower greenhouse gas (GHG) emissions, suggesting that replacing fossil sources with renewable energy is beneficial for the environment. Moreover, political commitment has its own influences, i.e., the supportive relationship between political institutions and renewable energy has affected the current positive trend toward consumption of renewable energy (Burke and Stephens, 2018; Sequeira and Santos, 2018).

It is a widely accepted view that the recent higher nonrenewable energy prices have coincided with a boost in renewable energy utilization of all kinds. Kilian (2008) provides evidence that gasoline consumption dramatically decreases in response to unexpected energy price increases.[2] In the US, pivotal factors explaining renewable energy consumption growth include the concerns surrounding the US dependency on foreign fossil energy (Bowden and Payne, 2010), the high volatility in energy market prices, and the fear of persistently high inflation caused by expensive oil prices (Kilian et al., 2021).[3]

Despite the rich literature on energy prices, there still remains a fundamental gap in both the theoretical and empirical literature. The implications of nonrenewable energy price shocks for clean energy forms are ambiguous at best, and the default approach focuses on immediate timing and current effects. In other words, it is unclear whether

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[1] Ivanovski et al. (2021) provides evidence that this effect is much more pronounced among higher income countries in particular OECD (Organization for Economic Cooperation and Development) countries.

[2] The estimated elasticity of demand for gasoline one year following a price shock is −0.48. There is a notable strong response for heating oil and coal with an elasticity of −1.87. This is attributed to households' greater storage capacity of heating oil via tanks (Kilian, 2008).

[3] Despite evidence to the contrary (Barsky and Kilian, 2004), there is also a common perception that high oil prices could be associated with productivity slowdown.

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energy price surges immediately affect renewable usage, if at all, or if policymakers and consumers should expect a short, medium, or long-term delay. Furthermore, it is also unclear whether energy prices can help forecast US renewable consumption. This is a significant gap for policymakers and researchers involved in sustainability efforts because they may benefit from further clarity surrounding these questions, especially in policy formulation.

The major contribution of this study is to examine the effects of nonrenewable energy prices on renewable energy consumption by considering the time horizon of the impacts. To achieve this goal, we estimate a series of bivariate Structural Vector Auto-Regressive (SVAR) models (Edelstein and Kilian, 2009) and using monthly data for the period 1974m1–2018m12. It is important to emphasize that our analysis focuses on US data and may not necessarily translate to countries at differing stages of industrial development.

Our analysis reveals that shocks to nonrenewable prices lead to significant increases in aggregate biomass, geothermal, solar, and wood energy usage. The magnitude and timing of these responses are different for each category. For example, solar energy usage spikes most around the 3rd and 14th months following a nonrenewable energy price surge compared to the 4th and 15th months for biomass. Our results also show that at least 8.7% of the long-run variation in solar energy consumption is attributable to changes in nonrenewable energy prices. Additionally, we find that under several specifications, forecasting renewable energy usage is significantly improved by including information on nonrenewable energy price fluctuations.

The rest of this paper is organized as follows. Section 2 provides an overview of the theoretical literature on the topic. Section 3 presents our data and preparatory procedures. Section 4 briefly describes our estimation methodology. Section 5 summarizes our results and includes the standard robustness analysis. Section 6 explores whether energy prices help forecast renewable energy demand, and we conclude in Section 7 along with a brief discussion of the policy implications of our results.

## 2. On the theoretical relationship between nonrenewable energy prices and renewable energy consumption

There is a sizeable theoretical literature on the link between nonrenewable energy prices and renewable energy consumption (see e.g. Nicolini and Tavoni (2017), Yang et al. (2019), Martelli et al. (2020) and Zeng et al. (2021)). Much of this literature argues that nonrenewable energy and renewable energy are substitutes. That is, a rise in nonrenewable energy prices, which, based on economic theory, should decrease its quantity demanded, will induce an increase in the consumption of its substitute (renewable energy). Fig. 1 provides the simple textbook rationale for this view. In Panel A, an increase in nonrenewable energy prices from $P_{n1}$ to $P_{n2}$ decreases the consumption of nonrenewable energy from $q_{n1}$ to $q_{n2}$. At the same time, the demand for renewable energy sources rises from $q_{r1}$ to $q_{r2}$, even though the price of renewables remains unchanged at $P_{r1}$.

An examination of the data seems consistent with this simple textbook view. Between January 1973 and December 2018, the index of nonrenewable energy prices, as measured by the Bureau of Labor Statistics (BLS) Intermediate Demand Producer Price Index (PPI) for Processed Fuels and Lubricants, rose from 20.8 to 183.5, representing almost an 800% increase. Over the same time period, the share of fossil fuel (coal, natural gas excluding supplemental gaseous fuels, and petroleum excluding biofuels) in total primary energy consumed dropped from 93% to 81%, representing a 13% decrease. Meanwhile, total renewable energy as a share of total primary energy rose by more than 90% over the same time period. This rise in nonrenewable energy prices, coupled with the increase in renewable energy consumption, has prompted many researchers to argue that renewable energy and nonrenewable energy are substitutes.

The 2006 Economic Report of the President notes that

> "In the long run, households and businesses respond to higher fuel prices by cutting consumption, purchasing products that are more efficient, and switching to alternative energy sources. Higher energy prices also encourage entrepreneurs to invest in the research and development of new energy-conserving technologies and alternative fuels, further expanding the opportunities available to households and businesses to reduce energy use and switch to low-cost energy sources". (page 243)

Thus, theoretically, this relationship depends on the time horizon considered. Consumers may change their response more in the medium or long run (Cooper, 2003; Coglianese et al., 2017; Mankiw, 2020). Salim et al. (2014), Ito (2017), and Opeyemi (2021) also provide support for this time-dependent substitutability. The importance of the medium-run and long-run horizons makes the VAR approach particularly suited to this question since it allows us to consider the impact of price shocks both on impact and as time passes.

The view that renewable and nonrenewable energy are theoretically substitutes is also supported by Sadorsky (2009), who develops and estimates a model of renewable energy consumption, $CO_2$ emissions, and oil prices for the G7 countries. On theoretical (and empirical) grounds, Silk and Joutz (1997) argue that a rise (fall) in natural gas prices will compel electric utilities to switch their facilities to burn alternative fuels at higher (lower) rates. Switching is incentivized by the prospect of losing future customers who may want to switch to the consumption of these alternative fuels. Zhao et al. (2021) build a dynamic recursive computable equilibrium model revealing that higher international oil prices can lead to larger investments and output of renewable energy. One central assumption of their model is that renewable energy is an effective alternative to fossil energy, especially oil. In addition, oil price shocks and renewable energy policy are combined in the model with a simultaneous scenario. They further provide evidence that renewable energy can mitigate the adverse impact of fossil fuel price fluctuations. Acemoglu et al. (2012, 2014) introduce endogenous and directed technical change in a model with environmental constraints and limited resources. In their model, a final good is produced using a combination "dirty" inputs (nonrenewable energy) and "clean" inputs. In the model, tax policies that maximize growth and welfare depend on the substitutability of the inputs. They show that temporary taxation of the dirty input results in sustainable long-run growth when the two inputs are sufficiently substitutable. In their theoretical framework, the degree of substitutability depends on price and market size effects. Other theoretical studies that show substitutability between nonrenewable and renewable energy include (Ambec and Crampes, 2012; Benchekroun et al., 2019).

Unless renewable and nonrenewable energy sources are perfectly substitutable (which is unlikely), some degree of complementarity between them is expected. If this is the case, a rise in nonrenewable energy prices, which decreases the quantity demanded, should decrease the consumption of renewables, as shown in Panel B of Fig. 1. Daly (1990) argues that "it is possible to exploit nonrenewables in a quasi-sustainable manner by limiting their rate of depletion to the rate of creation of renewable substitutes", further stating that this "quasi-sustainable use of nonrenewables requires that any investment in the exploitation of a nonrenewable resource must be paired with a compensating investment in a renewable substitute (e.g., oil extraction paired with tree planting for wood alcohol)". Bastianoni et al. (2009) build a theoretical model that incorporates the ideas of Daly (1990) into the two resources model of Odum and Odum (2011) and shows that effective sustainable environmental policy relies on complementarity between the use of nonrenewable resources to improve our capacity of capturing renewable resources in the future. Kumar et al. (2015) also find a complementary relationship from nonrenewable energy to renewable energy in eight industries, while the substitute relationship holds for four industries.

The main goal of this paper is to empirically estimate the impact of nonrenewable energy prices on renewable energy consumption

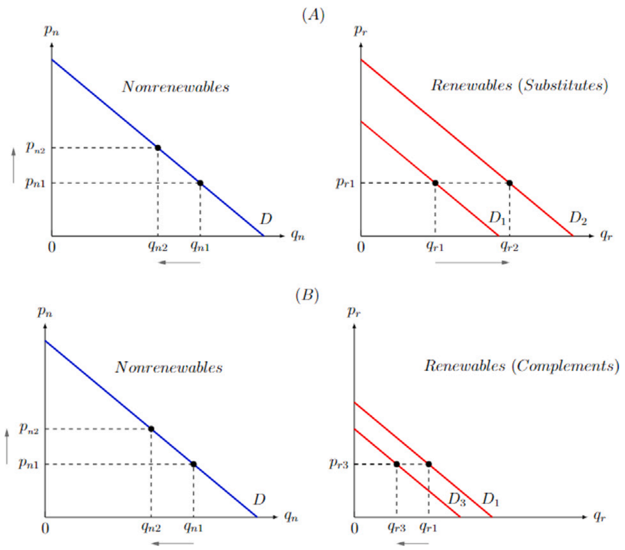


**Fig. 1.** The theoretical relationship between nonrenewable and renewable energies markets.

to understand the degree of substitutability and/or complementarity between them. A shock to nonrenewable energy prices that raises renewable energy consumption would provide support for the theoretical arguments in support of substitutability between two energy sources. In contrast, a decline in renewable energy consumption would suggest complementarity between the them. It is, however, possible to find both effects, as the theoretical literature suggests that the relationship between them depends on the time horizon (short versus medium versus long term) under consideration.

## 3. Data

### 3.1. Data on renewable energy consumption

Our data on renewable energy consumption cover the period from 1974 to 2018 at a monthly frequency. The data for wind and solar energy begins in January 1983, as data for these series prior to this date are unavailable. The data were collected from the Energy Information Administration (EIA) of the U.S. Department of Energy. We compiled the data on the total renewable energy, and five disaggregate measures of renewables, namely, biomass, geothermal, hydropower, solar, and wind. We also use two subcategories of biomass, namely waste and wood. The original series is expressed in British Thermal Units (BTU). As shown in Fig. 2, almost all renewable energy produced in the U.S. is consumed in the U.S. Hence, we do not distinguish between consumption and production. For ease of discussion, we use "consumption" throughout the paper.

We compute the consumption share of each renewable energy category by dividing these quantities by the total primary energy consumption. Fig. 3 depicts the percentage of total primary energy consumption by sources. The percentage of U.S. energy coming from fossil fuels has steadily declined over time, from over 93% in the early 1970s to under 81% in 2018. Meanwhile, there has been a corresponding increase in primary energy consumption from renewable energy sources. Among the renewable energy sources depicted in Fig. 3, the expansion has occurred primarily in biomass (including ethanol) and wind to a lesser extent. We observe that the share of energy consumption represented by hydropower has decreased since the mid-1980s, while solar and wind energy consumption has shown remarkable growth in recent years. The Energy Policy Act of (2005) and the Energy Independence and Security Act of (2007) have played an important role in stirring the domestic consumption of renewable fuels (Nyman, 2018; Mette, 2021).

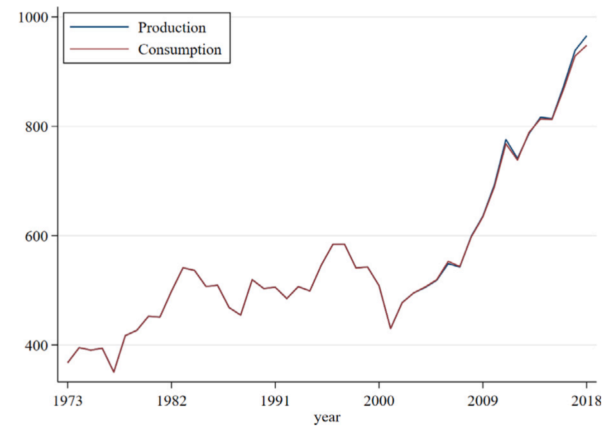


**Fig. 2.** U.S. Production and consumption of renewables (1973–2018, Trillion BTU).

### 3.2. Data on nonrenewable energy prices

Our data on nonrenewable energy prices are also monthly for the period January 1974 to December 2018. All data on nonrenewable energy prices and price deflators were collected from the Federal Reserve Economic Database (FRED) provided by the Federal Reserve Bank of St. Louis. As our main measure of nonrenewable energy prices, we use the Bureau of Labor Statistics (BLS) Producer Price Index (PPI) for Processed Fuels and Lubricants (Series *WPSID613: Producer Price Index by Commodity: Intermediate Demand by Commodity Type: Processed Fuels and Lubricants for Intermediate Demand* on FRED). We also use the Consumer Price Index (CPI) for energy. To study the role of nonlinearities in the effects of nonrenewable energy prices, we also consider two nonlinear transformations of the Processed Fuels and Lubricants PPI measure, which are common in the literature. When working with real nonrenewable energy prices, we deflate the nominal Processed Fuels and Lubricants PPI by the PPI for all commodities (Series *PPIACO: Producer Price Index by Commodity: All Commodities* on FRED) to express in real terms. Further details of the nonrenewable energy prices are provided below.

