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

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

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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. The former depend on many *a priori* assumptions and the parameter values adopted, and the latter do not include all mechanisms that might increase or reduce the rebound and mostly do not credibly identify the rebound effect. Using a structural vector autoregressive (SVAR) model, we identify the dynamic causal impact of structural shocks, including an energy efficiency shock, applying identification methods developed in machine learning. 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%. This implies that policies to encourage cost-reducing energy efficiency innovation are not likely to significantly reduce energy use and greenhouse gas emissions in the long run.

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

JEL classification: C32, Q43

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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, 2011b; Saunders, 2013; Turner, 2013). Previous empirical research uses either computable general equilibrium (CGE) models or partial equilibrium econometric models to estimate the economy-wide rebound effect. The former depend on many *a priori* assumptions and the parameter values adopted and the latter 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

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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%.

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 behavioral 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); the increase in the use of energy to produce other complementary goods and services; 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. Lemoine (2018) conducts a general equilibrium analysis of the rebound effect. Assuming that all sectors share the same technology, general equilibrium effects amplify the partial equilibrium rebound as investigated by Saunders (1992). With heterogeneous technologies general equilibrium effects amplify the rebound for low elasticities of substitution and reduce it for high elasticities of substitution between energy and non-energy inputs in production. Backfire is possible for elasticities of substitution less than unity, especially for innovations in those sectors that are relatively energy inefficient or energy intensive. In general, this analysis shows that the economy-wide rebound effect is likely to be large and backfire is likely. Lemoine assumes that there is a fixed endowment of capital and, by using a CES utility function, that all goods are p-substitutes (Stern, 2011a) in consumption. The former assumption reduces the rebound effect, as Saunders (1992) shows. Lemoine comments that allowing for complementarity in consumption could make negative rebound possible.

As mentioned above, evidence on the size of the economy-wide rebound effect to date depends on simulation models (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) or partial equilibrium econometric estimates (e.g. Adetutu et al., 2016; Saunders, 2013; Malpede and Verdolini, 2016; Orea et al., 2015; Shao et al., 2014; Lin and Du, 2015). 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, CGE models do not provide strong evidence on the size of the economy-wide rebound effect. A simpler simulation method was proposed by Saunders (1992, 2015). This "Solow approach" uses a CES production function with factor-augmenting technical change. Assuming that the energy price is constant, the model computes the effect of energy-augmenting technical change on energy use. The method depends on having good estimates of the production parameters – a notoriously difficult problem (León-

Ledesma et al., 2010) – assumes a very simple structure to the economy, and because the energy price is held constant is a partial equilibrium approach.[1]

In between these two extremes, Rausch and Schwerin (2018) build a small general equilibrium macro-economic model that is calibrated on U.S. annual data from 1960 to 2011. Their model is a so-called putty-clay model, where once a capital vintage is chosen, no substitutability 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 econometrically estimate the rebound effect (e.g. 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).[2] 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%.

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,

[1]If we relax the constant price assumption this would be a single sector CGE model. Brockway et al. (2017) provide an empirical implementation of Saunders approach that shows the difficulty of getting good empirical estimates of the production function.

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

van Benthem (2015) argues that the energy efficiency of many products currently sold in developing countries is much better than that of comparable products sold 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%. Hart (2018) provides a theoretical model of this shift to more energy intensive goods – this could be caused by changing patterns of consumption with rising income, and/or improvements in energy efficiency that reduce the costs of energy services – in other words, the rebound effect.

SVARs have several advantages in the context of estimating the economy-wide rebound effect. SVAR models are small, multivariate, dynamic, time series econometric models that are estimated directly from the data but have restrictions imposed to identify the effects of specific structural shocks. We use a data-driven approach to identify the model, based on general statistical assumptions, thus avoiding economic-theoretic restrictions. 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 true 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 is a lower bound on the true effect.

SVAR models have more parameters than reduced-form vector-autoregressive (VAR) models. The reduced form parameters can be estimated directly from the data using standard (e.g. OLS) regression methods. The structural parameters are then recovered by applying identifying restrictions, which are usually based on economic theory. Instead, we identify SVAR models exclusively based on statistical theory. 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.

Thus, in this paper we use a statistical identification procedure based on a quite different framework. This framework is called Independent Component Analysis, a set of tools that 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 theoretical approach that guides the development of an empirical model. The third section presents the econometric approach. The empirical model is laid out in the third section. The fourth section discusses the data and results, and the final section provides conclusions and discussion.

