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Macroeconomic Time-Series Evidence That Energy Efficiency Improvements Do Not Save Energy

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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 energy use and greenhouse gas emissions. We provide the first empirical general equilibrium estimate of the economy-wide rebound effect. We use a structural vector autoregressive (SVAR) model that is estimated using search methods developed in machine learning. 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.

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Macroeconomic Time-Series Evidence That Energy Efficiency Improvements Do Not Save Energy

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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 energy use and greenhouse gas emissions. We provide the first empirical general equilibrium estimate of the economy-wide rebound effect. We use a structural vector autoregressive (SVAR) model that is estimated using search methods developed in machine learning. 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.

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Introduction

Governments and international organizations are expecting energy efficiency improvements to make a major contribution to reducing greenhouse gas emissions (Stern, 2017). As energy is used to transform, move, and heat matter, reduced energy use can contribute to improving sustainability more generally. But increases in energy efficiency do not translate perfectly into reductions in energy use. Energy use “rebounds” due to the reduced cost of providing energy services and other flow-on effects. As a result, energy savings and emissions reductions, may be a lot less than expected. The size of this rebound effect at the economy-wide level is controversial (Gillingham *et al*., 2013). Existing estimates vary widely from “backfire” (also known as “Jevons paradox”), where energy use increases following an efficiency improvement, to super-conservation where energy use falls by more than the efficiency improvement (Saunders, 2013; Turner, 2013).

Previous research uses either computable general equilibrium (CGE) simulation models (e.g. Turner 2009; Barker *et.al*. 2009; Koesler *et al*., 2016; Lu *et al*., 2017, Wei and Liu, 2017) or partial equilibrium – where the prices of other goods and inputs are held constant – econometric models (e.g. Adetutu *et al*., 2016; Saunders, 2013; Orea *et al*., 2015, Shao *et al*., 2014; Lin and Du, 2015). 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. Furthermore, as discussed below in more detail, most of the econometric studies do not credibly identify the rebound effect.

Here, we develop a structural vector autoregressive (SVAR) model that is empirically identified using independent component analysis (ICA) (Comon, 1994; Hyvarinen *et al*., 2001; Gouriéroux *et al*., 2017) a search method developed in the machine learning literature. SVAR modeling imposes a minimum of assumptions (Sims, 1980) but allows for general equilibrium effects allowing energy prices and output to adapt dynamically in response to a change in energy efficiency. Changes in energy efficiency are modeled as independent exogenous shocks to energy use that are not explained by changes in prices and income. We apply the model to U.S. data, finding that the economy-wide rebound is around 100%.

The economy-wide rebound effect is the sum of the direct rebound effect at the microeconomic level and a series of indirect rebound effects. The direct rebound effect occurs when an energy efficiency innovation is adopted that reduces the energy required to provide an energy service such as heating, lighting, or transport, and, therefore, its cost. As a result, users consume more of the energy service offsetting some of the energy efficiency improvement. Specifically, we define energy efficiency improvements as those that save energy due to the adoption of more efficient cost-reducing technology. We 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.

Indirect rebound effects include: changes in energy use due to 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 (and reduction for substitute goods and services); the effect of reduced energy prices due to the fall in energy demand on energy use (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).

Previous Research

Most empirical research on the rebound effect focuses on the direct rebound effect (Sorrell *et al.*, 2009). Estimates of the size of the direct rebound effect tend to be fairly modest (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). However, it is possible that, instead, the indirect rebound could be negative and the economy-wide rebound might also be negative in the long run (Turner, 2013; Borenstein, 2015). Lemoine (2017) conducts a general equilibrium analysis of the rebound effect. Assuming that all sectors share the same technology, general equilibrium effects amplify the partial (with prices held constant) equilibrium rebound, which is positive. With heterogeneous technologies, general equilibrium effects amplify the rebound for low elasticities of substitution between energy and non-energy inputs in production and reduce it for high elasticities of substitution. 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.