#### 3.2.1. The baseline measure of nonrenewable energy prices

Following previous literature (see, e.g., Edelstein and Kilian (2009, 2007)), we rely on the BLS Processed Fuels and Lubricants PPI as our main measure of nonrenewable energy prices. While some studies have used crude oil prices as a proxy for nonrenewable energy prices, the price of crude oil does not accurately capture nonrenewable energy prices. As pointed out by Edelstein and Kilian (2007), household purchasing power depends heavily on processed petroleum products, such as gasoline and heating oil, while firms tend to primarily rely on electricity and natural gas for their energy needs. Therefore, using crude oil as a measure of nonrenewable energy prices ignores the important shocks that may arise during the processing of crude oil. Kilian (2009) shows that while shocks to the global crude market impact gasoline price movements, distinct demand and supply shocks specific to the U.S. gasoline market play a huge role in gasoline price movements. Similarly, Atems and Yimga (2021) shows that the response of various measures of U.S. airline industry performance to demand and supply shocks differs depending on whether the shocks emanate from the global crude oil market or from the U.S. jet fuel market. Therefore, to more accurately capture nonrenewable energy prices, a broad measure is needed.

The BLS Processed Fuels and Lubricants PPI measure includes the prices of all nonrenewable energy goods used by firms as inputs in production. Table 1 is a list of the components of the index, together with the weight of each component used in the construction of the index in the year 2018. Panel A shows the components and associated

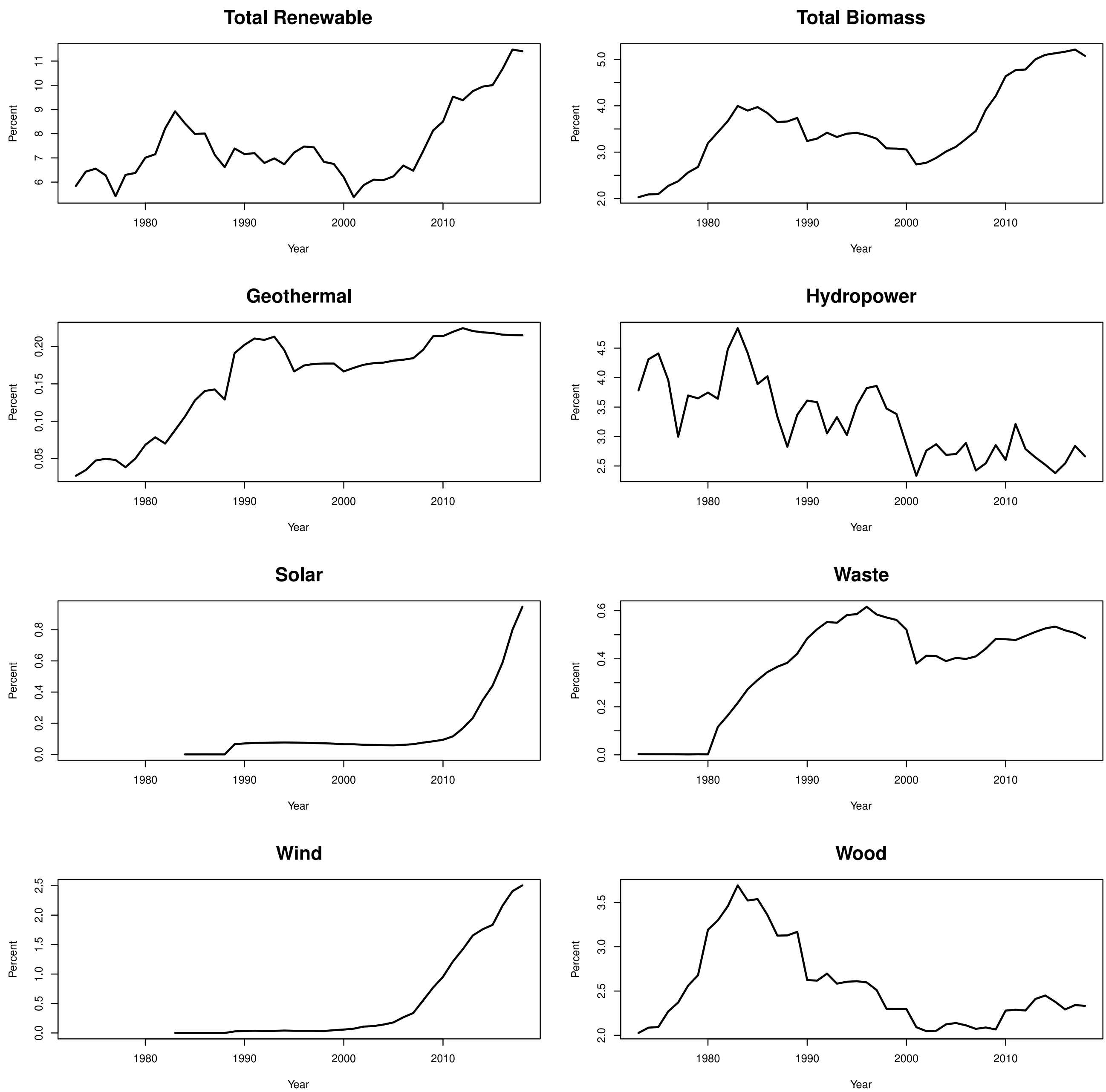


**Fig. 3.** Percentage of total primary energy consumption by energy sources (1974–2018).

weights for the industrial sector, while Panel B shows the components and weights for the nonindustrial sector. The largest components in the industrial sector include industrial electric power (62.23%), No. 2 diesel fuel (14.37%), whereas the largest components in the nonindustrial sector are commercial electric power (34.73%), No. 2 diesel fuel (21.03%), and unleaded regular gasoline (14.21%).

The weighted average of the industrial and nonindustrial sector through time gives the baseline measure of nonrenewable energy prices, which we collect directly from FRED (Series *WPSID613: Producer Price Index by Commodity: Intermediate Demand by Commodity Type: Processed Fuels and Lubricants for Intermediate Demand* on FRED). Fig. 4 shows the plots the baseline monthly renewable energy price measure for our sample period that runs from January 1973 to December 2018. The figure suggests that nonrenewable energy prices have risen considerably since the 1970s. This is not surprising as one of the reasons for the rise in renewable energy consumption (and government policies to encourage the consumption of renewables, such as the 2005 Energy Policy Act and the 2007 Energy Independence and Security Act) is to avoid the negative economic effects of nonrenewable energy price shocks.

### 3.2.2. *Other measures of nonrenewable energy prices*

While it is not uncommon to find papers in the literature that use changes in nominal energy prices (see e., e.g., Jones and Kaul (1996), Bachmeier and Cha (2011), and Gradstein and Klemp (2020)), theoretical models of the transmission of energy price shocks are based on real rather than nominal energy prices, as argued by, among others, Kilian and Vigfusson (2011) and Hamilton (2011). Therefore, in some VAR specifications, we use real nonrenewable energy prices constructed by deflating the nominal Processed Fuels and Lubricants PPI by the PPI for all commodities. Panel A of Fig. 5 displays the real Processed Fuels and Lubricants PPI. Similar to Fig. 4, we see a general upward trend in nonrenewable energy prices.

The Processed Fuels and Lubricants PPI captures the prices of all nonrenewable energy goods purchased by producers to use as inputs

**Table 1**
Relative importance of components in the producer price Index for processed fuels and lubricants.
*Source:* U.S. Bureau of Labor Statistics.

| A. Processed fuels and lubricants to industrial sector | |
|---|---|
| Component Series | Percent |
| Liquefied petroleum gas | 1.90 |
| Industrial electric power | 62.23 |
| Industrial natural gas | 3.44 |
| Unleaded premium gasoline | 0.09 |
| Unleaded regular gasoline | 0.53 |
| Unleaded mid-premium gasoline | 0.02 |
| Aviation gasoline | 0.02 |
| Kerosene | 0.02 |
| Home heating oil and distillates | 0.68 |
| No. 2 diesel fuel | 14.37 |
| Residual fuels | 0.56 |
| Lubricating grease | 0.15 |
| Lubricating and similar oils | 1.43 |
| Lubricating oil base stocks | 8.91 |
| Asphalt | 2.42 |
| Other petroleum and coal products, n.e.c. | 3.27 |
| B. Processed fuels and lubricants to nonindustrial sector | |
| Component Series | Percent |
| Liquefied petroleum gas | 2.17 |
| Commercial electric power | 34.73 |
| Transportation electric power | 0.23 |
| Commercial natural gas | 1.70 |
| Natural gas to electric power | 9.40 |
| Unleaded premium gasoline | 2.01 |
| Unleaded regular gasoline | 14.21 |
| Unleaded mid-premium gasoline | 0.32 |
| Aviation gasoline | 1.33 |
| Kerosene | 0.09 |
| Jet fuel | 5.19 |
| Home heating oil and distillates | 0.76 |
| No. 2 diesel fuel | 21.03 |
| Residual fuels | 2.23 |
| Lubricating grease | 0.31 |
| Lubricating and similar oils | 3.07 |
| Asphalt | 0.25 |
| Other petroleum and coal products, n.e.c. | 0.97 |

Notes: Based on 2018 weights in processed fuels and lubricants.

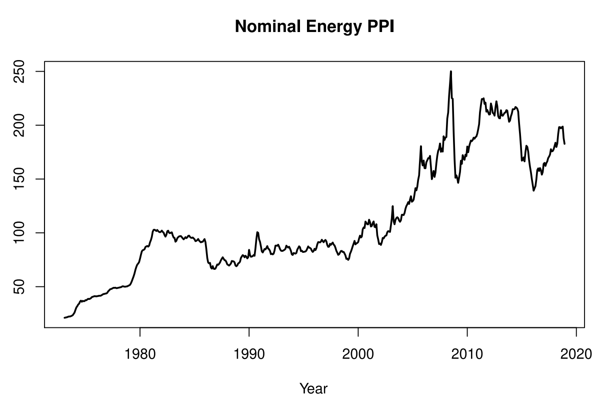


**Fig. 4.** Nominal energy producer price index.

during the production process. It does not directly take into account the energy consumption expenditures of households. Therefore we also use the CPI for Energy to capture households expenditures on energy.

There is substantial literature suggesting that energy prices have nonlinear or asymmetric effects or both. Mork (1989) showed that positive oil price shocks (oil price increases) had substantially larger and significant effects on the economy, while negative oil price shocks (oil price decreases) had no statistically significant economic effect. The literature (see, e.g., Bernanke et al. (1997)) has generally interpreted this as evidence that increases in oil prices are what impact the economy. As a result, we also use a measure of positive nonrenewable energy prices constructed as $\Delta p_t^+ = \left(p_t - p_{t-1}\right) \cdot 1\left(p_t - p_{t-1} > 0\right)$ where $\Delta$ is the change operator, $p_t$ denotes the natural logarithm of nonrenewable energy prices in month $t$, and $1(\cdot)$ is the indicator function. Hence $\Delta p_t^+$ takes the value of difference between $p_t$ and $p_{t-1}$ when the difference is positive and 0 otherwise. Building on the idea that oil price increases only are what matter for the economy, Hamilton (1996, 2003, 2010) proposed the "net oil price increase measure" (NOPI), which suggests that oil price increases that simply reverse recent oil price declines are unimportant for the economy. However, larger oil price increases that are unprecedented in recent history are what, in fact, impact the economy. Specifically, the NOPI measure is calculated as $\Delta P_t^{\#} = \left(p_t - p_{t-s}\right) \cdot 1\left(p_t - p_{t-s} > 0\right)$ where, as before $p_t$ is the natural logarithm of the price of oil in month $t$ and $p_{t-s}$ is the log of the highest price of oil in the previous $s$ months. Therefore $\Delta P_t^{\#}$ is the difference between current oil prices and the maximum price of oil in the past $s$ months. Typical values of $s$ when using monthly data are $s = 12$, corresponding to a 1-year net oil price increase (see e.g. Bachmeier (2008), and Jiménez-Rodríguez (2015)), and $s = 36$ corresponding to a 3-year net oil price increase (see e.g. Atems et al. (2015), Atems and Melichar (2019)). Using slope-based tests of the linear symmetric VAR model against the net increase VAR model, Kilian and Vigfusson (2011) find evidence of asymmetries using the 3-year net increase measure but no evidence using the 1-year measure. In this paper, we construct and use the 3-year net nonrenewable energy price increase, although our findings and conclusions remain unchanged when we use the 1-year net nonrenewable energy price increase.

### *3.3. Unit root and cointegration testing*

We begin analyzing the time series properties of the data by testing for stationarity of the nonrenewable energy prices and the measures of renewable energy consumption. Estimating a VAR model with a mix of stationary and non-stationary variables may lead to spurious regressions (Granger and Newbold, 1974; Atems and Lam, 2013). To verify whether our series are stationary, we use the Augmented Dickey–Fuller (ADF) test. The null hypothesis of this test is that a unit root exists in the time series. The value of the test statistic is then compared to the critical values from the Dickey–Fuller distribution. The first column in Table 2A reveals that the null of a unit root cannot be rejected at the 5% level of significance for all the variables. Column 1 in Table 2B, however, shows that all the variables are stationary after log first differences.

