Estimating the Economy-Wide Rebound Effect Using Empirically Identified Structural Vector Autoregressions

Stephan B. BRUNS Alessio MONETA David I. STERN*

April 14, 2023

Abstract

The size of the economy-wide rebound effect is crucial for estimating the contribution that energy efficiency improvements can make to reducing greenhouse gas emissions and for understanding the drivers of energy use. Existing estimates, which vary widely, are based on computable general equilibrium models or partial equilibrium econometric estimates. Using a structural vector autoregressive (SVAR) model, we identify the dynamic causal impact of structural shocks, including an energy efficiency shock. The identification method is based on independent component analysis. In this manner, we are able to estimate the rebound effect with a minimum of *a priori* assumptions. We apply the SVAR to U.S. monthly and quarterly data, finding that after four years rebound is around 100%, which implies that in the long run no energy is saved.

Keywords: Energy efficiency, Rebound effect, Structural VAR, Impulse response functions, Independent component analysis.

JEL classification: C32, Q43.

---

*Bruns: Centre for Environmental Sciences, Hasselt University, Belgium and Department of Economics, University of Göttingen, Germany (email: stephan.bruns@uhasselt.be). Moneta: Institute of Economics & EMbeDS, Scuola Superiore Sant'Anna, Pisa, Italy (email: a.moneta@santannapisa.it). Stern: Crawford School of Public Policy, Australian National University, Australia (email: david.stern@anu.edu.au). We thank the Australian Research Council for funding under Discovery Project DP160100756: "Energy Effi-

1 Introduction

Governments and international organizations are expecting energy efficiency improvements to make a major contribution to reducing greenhouse gas emissions and improving energy security (Stern, 2017). But energy savings are usually less than the improvement in energy efficiency. The size of this rebound effect is crucial for estimating the contribution that energy efficiency improvements can make to reducing greenhouse gas emissions as well as for understanding the drivers of energy use. The micro-economic direct rebound effect occurs when an energy efficiency innovation reduces the cost of providing an energy service, such as heating, lighting, or transport, and, as a result, users increase the use of the service offsetting some of the energy efficiency improvement. But there are also changes in the use of complementary and substitute goods or inputs and other flow-on effects that affect energy use across the economy known as indirect rebound effects. Together these constitute the economy-wide rebound effect.

The size of the economy-wide rebound effect is controversial (Gillingham et al., 2016) and insufficiently researched (Turner, 2013). Existing estimates vary widely from "backfire" (also known as the "Jevons paradox"), where energy use increases following an efficiency improvement, to super-conservation, where energy use falls by more than the efficiency improvement (Stern, 2011; Saunders, 2013; Turner, 2013). Previous research uses partial equilibrium econometric models, computable general equilibrium (CGE) models, or derives the effect from theoretical partial or general equilibrium models and quantifies

ciency Innovation, Diffusion and the Rebound Effect." This paper was presented at the 41st IAEE International Conference in Groningen, the 5th Asian Energy Modelling Workshop in Singapore, the Arndt Corden Department of Economics at the Australian National University, the 4th Monash Environmental Economics Workshop, the 8th Mannheim Energy Conference, the School of Management at the Polytechnic University of Milan, GREDEG, University of Nice - Sophia Antipolis, and the Leibniz Institute for Economic Research (RWI Essen). We thank Panittra Ninpanit, Don Fullerton, Mattia Guerini, Rocco Mosconi, and other attendees at our presentations for helpful comments.

it using existing estimates of elasticities and other parameters. The latter two approaches depend on many *a priori* assumptions and the parameter values adopted, while the econometric models do not include all mechanisms that might increase or reduce the rebound and mostly do not credibly identify the rebound effect. In this paper, we develop a structural vector autoregressive (SVAR) model that is empirically identified using independent component analysis, which imposes statistical conditions on the shocks. We apply the model to U.S. data, finding that after four years the economy-wide rebound is around 100%. This finding is robust to alternative data frequencies, alternative identification schemes, and various control variables, including indices of the changes in the composition of the economy and energy supply as well as weather effects.

Turner (2013) notes that there is a lack of consensus in the rebound literature on what is meant by energy efficiency. Some authors include substitution of capital or materials for energy, such as the installation of insulation, in their definition of energy efficiency improvements (e.g. Sorrell et al., 2009) or examine the secondary changes resulting from an initial behavioral energy conserving action (van den Bergh, 2011). We focus on rebound effects due to energy-saving technological change. Therefore, we define energy efficiency improvements as those that save energy due to the adoption of more efficient cost-reducing technology and define the rebound effect as the resulting responses of economic agents that cause the actual energy savings to differ from the potential energy savings.

Most empirical research on the rebound effect focuses on the direct rebound effect (Sorrell et al., 2009) where households and firms consume more energy services in response to efficiency improvements that reduce the energy required to provide the same level of service and, therefore, its cost. Indirect rebound effects include the energy use effects of: the increase in demand for complementary energy services (and reduction in demand for substitutes) (Berkhout et al., 2000); the increase in the use of energy to produce other complementary goods and services (Berkhout et al., 2000); the effect of reduced energy prices due to the fall in energy demand (Borenstein, 2015); and a long-run increase in total factor productivity, which increases capital accumulation and economic growth and, as a result, energy use (Saunders, 1992). These direct and indirect effects sum to the economy-wide rebound effect. Others (e.g. Azevedo, 2014; Gillingham et al., 2016) define changes in prices and growth effects as macro effects that are distinct from indirect rebound effects.

Estimates of the size of the direct rebound effect tend to be fairly modest positive numbers (Sorrell et al., 2009). It is usually assumed that the indirect rebound is positive and that the economy-wide rebound will be larger in the long run than in the short run (Saunders, 2008). Turner (2013) argues, instead, that because the energy used to produce a dollar's worth of energy is higher than the embodied energy in most other goods, the effect of consumers shifting spending to goods other than energy will mean that the indirect rebound could be negative and the economy-wide rebound may also be negative in the long run. Borenstein (2015) presents further arguments for negative rebound.

Saunders (1992, 2015) developed a simple partial equilibrium model using an aggregate CES production function with factor-augmenting technical change to compute the effect of energy-augmenting technical change on energy use. Evaluating the size of the rebound from the model depends on having good estimates of the production parameters —- a notoriously difficult problem (León-Ledesma et al., 2010) — and assumes that the economy has a very simple structure. Because the energy price is held constant, this is a partial equilibrium approach.

Lemoine (2019) conducts a general equilibrium analysis of the rebound effect with a large number of consumption goods sectors with heterogenous constant elasticity of substitution (CES) technologies and CES preferences with a common elasticity of substitution in consumption. Rebound is increasing in the elasticity of substitution in production between energy and labor (as found by Saunders (1992)) and the elasticity of substitution in consumption. General equilibrium effects tend to increase (decrease) rebound beyond the partial equilibrium effect in energy- (labor-) intensive sectors. Reduced (increased) energy use in the energy-intensive energy supply sector as a result of the fall (increase) in energy use elsewhere in the economy is important in reducing (magnifying) rebound when rebound is less (greater) than 100%. Both backfire and super-conservation are possible. By parameterizing the theoretical rebound effect, Lemoine estimates that economy-wide rebound due to energy efficiency innovations in all sectors in the US is 38%.

There are many CGE or other simulation model estimates of the economy-wide rebound (e.g. Turner, 2009; Barker et al., 2009; Turner and Hanley, 2011; Broberg et al., 2015; Adetutu et al., 2016; Koesler et al., 2016; Lu et al., 2017; Wei and Liu, 2017). However, Turner (2009) finds that, depending on the assumed values of the parameters in a CGE model, the rebound effect for the UK can range from negative to more than 100%. Therefore, most CGE models do not provide strong evidence on the size of the economy-wide rebound effect. Rausch and Schwerin (2018) build a small general equilibrium macro-economic model that is calibrated on U.S. annual data from 1960 to 2011. This is a putty-clay model, where once a capital vintage is chosen, no substitution between energy and capital is possible. The energy efficiency — energy services per unit energy — of energy-using capital vintages is chosen depending on capital and energy prices at the time of investment. Therefore, they do not distinguish between energy-capital substitution and energy augmenting technical change. The calibration compares observed and counterfactual scenarios with no energy efficiency improvements by holding energy and energy-using capital prices constant, finding a rebound of 102%.

Several methods have been proposed to empirically estimate the rebound effect (e.g.

Adetutu et al., 2016; Shao et al., 2014; Lin and Du, 2015; Galvin, 2014; Saunders, 2013; Orea et al., 2015), but all of these are partial equilibrium methods and/or do not credibly identify a causal effect of energy efficiency changes on energy use, which is needed to claim a rebound effect (Gillingham et al., 2016).[1] The best existing approach, in our opinion, is represented by Adetutu et al. (2016), who use a stochastic frontier model to estimate energy efficiency and then a dynamic panel model to estimate the effect of efficiency on energy use. Again, they control for energy prices and output resulting in a partial equilibrium estimate. They estimate that in the short run rebound is 90% while in the long run super-conservation occurs with a negative rebound of 36%. This is because their dynamic model set-up requires that if energy efficiency improvements reduce energy use in the short run, then they reduce energy use by more in the long run.

Historical research hints that the economy-wide rebound effect could be large. Both van Benthem (2015) and Csereklyei et al. (2016) find that energy intensity in developing countries today is similar to what it was in today's developed countries when they were at similar income levels. But, van Benthem (2015) argues that the energy efficiency of many current products in developing countries is much better than that of comparable products in developed countries when they were at the same income level. He finds that energy savings from access to more efficient technologies have been offset by other trends, including a shift toward more energy-intensive consumption bundles and compositional changes in industry such as outsourcing. Though such studies cannot identify causal effects, they suggest that the economy-wide rebound effect is close to 100%. [2]

[1]For example, some studies (e.g. Lin and Du, 2015) assume that changes in energy intensity are equivalent to changes in energy efficiency. But energy intensity already incorporates rebound as well as the effects of many other variables.

[2]Hart (2018) provides a theoretical model of this shift to more energy intensive goods. Energy efficiency improvements reduce the cost of energy intensive goods most, causing a shift to a more energy intensive consumption bundle over time.

SVAR models have several advantages in the context of estimating the economy-wide rebound effect. They are small, multivariate, dynamic, time series econometric models that are estimated directly from the data, with the main aim of estimating the dynamic causal effects of *structural shocks*, which are economically meaningful and mutually independent exogenous forces (Ramey, 2016). These shocks are not directly observed by the econometrician, but need to be identified. The standard approach imposes *a priori* restrictions on the structural model. We use a data-driven approach to identify the structural model, based on general statistical assumptions, thus avoiding economic-theoretic restrictions. In this framework, it is possible to measure the response of energy use (and other variables) to an energy efficiency shock. We use this impulse response function to calculate the rebound effect.

Unlike previous econometric approaches in the economy-wide rebound literature, impulse response functions derived from SVAR models can capture general equilibrium effects, as all the variables are endogenous and can evolve in response to a shock. Moreover, SVAR models can recover the response to truly exogenous shocks addressing the credible identification issue. On the other hand, some adaptation may already occur as an energy efficiency improvement is "installed" that our empirical measure of the energy efficiency shock will miss. Therefore, our estimate of the rebound effect will be biased in a predictable way, as discussed below.