2 Theoretical Background

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 Blanchard and Quah (1989), King et al. (1991), and Kilian (2009), we can represent this vector of three variables as the outcome of cumulative shocks to GDP, the price of energy, and a residual energy-specific shock:

$$\Delta x_t = \mu + \sum_{j=0}^{\infty} B_j \varepsilon_{t-j} \tag{1}$$

where $x_t = [e_t, p_t, y_t]'$ 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 shocks with var$(\varepsilon_t) = I$, and μ is a vector of constants.[3] We interpret ε_{et} as an energy efficiency shock, as it represents the exogenous reduction in energy use that are not due to exogenous shocks to GDP or energy prices.

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, we consider a second model that includes measures of the structure of the economy and energy quality. This five variable and shock framework accounts for the most important other factors:

$$\Delta\tilde{x}_t = \tilde{\mu} + \sum_{j=0}^{\infty} \tilde{B}_j \tilde{\varepsilon}_{t-j} \tag{2}$$

where $\tilde{x}_t = [e_t, p_t, y_t, s_t, q_t]'$ and s and q are the logs of structure (in practice the log of industrial production) and energy quality variables, $\tilde{\varepsilon}_t = [\tilde{\varepsilon}_{et}, \tilde{\varepsilon}_{pt}, \tilde{\varepsilon}_{yt}, \tilde{\varepsilon}_{st}, \tilde{\varepsilon}_{qt}]$ is the vector of shocks, and $\tilde{\mu}$ is a vector of constants.

The shocks are identified by estimating a structural vector autoregression as described in the following section. We use the impulse response function of energy with respect to the energy efficiency shock to measure the rebound effect. Using the subscript i to denote the number of periods since the energy efficiency improvement, the rebound effect is given by

$$R_i = 1 - \frac{\Delta e_i}{\Delta \hat{e}} = 1 - \frac{\text{Actual}}{\text{Potential}} \tag{3}$$

[3] As the model assumes it is equally likely that the stochastic component of a technology shock is positive or negative there should also be a constant negative drift term in log energy use (see King et al., 1991, Equation 2). This may be the case for log GDP too. Potential cointegrating relations may also need a constant term.

where $\Delta\hat{e}$ is the potential change in energy use, and Δe_i is the actual change in energy use.[4] We measure the potential energy savings as the energy efficiency shock.

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.

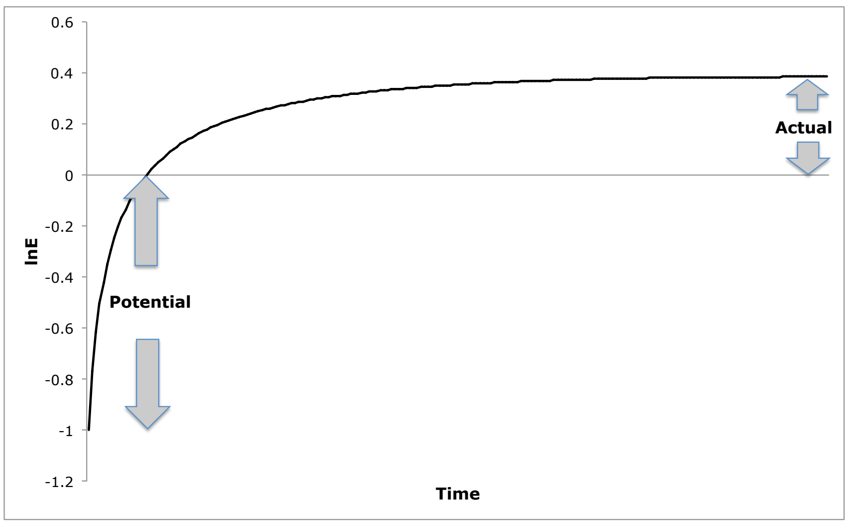

Figure 1: The rebound effect.

Assuming that our model captures the important factors that affect energy use apart from energy efficiency, there are two important limitations on our ability to identify energy efficiency shocks and the rebound effect. Not all energy efficiency changes might be captured by our identified energy efficiency shock and we will not be able to account for instantaneous rebound that takes place at $i = 0$.

[4]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 as a result 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.