Due to the low power of the ADF test (DeJong et al., 1992 and its poor performance in finite samples Davidson et al., 2004), we also perform the Elliott et al. (1996) modified Dickey–Fuller Generalized Least Squares (DF-GLS) test, as well as the Kwiatkowski et al. (1992) test known as KPSS, both of which have been shown to outperform the ADF test in terms of power and size. Like the ordinary Dickey–Fuller test, the null hypothesis of the DF-GLS test is that the time series contains a unit root. On the contrary, the null hypothesis of the KPSS test is that the series is stationary. The DF-GLS results in the second column of Table 2A show that the nonrenewable energy price series (PPI Energy) and renewable energy consumption variables (except for total renewable energy consumption) are nonstationary in log-levels but are all stationary after log first difference, as shown in the second column of Table 2B. The KPSS result in the third column of Table 2A shows that the null hypothesis of stationarity is rejected at the 5% level for all of the variables in log levels. In log first differences, the KPSS test results in column 3 of Table 2B, fail to reject the null hypothesis of stationarity after the nonrenewable energy price and renewable energy consumption variables are expressed in percentage change. Taken together, we estimate the VAR models in this paper with all the variables entered in percentage change.

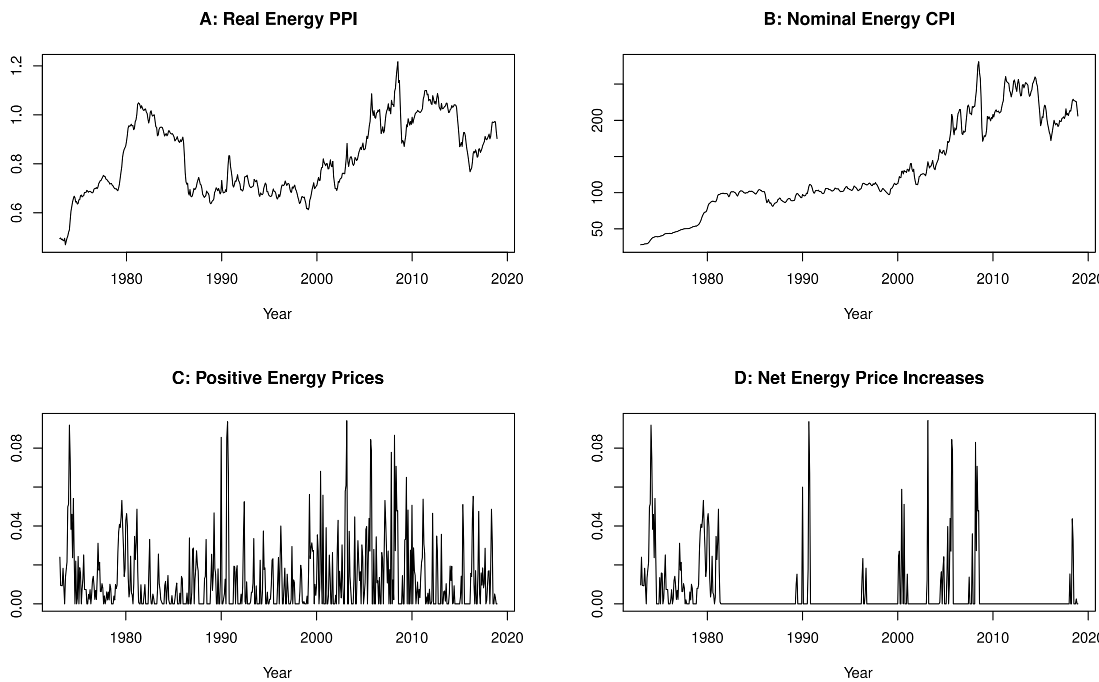


**Fig. 5.** Additional measures of energy prices.

**Table 2**
Unit root tests.

| | A: Level | | | B: Log first differences | | |
|---|---|---|---|---|---|---|
| | ADF | DF-GLS | KPSS | ADF | DF-GLS | KPSS |
| PPI Energy | 1.706 | 0.746 | 6.209 | −12.375 | −6.994 | 0.323 |
| Total renewables | −0.124 | −3.269 | 1.648 | −16.878 | −10.428 | 0.028 |
| Biomass | −0.324 | −1.002 | 0.898 | −19.017 | −13.503 | 0.045 |
| Geothermal | −0.916 | 0.030 | 4.744 | −17.079 | −14.596 | 0.207 |
| Hydropower | 0.179 | −1.797 | 6.782 | −15.439 | −12.423 | 0.006 |
| Solar | −0.367 | −0.596 | 3.128 | −8.958 | 0.044 | 0.225 |
| Waste | −1.210 | 0.070 | 4.153 | −16.910 | −10.883 | 0.237 |
| Wind | −0.576 | −0.960 | 5.673 | −18.186 | −0.319 | 0.116 |
| Wood | 0.114 | −1.924 | 6.223 | −19.830 | −14.178 | 0.052 |

*Notes*: The maximum lag length is based on the AIC. Tests do not include an intercept and/or a linear trend. The 5% critical values for the respective tests are −1.95, −1.94, and 0.46.

The finding that the nonrenewable energy prices and renewable energy consumption variables are nonstationary in levels leaves open the possibility that they are cointegrated. We investigate this possibility using the testing methodology of Johansen and Juselius (1990). Specifically, we carry out the Maximum Eigenvalue and Trace tests for the cointegrating rank of a VAR process. Each VAR process is a bivariate model of the nonrenewable energy price and each of the renewable energy consumption measures (in log-levels). In Panel A of Table 3 are the results of the eigenvalue test, while Panel B contains the results of the trace test. In all cases, the test statistics are less than the 5% critical value, suggesting that we cannot reject the null hypothesis of no cointegration. These results provide evidence in favor of VAR (rather than vector error correction) models with the variables in the first differences.

## 4. Estimation methodology

This section provides the details of the econometric methodology employed in this paper. We follow an extensive literature on the economic effects of energy price shocks that has employed VAR models (see e.g. Kilian (2008), Kilian and Lütkepohl (2017) and Baumeister and Hamilton (2019)). We specify and estimate a series of bivariate VAR models that include the monthly percent change in a measure of nonrenewable energy prices and the monthly percent change in a measure of renewable energy consumption:

$$\begin{bmatrix} p_t \\ r_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} p_t \\ r_t \end{bmatrix} + \begin{bmatrix} \epsilon_{p,t} \\ \epsilon_{r,t} \end{bmatrix} \tag{1}$$

where $p_t$ denotes the monthly percent change in the measure of nonrenewable energy prices, and $r_t$ represents the monthly percent change in the consumption of renewable. In Eq. (1), $L$ is the lag operator, $A_{ij}(\cdot)$ is a polynomial in $L$, $\epsilon_{p,t}$ and $\epsilon_{r,t}$ are the reduced form residuals for each equation. The lag order, $L$, is chosen by minimizing the Akaike Information Criteria (AIC).

We focus on bivariate VAR models where the various measures of renewable energy consumption enter the VAR model one at a time because including them all in one model would make identification of the structural shocks more difficult and questionable. While it is possible that a bivariate VAR model leaves out important information if there are shocks other than the nonrenewable energy price shocks that affect renewable energy consumption, it is common to find influential papers in the economics literature on the effects of energy price shocks that employ bivariate VAR models. Examples include Kilian and Park (2009), Elder and Serletis (2010), and Kilian and Vigfusson (2011, 2013).

Let $u_{p,t}$ and $u_{r,t}$ denote the structural shocks to renewable energy consumption and food prices, respectively. Assume further that the relationship between the reduced-form residuals and the structural shocks is given by:

$$\begin{bmatrix} \epsilon_{p,t} \\ \epsilon_{r,t} \end{bmatrix} = B_0^{-1} \begin{bmatrix} u_{p,t} \\ u_{r,t} \end{bmatrix}, \tag{2}$$

where the non-singular matrix, $B_0$, describes the contemporaneous relationship between the two variables:

$$B_0 = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}. \tag{3}$$

Further restrictions must be imposed on $B_0$ in order to identify the structural shocks $u_{p,t}$ and $u_{r,t}$. We employ the recursive identification strategy (Choleski identification) by assuming that shocks to nonrenewable energy prices affect renewable energy consumption on impact, but

**Table 3**
Johansen maximum eigenvalue and trace cointegration tests.

| Rank | Panel A: Johansen maximum eigenvalue test for cointegration | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Total renewables | Biomass | Geothermal | Hydropower | Solar | Waste | Wind | Wood |
| $r = 0$ | 14.776 | 12.857 | 15.515 | 12.582 | 18.730 | 15.496 | 11.208 | 13.783 |
| $r = 1$ | 2.201 | 5.491 | 2.600 | 4.826 | 2.579 | 4.168 | 4.839 | 2.623 |
| Rank | Panel B: Johansen trace test for cointegration | | | | | | | |
| | Total renewables | Biomass | Geothermal | Hydropower | Solar | Waste | Wind | Wood |
| $r = 0$ | 16.977 | 18.348 | 19.915 | 17.408 | 18.309 | 19.664 | 16.047 | 19.406 |
| $r = 1$ | 2.201 | 5.491 | 2.600 | 4.826 | 2.579 | 4.168 | 4.839 | 2.623 |

*Notes*: Numbers in table are the maximum eigenvalue test statistics (panel A) and the trace test statistics (panel B). The 5% critical value associated with rank $r = 0$ is 19.96 for the maximum eigenvalue test and 15.67 for the trace test. The 5% critical value associated with rank $r = 1$ is 9.24 for both tests.

that it takes at least a month for shocks to renewable consumption to affect nonrenewable energy prices. This assumption is reasonable because nonrenewable energy prices (e.g. crude oil prices) are determined in global markets, meaning that a change in the consumption of any single renewable energy source is unlikely to impact nonrenewable energy prices immediately. This assumption implies that $B_{12} = 0$ in Eq. (3), yielding Eq. (4):

$$B_0 = \begin{bmatrix} B_{11} & 0 \\ B_{21} & B_{22} \end{bmatrix}. \tag{4}$$

Premultiplying Eq. (1) by $B_0$ in Eq. (4) results in the structural VAR model in Eq. (5):

$$B_0 \begin{bmatrix} p_t \\ r_t \end{bmatrix} = B_0 \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} p_t \\ r_t \end{bmatrix} + \begin{bmatrix} u_{p,t} \\ u_{r,t} \end{bmatrix}. \tag{5}$$

As pointed by, among others, Edelstein and Kilian (2007, 2009), the advantage of this VAR approach in the energy price literature is that it enables us to isolate the linearly unpredictable component of changes in nonrenewable energy prices and renewable energy consumption, and also allows for reverse causality between the two variables. The impulse response functions (IRF) and forecast error variance decomposition (FEVD) analyses are done using this recursively identified VAR model.

## 5. Estimation results

This section presents the responses of aggregate and disaggregate measures of renewable energy consumption to a one-time, one standard deviation nonrenewable energy price shock. The solid lines in the figures presented hereinafter represent the cumulative impulse response estimates, whereas the dotted lines depict the 90% confidence bands obtained through the wild bootstrap procedure (Gonçalves and Kilian, 2004) with 1000 repetitions. We also report forecast error variance decompositions to evaluate the quantitative importance of the nonrenewable energy shocks for movements in the various renewable energy consumption categories.

### 5.1. The baseline model

Eight renewable categories plausibly affected by shocks to nonrenewable energy prices are studied. We analyze the aggregate consumption of renewable energy along with biomass, geothermal, hydropower, solar, waste, wind, and wood energy.[4] As stated previously, our baseline measure of nonrenewable energy prices is the BLS Processed Fuels and Lubricants PPI.

Fig. 6 presents the impulse responses of each of the eight renewable measures to a one standard deviation shock in nominal nonrenewable energy prices. The figure shows that the responses of total renewable energy consumption, hydropower, waste, and wind are not statistically different from zero at any forecast horizon. This finding is not surprising as total renewable energy consumption contains some renewable energy sources whose consumption by households and firms is not expected to change (at least in the short run) in response to a shock to nonrenewable energy prices. For example, while hydropower remains a reasonably cheap source of renewable energy, the costs associated with switching to a different source of energy are significant, implying that households and firms are unlikely to respond to an increase in nonrenewable energy prices by increasing their consumption of hydropower unless the increase in nonrenewable energy prices is large, widespread, and/or sustained. As noted by the New York State Energy Research and Development Authority (NYSERDA), the average time from when an individual makes the commitment to install a wind turbine until it is operational is two years (NYSERDA). Since our shocks are one-time shocks to nonrenewable energy prices, the finding that total renewable energy consumption, hydropower, wind, and waste respond in a statistically insignificant manner is not surprising.

Fig. 6 shows a statistically significant increase in total biomass consumption, as well as geothermal, solar, and wood consumption, following a one standard deviation shock to nonrenewable energy prices. Between months 1 and 5, the consumption of these categories increases respectively by around 1.8%, 2%, 3.2%, and 1.9%. At the first year and up until about eighteen months following the nonrenewable energy price shock, total biomass, geothermal, solar, and wood energy utilization increases by 0.9%, 1.2%, 2.3%, and 1%, respectively. These increases in renewable consumption arising from a nonrenewable energy price shock are what one would expect in light of the recent energy policy changes. Domestic concerns about nonrenewable energy price volatility and dependency on foreign fossil fuels prompted the US government to encourage more production and consumption of renewable fuels.[5] Our results are also consistent with other findings in the literature. For example, Guo et al. (2021) finds a 1% increase in oil prices leads to a long term increase in U.S. renewable energy consumption by 0.17%. Similarly, they find that a rise in oil prices of the same magnitude raises long term renewable energy consumption in Canada, Italy, Japan, and the U.K. by 0.18%, 0.53%, 0.16%, and 0.52%, respectively. Using generalized impulse response functions, Shah et al. (2018) find a positive and highly significant positive impact of oil prices on renewables, with a one standard deviation shock to oil prices increasing U.S. renewable energy by about 3%. Similar findings have been documented by Inchauspe et al. (2015), Managi and Okimoto (2013), and Haque (2021), among others.

Forecast error variance decompositions are typically used to analyze the contribution of structural shocks to the overall variability of the

[4] These categories are similar to the ones examined in the related literature (see, e.g., Dominioni et al., 2019).