There is a quite established econometric tradition of identification methods based on atheoretical search procedures (e.g. Swanson and Granger, 1997; Bessler and Lee, 2002; Demiralp and Hoover, 2003; Moneta, 2008). This literature shows that tests of zero partial correlations among the estimated errors of the VAR model allow partial identification of the SVAR model. This specific approach, although it eschews economic-theoretic assumptions, is based on graph-theoretic conditions (Pearl, 2009; Spirtes et al., 2000), whose reliability in an economic time-series context is often hard to assess (see Hoover, 2001). Moreover, it typically makes use of the normality assumption, which can fail to hold in economic data. In this paper, we use Independent Component Analysis, a statistical identification procedure based on a quite different framework. This set of tools has been shown to be particularly powerful in the statistical identification of SVAR models (see e.g. Moneta et al., 2013; Capasso and Moneta, 2016; Gouriéroux et al., 2017; Lanne et al., 2017; Herwartz, 2018). Its key assumptions are the statistical independence of the shocks and the non-Gaussianity of the data, which can be easily checked empirically.

The next section of the paper lays out our econometric approach and empirical model, the third section discusses the data and results, and the final section provides the discussion and conclusions.

2 Empirical Approach

2.1 The SVAR Model

We use an SVAR model to determine the effect of an exogenous improvement to energy efficiency that we identify as a "technology shock" (Gali, 1999). Thinking of energy use as the equilibrium outcome of the demand and supply of energy, the major factors resulting in changes in energy use will be changes in the price of energy and in income – at the macroeconomic level, GDP. Building on Gali (1999) and Kilian (2009),[3] we can represent this vector of three variables as the outcome of cumulative shocks to GDP, the price of

[3]Gali (1999) introduces the idea of a technology shock, though his model builds in turn on Blanchard and Quah (1989). Kilian (2009) uses a three-variable model including oil production, the price of oil, and output.

energy, and an energy-specific shock using the structural VAR:

$$A_0 x_t = A_0 \mu + \sum_{i=1}^{p} A_0 \Pi_i x_{t-i} + \varepsilon_t \tag{1}$$

where t indexes time, $x_t = [e_t, p_t, y_t]'$ is the vector of the logs of energy use, the price of energy, and GDP, respectively, $\varepsilon_t = [\varepsilon_{et}, \varepsilon_{pt}, \varepsilon_{yt}]'$ is the vector of white noise shocks with $\text{var}(\varepsilon_t) = I$. A_0 and the Π_i ($i = 1, \ldots, p$) are 3×3 matrices of parameters and μ is a 3×1 vector of constants, to be estimated. We interpret ε_{et} as an energy efficiency shock, as it represents the exogenous reduction in energy use that is not due to exogenous shocks to GDP or energy prices. The effects of shocks on the dependent variables can be independently assessed, as each is associated with a particular equation. The matrix A_0 is, therefore, the matrix of the contemporaneous effects of the endogenous variables on each other. This results in a simultaneity and identification problem. The reduced form VAR model that can be directly estimated from the data is given by

$$x_t = \mu + \sum_{i=1}^{p} \Pi_i x_{t-i} + u_t \tag{2}$$

where u_t is a vector of white noise errors that may be correlated across equations. We discuss in Sections 2.3 and 2.4 how the structural shocks, ε_t, can be recovered from the estimated residuals, $\hat{u}_t$.

We measure energy quantity here in BTU rather than a volume index because our focus is on the standard definition of the rebound effect, which refers to heat units of energy. The price of energy is, therefore, the total cost of energy divided by BTUs. Changes in this energy price may reflect a shift in the energy mix as well as changes in the prices of individual energy carriers. As energy inputs vary in their productivity or energy quality (Stern, 2010), a shift to higher quality energy carriers such as primary electricity instead of coal would tend to reduce energy use, *ceteris paribus*. Shifts in economic activity from more energy intensive sectors to less energy intensive sectors and *vice versa*, will also affect energy use (Stern, 2012). Therefore, as our main robustness check we consider a second model that includes measures of the structure of the economy and energy quality.[4] This five variable and shock framework accounts for the most important other factors:

$$A_0\tilde{x}_t = A_0\mu + \sum_{i=1}^{p} A_0\Pi_i\tilde{x}_{t-i} + \tilde{\varepsilon}_t \tag{3}$$

where $\tilde{x}_t = [e_t, p_t, y_t, s_t, q_t]'$ and s_t and q_t are the logs of structure (i.e. industrial production) and energy quality at time t, $\tilde{\varepsilon}_t = [\tilde{\varepsilon}_{et}, \tilde{\varepsilon}_{pt}, \tilde{\varepsilon}_{yt}, \tilde{\varepsilon}_{st}, \tilde{\varepsilon}_{qt}]$ is the vector of shocks, μ is now a 5×1 vector of constants, and the A_0 and Π_i $(i = 1, \ldots, p)$ are 5×5 matrices of parameters.

2.2 Estimating the Rebound

We use the impulse response function of energy with respect to the energy efficiency shock to measure the rebound effect. The SVARs are estimated using variables in levels to allow the energy efficiency shock to potentially have a permanent effect on energy use. Using the subscript i to denote the number of periods since the energy efficiency improvement, the rebound effect is given by

$$R_i = 1 - \frac{\Delta e_i}{\Delta \hat{e}} = 1 - \frac{\text{Actual}}{\text{Potential}} \tag{4}$$

where $\Delta \hat{e}$ is the potential change in energy use, and Δe_i is the actual change in energy use.[5] We measure the potential energy savings as the energy efficiency shock.

[4] We further explore robustness regarding weather effects and using energy use and GDP per capita instead of total GDP and energy use as discussed in Section 3.4.

[5] Usually, the rebound effect is presented in terms of the potential and actual energy savings. The signs of these terms are the opposite of the actual and potential change in energy use, but the rebound formula is identical. As our model tracks changes in energy use, we prefer to define the rebound effect in terms of changes in energy use rather than savings.

As an example, if in response to a 1% improvement in energy efficiency actual energy use declines 0.5%, the rebound effect is 50%. On the other hand, if energy use actually increased by 0.2%, rebound would be 120%. Figure 1 shows the impulse response function of the log of energy with respect to an energy-specific shock. Initially, energy use is reduced by 1% in response to the shock. Over time these savings decrease and, in this example, eventually energy use increases over its pre-shock level so that there is backfire.

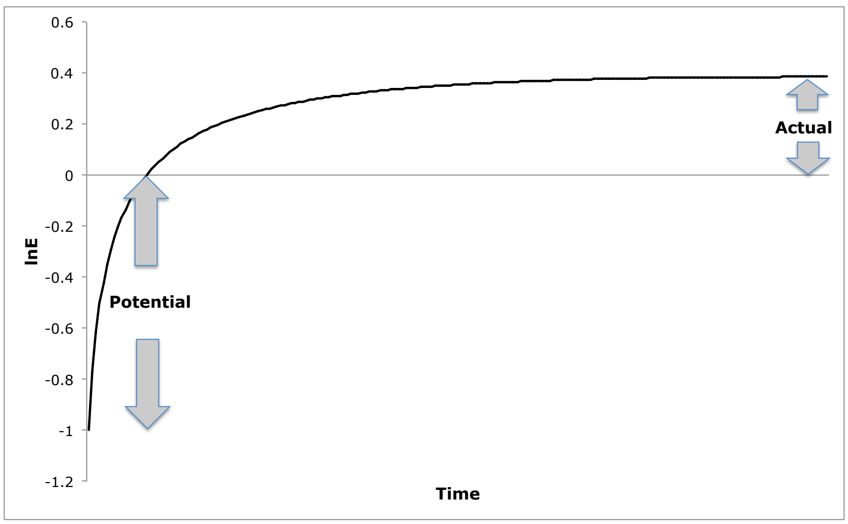

Figure 1: Impulse response function for energy use and the rebound effect. Notes: The vertical axis shows the log of energy use and the horizontal axis shows time. "Potential" depicts an example potential energy saving of 1% while "actual" depicts the actual change in energy use, which is given here as an increase in energy use (backfire). The rebound effect can then be estimated according to Equation (1).

There are three limitations on our ability to identify energy efficiency shocks and the rebound effect, assuming that our model captures the important factors that affect energy use apart from energy efficiency.

First, not all energy efficiency changes might be captured by our identified energy efficiency shock. Price shocks might affect the rate of energy efficiency improvements too. Note, however, that it is not changes in prices that directly cause changes in technology in the theory of directed technical change. Rather, the price level affects the rate of innovation (Acemoglu, 2002). If the elasticity of substitution between energy and other inputs is less than unity, then an increase in the price of energy relative to other inputs will increase the rate of energy-augmenting technical change (Shanker and Stern, 2018).

If energy efficiency improvements are positively correlated with labor-augmenting technical change then shocks to GDP due to labor-augmenting innovations will be associated with improvements in energy efficiency. Our energy efficiency shocks can only measure the part of energy efficiency improvements which are orthogonal to labor augmenting technical change shocks. Our estimate of the rebound effect will be only that in response to these energy-specific efficiency improvements. If the response of energy use to other innovations is different, then we will not capture the average rebound effect in response to all energy efficiency improvements.

Second, some of the rebound may happen instantaneously together with the energy efficiency improvement. For example, a car manufacturer might introduce a new model with a more fuel-efficient engine that is also larger and heavier than the previous model, so that the fuel economy of the new model shows less improvement than the engine efficiency improvement.[6] New more energy efficient houses might be larger than existing houses thus requiring more energy services than older houses. Consumers might also immediately adapt their behavior to the new technology. Our approach to measuring the size of the rebound relies on the rebound taking place over a period of time.

Figure 2 shows how this will affect the estimated rebound. Energy use is reduced by

[6] In both the U.S. (Knittel, 2011) and Austria (Meyer and Wessely, 2009) the weight and power of cars and light trucks increased in recent decades as engine fuel efficiency increased. In the U.S. the actual fuel economy of cars only increased by 6.5%, while horsepower increased by 80% and weight by 12%. There was also a strong shift towards light trucks, which have lower fuel economy and increased in power and weight by even more.

1% due to an efficiency improvement, but the observed energy efficiency shock reduces energy use by only 0.75%. In the energy saving case in Figure 2, the true rebound is $1 - \frac{0.5\%}{1.0\%} = 50\%$ but the estimated rebound is $1 - \frac{0.5\%}{0.75\%} = 33\%$. In the backfire case, the true rebound is $1 - \frac{-0.25\%}{1.0\%} = 125\%$, but the estimated rebound is $1 - \frac{-0.25\%}{0.75\%} = 133\%$. So, where there are energy savings our estimated rebound will underestimate the true rebound, and where there is backfire our estimated rebound will exaggerate the rebound. The closer the true rebound is to 100%, the smaller this error will be. Hence, monthly data should provide a better estimate of the size of the efficiency shock and rebound as it should capture more of the early changes in energy use. In our econometric analysis, we use both monthly and quarterly data, and we indeed find that the estimated rebound tends to be larger for quarterly data compared to monthly data if the estimated rebound is above 100% and *vice versa* if the estimated rebound is below 100% (Tables 4 and 5).

Third, an underlying assumption of SVARs is that the shocks are unanticipated.[7] If the efficiency improvement is anticipated, economic agents may plan in advance to increase energy use at the same time as the efficiency improvement actually takes place. For example, firms may plan to install more energy efficient machinery and plan in advance to increase output at the same time as the new machinery is installed. In this case, anticipated efficiency gains are a special case of the instantaneous rebound discussed above.