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 level of price 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.

Some of the rebound may happen contemporaneously 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.[5] 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. If all the rebound occurred instantaneously we would measure 0% rebound.

Figure 2 shows how this will affect the estimated rebound. The observed energy efficiency shock is a fraction of the true shock. The outcomes show two potential cases where we assume that the observed shock is 75% of the true energy efficiency shock. In the energy saving case in Figure

[5] 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.

2, the true rebound is 50% but the observed rebound is $1 - \frac{0.5}{0.75} = 33\%$. In the backfire case, the true rebound is 125%, but the observed 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 will this error likely be in percentage points. In the econometric analysis we use both monthly and quarterly data. Monthly data should provide a better estimate of the size of the efficiency shock.

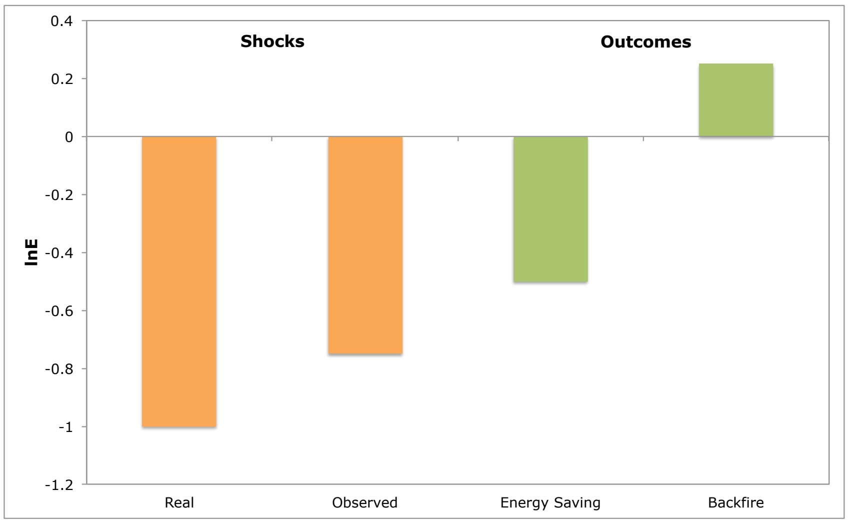

Figure 2: Observed vs. real rebound.

3 Empirical Approach

3.1 Structural Vector Autoregressions (SVARs)

We use an SVAR to determine the effect of a permanent exogenous improvement to energy efficiency that we identify as a "technology shock" (Gali, 1999) on macro-level energy use in future periods. The three-dimensional reduced form VAR model is given by

$$x_t = \xi + \sum_{i=1}^{p} \Pi_i x_{t-i} + u_t \tag{4}$$

where u_t is a vector of white noise errors that may be correlated across equations, the Π_i are matrices of parameters to be estimated, ξ is a vector of constants, and t indexes time. The structural model is given by:

$$A_0 x_t = A_0 \xi + \sum_{i=1}^{p} A_0 \Pi_i x_{t-i} + \varepsilon_t \tag{5}$$

where the diagonal entries of A_0 are unity (normalization), $\varepsilon_t = A_0 u_t$, and $\text{var}(\varepsilon_t) = I$. Now 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, which will be discussed below.

In the structural model (5), we need a total of $(n^2 - n)/2$ restrictions (where n is the number of variables) in order to identify the SVAR parameters. 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). Yet this is an area of economics 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 equalities or inequalities – known as "sign restrictions" (Kilian and Murphy, 2012; Fry and Pagan, 2011). But it is unclear which of the infinite number of impulse response functions admissible according to a sign restriction is the best (Fry and Pagan, 2011).[6]

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 restriction on the model.[7] We achieve

[6]Kilian and Lütkepohl (2017) outline various recent approaches to selecting the optimal model from among the set identified by sign restrictions.

[7]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

identification by restricting the space of possible structural models using an alternative framework, in which we maximally exploit the statistical information in the data.

3.2 Independent Component Analysis

Our empirical 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.[8] 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 the 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 first method is the distance covariance (dcov) approach recently proposed by Matteson and Tsay (2017). This approach minimizes a nonparametric measure of dependence among n linear

such as capital utilization, fluctuations in true productivity are only about half those in raw TFP.

[8]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).