[5] The Energy Act of 2005 and the Energy Independence Act of 2007 raised the target for various renewable sources' consumption. Among others, the bills also featured provisions for renewable energy R&D funding and tax breaks to incentivize clean energy production. Since 2005, the share of per capita primary energy consumption represented by renewable energy has more than doubled.

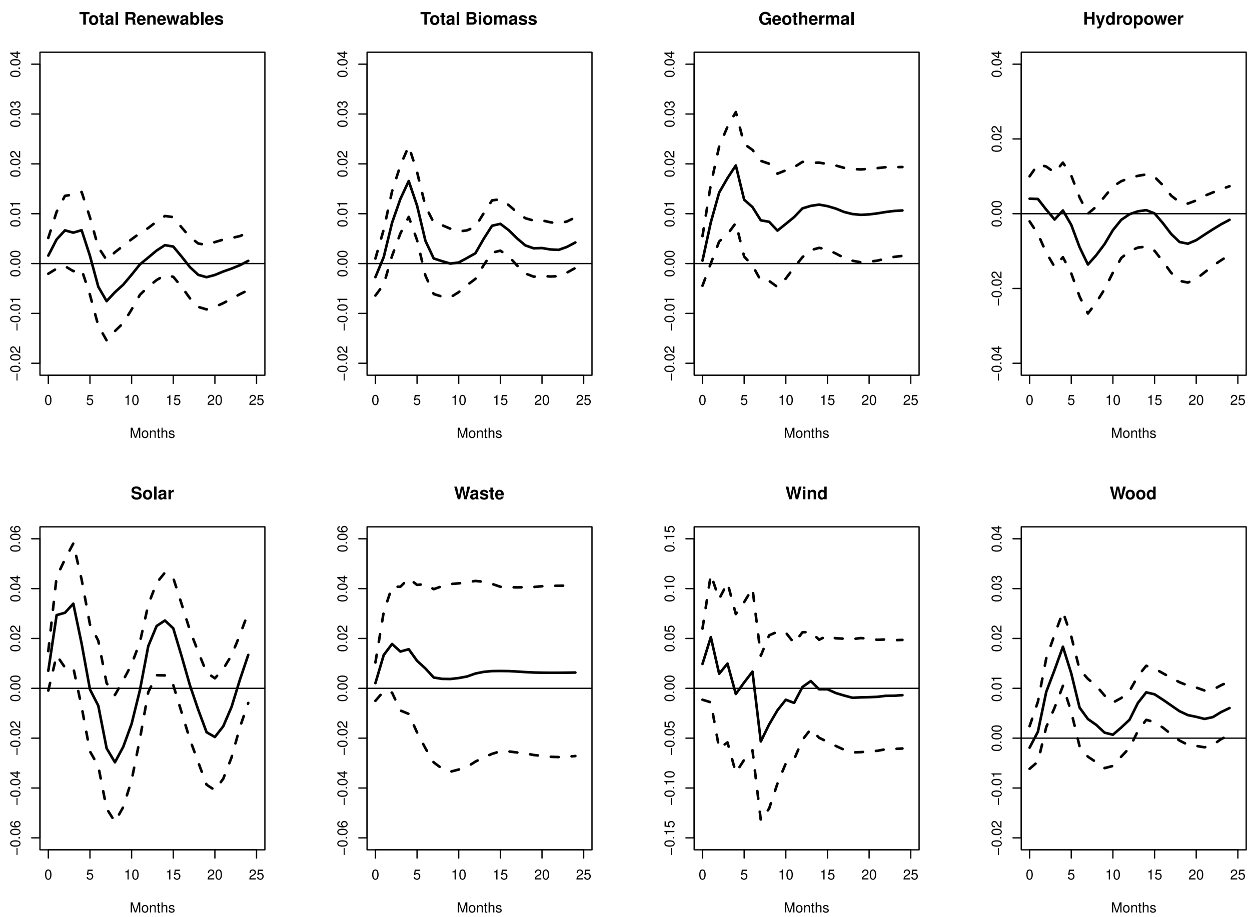


**Fig. 6.** Response of renewable energy consumption to a nominal nonrenewable energy price shock.

**Table 4**
Percent contribution of nonrenewable energy price shocks to the overall variability of renewable energy consumption.

| Horizon | Renewable | Biomass | Geothermal | Hydropower | Solar | Waste | Wind | Wood |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.113 | 0.273 | 0.213 | 0.008 | 0.013 | 0.002 | 0.631 | 0.246 |
| 2 | 0.444 | 0.274 | 0.224 | 0.693 | 0.014 | 0.419 | 0.657 | 0.253 |
| 3 | 1.501 | 0.712 | 0.223 | 3.142 | 0.062 | 0.440 | 0.748 | 0.703 |
| 6 | 2.458 | 2.126 | 0.543 | 3.751 | 2.115 | 0.697 | 1.138 | 1.674 |
| 12 | 3.877 | 3.394 | 0.957 | 5.046 | 5.821 | 0.870 | 1.156 | 2.496 |
| 24 | 4.713 | 3.717 | 1.006 | 6.386 | 7.882 | 0.883 | 1.154 | 2.732 |
| ∞ | 4.824 | 3.748 | 1.008 | 6.673 | 8.720 | 0.883 | 1.154 | 2.754 |

Notes: Forecast error variance decompositions based on structural VAR model. The sample period is 1973–2018.

variables in a VAR analysis. These forecast error variance decompositions show not only the importance of structural shocks to the overall variability of the variables in the model, but they also show how this importance varies through time. Table 4 presents the results of the forecast error variance decompositions from our baseline SVAR specification. It is clear that, in general, a shock to nonrenewable energy prices has a small explanatory power for the short and long-run movements in US renewable energy consumption. After two years, a shock to nonrenewable energy prices explains only about 3.7% and 4.7% of the fluctuations in total biomass and aggregate renewable energy consumption, respectively. Solar and hydropower consumption exhibit the largest response, with the shock to nonrenewable energy prices explaining 7.8% of the variation in solar energy consumption and 6.4% of the movements in hydropower consumption at the two-year forecast horizon. A similar shock has the least explanatory power for fluctuations in waste, wind, wood, and geothermal energy consumption. More precisely, after two years, the proportions of unpredictable movements in geothermal, waste, wind, and wood energy consumption explained by the nonrenewable price shock is equal are 1.01%, 0.88%, 1.15%, and 2.73%, respectively.

Historical decompositions (Wong, 2017; Balcilar et al., 2018) are another common output of VAR models, used to analyze the historical contribution of shocks to movements in variables in the VAR model. Specifically, the historical decompositions show how variables would have changed over time if a specific history of shocks had occurred. Fig. 7 presents the influence of the nonrenewable energy price shocks in driving fluctuations in renewable energy consumption of the eight different renewable energies in the predefined period. The solid lines display the historical decomposition, whereas the dashed lines are the actual time series of renewable energy consumption measures. The historical decomposition analysis shows that during the sample period (1970–2018), the nonrenewable energy price shock has a minor influence for historical fluctuations in the growth of the renewable energy consumption measures. As shown in the figure, the historical decompositions are essentially flat at zero at most time periods.

### *5.2. Sensitivity of the results to the measure of nonrenewable energy prices*

The impulse response functions, variance decompositions, and historical decompositions presented and discussed in Section 5.1 are based

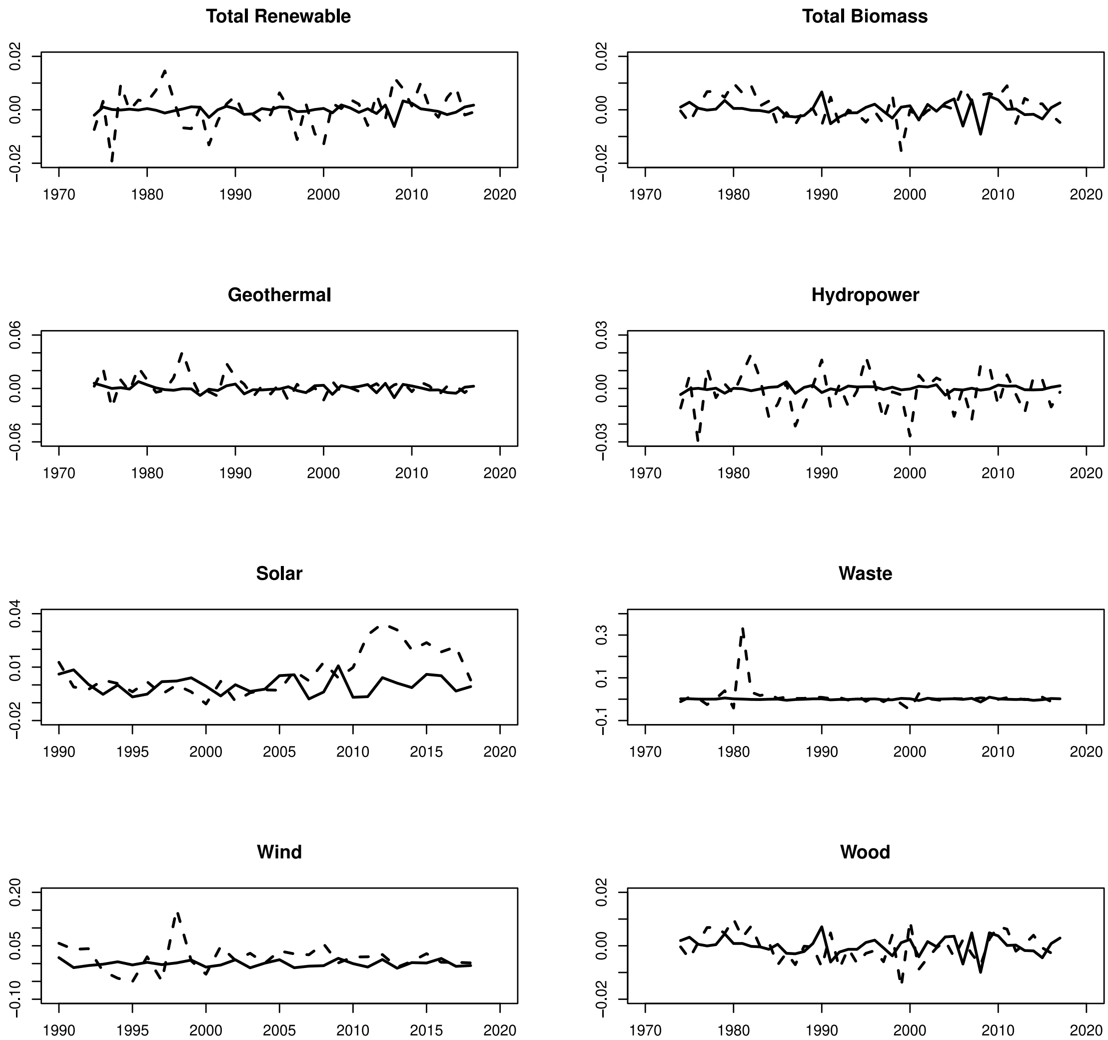


**Fig. 7.** Historical decomposition.

on VAR models estimated using nominal nonrenewable energy prices. In this section, we investigate the robustness of the findings when we use real nonrenewable energy prices. We also consider specifications in which nonlinear transformations of nonrenewable prices are used in the VAR models.

#### 5.2.1. Renewable energy consumption responses to a real nonrenewable energy shocks

As previously mentioned, while a plethora of papers in the literature use changes in nominal energy prices (see e., e.g., Jones and Kaul (1996), Bachmeier and Cha (2011), and Gradstein and Klemp (2020)), theoretical models of the transmission of energy price shocks are based on real rather than nominal energy prices. Consistent with that theoretical literature, we now study the responses of renewable energy consumption measures to a real nonrenewable energy price shock. Fig. 8 presents the results of this specification. The figure shows that using real nonrenewable energy prices leaves the baseline results qualitatively and quantitatively unchanged. Total biomass, geothermal, solar, and wood energy continue to exhibit positive and statistically significant increases following a shock of one standard deviation to real nonrenewable energy prices. In addition, the magnitude and timing are very similar. For example, the impulse responses displayed in Fig. 6 reported that total biomass consumption peaked at 5 and 15 months after a nonrenewable energy price spike at around 1.8% and 0.9% while for the case of real energy price shock shown in Fig. 8, the peaks are also recorded in the same months with a magnitude of 1.7% and 0.9%. Total renewable energy consumption, as well as hydropower, waste, and wind, also display insignificant responses as in the case of the nominal nonrenewable energy price shock shown in Fig. 6.

#### 5.2.2. Other measures of nonrenewable energy prices

While there are several reasons to expect the PPI of energy to be a reliable measure of energy price, especially from the producer's side (Edelstein and Kilian, 2009) it is not certain that the impact is the same for consumers. In Fig. 9, the CPI of nonrenewable energy is used. The results are very similar to the previous results in Figs. 6 and 9. The same categories of renewable consumption show medium to long-run increases in response to a one standard deviation nonrenewable energy price shock derived from the CPI for energy. Notably, in response to this shock, total biomass consumption increases by more than 1% after 5 and 10 months. Geothermal, solar, and wood energy also record a significant and similar rise. In addition, total renewable energy consumption displays a statistically significant but short-lived increase.

Table 5 shows the percentage of the forecast error variance of renewable energy consumption in each category explained under two specifications. This is based on the structural VAR models in response to a one standard deviation shock in nonrenewable energy prices. Panel A shows the percent contribution of real nonrenewable energy prices to the overall fluctuations in the various renewable energy measures, whereas in Panel B are the corresponding contributions of the CPI energy measure to the variability in renewable energy consumption.