Alternatively, anticipated efficiency improvements may mean that due to investment decisions energy use increases well before the efficiency improvement takes place. For example, commuters may choose to live further from work in anticipation of more fuel efficient vehicles in the future. We would observe most of the true shock to energy effi-

[7]This corresponds to the assumption of "fundamental shocks" in the moving-average representation through which the impulse response functions are calculated (see e.g. Kilian and Lütkepohl, 2017, Chapter 17). Non-fundamentalness means that economic agents use additional information beyond the variable set modeled. In our specific case, this would correspond to economic agents anticipating an energy efficiency shock.

ciency, but the observed increase in energy use following the shock underestimates the full rebound in energy use. As a result, the estimated rebound will be biased downwards compared to the true rebound in both the energy-saving and backfire cases. As an example, consider for the moment only the change in energy use following the efficiency improvement and assume that only 75% of the rebound in energy use in reaction to the shock is observed. In the energy-saving case discussed above where the true rebound is 50%, we observe a (-1+0.75*0.5)% change in energy use following the shock and so the estimated rebound will be $1 - \frac{(1-0.75*0.5)\%}{1\%} = 37.5\%$. In the backfire case where the true rebound is 125%, we observe a (-1+0.75*1.25)% change in energy use, and so the estimated rebound is $1 + \frac{(1-0.75*1.25)}{1\%} = 106.25\%$.

But we also need to consider the increase in energy use prior to the efficiency improvement. This will appear as a positive shock to energy use. In the moving average representation the rebound following an efficiency improvement (assuming no backfire or super-conservation) can be seen as a series of (positive) moving average coefficients that decline with increasing lags so that efficiency shocks have less and less effect on energy use.[8] But following the positive shock due to an anticipated improvement (and assuming that there is no backfire or super-conservation before the efficiency shock actually occurs), the moving average coefficients would have to increase with increasing lags or at least not decline. We will observe a mixture of these two impulse response functions. As a result, we will further underestimate the rebound effect.

In conclusion, we capture only energy-specific efficiency improvements and the estimated rebound will be biased away from 100% in the case of instantaneous effects (and be least biased if the true effect is close to 100%) and will be biased downwards in the case of energy use increasing before the efficiency improvement occurs. Hence, the estimated

[8]In the case of backfire, with sufficient lags the coefficients become negative instead of positive.

rebound represents a lower bound if it is smaller than 100% or close to 100%, but the direction of bias becomes increasingly unclear for estimated rebounds that are well above 100%.

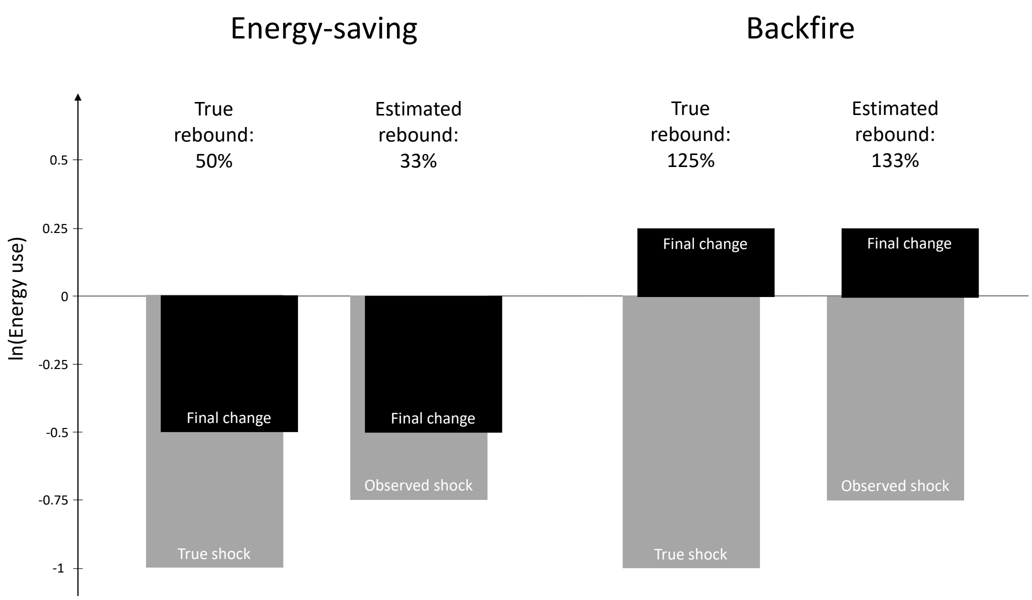

Figure 2: True vs. estimated rebound in the presence of instantaneous rebound effects. Notes: The vertical axis shows the log of energy use. The left panel (energy-saving) shows for a true rebound of 50% how observing only a fraction of the true shock results in an estimated rebound of 33%. The right panel (backfire) shows for a true rebound of 125% how observing only a faction of the true shock results in an estimated rebound of 133%.

2.3 Approaches to Identification

The parameters in the SVAR model (1) are typically identified by imposing at least $(n^2 - n)/2$ restrictions, where n is the number of variables. Restrictions that involve just the matrix of the contemporaneous coefficients, A_0, are called "short-run restrictions," while restrictions that involve the long term impact matrix (a combination of A_0 with the matrices of lagged coefficients Π_i) are referred to as "long-run restrictions" (Shapiro and Watson, 1988). Equality restrictions, typically zero-restrictions, are usually motivated by economic theory or background knowledge such as information about institutional mechanisms. Yet energy economics is an area where theory is contested and uncertain (Bruns et al., 2014) so that imposing zero restrictions on parameters on *a priori* theoretical grounds is undesirable. Restrictions can also take the form of inequalities — known as "sign restrictions" (Kilian and Murphy, 2012; Fry and Pagan, 2011) — which determine set identification, rather than point identification. Researchers then need to determine which of the infinite number of impulse response functions admissible according to a sign restriction is the best (Fry and Pagan, 2011).[9]

Gali (1999) attempts to identify a technology shock to labor productivity by assuming that only the "technology shock" can have a long-run impact on labor productivity. However, in the case of 100% rebound, the effect of the energy efficiency shock on energy use will be zero in the long run. Therefore, it is undesirable, *a priori*, to impose these types of restrictions on the model.[10] We achieve identification by restricting the space of possible structural models using an alternative framework, which maximally exploits the statistical information in the data.

[9]Kilian and Lütkepohl (2017) (Chapter 13) outline approaches to selecting the optimal model from among the set identified by sign restrictions using either Bayesian (Inoue and Kilian, 2013) or penalty function (Uhlig, 2005) methods.

[10]Ramey (2016) notes that several papers have questioned Galí's (1999) basic identifying assumption that technology shocks are the only shocks that have a long-run effect on labor productivity including Uhlig (2004) and Mertens and Ravn (2011) who look at the effect of changes in capital taxation. Basu et al. (2006) show that accounting for factors such as capital utilization, fluctuations in true productivity are only about half those in raw TFP.

2.4 Independent Component Analysis

Our identification approach is based on a theorem, first proved by Comon (1994, Th. 11) (see also Gouriéroux et al., 2017), according to which if we assume that the elements of ε_t are (mutually) independent and non-Gaussian (with at maximum one exception), then the invertible matrix A_0^{-1}, such that $\varepsilon_t = A_0 u_t$, is "almost identifiable." This means that A_0^{-1} is identifiable up to a column permutation and the multiplication of each of its diagonal elements by an arbitrary non-zero scalar.[11] In the Independent Component Analysis (ICA) literature, several techniques have been developed to estimate the matrices A_0^{-1} and A_0, where they are usually referred to as the *mixing* and *unmixing* matrix, respectively (Hyvärinen et al., 2001). These techniques are usually based on searching for the linear combinations of the reduced form residuals (u_t in our case) that are maximally independent. This is done in the style of unsupervised statistical learning that is typical of machine learning research (Hyvärinen et al., 2001).

We apply three ICA techniques to estimate A_0^{-1} and A_0. Using three different approaches allows us to explore the robustness of our rebound estimates. The first two approaches — distance covariance (dcov) proposed by Matteson and Tsay (2017) and non-Gaussian Maximum Likelihood (ngml) proposed by Lanne et al. (2017) — have been recently studied in the econometric literature in the context of SVAR models (see Herwartz, 2018), and the third approach is the FastICA algorithm (Hyvärinen and Oja, 1997), which is the most popular approach to ICA estimation in machine learning.

The distance covariance (dcov) approach minimizes a nonparametric measure of dependence among n linear combinations of the observed data (u_t), namely the distance

[11] In other words, the matrix is identifiable up to the post multiplication by DP where P is a column permutation matrix and D a diagonal matrix with non-zero diagonal elements (see Gouriéroux et al., 2017, p. 112).

covariance of Székely et al. (2007). For example, the distance covariance between, say, u_{1t} and u_{2t} is defined as:

$$I(u_{1t}, u_{2t}) = E|u_{1t} - u_{1t}^*||u_{2t} - u_{2t}^*| + E|u_{1t} - u_{1t}^*|E|u_{2t} - u_{2t}^*| \\ - E|u_{1t} - u_{1t}^*||u_{2t} - u_{2t}^{**}| - E|u_{1t} - u_{1t}^{**}||u_{2t} - u_{2t}^*| \quad (5)$$

where $|\cdot|$ denotes the Euclidean distance and (u_{1t}^*, u_{2t}^*) and $(u_{1t}^{**}, u_{2t}^{**})$ denote two distinct i.i.d. samples of (u_{1t}, u_{2t}). On the basis of this measure of dependence, Matteson and Tsay (2017) define an objective function $\mathfrak{I}(\theta)$, whose argument is a vector of rotation angles θ. Each choice of θ determines a product of rotation matrices $G(\theta)$, which in turn determines a mixing matrix $A_0(\theta)^{-1}$ and a vector of structural shocks $\varepsilon_t(\theta) = A_0(\theta)u_t$. Matteson and Tsay (2017) show that the choice of θ that corresponds to $\arg\min_\theta \mathfrak{I}(\theta)$ determines a consistent estimator of $A_0(\theta)^{-1}$ and that this mixing matrix is associated with structural shocks $\varepsilon_t(\theta) = A_0(\theta)u_t$ that are maximally independent (i.e. least dependent).

In contrast to other ICA estimators, the Maximum Likelihood estimator proposed by Lanne et al. (2017) is parametric because it assumes that the n structural shocks are distributed according to specific distributions, besides assuming their mutual independence. The distributions of the shocks may be different, even belonging to different families of densities with their own parameters, but at most one is allowed to be Gaussian. To construct the likelihood function, one has to choose the non-Gaussian distributions. In our application, we employ the t-distribution with different degrees of freedom. The likelihood function allows us to estimate the unmixing matrix A_0 and the independent components (i.e. the structural shocks ε_t).

The fastICA algorithm Hyvärinen and Oja (1997) is based on minimization of mutual information and maximization of negentropy. These two notions come from information theory, and in particular the notion of differential entropy. Let x be a random vector and

$f(x)$ its density, then the differential entropy H of x is defined as (Papoulis and Pillai, 2002)

$$H(x) = -\int f(x) \ln f(x) dx. \tag{6}$$

A fundamental result in information theory is that if x is Gaussian, then it has the largest entropy among all the random vectors with the same covariance matrix (see again Papoulis and Pillai, 2002). Let x^G be a Gaussian random vector with the same covariance as x. Negentropy is defined as

$$J(x) = H(x^G) - H(x) \tag{7}$$

which is necessarily non-negative and is zero if x is Gaussian. It is then a measure of non-Gaussianity (Hyvärinen and Oja, 2000). Let $x_1, \ldots, x_m$ be a set of (scalar) random variables and let $x = (x_1, \ldots, x_m)'$. The mutual information I between the m scalar random variables is defined as

$$I(x_1, \ldots, x_m) = \sum_{i=1}^{m} H(x_i) - H(x). \tag{8}$$

Mutual information is a measure of (mutual) statistical dependence (Hyvärinen and Oja, 2000). It turns out that finding linear combinations of the observed variables (e.g. $u_{1t}, \ldots, u_{nt}$) that minimize mutual information (i.e. are maximally independent) is equivalent to finding directions in which the negentropy (i.e. non-Gaussianity) is maximized (Hyvärinen, 1997). A potential problem is that estimating mutual information or negentropy would require estimating the probability density function $f(x)$ (see Equation 6). The FastICA algorithm circumvents this problem using an approximation of negentropy (see Hyvärinen and Oja, 2000). Given such an approximation, the algorithm is based on a fixed-point iteration scheme for finding linear combinations of the data that maximize non-Gaussianity. Given the tight link between mutual information and negentropy, this is equivalent to finding linear combinations that are maximally independent.