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

$$I(u_{1t}, u_{2t}) = E|u_{1t} - u^*_{1t}||u_{2t} - u^*_{2t}| + E|u_{1t} - u^*_{1t}|E|u_{2t} - u^*_{2t}| \\ - E|u_{1t} - u^*_{1t}||u_{2t} - u^{**}_{2t}| - E|u_{1t} - u^{**}_{1t}||u_{2t} - u^*_{2t}| \quad (6)$$

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). The second ICA estimator we consider in our study is the Maximum Likelihood estimator proposed by Lanne et al. (2017). In contrast to other ICA estimators, this approach 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 maximum one is allowed to be Gaussian. To construct the likelihood function, one has to choose the non-Gaussian error 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 third ICA estimator is the fastICA algorithm Hyvärinen and Oja (1997), which is based on minimization of mutual information and maximization of negentropy. These two notions are based on information theory, and in particular on 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)

$$H(x) = -\int f(x) \ln f(x) dx. \tag{7}$$

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

$$J(x) = H(x^G) - H(x) \tag{8}$$

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

$$I(x_1, \ldots, x_m) = \sum_{i=1}^{m} H(x_i) - H(x). \tag{9}$$

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 (3.4)). 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 find 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 scale 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[9]. 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 impact maximally on the variable of interest.[10] This is, of course, a further *a priori* assumption that we impose on the system to achieve identification, jointly with non-Gaussianity (which can be indirectly tested) and independence of the shocks. These assumptions are detached from any specific economic-theoretical model, but still form those *a priori* conditions needed to achieve SVAR identification.

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

3.3 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

[9]This can be done according to the following procedure: (i) if the maximum entry of $A_0^{-1}D$ lies in position (row, column) (i, j), then the j^{th} column will permuted to i^{th} column in $A_0^{-1}DP$; (ii) repeat the same procedure starting from $A_0^{-1}D$ but computing 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.

[10]In other words, supposing that energy consumption is the first entry in x_t, the j^{th} shock will be labelled 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.

(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 right 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 with the criterion, mentioned above, to identify the energy shock simply based on 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 to estimate the dcov and ngml models and own code for the FastICA and LiNGAM models. More information can be found in the replication package.

3.4 Data

We estimate vector autoregressive models for the United States using monthly and quarterly data. Identifying restrictions are generally more plausible the more frequent the data is (Kilian, 2009).

While estimates using quarterly data may produce a biased estimate of the potential (instantaneous) effect, 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 (separately) both frequencies. Monthly data run from January 1992 to October 2016 (298 observations), quarterly data from 1973 (first quarter) to 2016 (third quarter) (175 observations). We will also, for the sake of comparison, estimate the model using quarterly data from 1992 to 2016 (99 observations). All data are taken in natural logarithms and multiplied by 100. Appendix A discusses the sources of the data in detail.

4 Results

4.1 Reduced-form VARs

Based on Kilian and Lütkepohl (2017), we use the Akaike Information Criterion (AIC) to choose the lag length. Based on the Schwert (1989) criterion, we use a maximum of 5 lags for the quarterly data and a maximum of 6 lags for the monthly data. We select 3 lags for both frequencies. Identification of the energy efficiency shock 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: if the reduced-form residuals, which are linear combinations of independent shocks, are non-Gaussian this implies that the structural shocks are also non-Gaussian, since a linear combination of independent and normally distributed random variables also has a normal distribution. 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[11].

[11] We obtain only isolated cases (monthly data, 3 variables model) in which the normality of the reduced-form residual associated to energy use is not rejected at 0.05 level of significance.

4.2 Identification of SVARs

Our focus here is on the energy efficiency shock and the partial identification of the SVAR (i.e. the labeling of one of the identified shocks as the energy shock), which is sufficient to estimate the rebound effect. However, 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, if at all, negative and small, especially in 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. 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 comparably small and effects on GDP and energy prices as expected from economic theory. The bootstrapped confidence intervals of these effects also include zero. We, therefore, conclude that these energy efficiency shocks conform with economic theory. Applying LiNGAM, we estimate the causal order as $y \longrightarrow e \longrightarrow p$ assuming a recursive causal structure.[12] While the effect 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.

[12]Note that 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 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 95.4% of the time. Our conclusion is that the causal order $y \longrightarrow e \longrightarrow p$ output of LiNGAM is satisfactorily stable.