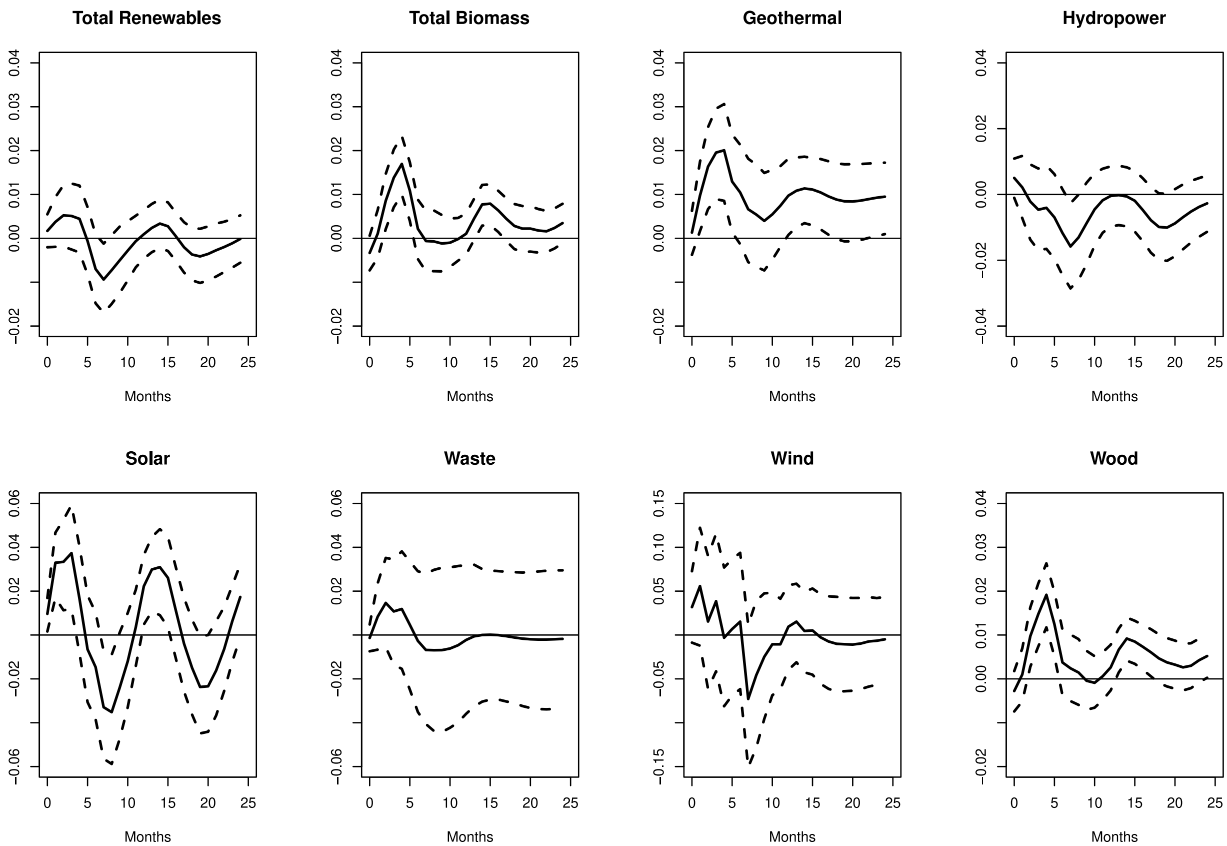


**Fig. 8.** Response of renewable energy consumption to a real nonrenewable energy price shock.

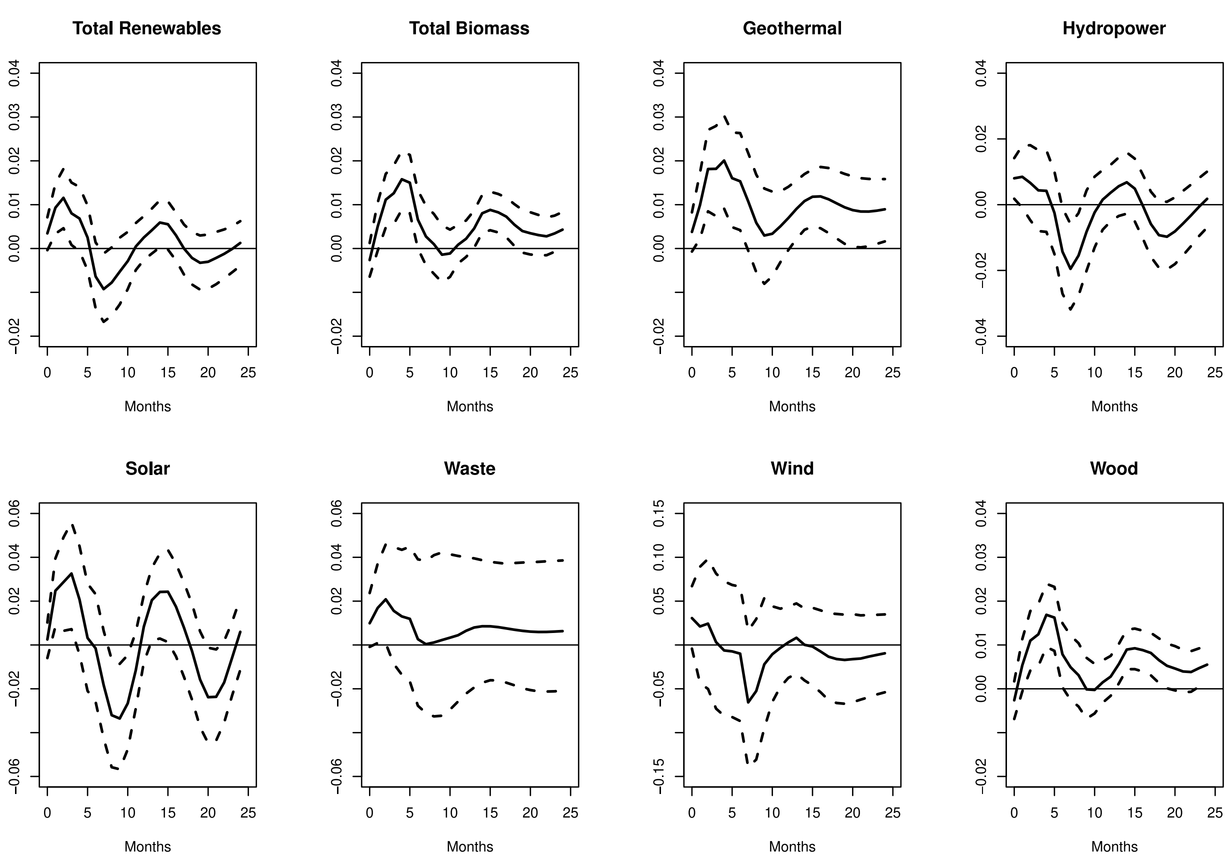


**Fig. 9.** Response of renewable energy consumption to a nonrenewable energy price shock: CPI energy.

**Table 5**
Percent contribution of nonrenewable energy price shocks to the overall variability of renewable energy demand: alternative nonrenewable energy price shocks.

| Horizon | Renewable | Biomass | Geothermal | Hydropower | Solar | Waster | Wind | Wood |
|---|---|---|---|---|---|---|---|---|
| Panel A: Percent contribution of real nonrenewable energy price shocks | | | | | | | | |
| 1 | 0.136 | 0.199 | 0.217 | 0.035 | 0.023 | 0.000 | 1.046 | 0.220 |
| 2 | 0.411 | 0.200 | 0.228 | 0.549 | 0.042 | 0.455 | 1.078 | 0.227 |
| 3 | 1.988 | 0.603 | 0.249 | 3.912 | 0.057 | 0.494 | 1.228 | 0.688 |
| 6 | 3.067 | 1.901 | 0.574 | 4.698 | 2.532 | 0.883 | 1.696 | 1.585 |
| 12 | 4.463 | 3.530 | 1.114 | 6.054 | 7.107 | 1.053 | 1.698 | 3.050 |
| 24 | 5.522 | 3.985 | 1.198 | 7.675 | 9.518 | 1.078 | 1.690 | 3.050 |
| ∞ | 5.679 | 4.034 | 1.200 | 8.032 | 10.534 | 1.079 | 1.689 | 3.084 |
| Panel B: Percent contribution of nonrenewable energy price shocks: CPI energy | | | | | | | | |
| 1 | 0.124 | 0.332 | 0.189 | 0.115 | 0.016 | 0.060 | 0.080 | 0.289 |
| 2 | 0.384 | 0.586 | 0.288 | 1.077 | 0.017 | 0.123 | 0.080 | 0.448 |
| 3 | 1.258 | 1.166 | 0.289 | 3.518 | 0.056 | 0.125 | 0.132 | 0.913 |
| 6 | 3.670 | 2.528 | 0.737 | 4.701 | 4.038 | 0.211 | 0.303 | 1.708 |
| 12 | 6.874 | 3.995 | 1.140 | 8.359 | 7.701 | 0.237 | 0.338 | 2.695 |
| 24 | 8.681 | 4.533 | 1.207 | 11.485 | 11.270 | 0.244 | 0.337 | 3.087 |
| ∞ | 8.976 | 4.583 | 1.208 | 12.275 | 12.615 | 0.244 | 0.337 | 3.118 |

Notes: Forecast error variance decomposition based on structural VAR model. The sample period is 1973–2018.

Panel A shows that a real nonrenewable energy price shock is quantitatively important to explain consumption changes in the various categories of renewable sources. Solar power displays the largest variability, rising by 9.5% within two years after the price shock. Next comes hydropower (7.6%), total renewables (5.5%), biomass (3.9%), wood (3.1%), wind (1.7%), geothermal(1.2%) and waste (1.1%). In Pane B, hydropower displays the largest variability (11.5%) two years after the shock. This is followed by solar (11.2%), total renewable (8.7%), biomass (4.5%), wood (3.1%), geothermal(1.2%), wind (0.3%) and finally waste (0.2%). These results imply that nonrenewable energy price shocks do not have much explanatory power for unpredictable movements in renewable energy consumption.

### 5.3. The role of asymmetries and nonlinearities

To investigate whether the impact of nonrenewable energy prices has asymmetric effects on renewable energy consumption, we now plot cumulative impulse response functions (together with their 90% confidence bands) of the renewable energy consumption measures to a one standard deviation positive nonrenewable energy price shock. As with the baseline results, the impulse response functions are from a series of bivariate VAR models containing the measure of renewable energy consumption of interest and the nonrenewable energy price measure, which in this case is the positive nonrenewable energy prices as defined and constructed in Section 3.2.2. Fig. 10 present the results with this approach.

Several striking features emerge from this specification. All categories of renewable energy consumption rise significantly following a one standard deviation shock to a positive nonrenewable energy price shock, albeit at different horizons. For example, the responses of total renewable energy consumption, biomass, waste, and wood are not statistically different from zero on impact, but turn significant between months one and six, after which they lose statistical significance. Hydropower and solar display significant contemporaneous increases following the shock, but these positive responses lose significance quickly (by the fourth month). For waste energy consumption, only the contemporary response is statistically different from zero. We do not present the responses to negative nonrenewable energy price shocks as they are all indistinguishable from zero in a statistical sense.

The empirical literature on the effect of oil price shocks has found that positive oil price shocks (oil price increases) have substantially larger and significant effects on the economy, while negative oil price shocks (oil price decreases) have no statistically significant economic effect (see, e.g., Mork (1989), Bernanke et al. (1997), and Edelstein and Kilian (2007, 2009)). Our finding that all measures of renewable energy consumption rise following a positive nonrenewable energy price shock (although of different magnitudes and at different horizons), while the responses to negative nonrenewable energy price shocks are insignificant bolsters the general argument in the literature that increases in oil prices, in particular, and energy prices more generally are what impact the economy.

The previous approach assumes that any positive change in nonrenewable energy prices, regardless of the magnitude, impacts renewable energy consumption. It is possible, however, that consumers and firms switch or increase their consumption of renewables mostly following large increases in nonrenewable energy prices that are unprecedented in recent history. We consider this possibility by replacing the percentage change in nonrenewable energy prices in the bivariate VAR models with the 3-year net nonrenewable energy price measure defined in Section 3.2.2.

The impulse response functions to a net price shock are shown in Fig. 11. All the renewable energy consumption measures, except wind energy, display positive and statistically significant responses at various forecast horizons. Total renewable, biomass, hydropower, waste, and wood consumption are insignificant on impact but show a significant increase two to five months after the shock. Solar energy consumption rises contemporaneously, but the increase is shortlived, whereas geothermal is insignificant instantaneously but exhibits a long-term significant increase for two years after the shock.

## 6. Do nonrenewable energy price shocks help forecast renewable energy consumption?

The findings above that nonrenewable energy price shocks increase renewable energy consumption beg the question of whether nonrenewable energy prices have predictive content for renewable energy consumption. We investigate this possibility by comparing the out-of-sample forecasting performance of a benchmark autoregressive AR($p$) model with the forecasting performance of several alternatives that include measures of nonrenewable energy prices.

The benchmark AR($p$) model is:

$$r_t = \alpha + \sum_{i=1}^{p} \beta_i r_{t-i} + \epsilon_t, \tag{6}$$

where $r_t$ is a measure of renewable energy consumption, $\epsilon_t$ is the error term, and $p$ denotes the lag length based on the Akaike Information Criterion (AIC) with $1 \leq p \leq 12$.