As mentioned above, ICA *per se* does not deliver full identification of A_0^{-1}; one still needs to find the right order and scaling of its columns. The scale indeterminacy is easily solved by post-multiplying the ICA-estimated A_0^{-1} in $u_t = A_0^{-1}\varepsilon_t$ by a matrix DD^{-1} such that D is diagonal (with non-zero diagonal elements) and $D^{-1}\varepsilon_t$ has unit variance. In this manner, the rescaled mixing matrix becomes $A_0^{-1}D$, and the rescaled structural shocks become the elements of $D^{-1}\varepsilon_t$. The column indeterminacy is solved by searching for a column permutation P of A_0^{-1} such that the i^{th} shock maximally (as close as possible) impacts on the i^{th}-variable.[12] Notice that if one is interested in identifying a single shock, say the energy efficiency shock, it is not necessary to recover the entire permutation matrix P. It is sufficient to label one of the n shocks as the shock of interest if this shock impacts maximally on the variable of interest.[13] This solution to the column-indeterminacy problem can be seen as a further *a priori* assumption that we impose on the system to achieve identification jointly with the assumptions of non-Gaussianity (which can be actually indirectly tested) and independence of the shocks. Notice that none of these assumptions involve any specific economic-theoretical considerations.

Lastly, exploiting the sign indeterminacy, each column of $A_0^{-1}DP$ is multiplied by 1 or -1 in order that the diagonal elements of $A_0^{-1}DP$ have entries greater than zero, except the entry corresponding to energy use, the entry $(1,1)$ in our application, which we set as negative. We impose this sign-rescaling because we want to study the impact of a

[12]The following procedure can deliver a unique solution: (i) If the maximum entry of $A_0^{-1}D$ lies in position (row, column) (i,j), then the j^{th} column becomes the i^{th} column in $A_0^{-1}DP$. (ii) Repeat the same procedure starting from the output of the previous step, $A_0^{-1}DP$, but compute the maximum entry neglecting all the entries lying in the column and row in which the maximum was found in the previous step until the n^{th} column has been permuted.

[13]In other words, supposing that energy consumption is the first entry in x_t, the j^{th} shock will be labeled as the energy shock if the maximum entry of the first row of $A_0^{-1}D$ lies in the j^{th} column. This would avoid the procedure described in the previous footnote.

reduction in energy use (i.e. increase in energy efficiency).

2.5 Linear non-Gaussian Acyclic Model (LiNGAM)

We further probe the robustness of our results by applying an ICA-based identification scheme, which, besides assuming non-Gaussianity and independence of the structural shocks, makes the further assumption of *recursiveness*. This identification scheme is called Linear Non-Gaussian Acyclic Model (LiNGAM) (Shimizu et al., 2006; Hoyer et al., 2008; Moneta et al., 2013). Recursiveness here means that there is a particular contemporaneous causal order of the variables (which the algorithm is able to identify from the data), such that the unmixing (or, equivalently, mixing) matrix can be rearranged into a lower-triangular matrix (after a rows/columns permutation). In other words, the contemporaneous causal order of the variables can be represented as a directed acyclic graph (Moneta et al., 2013). The standard Choleski identification scheme (Sims, 1980) also makes the assumption that the instantaneous impact matrix (i.e. the mixing matrix) is lower triangular. In the Choleski scheme, however, the order of the variables that enter in the vector x_t is given *a priori* and, in many applications, may appear arbitrary. In LiNGAM the ordering is discovered from the data. Given an arbitrary initial variable order, FastICA is first used to estimate the unmixing matrix A_0 and the mixing matrix A_0^{-1}. Then, in a second step, LiNGAM finds the correct permutation matrix P, which we mentioned above as fundamental to solving the ICA indeterminacy problem. To obtain P, the algorithm makes use of recursiveness: if the underlying contemporaneous causal structure among the time-series variables is recursive (acyclic), then there will be a row-column permutation that makes A_0 and A_0^{-1} lower triangular. Since these matrices are estimated with errors, the algorithm searches for the row-column permutation which makes one of these matrices the closest as possible to lower triangular. In comparison to identifying the energy shock by simply picking the shock that has maximal contemporaneous impact on the energy time series variable (our baseline rebound effects estimates will hinge on this criterion), LiNGAM has the clear advantage of providing a complete identification of the mixing and unmixing matrix, with the entire causal graph of the contemporaneous structure. It has, however, the disadvantage of relying heavily on a lower-triangular scheme, which is the reason why we use it only for robustness analysis.

We use the R package svars (Lange et al., 2019) to estimate the dcov and ngml models and own code for the FastICA and LiNGAM models. A link to the data and R code is in Appendix D.

2.6 Data

We estimate VAR models for the United States using monthly and quarterly data. Identifying restrictions are generally more plausible the more frequent the data is (Kilian, 2009). In Section 2.2 we explained why estimates using quarterly data may be more biased than estimates using monthly data. However, it is also possible that estimates using monthly data will focus on the short run and underestimate the long-run effects. This is why we estimated models using each frequencies. Monthly data run from January 1992 to October 2016 (298 observations), quarterly data from 1973 (first quarter) to 2016 (third quarter) (175 observations). For the sake of comparison, we also estimate the model using quarterly data from 1992 to 2016 (99 observations). Based on Augmented Dickey Fuller tests, we cannot reject the hypothesis that all time series are I(1). However, we estimate the model in log levels in order to avoid imposing potentially spurious unit root or cointegration conditions on the model. For the sake of easier presentation, all log time series are multiplied by 100 to reduce the number of decimals in the mixing matrices. Appendix A discusses the sources of the data in detail.

Figure 3 presents the time series used in this study. In the short run, energy consumption fluctuates more than its price, presumably because of the effect of weather. However, the variance of the price of energy in the long run is much larger. Industrial production has grown more slowly than GDP in the last two decades suggesting a shift towards services, though as the former is a gross output measure, it cannot strictly be compared to GDP. Finally, energy quality, which reflects the mix of primary energy types shows a shift towards cheaper energy sources and has been particularly volatile in the era of fracking and new renewables.

3 Results

3.1 Reduced-form VARs

Based on the Schwert (1989) criterion, we consider a maximum of 5 lags for the quarterly data and a maximum of 6 lags for the monthly data. We use the Akaike Information Criterion (AIC), which Kilian and Lütkepohl (2017) find to be the best of the lag order selection critieria. The AIC suggests a lag length of three for both frequencies.

Identification of the shocks requires that at most one of the structural shocks is Gaussian. Since we do not observe the structural shocks, we cannot directly test their Gaussianity. However, we can test it indirectly: since reduced-form residuals are linear combinations of independent shocks, by construction they tend to be closer to a Gaussian distribution than the structural shocks. Using a Jarque-Bera test with $\alpha = 0.05$, we find that for all reduced-form VAR models used in the subsequent analysis, at most one of the reduced-form residuals exhibits a Gaussian distribution.[14] Appendix C contains the

[14]We obtain only isolated cases (monthly data, three-variable model) in which the normality of the reduced-form residual associated with energy use is not rejected at the 5% significance level.

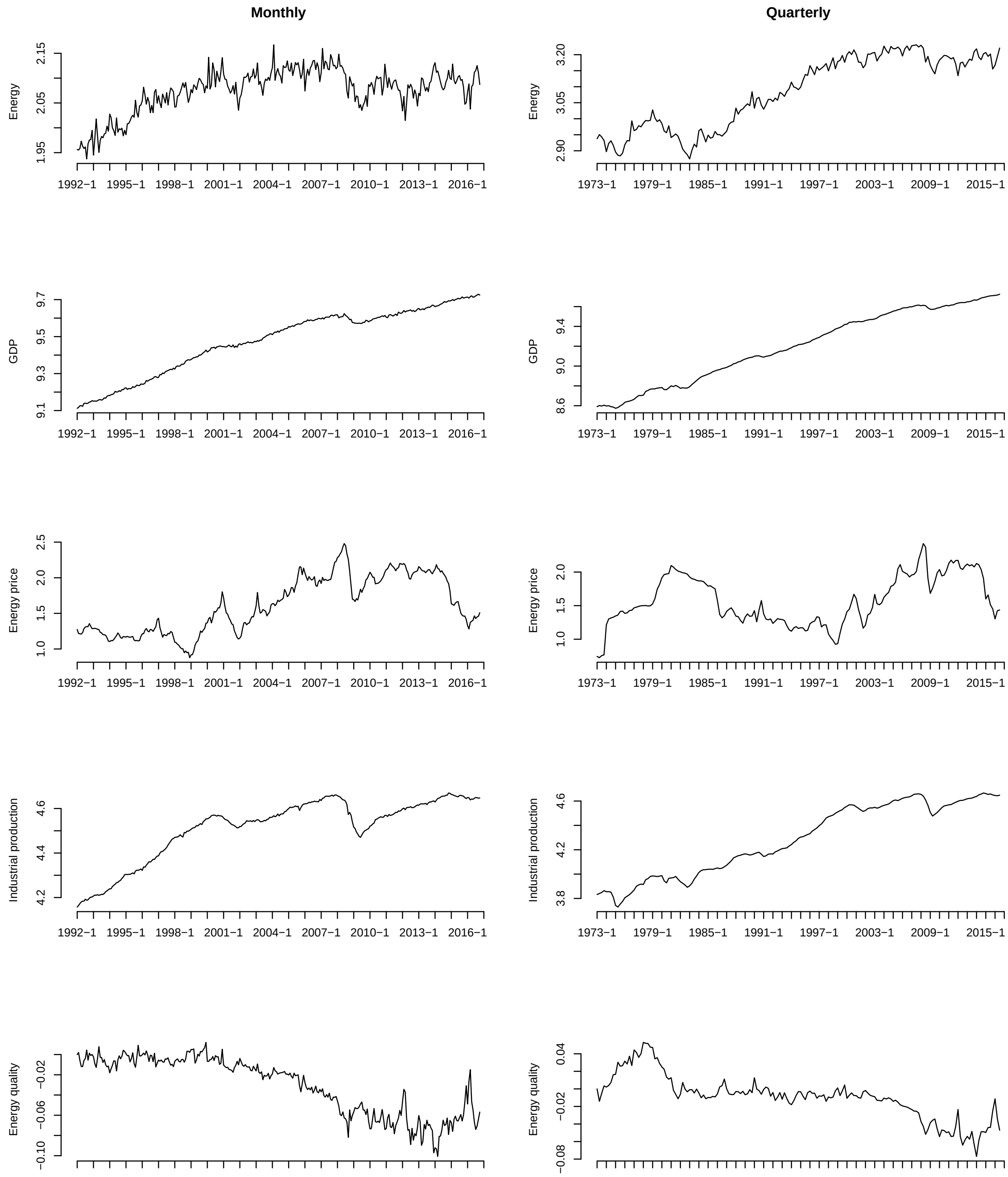

Figure 3: Overview of the time series (in logs). Notes: The left column presents the monthly time series (1992-1 to 2016-10) and the right column presents the quarterly time series (1973-1 to 2016-3).

estimated parameters of the reduced-form VAR (Π and constants) for monthly data.