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 price). 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 ($y \longrightarrow e \longrightarrow p$).[13]

Analogously to the findings for monthly data, 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. An exception is LiNGAM for which the GDP shock affects all three variables.

Regarding the expected long-run effects, we expect an energy efficiency shock to have a large negative effect on energy use. Figure 3 shows the impulse response functions for an SVAR identified with the distance 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).[14] We also expect the energy efficiency shock to have a positive effect on GDP and a negative on energy prices in the long-run. While energy prices decrease first, they eventually return to the initial level, but the effects

[13]While resampling initial conditions we also have here complete stability, but bootstrap stability (resampling the observed data) is a bit lower: 91.8%.

[14]We carried out some exploratory analysis of potential cointegrating relations in our model. We found that there might be either one or two cointegrating vectors. In the latter case, our impulse response functions suggest that the price shock is also transitory and the GDP shock is permanent.

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, -1.24]	[-0.59, 0.86]	[-0.33, 0.87]
y_t	0.09	0.51	0.03
	[-0.18, 0.27]	[0.38, 0.51]	[-0.15, 0.27]
p_t	-0.02	0.57	5.04
	[-1.89, 1.55]	[-1.95, 2.38]	[4.04, 5.06]
Non-Gaussian Maximum Likelihood (ngml)			
e_t	-1.50	-0.66	0.47
	[-1.71, -0.82]	[-1.40, 0.52]	[-0.32, 0.75]
y_t	-0.21	0.45	0.03
	[-0.40, 0.16]	[0.25, 0.50]	[-0.15, 0.26]
p_t	0.14	0.51	4.81
	[-1.89, 1.37]	[-1.87, 2.17]	[4.07, 4.97]
FastICA			
e_t	-1.61	-0.39	0.43
	[-1.71, -1.15]	[-1.18, 0.59]	[-0.29, 0.73]
y_t	-0.13	0.49	-0.01
	[-0.34, 0.17]	[0.33, 0.50]	[-0.21, 0.26]
p_t	0.07	0.99	4.90
	[-1.80, 1.31]	[-1.99, 2.67]	[3.84, 4.97]
LiNGAM			
e_t	-2.18	0.00	0.00
	[-2.33, -2.02]	[-0.19, 0.20]	
y_t	0.00	0.69	0.00
		[0.64, 0.73]	
p_t	-1.25	1.23	8.93
	[-2.01, -0.36]	[0.39, 2.08]	[8.36, 9.49]

Notes: *Bootstrapped* 0.90 *confidence intervals in brackets. LiNGAM (Causal structure* $y \longrightarrow e \longrightarrow p$*): 95.4 % bootstrap stability; 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	0.51	0.05
	[-1.63, -1.45]	[-0.40, 0.54]	[-0.46, 0.45]
y_t	0.16	0.71	0.03
	[-0.24, 0.18]	[0.63, 0.72]	[-0.23, 0.18]
p_t	0.05	-0.52	8.59
	[-2.47, 2.36]	[-2.29, 2.58]	[7.51, 8.59]
Non-Gaussian Maximum Likelihood (ngml)			
e_t	-1.55	0.42	0.14
	[-1.62, -1.51]	[-0.32, 0.40]	[-0.23, 0.25]
y_t	0.15	0.72	0.07
	[-0.21, 0.12]	[0.64, 0.73]	[-0.16, 0.14]
p_t	-0.05	-0.74	8.85
	[-1.20, 1.24]	[-1.61, 1.63]	[7.79, 9.30]
FastICA			
e_t	-1.53	0.41	0.02
	[-1.59, -1.52]	[-0.32, 0.40]	[-0.21, 0.23]
y_t	0.12	0.69	0.006
	[-0.21, 0.11]	[0.67, 0.70]	[-0.12, 0.10]
p_t	-0.15	-0.80	8.33
	[-1.08, 1.13]	[-1.31, 1.34]	[8.17, 8.37]
LiNGAM			
e_t	-2.05	0.52	0.00
	[-2.28, -1.82]	[0.23, 0.80]	
y_t	0.00	1.30	0.00
		[1.17, 1.43]	
p_t	-1.90	0.731	15.25
	[-3.94, 0.22]	[1.17, 1.43]	[13.81, 16.75]

Notes: *Bootstrapped* 0.90 *confidence intervals in brackets. LiNGAM (Causal structure* $y \longrightarrow e \Longrightarrow p$*): 91.8 % bootstrap stability; 100% initial conditions stability.*

remain mostly statistically non-significant. The long-run effect on GDP is positive, but statistically non-significant.