The alternative forecasting models are bivariate Autoregressive Distributed Lag (ADL) models of the form represented by Eq. (7),

$$r_t = \alpha + \sum_{i=1}^{p} \beta_i r_{t-i} + \sum_{i=0}^{q} \delta_i \Delta p_{t-i} + \epsilon_t, \tag{7}$$

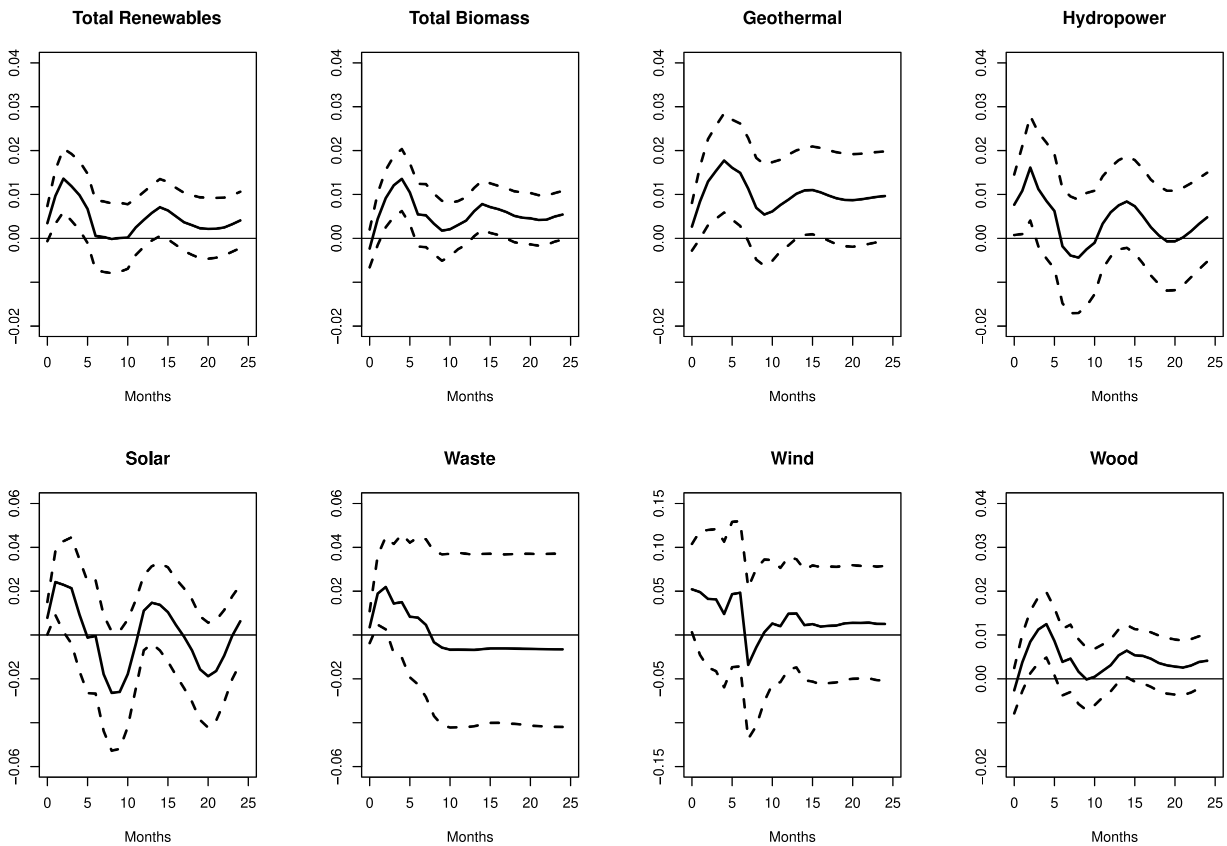


**Fig. 10.** Response of renewable energy consumption to positive nonrenewable energy price shocks.

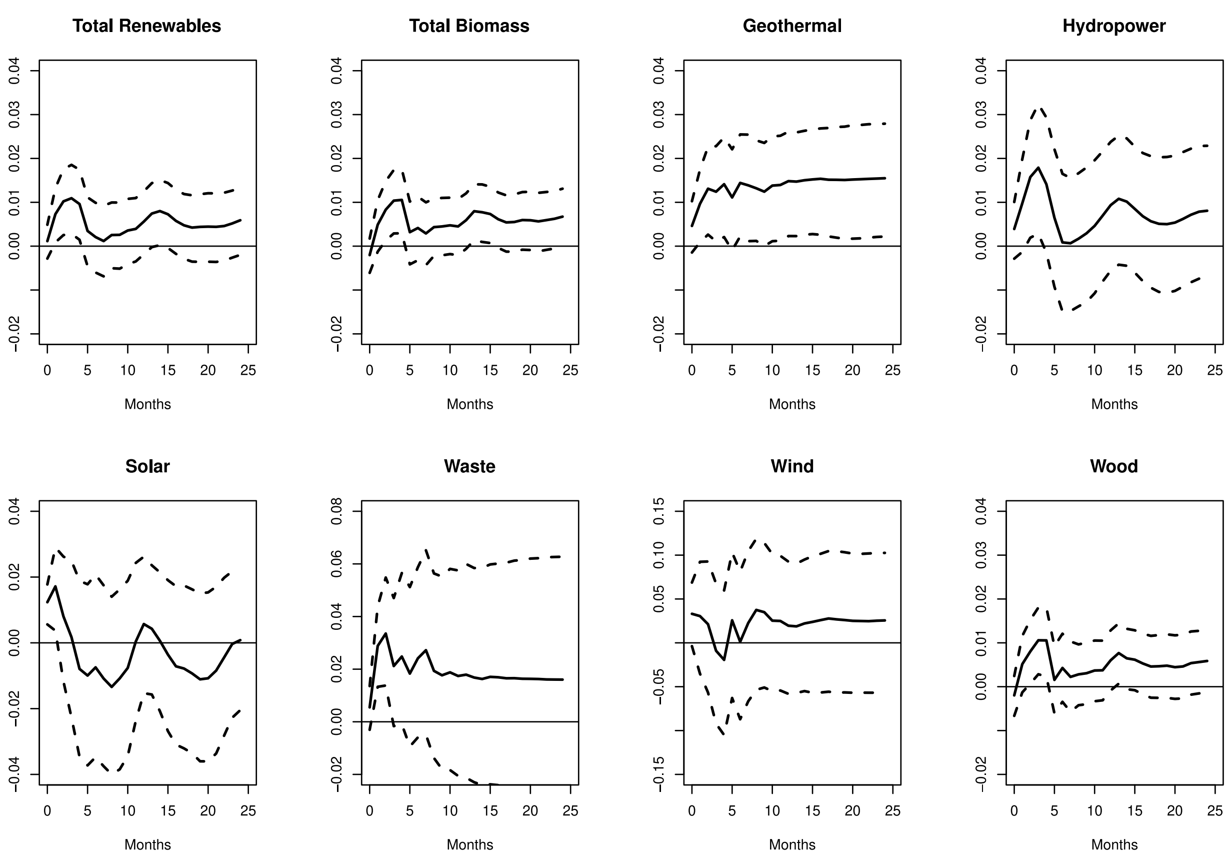


**Fig. 11.** Response of renewable energy consumption to net nonrenewable energy price shocks.

where, $\Delta p_t$ represents a measure of nonrenewable energy prices. In the first alternative model, which we denote by MODEL 1 in Tables 6 and 7, $\Delta p_t$ is the percentage change in the nominal PPI for Energy. In the second alternative forecasting model, denoted MODEL 2 in Tables 6 and 7, $\Delta p_t$ is the percentage change in the nominal CPI for Energy. MODEL 3 contains the percentage change in the real PPI for Energy as the measure of nonrenewable energy prices. In MODELS 4 and 5, the positive nonrenewable energy price change and the net nonrenewable energy price increase are used. These five models are the equivalent of the VAR models used to estimate the impulse response functions shown in Figs. 6 to 11. We also compare the forecasting performance of the benchmark AR($p$) model with forecasts from the random walk model. In all models, the lag length is determined by the AIC, as before. We use a recursive forecasting scheme in all forecasting models.

We evaluate the forecasting performance of the alternative forecasting models relative to the benchmark model by analyzing the Mean Squared Forecast Errors (MSFE) of each model relative to the MSFE of the benchmark AR($p$) model. This is calculated in relation to the benchmark AR($p$) model forecasts. We use a subset of the data as the training dataset and the other for prediction. Here, the training sample starts in January 1973 and ends in December 2005. For wind and solar energy, we begin in January 1989 because only then data become available for these series. Our choice for the end date is motivated by the concern created by the 2007–2009 recession. The relative MSFE measures the ratio of the MSFE of the $j$th candidate model forecasts relative to the benchmark AR($p$) model forecasts. Specifically, let $\Delta\widehat{r_{j,t+h}}$ denote the out-of-sample forecast of $\Delta r_{t+h}$ based on the $j$th forecasting model. Similarly, we denote forecasted values from the AR($p$) benchmark model by $\Delta\widehat{r_{1,t+h}}$. The relative MSFE of model $j$ relative to the AR($p$) benchmark is given by Eq. (8),

$$\text{relative MSFE} = \frac{\sum_{t=T_1}^{T_2-h}(\Delta r_{t+h} - \Delta\widehat{r_{j,t+h}})^2}{\sum_{t=T_1}^{T_2-h}(\Delta r_{t+h} - \Delta\widehat{r_{1,t+h}})^2} \tag{8}$$

where $T_1$ and $T_2$ denote the start and end dates over which the $h$-step-ahead forecasts are constructed. In this paper, $T_1$ is January 2006 and $T_2$ is December 2018. A value of the relative $MSFE < 1$ indicates that forecasts based on the $j$th model outperform the AR(1) benchmark forecasts. In other words, there is a smaller discrepancy between the actual renewable consumption series and the forecast when including information on nonrenewable prices. Moreover, the MSFE of a random walk model is compared to the AR($p$) model as additional evidence of improved performance.

### 6.1. One-step-ahead forecasts

Table 6 reports the results of the one-step-ahead forecast of the eight renewable categories under the six different forecasting model specifications. The main interest is to determine what happens to the forecast when we include nonrenewable energy prices via ADL($p,q$) models. MODEL 1 results in the table show that including the percentage change in the PPI for energy improves the forecasts of total renewable energy consumption, as well as for biomass and solar consumption. We arrive at a similar conclusion when instead, the forecasting model contains the CPI for energy (MODEL 2) or the real PPI for energy (MODEL 3). MODEL 4 and MODEL 5 indicate that considering asymmetries in nonrenewable energy prices helps improve the forecast of renewable energy consumption. In addition to total renewables, biomass, and solar, the MSFE for hydropower is now less than one in both MODELS 4 and 5. For the remaining measures of renewable energy consumption, our results demonstrate that the autoregressive model outperforms the forecasting models that contain measures of nonrenewable energy prices. In addition, we find that the benchmark AR($p$) model always forecasts better than the no change (random walk) model.

### 6.2. Multi-steps-ahead forecasts

Until now, we have focused on the one-step-ahead forecasts. However, it may take time for consumers and firms to switch to or increase their consumption of renewable energy sources following a nonrenewable energy price shock. Therefore it is important to consider the effect of the forecast horizon. Table 7 presents the MSFE of the various forecasting models relative to the MSFE of the benchmark autoregressive model at longer forecast horizons. Panel A shows that the MSFE of total renewable, total biomass, geothermal, hydropower, waste, and wood consumption resulting from the bivariate ADL($p,q$) models containing the nominal and real PPI for energy as the measure of nonrenewable energy (i.e., MODEL 1 and MODEL 3) relative to the MSFE of the benchmark AR($p$) model are all less than unity at the three-months-ahead horizon, suggesting that these outperform the benchmark AR($p$) forecasting model. At the same horizon, the ADL($p,q$) models containing nonlinear/asymmetric transformations of nonrenewable energy prices perform better than the AR($p$) model in forecasting five of the eight renewable energy consumption variables (total renewable, biomass, geothermal, hydropower, and wood).

At the six-months-ahead forecast horizon, we observe from Panel B of Table 7 the MSFE is less than one for all but two of the renewable energy consumption measures in MODEL 1, implying higher forecast accuracy of that model. As with the three-step-ahead, we find that adding nonlinear transformations of nonrenewable energy prices or the CPI for energy to the AR($p$) model helps improve forecasts of many of the measures of renewable energy consumption. The general conclusions from the twelve-months-ahead relative MSFE in Panel C are generally consistent with those found at shorter horizons. Taken together, the results in Tables 6 and 7 imply that nonrenewable energy price movements contain information about future changes in U.S. renewable energy consumption.

## 7. Conclusion and policy implications

### 7.1. Conclusions

The role of renewable energy in amending greenhouse gas emissions and the environmental crisis is well documented (see, e.g., Destek and Sinha (2020), Chen (2018)). As a consequence, global production and consumption of renewable sources of energy have risen considerably over the last several decades. Over the same time, nonrenewable energy prices have seen significant increases. One important question is whether and to what extent the rise in renewable energy consumption can be attributed directly to the increase in nonrenewable energy prices.