3.2 Identification of SVARs

Though our focus here is on the energy efficiency shock, we also discuss the GDP and energy price shocks, and we ascertain whether the estimated SVAR is generally consistent with economic theory. The contemporaneous effect of an improvement in energy efficiency on GDP should be positive due to the increase in TFP this represents, while the effect on energy prices should be negative due to the reduction in demand for energy. However, we expect the contemporaneous effects of energy efficiency improvements on GDP and energy prices to be small as the transmission of these effects is likely to take some time. We expect the contemporaneous effects of a positive energy price shock on energy use and GDP to be negative and small, especially for monthly data. We also do not expect strong contemporaneous effects of a positive GDP shock on energy use and energy prices, but these effects should be positive.

Table 1 shows the $A_0^{-1}DP$ matrices obtained by the four identification methods for monthly data with confidence intervals produced using the wild bootstrap procedure (see Chapter 12 in Kilian and Lütkepohl (2017)). For the three ICA approaches (dcov, ngml, FastICA) the first column shows what we label as the contemporaneous impact of the energy efficiency shock. This shock has the largest contemporaneous effect on energy use and small effects on GDP and energy prices. The bootstrapped confidence intervals of the latter effects also include zero. Therefore, we cannot reject the hypothesis that these contemporaneous impacts of the energy efficiency shocks conform with economic theory. Applying LiNGAM, we estimate the causal order as $y \longrightarrow e \longrightarrow p$.[15] While the effect

[15]The mixing matrix reported in Table 1 and 2 for LiNGAM results in a lower triangular impact (mixing) matrix as required by a recursive causal structure. It is important to assess how stable this causal order is

of energy efficiency improvements on GDP is set to zero, the effect on energy prices is relatively large, but the sign conforms to economic theory.

Regarding the GDP shock, the bootstrapped confidence intervals again suggest that only the contemporaneous effect on GDP is statistically significant (except for LiNGAM in which there is also a positive and significant effect of the GDP shock on the price of energy). Regarding the energy price shock, it is again only the contemporaneous effect on energy prices that is statistically significant. Overall, we conclude that the identified shocks are consistent with economic theory.

Table 2 shows the $A_0^{-1}DP$ matrices for quarterly data. Results for the energy efficiency shock are very similar to those obtained for monthly data. The contemporaneous effects on GDP and energy prices tend to zero and the bootstrapped confidence intervals include zero. For quarterly data, the energy efficiency shock identified by LiNGAM is also more consistent with economic theory. LiNGAM suggests the same contemporaneous causal structure as for monthly data ($y \longrightarrow e \longrightarrow p$).[16]

As was the case for the monthly data, with the exception of the LiNGAM estimates, the GDP shocks only affect GDP and the energy price shocks only affect energy prices, i.e. the bootstrapped confidence interval does not include zero. For the LiNGAM estimates, the GDP shock affects all three variables.

Figure 4 shows the impulse response functions for an SVAR identified with the dis-

when we change the initial condition of the FastICA algorithm (which constitutes the first step of LiNGAM). We run a simulation where LiNGAM is iteratively applied to the same data set but resampling the initial conditions each time. LiNGAM results in this case are 100% stable. A further, and more severe, exercise to check stability is to run a bootstrap in which we do not only change initial conditions of the algorithm, but also resample the data. In this case, we get the same causal structure 94.9% of the time (for monthly data). Our conclusion is that the causal order $y \longrightarrow e \longrightarrow p$ obtained by LiNGAM is satisfactorily stable.

[16]While resampling initial conditions, we also have here 100% stability and 94.2% bootstrap stability (resampling the observed data).

Table 1: Mixing Matrices ($A_0^{-1}DP$) for Monthly Data

	ε_e	ε_y	ε_p
Distance covariance (dcov)			
e_t	-1.68	0.32	0.29
	[-1.73, -1.27]	[-0.61, 0.90]	[-0.33, 0.81]
y_t	0.09	0.51	0.03
	[-0.19, 0.27]	[0.37, 0.51]	[-0.15, 0.28]
p_t	-0.02	0.57	5.04
	[-1.84, 1.62]	[-1.99, 2.24]	[4.03, 5.06]
Non-Gaussian Maximum Likelihood (ngml)			
e_t	-1.49	-0.66	0.47
	[-1.71, -0.90]	[-1.17, 0.54]	[-0.28, 0.82]
y_t	-0.21	0.46	-0.08
	[-0.38, 0.16]	[0.25, 0.50]	[-0.23, 0.25]
p_t	0.20	1.65	4.60
	[-1.68, 1.46]	[-1.72, 3.42]	[3.22, 4.98]
FastICA			
e_t	-1.61	-0.39	0.43
	[-1.71, -1.12]	[-1.18, 0.60]	[-0.34, 0.76]
y_t	-0.13	0.49	-0.01
	[-0.35, 0.18]	[0.32, 0.50]	[-0.21, 0.26]
p_t	0.07	0.99	4.90
	[-2.05, 1.42]	[-1.96, 2.66]	[3.76, 4.97]
LiNGAM			
e_t	-2.17	-0.001	0.00
	[-2.33, -2.02]	[-0.20, 0.19]	
y_t	0.00	0.69	0.00
		[0.64, 0.73]	
p_t	-1.24	1.22	8.93
	[-2.12, -0.32]	[0.33, 2.08]	[8.36, 9.49]

Notes: *Bootstrapped* 0.90 *confidence intervals in brackets. LiNGAM (Causal structure* $y \longrightarrow e \longrightarrow p$*): 94.9 % bootstrap stability and 100% initial conditions stability.*

Table 2: Mixing Matrices ($A_0^{-1}DP$) for Quarterly Data

	ε_e	ε_y	ε_p
Distance covariance (dcov)			
e_t	-1.55 [-1.63, -1.43]	0.51 [-0.40, 0.54]	0.05 [-0.50, 0.46]
y_t	0.16 [-0.24, 0.16]	0.71 [0.63, 0.72]	0.03 [-0.24, 0.19]
p_t	0.05 [-2.64, 2.34]	-0.52 [-2.47, 2.48]	8.59 [7.36, 8.59]
Non-Gaussian Maximum Likelihood (ngml)			
e_t	-1.55 [-1.63, -1.51]	0.42 [-0.31, 0.40]	0.14 [-0.22, 0.26]
y_t	0.15 [-0.20, 0.12]	0.72 [0.65, 0.73]	0.07 [-0.15, 0.14]
p_t	-0.05 [-1.22, 1.23]	-0.74 [-1.60, 1.57]	8.85 [7.81, 9.23]
FastICA			
e_t	-1.53 [-1.59, -1.53]	0.41 [-0.32, 0.39]	0.02 [-0.21, 0.23]
y_t	0.12 [-0.21, 0.11]	0.69 [0.67, 0.70]	0.06 [-0.12, 0.10]
p_t	-0.15 [-1.08, 1.13]	-0.80 [-1.30, 1.31]	8.33 [8.18, 8.37]
LiNGAM			
e_t	-2.04 [-2.27, -1.82]	0.52 [0.22, 0.81]	0.00
y_t	0.00	1.30 [1.18, 1.43]	0.00
p_t	-1.97 [-4.11, 0.26]	0.74 [-1.53, 3.08]	15.22 [13.77, 16.74]

Notes: *Bootstrapped* 0.90 *confidence intervals in brackets. LiNGAM (Causal structure* $y \longrightarrow e \longrightarrow p$*): 94.2 % bootstrap stability and 100% initial conditions stability.*

tance covariance method using monthly data. The first column shows the effect of the energy efficiency shock on energy use, GDP, and the energy price. The energy efficiency shock results in a strong decrease in energy use initially, but this effect is eliminated over time resulting in backfire. Therefore, it appears that this shock is transitory, which is consistent with the presence of a cointegrating relationship (Pagan and Pesaran, 2008). We have also investigated potential cointegrating relations in our model. We found that there might be either one or two cointegrating vectors, which implies the presence of one or two transitory shocks. *Ex post*, our impulse response functions suggest that the energy and price shocks are transitory and the GDP shock is permanent, which is consistent with the presence of two cointegrating relationships. However, we do not impose cointegration in our estimation, and the transitoriness or permanence of each shock is not pre-determined. Thus, the finding of 100% rebound is not predetermined by our method. We also expect the energy efficiency shock to have a positive effect on GDP and a negative effect on energy prices in the long run. While energy prices do decrease, they eventually return to their initial level and the effects are never statistically significant. The long-run effect on GDP is positive, but statistically insignificant.

We also see that though the initial effect of the price shock on energy use and GDP is positive (but not statistically significant), in the longer run it has the expected negative and statistically significant effects on both variables. On the other hand, the price shock appears to have transitory effects on the price of energy but what look like permanent effects on at least GDP. The GDP shock has positive long-run effects on all three variables. The long-run effects, therefore, also conform with economic theory.

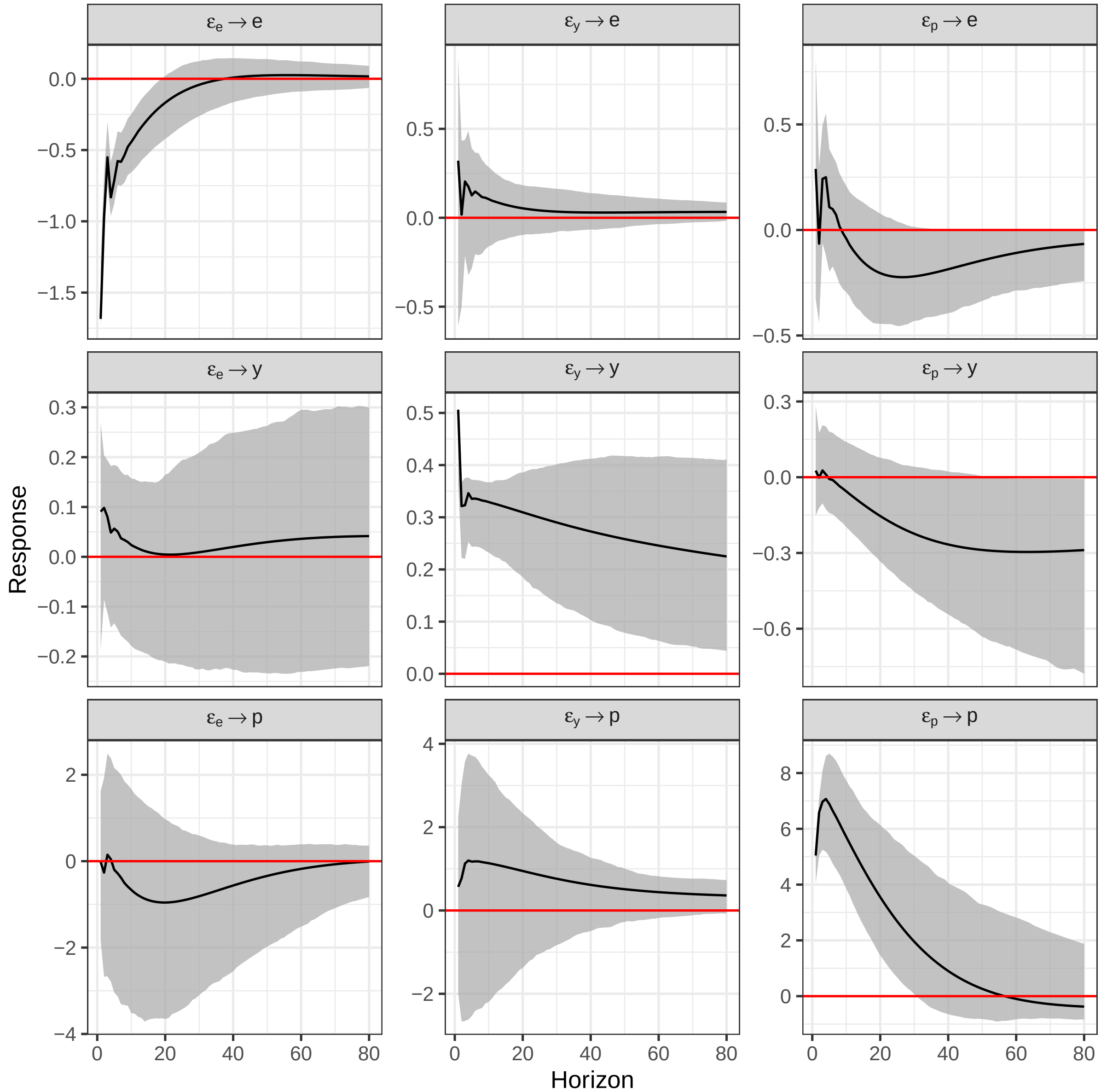

Figure 4: Impulse response functions for monthly data (Distance covariance). Notes: The first column shows the effects of the energy efficiency shock (ε_e) on energy use (e), GDP (y), and the energy price (p). Analogously, the second column shows the effects of the GDP shock (ε_y) and the third column shows the effects of the price shock (ε_p). 0.90 confidence intervals are computed by using the wild bootstrap and represented by the shaded areas.