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 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.

4.3 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) compared to 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. We also estimate the rebound effect using quarterly data for the time span 1992-2016 (Models 9 to 12) and the differences in estimated long-run rebound effects reduce suggesting that the time period explains most of the differences. As discussed in Section 2, the quarterly data should estimate a lower rebound than monthly data when the rebound is less than unity and a greater rebound than monthly data when it is greater than unity.

4.4 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 identifying the energy efficiency shock. The $A_0^{-1}DP$ matrices for monthly and quarterly data can be found in the Appendix B (Tables 5 and 6). Labeling shocks by the largest

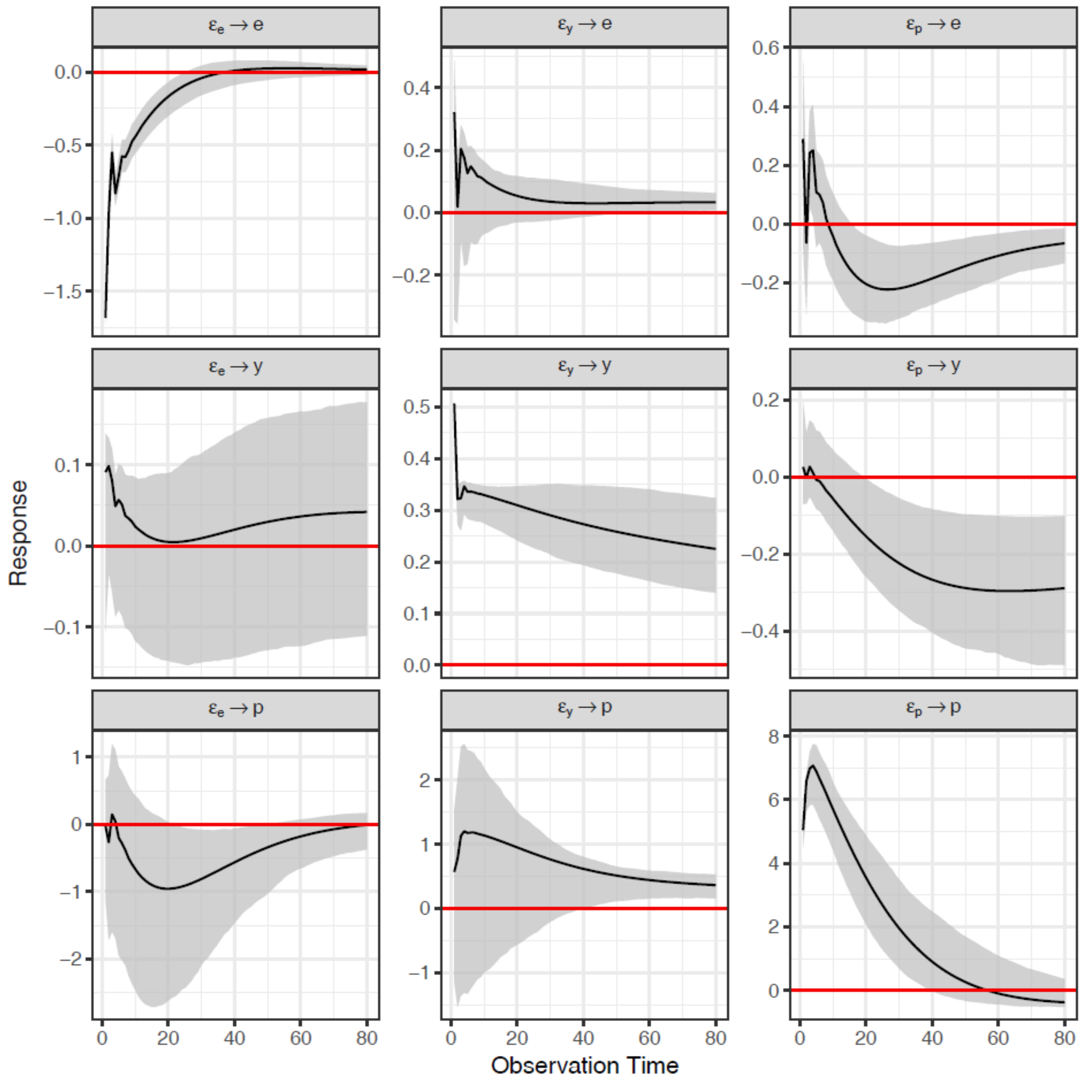

Figure 3: Impulse Response Functions for Monthly Data (Distance Covariance). 0.90 confidence intervals computed using wild bootstrap.