We address this question by estimating and analyzing impulse response functions from a series of bivariate VAR models. Each VAR model contains an appropriately defined transformation of nonrenewable energy prices and the percentage change in a measure of U.S. renewable energy consumption. We use as our main measure of nonrenewable energy prices the BLS Processed Fuels and Lubricants producer price index (PPI Energy). The advantage of this index is that it is a summary index of the prices of all energy goods used by firms as inputs in the production process. If firms, however, respond mainly to changes in the consumers demand for their goods and services, then a more appropriate measure of nonrenewable energy prices should be used for consumer energy prices rather than PPI Energy. For this reason, we also use the Consumer Price Index (CPI) for energy. We allow for the possibility that nonlinear transformations of nonrenewable energy prices may impact renewable energy consumption by including positive and net nonrenewable energy prices in some VAR specifications. The measures of renewable energy consumption we consider include total U.S. renewable energy consumption, as well as the consumption of biomass (including waste and wood), geothermal, hydropower, solar, and wind. In estimating the VAR models, we use monthly data spanning

 

**Table 6**
One-step-ahead MSFE of candidate models relative to AR($p$) benchmark.

| Renewable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Model 1* | *Model 2* | *Model 3* | *Model 4* | *Model 5* | *Model 6* |
| | ADL($p, q$) including energy prices | | | | | Random Walk |
| | PPI price | CPI price | Real price | Positive price | NOPI | |
| Total renewables | **.820** | **.911** | **.882** | **.722** | **.729** | 1.796 |
| Total biomass | **.673** | **.928** | **.880** | **.474** | **.546** | 6.781 |
| Geothermal | 180.400 | 345.600 | 267.100 | 96.900 | 113.200 | 5360.700 |
| Hydropower | 1.017 | 1.074 | 1.063 | **.958** | **.977** | 1.208 |
| Solar | **.805** | **.808** | **.708** | **.989** | **.957** | 3.831 |
| Waste | 2.131 | 3.643 | 3.003 | 1.383 | 1.55 | 37.244 |
| Wind | 1.437 | 1.499 | 1.492 | 1.346 | 1.358 | 1.706 |
| Wood | 1.365 | 1.795 | 1.682 | 1.067 | 1.203 | 9.567 |

Notes: Bold figures show higher accuracy relative to the benchmark AR($p$) model. Figures represent the ratio of MSFE between the benchmark and the comparison models.

**Table 7**
Multi-steps-ahead MSFE of candidate models relative to AR($p$) benchmark.

| Renewable | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Model 1* | *Model 2* | *Model 3* | *Model 4* | *Model 5* | *Model 6* |
| | ADL($p, q$) including energy prices | | | | | Random Walk |
| | PPI price | CPI price | Real price | Positive price | NOPI | |
| | Panel A: Three-steps-ahead MSFE of candidate models relative to AR($p$) benchmark | | | | | |
| Total renewables | **.702** | **.742** | **.726** | **.713** | **.746** | 1.572 |
| Total biomass | **.321** | **.738** | **.417** | **.572** | **.699** | 5.072 |
| Geothermal | **.519** | 2.447 | **.857** | **.566** | **.698** | 13.882 |
| Hydropower | **.884** | **.835** | **.886** | **.876** | **.904** | **.945** |
| Solar | 1.457 | 1.635 | 1.478 | 1.198 | 1.148 | 5.280 |
| Waste | **.612** | **.862** | **.624** | 1.089 | 1.341 | 11.271 |
| Wind | 1.109 | 1.303 | 1.169 | 1.094 | 1.141 | 1.395 |
| Wood | **.539** | **.816** | **.623** | **.840** | **.974** | 4.371 |
| | Panel B: Six-steps-ahead MSFE of candidate models relative to AR($p$) benchmark | | | | | |
| Total renewables | **.819** | **.792** | **.900** | **.808** | **.797** | 2.303 |
| Total biomass | **.346** | **.669** | **.492** | **.545** | **.615** | 7.902 |
| Geothermal | **.756** | **1.537** | **.818** | **.780** | **.875** | 9.847 |
| Hydropower | 1.031 | **.952** | 1.078 | 1.013 | 1.011 | 1.327 |
| Solar | 1.354 | 1.421 | 1.409 | 1.126 | 1.09 | 6.252 |
| Waste | **.752** | 1.048 | **.739** | 1.036 | 1.121 | 7.466 |
| Wind | **.993** | 1.109 | 1.03 | **.999** | 1.013 | 1.156 |
| Wood | **.661** | **.946** | **.726** | **.961** | 1.054 | 6.446 |
| | Panel C: Twelve-steps-ahead MSFE of candidate models relative to AR($p$) benchmark | | | | | |
| Total renewables | 1.004 | 1.054 | 1.033 | 1.025 | **.999** | 1.915 |
| Total biomass | **.663** | **.919** | **.709** | **.834** | **.944** | 6.501 |
| Geothermal | **.973** | 1.329 | **.954** | 1.054 | 1.151 | 9.606 |
| Hydropower | 1.237 | 1.222 | 1.247 | 1.239 | 1.224 | 1.304 |
| Solar | **.673** | **.690** | **.683** | **.656** | **.647** | 2.303 |
| Waste | **.807** | 1.286 | **.776** | 1.092 | 1.223 | 7.139 |
| Wind | **.993** | 1.072 | 1.015 | **.995** | **.999** | 1.095 |
| Wood | **.703** | **.975** | **.709** | **.966** | 1.089 | 5.394 |

Notes: Bold figures show higher accuracy relative to the benchmark AR($p$) model. Figures represent the ratio of MSFE between the benchmark and the comparison models.

the period January 1973 to December 2018. We apply a recursive identification scheme with nonrenewable energy prices ordered ahead of the renewable energy consumption measures. This reflects the assumption that whereas nonrenewable energy prices impact renewable energy consumption contemporaneously, innovations to renewable energy consumption impact nonrenewable energy prices with a lag of at least one month.

For many purposes, however, an equally relevant question is whether the information on nonrenewable energy prices can help to improve forecasts of renewable energy consumption. To answer this question, it is important to assess the historical out-of-sample forecasting performance of models that include nonrenewable prices. The reason is that the analysis of impulse response functions and hypotheses cannot estimate how much of out-of-sample forecasts can be improved. Accordingly, we investigate how well several bivariate autoregressive distributed lag models that contain nonrenewable energy prices perform out-of-sample relative to an autoregressive benchmark.

Our empirical analysis yields the following primary conclusions:

1. Shocks to nonrenewable energy prices have positive and statistically significant impacts on renewable energy consumption. Impulse response functions resulting from the baseline bivariate VAR model indicate that total biomass, geothermal, solar, and wood energy consumption rise significantly, although the magnitude and the timing of these effects vary. For instance, the peak response of total biomass is approximately 2%, which occurs four months after the shock to nonrenewable energy prices, whereas the peak response of solar energy consumption is about 4%. Furthermore, allowing for nonrenewable energy prices to have asymmetric effects results in statistically significant responses of all renewable energy consumption measures, highlighting the importance, as emphasized in the related economics literature, of considering asymmetric and nonlinear effects of energy price shocks.
2. The explanatory power of nonrenewable energy prices for the overall variability in renewable energy consumption is quantitatively small. Forecast error variance decomposition analyses

**Table 8**
Seasonality tests.

| Months | PPI Energy | Real prices | CPI energy |
|---|---|---|---|
| January | 4.80 | 0.03 | 4.75 |
| | (11.24) | (0.03) | (13.25) |
| February | 0.62 | 0.00 | −2.20 |
| | (11.24) | (0.03) | (13.25) |
| March | −2.16 | −0.01 | −4.37 |
| | (11.24) | (0.03) | (13.25) |
| April | −2.22 | −0.01 | −5.11 |
| | (11.24) | (0.03) | (13.25) |
| May | 4.77 | 0.02 | 5.02 |
| | (11.24) | (0.03) | (13.25) |
| June | 4.12 | 0.02 | 5.34 |
| | (11.24) | (0.03) | (13.25) |
| July | −0.88 | −0.00 | −2.24 |
| | (11.24) | (0.03) | (13.25) |
| August | 1.79 | 0.01 | 2.73 |
| | (11.24) | (0.03) | (13.25) |
| September | 1.90 | 0.01 | −0.62 |
| | (11.24) | (0.03) | (13.25) |
| October | 3.40 | 0.02 | 1.86 |
| | (11.24) | (0.03) | (13.25) |
| November | 5.52 | 0.03 | 5.00 |
| | (11.24) | (0.03) | (13.25) |
| Observations | 552 | 552 | 552 |
| R-squared | 0.00 | 0.01 | 0.00 |

**Table 9**
Wald test of structural break.

| | Estimated break date | Wald statistic |
|---|---|---|
| PPI energy | April, 2005 | 2148.58 |
| Real energy PPI | November, 2004 | 476.13 |
| CPI Energy | July, 2004 | 2192.70 |
| Total renewables | November, 1987 | 135.60 |
| Biomass | May, 2009 | 164.30 |
| Hydropower | August, 1987 | 740.04 |
| Geothermal | November, 1984 | 1841.60 |
| Wood | December, 1995 | 1029.63 |
| Waste | July, 1983 | 1788.87 |
| Solar | October 2013 | 1038.72 |
| Wind | June 2010 | 1948.60 |

reveal that regardless of the measure of nonrenewable energy prices or renewable energy consumption, the percentage of the variation in renewable energy consumption that is explained by nonrenewable energy prices does not exceed 13% in the long run.

3. In many cases, models with nonrenewable energy prices improve the forecast performance of simple AR models. This finding is generally robust to the measure of nonrenewable energy prices, changes in specification to allow for nonlinear transformations of nonrenewable energy prices, and changes in the forecast horizon. We, therefore, conclude that nonrenewable energy prices contain relevant information that helps to improve forecasts of renewable energy consumption.

The analysis in this paper relied on simple recursively identified bivariate linear SVAR models. Future research could consider alternative identification schemes that explicitly allow for nonlinearities and asymmetries, such as threshold regression models, or models time series models that require few identification restrictions, such as the method of local projections (Jorda, 2005).

### *7.2. Policy implications*

Sustainable development is crucial for modern economies (Zhou et al., 2008; Choi et al., 2012; Zhang et al., 2013; Bi et al., 2014). Our findings can be used by policymakers, business observers, and other stakeholders to profoundly understand the impact of nonrenewable energy costs/prices on the future of renewable energy. More specifically, recent nonrenewable energy price surges have reasserted the need for accelerated adoption of renewable energy.

Renewable adoption remains an important target for the US, as shown by the enactment of the Energy Act of 2005 and the Energy Independence Act of 2007. Insights from our results may contribute to policy formulation in several ways as follows. Policies that target the expansion of renewable energy consumption through taxation of fossil fuels ought to be formulated in a medium to long-term perspective as these impacts are delayed (the time horizon is crucial). We have also shown that consumers are relatively reactive to both real and nominal price fluctuations. This has important implications in the post-pandemic context. According to the US Department of Labor, general consumer year-to-year inflation has been at the highest in 40 years. CPI index rose by an estimated 9.1% since 2020. The energy component surged by a dramatic 41.6% during the same period.[6]

Our findings reassert the importance of the renewable energy tax breaks programs such as the Federal Investment Tax Credit (ITC). Given that renewable consumption is reactive to nonrenewable price changes, such initiatives lower the opportunity cost of renewable energy and incentive their utilization. Comello and Reichelstein (2016) report that the recent drop in the ITC program is anticipated to increase the cost of solar power by a nontrivial margin. We also know that energy prices vary greatly across US regions (Brown and Yücel, 2008). Our results contribute to the literature in favor of the fiscal decentralization of renewable energy incentive programs (Zhang et al., 2022) because some renewable sources are more abundant in different regions. The adequately formulated policy may improve local policy makers' decisions. This is crucial because renewable energy developers struggle with regional regulatory requirements. Susskind et al. (2022) show that developers are likely to abandon new projects when facing multiple financial roadblocks. An appropriate approach which is adequately tailored for each energy category may help formulate better policy. Given that many projects include power-purchase-agreements (PPA) with set rates approved by the Public Utility Commission, if federal and state requirement increase cost too much, renewable energy project are stalled or never started, adversely affecting the supply of these clean energies at a time of great price volatility in fossil fuel markets.

## CRediT authorship contribution statement

**Bebonchu Atems:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Jehu Mette:** Conceptualization, Methodology, Software, Data curation, Writing – original draft, Writing – review & editing. **Guoyu Lin:** Methodology, Data curation, Writing – original draft, Writing – review & editing. **Golshan Madraki:** Writing – original draft, Writing – review & editing, Investigation, Validation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[6] US Bureau of Labor Statistics (BLS).

## Data availability

Data will be made available on request.

## Appendix

### A.1. Checking for seasonality

Another concern may be the existence of a seasonal component in the series. We regress our series on monthly dummies (see Appendix-Table 8) but do not find evidence of seasonality driving nonrenewable energy prices.

We check whether a significant monthly seasonal component can be found in the price data by running a simple regression on 11 monthly binary indexes[7]:

$$y_t = \alpha + \beta_1 Jan + \beta_2 Feb + \cdots \beta_{11} Nov + u$$

where $y_t$ is the series of interest. Results from Table 8 show the absence of consistent monthly seasonality.

### A.2. Structural break testing

Over the decades spanning our dataset, the dynamic between nonrenewable energy price and renewable energy consumption may have changed substantially. For example, US solar and wind energy data does not become available until 1989. Even then, wind energy consumption remained a relatively minor component of the primary energy consumption for several years afterward. Events such as the Great Recession, and structural disturbances in energy markets due to wars may have caused structural changes in the relationship between renewable energy consumption and nonrenewable energy prices. Accordingly, in Table 9, we present the Wald test to investigate the existence of a structural break. Overall, the results do not show a consistent candidate date for a structural break within the series (see Appendix-Table 9). We leave a detailed analysis of structural breaks for future research.

## References

Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D., 2012. The environment and directed technical change. Amer. Econ. Rev. 102 (1), 131–166.

Acemoglu, D., Aghion, P., Hémous, D., 2014. The environment and directed technical change in a North–South model. Oxf. Rev. Econ. Policy 30 (3), 513–530.

Alvarado, R., Ponce, P., Alvarado, R., Ponce, K., Huachizaca, V., Toledo, E., 2019. Sustainable and non-sustainable energy and output in Latin America: A cointegration and causality approach with panel data. Energy Strategy Rev. 26, 100369.