3.3 Rebound Effect

Estimates for the rebound effect after 1, 2, 4, and 6 years are presented in Table 3. The estimates of the rebound effect are very similar for the four methods of identification and approach 100% after 4 years. However, the rebound effect after 6 years tends to be smaller for monthly data (Models 1 to 4) than for quarterly data (Models 5 to 8). The different estimates of the rebound effect may result from the different frequencies of the data or from the different time periods covered. As discussed in Section 2, the quarterly data should estimate a lower rebound than monthly data when the rebound is less than 100% and a greater rebound than monthly data when it is greater than 100%, if instantaneous rebound is important. We also estimate the rebound effect using quarterly data for the time span 1992-2016 (Models 9 to 12). The differences in estimated long-run rebound effects between the two frequencies become smaller suggesting that the change in time period explains most of the differences.

3.4 Robustness Analyses

We extend the VAR with energy use, GDP, and the price of energy by adding two further control variables – the log of industrial production and the log of energy quality – to reduce potential omitted-variable biases in estimating the rebound effect. The $A_0^{-1}DP$ matrices for monthly and quarterly data can be found in Appendix B (Tables 5 and 6). Table 4 again presents the rebound effect after 1, 2, 4, and 6 years. The estimated rebound effects are very similar to those for the SVARs with three variables.

For LiNGAM, the identified contemporaneous causal structures are much less stable than they are for the three-variable VARs. For both monthly and quarterly data, the most stable structure is $q \to y \to s \to e \to p$. However, this structure reaches only 64% sta-

Table 3: Rebound Effect

Model	Frequency	Period	Method	1 year	2 years	4 years	6 years
1	Monthly	1992-2016	dcov	0.78	0.94	1.01	1.01
				[0.63, 0.89]	[0.78, 1.05]	[0.92, 1.09]	[0.95, 1.07]
2			ngml	0.76	0.91	0.99	0.99
				[0.62, 0.88]	[0.75, 1.05]	[0.89, 1.09]	[0.93, 1.07]
3			fastICA	0.77	0.92	1.00	1.00
				[0.63, 0.88]	[0.77, 1.06]	[0.90, 1.10]	[0.94, 1.08]
4			LiNGAM	0.90	0.99	1.01	1.00
				[0.86, 0.93]	[0.98, 1.01]	[1, 1.02]	[1, 1.01]
5	Quarterly	1973-2016	dcov	0.61	0.90	1.16	1.23
				[0.35, 0.67]	[0.58, 1.04]	[0.84, 1.40]	[0.95, 1.48]
6			ngml	0.61	0.90	1.17	1.24
				[0.36, 0.64]	[0.58, 0.97]	[0.83, 1.30]	[0.94, 1.43]
7			fastICA	0.59	0.88	1.16	1.23
				[0.35, 0.64]	[0.59, 0.97]	[0.84, 1.31]	[0.95, 1.45]
8			LiNGAM	0.62	0.89	1.08	1.12
				[0.57, 0.69]	[0.82, 0.95]	[1.02, 1.14]	[1.07, 1.17]
9	Quarterly	1992-2016	dcov	0.58	0.91	1.09	1.07
				[0.32, 0.80]	[0.58, 1.19]	[0.81, 1.34]	[0.89, 1.28]
10			ngml	0.45	0.77	1.01	1.03
				[0.31, 0.77]	[0.57, 1.11]	[0.77, 1.32]	[0.84, 1.26]
11			fastICA	0.54	0.88	1.08	1.06
				[0.19, 0.83]	[0.47, 1.28]	[0.73, 1.40]	[0.85, 1.30]
12			LiNGAM	0.72	0.96	1.03	1.03
				[0.62, 0.82]	[0.86, 1.06]	[0.97, 1.11]	[0.99, 1.07]

Notes: *Bootstrapped 0.90 confidence intervals in brackets.*

Table 4: Rebound Effect (Robustness Analysis, Five-Variable Model)

Model	Frequency	Period	Method	1 year	2 years	4 years	6 years
1	Monthly	1992-2016	dcov	0.94	1.03	1.09	1.06
				[0.67, 1.20]	[0.86, 1.29]	[0.96, 1.43]	[0.96, 1.34]
2			ngml	0.98	1.06	1.13	1.09
				[0.63, 1.89]	[0.81, 1.86]	[0.96, 2.02]	[0.96, 1.80]
3			fastICA	0.77	0.92	0.97	0.97
				[0.63, 0.99]	[0.80, 1.12]	[0.87, 1.14]	[0.88, 1.13]
4			LiNGAM	0.86	0.93	0.98	1.00
				[0.77, 0.94]	[0.89, 0.97]	[0.95, 1.00]	[0.97, 1.02]
5	Quarterly	1973-2016	dcov	0.72	0.85	0.93	0.97
				[0.52, 1.47]	[0.66, 1.95]	[0.66, 1.85]	[0.55, 1.67]
6			ngml	0.63	0.82	1.16	1.30
				[-0.02, 0.63]	[-0.05, 0.90]	[0.30, 1.45]	[0.52, 1.74]
7			fastICA	0.59	0.83	1.16	1.28
				[-0.06, 0.6]	[-0.01, 0.9]	[0.32, 1.43]	[0.54, 1.82]
8			LiNGAM	0.70	0.85	0.99	1.04
				[0.60, 0.81]	[0.75, 0.96]	[0.89, 1.09]	[0.96, 1.12]

Notes: *Bootstrapped 0.90 confidence intervals in brackets.*

bility under random variation of the algorithm's initial conditions and only 11.4% stability under bootstrap resampling of the data for monthly data. For quarterly data, the same structure reaches only 52% initial conditions stability and 30% bootstrap stability. Therefore, we also examined the robustness of our results under the second most stable causal structure ($q \to s \to y \to e \to p$ for monthly data and $s \to y \to q \to e \to p$ for quarterly data) and find that the estimated rebound effect is robust to these causal structures as well.

In conclusion, LiNGAM does not provide stable and sufficiently reliable results for the SVAR with five variables. It is interesting to note, however, that among the diverse causal structures suggested by the algorithm (including others that we did not present), in most cases y comes before e and e before p in the contemporaneous causal chain, which was also the case for the SVAR with three variables.[17] This means that the structure $y \to e \to p$ is remarkably stable, with the other variables (s, q) playing diverse causal roles that cannot be described by a recursive scheme. This is why it is important to show results with methods that are not committed to such a scheme (dcov, ngml, FastICA).

We also extended the three-variable VAR by adding the logs of heating degree days and cooling degree days to control for the influence of the weather. The results are reported in Appendix B and show that the estimated rebound effect is again about 100%. Moreover, our findings are robust if GDP per capita and energy use per capita are considered (results not reported).

As is shown in the previous sections, the estimated rebound effect of about 100% is robust to both different data frequencies and identification schemes. In this section, we explored robustness with respect to alternative sets of control variables and the estimated rebound effects are again about 100%.

[17] This holds in 100% of cases under variation of the initial conditions, in 96.3% of cases under bootstrap resampling for quarterly data and in 75% of cases under bootstrap resampling for monthly data.

4 Discussion and Conclusions

We have produced the first econometric general equilibrium estimate of the economy-wide rebound effect, which we think is credibly identified, using an empirically identified time-series model. Estimates of the rebound effect after 4 years are close to 100%, regardless of the method of identification, data frequency used, and control variables included, such as structure of the economy, the composition of energy supply, and heating and cooling degree days. Our estimates may differ from the true rebound. As discussed in Section 2.2, in the case of some instantaneous rebound the true rebound is likely to be closer to 100% than the estimated rebound. If economic agents anticipate energy efficiency improvements and start using more energy before the actual efficiency improvements take place, the estimated rebound would be biased downwards and represent a lower bound. Therefore, these caveats do not change our conclusion that the rebound is large. Also, we capture rebound effects in response to energy-specific energy improvements which precludes improvements that are correlated with shocks to GDP or the energy price.

These results are congruent with the historical research (van Benthem, 2015; Cserekyei et al., 2016; Hart, 2018) that hints that the economy-wide rebound effect could be large. This implies that policies to encourage costless energy efficiency innovation are not likely to significantly reduce energy use in the long run, which has important implications for climate mitigation policies. On the other hand, there are short-run energy savings that will reduce cumulative energy use and greenhouse gas emissions.[18] Our approach is equivalent to applying the same size efficiency improvement to all sectors of the economy, which could also be seen as a typical or average effect. Policymakers may be more con-

[18]Of course, policies that impose costly energy efficiency mandates on energy consumers are likely to reduce energy use by more than the mandate requires (Fullerton and Ta, 2019). On the other hand, Fullerton and Ta (2019) show that in the presence of binding energy efficiency standards energy efficiency innovation will result in backfire.

cerned with the effects of efficiency improvements in specific sectors. These should be explored with more disaggregated models.

Despite this large rebound effect, energy intensity has declined over time in the United States. How can this fact be compatible with our results? Based on our three-variable VAR, there are three possible mechanisms that can explain this. First, energy efficiency shocks may increase GDP by more than they increase energy use. In Figure 4 this seems to be the case, if we ignore the very wide confidence interval around the impulse response function for the effect of an energy efficiency shock on GDP. Second, GDP shocks tend to increase GDP by much more than they increase energy use, which is strongly supported by Figure 4. In a simple aggregate model of the economy, as in Shanker and Stern (2018) or Saunders (2008), if the price of energy is constant then labor-augmenting technical change cannot change energy intensity because the marginal product of energy is a function of energy intensity alone. However, we see that GDP shocks increase the price of energy as well and this is what allows energy intensity to decline. Population growth can also increase GDP, but it is not clear why it would increase energy use by less than GDP. Finally, increasing energy prices can reduce energy use though they also reduce GDP. However, as shown in Figure 4, they reduce GDP by more than they reduce energy use in the long run.

Appendix A: Data

Monthly Data

As energy intensity is conventionally measured in terms of primary energy, we use both primary energy quantities and prices that are as close as possible to the price of primary energy. We compile a data set for the period January 1992 to October 2016, which is restricted by the availability of monthly GDP (beginning of sample) and monthly energy use data and prices (end of sample).

Energy Quantities: We use Energy Information Administration (EIA) data on consumption of primary energy from various sources measured in quadrillion BTU. This data is reported in the *Monthly Energy Review* (MER) and available from the EIA website. The primary sources are petroleum, natural gas, coal, primary electricity (which is reported for several sources), and biomass energy. We assume that geothermal and solar power is all in the form of primary electricity in our computation of the aggregate energy price index and energy quality. We deseasonalize the energy quantity series at the fuel level using the X11 procedure as implemented in RATS using a multiplicative seasonality model.