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
				[0.61,0.88]	[0.76,1.04]	[0.91,1.1]	[0.95,1.08]
2			ngml	0.76	0.91	0.99	0.99
				[0.62,0.89]	[0.76,1.04]	[0.9,1.09]	[0.94,1.06]
3			fastICA	0.77	0.92	1.00	1.00
				[0.85, 0.93]	[0.93, 1.06]	[0.96, 1.06]	[0.97, 1.04]
4			LiNGAM	0.90	0.99	1.01	1.00
				[0.88, 0.92]	[0.98, 1.01]	[1, 1.02]	[1, 1.01]
5	Quarterly	1973-2016	dcov	0.61	0.90	1.16	1.23
				[0.34,0.68]	[0.57,1.03]	[0.81,1.38]	[0.94,1.47]
6			ngml	0.61	0.90	1.17	1.24
				[0.35,0.63]	[0.6,0.97]	[0.84,1.32]	[0.96,1.45]
7			fastICA	0.59	0.88	1.16	1.23
				[0.52, 0.75]	[0.55, 1.14]	[0.80, 1.37]	[0.88, 1.35]
8			LiNGAM	0.63	0.88	1.08	1.12
				[0.61, 0.64]	[0.84, 0.95]	[1.01, 1.16]	[1.06, 1.18]
9	Quarterly	1992-2016	dcov	0.58	0.91	1.09	1.07
				[0.35,0.81]	[0.58,1.2]	[0.8,1.35]	[0.87,1.3]
10			ngml	0.45	0.77	1.01	1.03
				[0.34,0.8]	[0.58,1.14]	[0.8,1.31]	[0.88,1.28]
11			fastICA	0.54	0.88	1.08	1.06
				[0.62, 0.8]	[0.78, 1.16]	[0.89, 1.18]	[0.94, 1.12]
12			LiNGAM	0.71	0.95	1.03	1.02
				[0.67, 0.79]	[0.87, 1.06]	[0.98, 1.11]	[0.99, 1.08]

Notes: *Bootstrapped 0.90 confidence intervals in brackets.*

Table 4: Rebound Effect (Robustness Analysis, 5 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
				[0.65,1.19]	[0.83,1.32]	[0.94,1.43]	[0.95,1.33]
2			ngml	0.98	1.06	1.13	1.09
				[0.64,1.93]	[0.83,2]	[0.97,2.22]	[0.97,1.91]
3			fastICA	0.84	0.94	0.99	1.00
				[0.89, 1.03]	[0.91, 1.07]	[0.91, 1.08]	[0.94, 1.07]
4			LiNGAM	0.96	0.97	0.98	0.99
				[0.94, 0.98]	[0.95, 1]	[0.96, 1.01]	[0.98, 1.01]
5	Quarterly	1973-2016	dcov	0.72	0.85	0.93	0.97
				[0.52,1.42]	[0.66,1.92]	[0.65,1.84]	[0.64,1.64]
6			ngml	0.63	0.82	1.16	1.30
				[-0.07,0.63]	[-0.1,0.91]	[0.31,1.46]	[0.54,1.84]
7			fastICA	0.59	0.83	1.16	1.28
				[0.55, 1.13]	[0.61, 1.41]	[0.78, 1.43]	[0.87, 1.36]
8			LiNGAM	0.71	0.84	0.97	1.03
				[0.64, 0.78]	[0.77, 0.93]	[0.89, 1.08]	[0.96, 1.12]

Notes: *Bootstrapped 0.90 confidence intervals in brackets.*

contemporaneous effect size is not unique for the VAR with five variables as in some cases the same shock has the largest contemporaneous effect for two variables – GDP and economic structure (industrial production). As our interest is in the robustness of the rebound effect, we focus on the energy efficiency shock. 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 VARs with three variables.