Ambec, S., Crampes, C., 2012. Electricity provision with intermittent sources of energy. Resour. Energy Econ. 34 (3), 319–336.

Apergis, N., Payne, J.E., 2010. Renewable energy consumption and economic growth: evidence from a panel of OECD countries. Energy Policy 38 (1), 656–660.

Atems, B., Hotaling, C., 2018. The effect of renewable and nonrenewable electricity generation on economic growth. Energy Policy 112, 111–118.

Atems, B., Kapper, D., Lam, E., 2015. Do exchange rates respond asymmetrically to shocks in the crude oil market? Energy Econ. 49, 227–238.

Atems, B., Lam, E., 2013. The response of US States to exogenous oil supply and monetary policy shocks. Res. Appl. Econ. 5 (3), 106.

Atems, B., Melichar, M., 2019. Do global crude oil market shocks have differential effects on US regions? Macroecon. Dyn. 23 (5), 1978–2008.

Atems, B., Yimga, J., 2021. Quantifying the impact of the COVID-19 pandemic on US airline stock prices. J. Air Transp. Manag. 97, 102141.

Bachmeier, L., 2008. Monetary policy and the transmission of oil shocks. J. Macroecon. 30 (4), 1738–1755.

Bachmeier, L.J., Cha, I., 2011. Why don't oil shocks cause inflation? Evidence from disaggregate inflation data. J. Money Credit Bank. 43 (6), 1165–1183.

Balcilar, M., Ozdemir, Z.A., Ozdemir, H., Shahbaz, M., 2018. The renewable energy consumption and growth in the G-7 countries: Evidence from historical decomposition method. Renew. Energy 126, 594–604.

Barsky, R.B., Kilian, L., 2004. Oil and the macroeconomy since the 1970s. J. Econ. Perspect. 18 (4), 115–134.

Bastianoni, S., Pulselli, R.M., Pulselli, F.M., 2009. Models of withdrawing renewable and non-renewable resources based on Odum's energy systems theory and Daly's quasi-sustainability principle. Ecol. Model. 220 (16), 1926–1930.

Baumeister, C., Hamilton, J.D., 2019. Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. Amer. Econ. Rev. 109 (5), 1873–1910.

Benchekroun, H., van der Meijden, G., Withagen, C., 2019. An oligopoly-fringe non-renewable resource game in the presence of a renewable substitute. J. Econom. Dynam. Control 105, 1–20.

Bernanke, B.S., Gertler, M., Watson, M., Sims, C.A., Friedman, B.M., 1997. Systematic monetary policy and the effects of oil price shocks. Brook. Pap. Econ. Act. 1997 (1), 91–157.

Bi, G.-B., Song, W., Zhou, P., Liang, L., 2014. Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model. Energy Policy 66, 537–546.

Bowden, N., Payne, J.E., 2010. Sectoral analysis of the causal relationship between renewable and non-renewable energy consumption and real output in the US. Energy Sources B 5 (4), 400–408.

Brown, S.P., Yücel, M.K., 2008. Deliverability and regional pricing in US natural gas markets. Energy Econ. 30 (5), 2441–2453.

Burke, M.J., Stephens, J.C., 2018. Political power and renewable energy futures: A critical review. Energy Res. Soc. Sci. 35, 78–93.

Carfora, A., Scandurra, G., 2019. The impact of climate funds on economic growth and their role in substituting fossil energy sources. Energy Policy 129, 182–192.

Chen, Y., 2018. Factors influencing renewable energy consumption in China: An empirical analysis based on provincial panel data. J. Clean. Prod. 174, 605–615.

Choi, Y., Zhang, N., Zhou, P., 2012. Efficiency and abatement costs of energy-related CO2 emissions in China: A slacks-based efficiency measure. Appl. Energy 98, 198–208.

Coglianese, J., Davis, L.W., Kilian, L., Stock, J.H., 2017. Anticipation, tax avoidance, and the price elasticity of gasoline demand. J. Appl. Econometrics 32 (1), 1–15.

Comello, S., Reichelstein, S., 2016. The US investment tax credit for solar energy: Alternatives to the anticipated 2017 step-down. Renew. Sustain. Energy Rev. 55, 591–602.

Cooper, J.C., 2003. Price elasticity of demand for crude oil: estimates for 23 countries. OPEC Rev. 27 (1), 1–8.

Daly, H.E., 1990. Sustainable development: from concept and theory to operational principles. Popul. Dev. Rev. 16, 25–43.

Davidson, R., MacKinnon, J.G., et al., 2004. Econometric Theory and Methods, Vol. 5. Oxford University Press, New York.

DeJong, D.N., Nankervis, J.C., Savin, N.E., Whiteman, C.H., 1992. The power problems of unit root test in time series with autoregressive errors. J. Econometrics 53 (1–3), 323–343.

Destek, M.A., Sinha, A., 2020. Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic Co-operation and development countries. J. Clean. Prod. 242, 118537.

Dogan, E., Altinoz, B., Madaleno, M., Taskin, D., 2020. The impact of renewable energy consumption to economic growth: a replication and extension of. Energy Econ. 90, 104866.

Dominioni, G., Romano, A., Sotis, C., 2019. A quantitative study of the interactions between oil price and renewable energy sources stock prices. Energies 12 (9), 1693.

Edelstein, P., Kilian, L., 2007. The response of business fixed investment to changes in energy prices: a test of some hypotheses about the transmission of energy price shocks. BE J. Macroecon. 7 (1).

Edelstein, P., Kilian, L., 2009. How sensitive are consumer expenditures to retail energy prices? J. Monetary Econ. 56 (6), 766–779.

Elder, J., Serletis, A., 2010. Oil price uncertainty. J. Money Credit Bank. 42 (6), 1137–1159.

Elliott, G., Rothenberg, T.J., Stock, J.H., 1996. Efficient tests for an autoregressive unit root. Econometrica 64 (4), 813–836.

Gonçalves, S., Kilian, L., 2004. Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. J. Econometrics 123 (1), 89–120.

Gradstein, M., Klemp, M., 2020. Natural resource access and local economic growth. Eur. Econ. Rev. 127, 103441.

Granger, C.W., Newbold, P., 1974. Spurious regressions in econometrics. J. Econometrics 2 (2), 111–120.

Guo, Y., Yu, C., Zhang, H., Cheng, H., 2021. Asymmetric between oil prices and renewable energy consumption in the G7 countries. Energy 226, 120319.

Hamilton, J.D., 1996. This is what happened to the oil price-macroeconomy relationship. J. Monetary Econ. 38 (2), 215–220.

Hamilton, J.D., 2003. What is an oil shock? J. Econometrics 113 (2), 363–398.

Hamilton, J.D., 2010. Historical oil shocks. In: Handbook of Major Events in Economic History. Citeseer.

Hamilton, J.D., 2011. Nonlinearities and the macroeconomic effects of oil prices. Macroecon. Dyn. 15 (S3), 364–378.

Haque, M.I., 2021. Oil price shocks and energy consumption in GCC countries: a system-GMM approach. Environ. Dev. Sustain. 23 (6), 9336–9351.

[7] One month is left out to avoid the dummy variable trap (Wooldridge, 2015). We experiment with different benchmark months with similar results.

Inchauspe, J., Ripple, R.D., Trück, S., 2015. The dynamics of returns on renewable energy companies: A state-space approach. Energy Econ. 48, 325–335.
Ito, K., 2017. CO2 emissions, renewable and non-renewable energy consumption, and economic growth: Evidence from panel data for developing countries. Int. Econ. 151, 1–6.
Ivanovski, K., Hailemariam, A., Smyth, R., 2021. The effect of renewable and non-renewable energy consumption on economic growth: Non-parametric evidence. J. Clean. Prod. 286, 124956.
Jiménez-Rodríguez, R., 2015. Oil price shocks and stock markets: testing for non-linearity. Empir. Econ. 48 (3), 1079–1102.
Johansen, S., Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money. Oxf. Bull. Econ. Stat. 52 (2), 169–210.
Jones, C.M., Kaul, G., 1996. Oil and the stock markets. J. Finance 51 (2), 463–491.
Kaygusuz, K., 2007. Energy for sustainable development: key issues and challenges. Energy Sources B 2 (1), 73–83.
Keček, D., Mikulić, D., Lovrinčević, Ž., 2019. Deployment of renewable energy: Economic effects on the Croatian economy. Energy Policy 126, 402–410.
Kilian, L., 2008. The economic effects of energy price shocks. J. Econ. Lit. 46 (4), 871–909.
Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. Amer. Econ. Rev. 99 (3), 1053–1069.
Kilian, L., Lütkepohl, H., 2017. Structural Vector Autoregressive Analysis. Cambridge University Press.
Kilian, L., Park, C., 2009. The impact of oil price shocks on the US stock market. Internat. Econom. Rev. 50 (4), 1267–1287.
Kilian, L., Vigfusson, R.J., 2011. Are the responses of the US economy asymmetric in energy price increases and decreases? Quant. Econ. 2 (3), 419–453.
Kilian, L., Vigfusson, R.J., 2013. Do oil prices help forecast US real GDP? The role of nonlinearities and asymmetries. J. Bus. Econom. Statist. 31 (1), 78–93.
Kilian, L., Zhou, X., et al., 2021. The Impact of Rising Oil Prices on US Inflation and Inflation Expectations in 2020-23. Technical Report.
Kumar, S., Fujii, H., Managi, S., 2015. Substitute or complement? Assessing renewable and nonrenewable energy in OECD countries. Appl. Econ. 47 (14), 1438–1459.
Kwiatkowski, D., Phillips, P.C., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? J. Econometrics 54 (1–3), 159–178.
Managi, S., Okimoto, T., 2013. Does the price of oil interact with clean energy prices in the stock market? Japan World Econ. 27, 1–9.
Mankiw, N.G., 2020. Principles of Economics. Cengage Learning.
Martelli, E., Freschini, M., Zatti, M., 2020. Optimization of renewable energy subsidy and carbon tax for multi energy systems using bilevel programming. Appl. Energy 267, 115089.
Mette, J.A., 2021. An Econometric Study of Public Policy Applied to Renewable Energy, Economic Growth and Taxation (Ph.D. thesis). Kansas State University.
Mork, K.A., 1989. Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results. J. Polit. Econ. 97 (3), 740–744.
Nicolini, M., Tavoni, M., 2017. Are renewable energy subsidies effective? Evidence from Europe. Renew. Sustain. Energy Rev. 74, 412–423.
Nyman, J., 2018. Rethinking energy, climate and security: a critical analysis of energy security in the US. J. Int. Relat. Dev. 21 (1), 118–145.
Odum, H.T., Odum, E.C., 2011. A Prosperous Way Down: Principles and Policies. University Press of Colorado.
Opeyemi, B.M., 2021. Path to sustainable energy consumption: The possibility of substituting renewable energy for non-renewable energy. Energy 228, 120519.
Sadorsky, P., 2009. Renewable energy consumption, CO2 emissions and oil prices in the G7 countries. Energy Econ. 31 (3), 456–462.
Salim, R.A., Hassan, K., Shafiei, S., 2014. Renewable and non-renewable energy consumption and economic activities: Further evidence from OECD countries. Energy Econ. 44, 350–360.
Sequeira, T.N., Santos, M.S., 2018. Renewable energy and politics: A systematic review and new evidence. J. Clean. Prod. 192, 553–568.
Shah, I.H., Hiles, C., Morley, B., 2018. How do oil prices, macroeconomic factors and policies affect the market for renewable energy? Appl. Energy 215, 87–97.
Silk, J.I., Joutz, F.L., 1997. Short and long-run elasticities in US residential electricity demand: a co-integration approach. Energy Econ. 19 (4), 493–513.
Susskind, L., Chun, J., Gant, A., Hodgkins, C., Cohen, J., Lohmar, S., 2022. Sources of opposition to renewable energy projects in the United States. Energy Policy 165, 112922.
Wang, S.S., Zhou, D.Q., Zhou, P., Wang, Q., 2011. CO2 emissions, energy consumption and economic growth in China: A panel data analysis. Energy Policy 39 (9), 4870–4875.
Wong, B., 2017. Historical Decompositions for Nonlinear Vector Autoregression Models. Technical Report, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.
Wooldridge, J.M., 2015. Introductory Econometrics: A Modern Approach. Cengage learning.
Yang, X., He, L., Xia, Y., Chen, Y., 2019. Effect of government subsidies on renewable energy investments: The threshold effect. Energy Policy 132, 156–166.
Zafar, M.W., Shahbaz, M., Hou, F., Sinha, A., 2019. From nonrenewable to renewable energy and its impact on economic growth: the role of research & development expenditures in Asia-Pacific Economic Cooperation countries. J. Clean. Prod. 212, 1166–1178.
Zeng, B., Liu, Y., Xu, F., Liu, Y., Sun, X., Ye, X., 2021. Optimal demand response resource exploitation for efficient accommodation of renewable energy sources in multi-energy systems considering correlated uncertainties. J. Clean. Prod. 288, 125666.
Zhang, N., Zhou, P., Choi, Y., 2013. Energy efficiency, CO2 emission performance and technology gaps in fossil fuel electricity generation in Korea: A meta-frontier non-radial directional distance functionanalysis. Energy Policy 56, 653–662.
Zhang, C., Zhou, D., Wang, Q., Ding, H., Zhao, S., 2022. Will fiscal decentralization stimulate renewable energy development? Evidence from China. Energy Policy 164, 112893.
Zhao, Y., Zhang, Y., Wei, W., 2021. Quantifying international oil price shocks on renewable energy development in China. Appl. Econ. 53 (3), 329–344.
Zhou, P., Ang, B.W., Poh, K.L., 2008. A survey of data envelopment analysis in energy and environmental studies. European J. Oper. Res. 189 (1), 1–18.