Energy Prices and Quality: EIA provide a variety of energy price series. For crude oil we use the "Refiner Acquisition Cost of Crude Oil, Composite" series from Table 9.1 in the MER. For electricity prices we use "Average Retail Price of Electricity, Industrial" from Table 9.8 in the MER.[19] Monthly electricity prices are not available for 1992-1994

[19] In order to be comparable with the prices for the other energy sources we would actually like to use the wholesale price of electricity. However, using these wholesale prices would further restrict our sample to start in January 2001 and not all of the US has liberalized electricity markets. The "Average Retail Price of Electricity, Industrial" averaged $61 per MWh from January 2001 to December 2013. Over the same period the Northeast Pool wholesale electricity price also averaged $61, the Mid-Columbia wholesale price averaged $42, Palo Verde $49, and PJM West $54 (https://www.eia.gov/electricity/wholesale/#history).

and we used annual prices for this period.

For natural gas prices we use the Henry Hub spot prices available on this page:

http://www.eia.gov/dnav/ng/hist/rngwhhdA.htm

from January 1997. Prior to that we use EIA's "Natural Gas Price, Wellhead" from Table 9.10 in the *MER*. For the price of coal we use "Cost of Coal Receipts at Electric Generating Plants" from Table 9.9 in the MER.

Annual biomass prices for 1970 to 2014 are available from this webpage:

http://www.eia.gov/state/seds/data.cfm?incfile=/state/seds/sep_prices/total/pr_tot_US.html&sid=US

For months after 2014 we applied the growth rate of the price of crude oil as the correlation between the price of oil and biomass was 0.92 from 1992 to 2014.

All these prices are converted to prices per BTU using standard conversion factors. For primary electricity we use the ratio of primary energy to electricity produced to obtain a price for primary energy from the price of electricity. Table 7.2 in the MER provides the generation of electricity from various sources. We use this to get conversion factors for nuclear, hydropower, solar, and wind. For geothermal and solar energy we use the data in this table and the amount of geothermal power used in electricity generation in MER Table 10.2c. But we apply the derived price to all geothermal and solar energy as described above.

As monthly energy quantities and prices are often highly seasonal, we deseasonalized each series at the fuel level before aggregating using the X11 procedure in RATS and a multiplicative specification of the seasonal factor. To obtain the price of energy we simply compute the total cost of energy in our data and divide by total BTUs of primary energy.

As discussed in Section 2.1, energy quality is a measure of shifts in the the mix of energy carriers (fuels and primary electricity). If the share of each energy carrier remains constant then a volume index of energy use, such as a Divisia Index, will grow at the same rate as the simple sum of BTU. To obtain the energy quality index we compute a Divisia energy volume index of energy use and divide this by total BTUs. The energy quality index will increase if there is a shift towards the more expensive energy carriers.

GDP: Macroeconomic Advisers have interpolated a monthly GDP series, which appears to be seasonally adjusted, for the U.S. using many of the underlying variables used by the Bureau of Economic Analysis to update quarterly GDP:

http://www.macroadvisers.com/monthly-gdp/

This data includes nominal and real series, which can be used to compute a monthly GDP deflator, which we use to deflate energy prices.

Industrial Structure: McCracken and Ng (2015) have compiled a large monthly macroeconomic data set for the United States ("FRED-MD"), which is available through the Federal Reserve Bank of St. Louis FRED data tool at

https://research.stlouisfed.org/econ/mccracken/fred-databases/

We use their series for industrial production, which is seasonally adjusted. Though industrial production is a gross output measure and GDP is a value added measure, we believe that changes in industrial production while holding GDP constant can account somewhat for changes in the mix of output.

Weather: We use population-weighted heating and cooling degree day data for the United States as a whole reported in the MER and available from the EIA website. We deseasonalize these series using the X11 procedure as implemented in RATS using an additive seasonality model.

Quarterly Data

We compiled a quarterly dataset for 1973:1 to 2016:3.

We use quarterly GDP data from the Bureau of Economic Analysis (BEA) *National Income and Product Accounts* (NIPA). GDP data is real GDP in chained 2009 dollars. All other data is from the same sources as the monthly data. We aggregated the monthly data into quarterly data and deseasonalized the energy series before computing energy quantity and price aggregates as described for the monthly data.

Monthly oil prices are only available from 1974 and electricity and gas prices from 1976. Monthly electricity prices are not available for 1984-1994 either. We used annual prices for this missing data.

Appendix B: Robustness Analyses

Mixing matrices for SVARs with five variables

Table 5: Monthly Data.

	ε_e	ε_y	ε_p	ε_s	ε_q
Distance Covariance					
e_t	-1.24	0.40	0.29	0.52	-0.77
y_t	0.22	0.37	0.08	0.16	-0.05
p_t	-0.09	-0.01	5.02	-0.23	-0.06
s_t	0.14	-0.08	0.03	0.54	-0.17
q_t	-0.07	0.03	0.07	0.20	0.63
Non-Gaussian Maximum Likelihood					
e_t	-1.14	-0.09	0.43	0.55	-1.01
y_t	0.02	0.46	0.01	0.07	-0.07
p_t	-0.06	0.73	4.57	-1.13	-0.44
s_t	0.26	0.07	0.10	0.42	-0.21
q_t	-0.07	0.05	0.14	0.22	0.63
FastICA					
e_t	-1.04	-0.61	0.60	0.65	0.54
y_t	-0.07	0.38	0.07	0.01	0.24
p_t	-0.10	0.27	4.55	-1.74	-0.28
s_t	-0.18	0.32	0.11	0.38	-0.20
q_t	0.56	0.00	0.17	0.25	0.11
LiNGAM					
e_t	-1.73	0.01	0.00	0.42	-0.51
y_t	0.00	0.64	0.00	0.00	0.04
p_t	-1.07	0.78	8.63	1.19	-0.14
s_t	0.00	0.46	0.00	0.86	-0.03
q_t	0.00	0.00	0.00	0.00	0.82

Notes: *LiNGAM (Causal structure: $q \rightarrow y \rightarrow s \rightarrow e \rightarrow p$): 11.7% bootstrap stability and 64% initial conditions stability.*

Table 6: Quarterly Data.

	ε_e	ε_y	ε_p	ε_s	ε_q
Distance Covariance					
e_t	-1.28	-0.20	0.05	0.43	-0.79
y_t	-0.06	0.63	0.22	0.19	-0.06
p_t	2.20	-2.74	7.61	-0.42	-2.21
s_t	-0.12	0.48	0.35	0.96	-0.01
q_t	0.45	0.18	-0.23	0.10	-0.32
Non-Gaussian Maximum Likelihood					
e_t	-1.06	0.44	-0.23	0.13	-1.04
y_t	0.15	0.64	0.08	-0.21	0.01
p_t	-1.60	-0.68	8.11	0.19	-0.26
s_t	0.11	0.93	0.18	0.47	-0.07
q_t	-0.17	0.15	-0.06	-0.03	0.64
FastICA					
e_t	-1.11	0.11	-0.20	0.35	-0.93
y_t	0.12	0.46	0.09	0.46	-0.01
p_t	-1.38	-1.28	8.06	-0.35	-0.15
s_t	-0.03	0.03	0.13	1.07	-0.06
q_t	-0.16	0.14	-0.06	0.07	0.56
LiNGAM					
e_t	-1.64	0.48	0.00	0.54	-0.16
y_t	0.00	1.22	0.00	0.00	0.22
p_t	0.59	1.16	13.66	4.65	-4.64
s_t	0.00	1.75	0.00	1.30	0.08
q_t	0.00	0.00	0.00	0.00	0.80

Notes: *LiNGAM (Causal structure: $q \longrightarrow y \longrightarrow s \longrightarrow e \longrightarrow p$): 30% bootstrap stability and 52% initial conditions stability.*

Heating and Cooling Degree Days

We estimate a VAR with energy use, GDP, and the price of energy as endogenous variables and add heating degree days (hdd) and cooling degree days (cdd) as exogenous variables:

$$x_t = \xi + \sum_{i=1}^{p} \Pi_i x_{t-i} + \Gamma z_t + u_t \tag{9}$$

where x_t, Π_i and u_t are the same as in Equation (1), z_t is a $s-$dimensional vector of exogenous variables, and Γ is a $n \times s$ matrix. In our case, $s = 2$ and $z = (hdd, cdd)'$. For the robustness check, we focus on the results of fastICA (as it is the most popular approach in the machine learning literature and the main findings are robust with respect to the alternative identification methods) for monthly data (as the main results are robust with respect to the data frequency).

Table 7 shows the $A_0^{-1}DP$ matrix which provides very similar results to those obtained without including hdd and cdd as exogenous variables. The rebound effect with 0.90 confidence intervals in brackets is 0.52 $[0.45, 0.59]$ after one year, 0.68 $[0.57, 0.80]$ after two years, 0.84 $[0.68, 1]$ after four years and 0.92 $[0.76, 1.08]$ after six years.

We also estimated the VAR with five endogenous variables (energy use, GDP, the price of energy, industrial production, and energy quality) but again added hdd and cdd as exogenous variables. The rebound effect is also 0.82 $[0.62, 1.45]$ after one year, 0.93 $[0.75, 1.39]$ after two years, 0.95 $[0.80, 1.28]$ after four years and 0.96 $[0.75, 1.20]$ after six years, with 0.90 confidence intervals in brackets.

Table 7: Mixing Matrix ($A_0^{-1}DP$) for Monthly Data

	ε_e	ε_y	ε_p
FastICA			
e_t	-1.39	-0.29	0.38
	[-1.46, -0.92]	[-0.90, 0.58]	[-0.34, 0.68]
y_t	-0.14	0.48	-0.03
	[-0.34, 0.18]	[0.31, 0.50]	[-0.27, 0.28]
p_t	0.35	1.31	4.73
	[-1.78, 1.62]	[-2.04, 3.73]	[2.89, 4.87]

Notes: *Bootstrapped* 0.90 *confidence intervals in brackets.*

Appendix C: Estimated Parameters of the Reduced-form VAR

Table 8: Estimated Π and constants (Three-variable VAR and monthly data)

	e_t	y_t	p_t
e_{t-1}	0.56	-0.02	0.14
	(0.06)	(0.02)	(0.17)
y_{t-1}	-0.27	0.65	-0.02
	(0.20)	(0.06)	(0.58)
p_{t-1}	-0.04	0.00	1.30
	(0.02)	(0.01)	(0.06)
e_{t-2}	0.02	0.02	-0.33
	(0.06)	(0.02)	(0.19)
y_{t-2}	0.49	0.21	0.79
	(0.24)	(0.07)	(0.69)
p_{t-2}	0.11	0.01	-0.30
	(0.03)	(0.01)	(0.10)
e_{t-3}	0.28	0.02	0.28
	(0.06)	(0.02)	(0.16)
y_{t-3}	-0.19	0.13	-0.75
	(0.20)	(0.06)	(0.58)
p_{t-3}	-0.07	-0.01	-0.03
	(0.02)	(0.01)	(0.06)
Constant	-0.99	1.56	-37.61
	(8.22)	(2.44)	(23.99)

Notes: Standard errors in parentheses.

Appendix D: Data and R Code

The data and R code to replicate the results reported in this article are available at:

https://github.com/stephanbruns/SVARs_and_the_US_rebound_effect

References

Acemoglu, D. (2002). Directed technical change. *Review of Economic Studies 69*(4), 781–809.

Adetutu, M., A. Glass, and T. Weyman-Jones (2016). Economy-wide estimates of rebound effects: Evidence from panel data. *Energy Journal 37*(3), 251–269.