For LiNGAM, the identified contemporaneous causal structures are much less stable than they are for the three variable VARs. For monthly data, the most stable structure is $y \rightarrow s \rightarrow q \rightarrow e \rightarrow p$. However, this structure reaches only 58% stability under random variation of the algorithm's initial conditions and 64.5% stability under bootstrap resampling of the data. Therefore, we examined the robustness of our results under the second most stable causal structure ($s \rightarrow y \rightarrow q \rightarrow e \rightarrow p$) and find that the estimated rebound effect is robust to this second causal structure as well. For quarterly data, the most stable causal structures is $q \rightarrow y \rightarrow s \rightarrow e \rightarrow p$ (73% initial conditions stability, 38.7% bootstrap stability). We also find the rebound effect to be robust if the second most stable structure $s \rightarrow q \rightarrow y \rightarrow e \rightarrow p$ is used.

In conclusion, LiNGAM does not provide stable and sufficiently reliable results for the VAR with five variables. It is interesting to note, however, that among the diverse causal structures suggested by the algorithm (including others we did not present), each of them singularly unstable, it is always the case that y comes before e and e before p in the contemporaneous causal chain, which was also the output of the 3-variable model. This probably means that the structure $y \rightarrow e \rightarrow p$ 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 was important to show results with methods not committed to such a scheme (dcov, ngml, FastICA).

The robustness analysis shows that the magnitude of the rebound effect obtained by the VAR with three variables is robust to controlling for two further determinants of energy use.

5 Conclusions and discussion

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 or data frequency used. As some part of the rebound might occur instantaneously, our estimates may differ from the true rebound. However, the true rebound is likely to be closer to 100% than the estimated rebound and our estimates of the long-run rebound are almost exactly 100%. These results are congruent with the historical research (van Benthem, 2015; Csereklyei 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. [15] 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 concerned 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 3 this seems to be the case, if we ignore the very wide confidence interval around the IRF 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 3. 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

[15] Of course, policies that impose costly energy efficiencies on energy consumers are likely to have a reduce energy use by more than the engineering effect (Fullerton and Ta, 2019).

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 3, they reduce GDP by more than they reduce energy use in the long run.

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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 primary electricity in our computation of the aggregate energy price index and energy quality. We treat biomass as primary energy whether it is used to generate electricity or not. We deseasonalize energy quantity and price data 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. This price averaged \$61 per MWh from January 2001 to December 2013. Using data on wholesale electricity prices provided by the Intercontinental Exchange to EIA (https://www.eia.gov/electricity/wholesale/#history), 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. 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. Monthly electricity prices are not available for 1992-1994 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, 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. The ratio of industrial production to GDP is our measure of industry structure.

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 de-seasonalized 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: 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 (Negentropy)					
e_t	-1.15	-0.21	-0.12	-0.13	1.09
y_t	-0.12	0.36	-0.21	0.24	0.01
p_t	-0.80	-0.13	-4.37	-2.17	-0.32
s_t	0.13	-0.45	0.15	-0.17	-0.02
q_t	-0.29	0.00	0.05	-0.04	-0.56
LiNGAM					
e_t	-1.57	0.19	0.00	0.11	-0.11
y_t	0.00	0.49	0.00	0.00	0.00
p_t	-0.88	1.00	4.71	0.66	0.21
s_t	0.00	-0.51	0.00	0.13	0.00
q_t	0.00	0.00	0.00	0.02	0.63

Notes: *LiNGAM (Causal structure: $y \longrightarrow s \longrightarrow q \longrightarrow e \longrightarrow p$) 64.5% bootstrap stability, 58% 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 (Negentropy)					
e_t	-1.07	0.45	0.18	0.24	-0.91
y_t	0.16	0.64	-0.09	-0.09	0.00
p_t	-1.39	-1.06	-8.10	0.14	-0.19
s_t	-0.05	0.21	-0.11	0.72	-0.07
q_t	-0.14	0.15	0.06	-0.02	0.57
LiNGAM					
e_t	-1.36	0.05	0.00	0.34	-0.35
y_t	0.00	0.66	0.00	0.00	0.05
p_t	0.98	1.35	8.38	2.12	-0.61
s_t	0.00	0.00	0.00	0.76	-0.06
q_t	0.00	0.00	0.00	0.00	0.60

Notes: *LiNGAM (Causal structure: $q \longrightarrow y \longrightarrow s \longrightarrow e \longrightarrow p$) 38.7% bootstrap stability, 73% initial conditions stability*