Azevedo, I. M. (2014). Consumer end-use energy efficiency and rebound effects. *Annual Review of Environment and Resources 39*, 393–418.

Barker, T., A. Dagoumas, and J. Rubin (2009). The macroeconomic rebound effect and the world economy. *Energy Efficiency 2*(4), 411.

Basu, S., J. G. Fernald, and M. S. Kimball (2006). Are technology improvements contractionary? *American Economic Review 96*(5), 1418–1448.

Berkhout, P. H., J. C. Muskens, and J. W. Velthuijsen (2000). Defining the rebound effect. *Energy policy 28*(6-7), 425–432.

Bessler, D. A. and S. Lee (2002). Money and prices: US data 1869–1914 (a study with directed graphs). *Empirical Economics 27*(3), 427–446.

Blanchard, O. J. and D. Quah (1989). The dynamic effects of aggregate demand and aggregate supply. *American Economic Review 79*(4), 655–73.

Borenstein, S. (2015). A microeconomic framework for evaluating energy efficiency rebound and some implications. *Energy Journal 36*(1), 1–21.

Broberg, T., C. Berg, and E. Samakovlis (2015). The economy-wide rebound effect from improved energy efficiency in Swedish industries—A general equilibrium analysis. *Energy Policy 83*, 26–37.

Bruns, S. B., C. Gross, and D. I. Stern (2014). Is there really Granger causality between energy use and output? *Energy Journal 35*(4), 101–133.

Capasso, M. and A. Moneta (2016). Macroeconomic responses to an independent monetary policy shock: A (more) agnostic identification procedure. LEM Working Paper Series 2016/36, Scuola Superiore Sant'Anna.

Comon, P. (1994). Independent component analysis, a new concept? *Signal Processing 36*(3), 287–314.

Csereklyei, Z., M. Rubio- Varas, and D. Stern (2016). Energy and economic growth: The stylized facts. *Energy Economics 37*(2), 223–255.

Csereklyei, Z., M. d. M. Rubio-Varas, and D. I. Stern (2016). Energy and economic growth: The stylized facts. *Energy Journal 37*(2), 223–255.

Demiralp, S. and K. D. Hoover (2003). Searching for the causal structure of a vector autoregression. *Oxford Bulletin of Economics and Statistics 65*(s1), 745–767.

Fry, R. and A. Pagan (2011). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature 49*(4), 938–60.

Fullerton, D. and C. L. Ta (2019). Costs of energy efficiency mandates can reverse the sign of rebound. NBER Working Paper 25696.

Gali, J. (1999). Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review 89*(1), 249.

Galvin, R. (2014). Estimating broad-brush rebound effects for household energy consumption in the EU 28 countries and Norway: some policy implications of odyssee data. *Energy Policy 73*, 323–332.

Gillingham, K., D. Rapson, and G. Wagner (2016). The rebound effect and energy efficiency policy. *Review of Environmental Economics and Policy 10*(1), 68–88.

Gouriéroux, C., A. Monfort, and J.-P. Renne (2017). Statistical inference for independent component analysis: Application to structural VAR models. *Journal of Econometrics 196*(1), 111–126.

Hart, R. (2018). Rebound, directed technological change, and aggregate demand for energy. *Journal of Environmental Economics and Management 89*, 218 – 234.

Herwartz, H. (2018). Hodges-Lehmann detection of structural shocks—An analysis of macroeconomic dynamics in the Euro area. *Oxford Bulletin of Economics and Statistics 80*(4), 736–754.

Hoover, K. D. (2001). *Causality in Macroeconomics*. Cambridge University Press.

Hoyer, P. O., S. Shimizu, A. J. Kerminen, and M. Palviainen (2008). Estimation of causal effects using linear non-Gaussian causal models with hidden variables. *International Journal of Approximate Reasoning 49*(2), 362–378.

Hyvärinen, A. (1997). Independent component analysis by minimization of mutual information. Helsinki University of Technology.

Hyvärinen, A., J. Karhunen, and E. Oja (2001). *Independent Component Analysis*. Wiley.

Hyvärinen, A. and E. Oja (1997). A fast fixed-point algorithm for independent component analysis. *Neural Computation 9*(7), 1483–1492.

Hyvärinen, A. and E. Oja (2000). Independent component analysis: Algorithms and applications. *Neural Networks 13*(4-5), 411–430.

Inoue, A. and L. Kilian (2013). Inference on impulse response functions in structural var models. *Journal of Econometrics 177*(1), 1–13.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review 99*(3), 1053–69.

Kilian, L. and H. Lütkepohl (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press.

Kilian, L. and D. P. Murphy (2012). Why agnostic sign restrictions are not enough: Understanding the dynamics of oil market var models. *Journal of the European Economic Association 10*(5), 1166–1188.

Knittel, C. R. (2011). Automobiles on steroids: Product attribute trade-offs and technological progress in the automobile sector. *American Economic Review 101*(7), 3368–99.

Koesler, S., K. Swales, and K. Turner (2016). International spillover and rebound effects from increased energy efficiency in Germany. *Energy Economics 54*, 444–452.

Lange, A., B. Dalheimer, H. Herwartz, and S. Maxand (2019). svars: An r package for data-driven identification in multivariate time series analysis. *Journal of Statistical Software*.

Lanne, M., M. Meitz, and P. Saikkonen (2017). Identification and estimation of non-Gaussian structural vector autoregressions. *Journal of Econometrics 196*(2), 288–304.

Lemoine, D. (2019, September). General equilibrium rebound from energy efficiency innovation. NBER Working Paper 25172.

León-Ledesma, M. A., P. McAdam, and A. Willman (2010). Identifying the elasticity of substitution with biased technical change. *American Economic Review 100*(4), 1330–57.

Lin, B. and K. Du (2015). Measuring energy rebound effect in the chinese economy: An economic accounting approach. *Energy Economics 50*, 96–104.

Lu, Y., Y. Liu, and M. Zhou (2017). Rebound effect of improved energy efficiency for different energy types: A general equilibrium analysis for china. *Energy Economics 62*, 248–256.

Matteson, D. S. and R. S. Tsay (2017). Independent component analysis via distance covariance. *Journal of the American Statistical Association 112*(518), 623–637.

Mertens, K. and M. O. Ravn (2011). Technology-hours redux: Tax changes and the measurement of technology shocks. In *NBER International Seminar on Macroeconomics*, Volume 7, pp. 41–76.

Meyer, I. and S. Wessely (2009). Fuel efficiency of the Austrian passenger vehicle fleet—analysis of trends in the technological profile and related impacts on CO2 emissions. *Energy Policy 37*(10), 3779–3789.

Moneta, A. (2008). Graphical causal models and VARs: An empirical assessment of the real business cycles hypothesis. *Empirical Economics 35*(2), 275–300.

Moneta, A., D. Entner, P. O. Hoyer, and A. Coad (2013). Causal inference by independent component analysis: Theory and applications. *Oxford Bulletin of Economics and Statistics 75*(5), 705–730.

Orea, L., M. Llorca, and M. Filippini (2015). A new approach to measuring the rebound effect associated to energy efficiency improvements: An application to the US residential energy demand. *Energy Economics 49*, 599–609.

Pagan, A. R. and M. H. Pesaran (2008). Econometric analysis of structural systems with permanent and transitory shocks. *Journal of Economic Dynamics and Control 32*(10), 3376–3395.

Papoulis, A. and S. U. Pillai (2002). *Probability, random variables, and stochastic processes*. Tata McGraw-Hill Education.

Pearl, J. (2009). *Causality: Models, Reasoning, and Inference*. Cambridge University Press.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. In J. B. Taylor and H. Uhlig (Eds.), *Handbook of macroeconomics*, Volume 2, pp. 71–162. Elsevier.

Rausch, S. and H. Schwerin (2018). Does higher energy efficiency lower economy-wide energy use? Economics Working Paper 18/299, Center of Economic Research at ETH Zurich.

Saunders, H. D. (1992). The Khazzoom-Brookes postulate and neoclassical growth. *Energy Journal 13*(4), 131–148.

Saunders, H. D. (2008). Fuel conserving (and using) production functions. *Energy Economics 30*, 2184–2235.

Saunders, H. D. (2013). Historical evidence for energy efficiency rebound in 30 US sectors and a toolkit for rebound analysts. *Technological Forecasting and Social Change 80*(7), 1317–1330.

Saunders, H. D. (2015). Recent evidence for large rebound: elucidating the drivers and their implications for climate change models. *Energy Journal 36*(1), 23–48.

Schwert, G. W. (1989). Tests for unit roots: A monte carlo investigation. *Journal of Business & Economic Statistics 7*, 147–160.

Shanker, A. and D. I. Stern (2018). Energy intensity, growth and technical change. CAMA Working Paper 46/2018.

Shao, S., T. Huang, and L. Yang (2014). Using latent variable approach to estimate China s economy-wide energy rebound effect over 1954–2010. *Energy Policy 72*, 235–248.

Shapiro, M. D. and M. W. Watson (1988). Sources of business cycle fluctuations. *NBER Macroeconomics Annual 3*, 111–148.

Shimizu, S., P. O. Hoyer, A. Hyvärinen, and A. Kerminen (2006). A linear non-Gaussian acyclic model for causal discovery. *Journal of Machine Learning Research 7*, 2003–2030.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica 48*(1), 1–48.

Sorrell, S., J. Dimitropoulos, and M. Sommerville (2009). Empirical estimates of the direct rebound effect: A review. *Energy Policy 37*(4), 1356–1371.

Spirtes, P., C. N. Glymour, and R. Scheines (2000). *Causation, Prediction, and Search*. MIT press.

Stern, D. I. (2010). Energy quality. *Ecological Economics 69*(7), 1471–1478.

Stern, D. I. (2011). The role of energy in economic growth. *Annals of the New York Academy of Sciences 1219*(1), 26–51.

Stern, D. I. (2012). Modeling international trends in energy efficiency. *Energy Economics 34*(6), 2200–2208.

Stern, D. I. (2017). How accurate are energy intensity projections? *Climatic Change 143*(3-4), 537–545.

Swanson, N. R. and C. W. Granger (1997). Impulse response functions based on a causal approach to residual orthogonalization in vector autoregressions. *Journal of the American Statistical Association 92*(437), 357–367.

Székely, G. J., M. L. Rizzo, N. K. Bakirov, et al. (2007). Measuring and testing dependence by correlation of distances. *Annals of Statistics 35*(6), 2769–2794.

Turner, K. (2009). Negative rebound and disinvestment effects in response to an improvement in energy efficiency in the UK economy. *Energy Economics 31*(5), 648–666.

Turner, K. (2013). "Rebound" effects from increased energy efficiency: A time to pause and reflect. *Energy Journal 34*(4), 25–42.

Turner, K. and N. Hanley (2011). Energy efficiency, rebound effects and the environmental Kuznets curve. *Energy Economics 33*(5), 709–720.

Uhlig, H. (2004). Do technology shocks lead to a fall in total hours worked? *Journal of the European Economic Association 2*(2-3), 361–371.

Uhlig, H. (2005). What are the effects of monetary policy on output? results from an agnostic identification procedure. *Journal of Monetary Economics 52*(2), 381–419.

van Benthem, A. A. (2015). Energy leapfrogging. *Journal of the Association of Environmental and Resource Economists 2*(1), 93–132.

van den Bergh, J. C. (2011). Energy conservation more effective with rebound policy. *Environmental and Resource Economics 48*(1), 43–58.

Wei, T. and Y. Liu (2017). Estimation of global rebound effect caused by energy efficiency improvement. *Energy Economics 66*, 27–34.