Evidence on the size of the economy-wide rebound effect to date depends on CGE simulation models and partial equilibrium econometric estimates. 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%. Single sector simulation methods (e.g. Saunders, 1992, 2014) reduce the degrees of freedom in CGE models but, therefore, impose far more restrictions and still depend on good estimates of the production parameters – a notoriously difficult problem (Leon-Ledesma *et al*., 2010). Several methods have been proposed to econometrically estimate the rebound effect, but all of these are partial equilibrium methods and, in most cases, 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). 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.

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) shows 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, because they do not control for other relevant variables such as the price of energy and other sources of economic growth, they suggest that the economy-wide rebound effect is close to 100%.

Our Approach

Structural vector autoregressive (SVAR) models 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. SVAR models originated in the work of Sims (1980) and are widely used in empirical macroeconomic research. We use a data-driven approach to identify the model, based on general statistical assumptions, thus avoiding the usual practice of imposing restrictions based on economic theory. 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.

Thinking of energy use as the equilibrium outcome of the demand and supply of energy, the major factors driving changes in energy use will be changes in the price of energy and in income – at the macroeconomic level, gross domestic product (GDP). 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:

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

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 observed in period *t*, $\varepsilon_t = \left[\varepsilon_{et}, \varepsilon_{pt}, \varepsilon_{yt}\right]'$ is the vector of exogenous shocks with $\mathrm{var}(\varepsilon_t) = I$, μ is a vector of constants, and *B* and the Π_i are matrices of parameters 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 and previous changes in those variables themselves. The mixing matrix, *B*, transmits the effect of the shocks to the dependent variables. Therefore, each of the shocks can have immediate effects on each of the variables.

The matrix *B* is estimated and hence the shocks are identified using four different search methods that use unsupervised statistical learning typical of machine learning research. Each of these makes assumptions about the statistical properties of the vector of shocks, ε_t. The key assumptions are the statistical independence of the shocks and the non-Gaussianity of the data, which can be easily checked empirically. The first two approaches – distance covariance (dcov) (Matteson and Tsay, 2011) and non-Gaussian Maximum Likelihood (ngml) (Lanne *et al*., 2017) – have been recently studied in the econometric literature in the context of SVAR models (Herwartz, 2018). The third approach is the FastICA algorithm (Hyvärinen and Oja, 1997) which is the most popular approach to Independent Component Analysis (ICA) estimation in machine learning. We further probe the robustness of our results by applying an ICA-based identification scheme – Linear Non-Gaussian Acyclic Model (LiNGAM) which, besides assuming non-Gaussianity and independence of the structural shocks, makes the further assumption of recursiveness (Shimizu *et al*., 2006; Hyvärinen *et al*., 2008; Moneta *et al*., 2013).

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:

$$R_i = 1 - \frac{\Delta \hat{e}_i}{\varepsilon_{e1}} = 1 - \frac{Actual}{Potential} \quad (2)$$

where ε_{e1} the energy efficiency shock in the initial period that represents the potential "engineering" change in log energy use, *e*, and $\Delta \hat{e}_i$ is the actual change in log energy use due to the shock as given by the impulse response function.

As an example, if in response to a 1% improvement in energy efficiency actual energy use declines by 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 an example impulse response function of the log of energy with respect to an energy-specific shock of -1. Initially, energy use is reduced 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.

Results

We apply our approach to U.S. monthly and quarterly data shown in Figure 2. Energy intensity – energy use per dollar of GDP – has declined fairly consistently over the last quarter century and at a casual glance seems unaffected by the large fluctuations in the price of energy over the same period (Figure 2a). There is more variation in the rate of decline in the quarterly data, which extend over a longer period. The rate of decline does seem to negatively correlate with the price changes in the 1970s and 80s (Figure 2b). Primary energy use has not increased since 2007 partly due to the slowdown in the rate of economic growth since the Great Recession. Note that our model actually uses GDP rather than energy intensity. GDP can be recovered by dividing energy use by energy intensity.

Figure 3 shows the impulse response functions for an SVAR identified using the distance covariance method and monthly data. The first column shows the effect of the energy efficiency shock on energy use, GDP, and the energy price. The effects on GDP and the energy price are generally not statistically significant. The energy efficiency shock results in a strong decrease in energy use initially, but this effect is eliminated over time resulting in backfire.

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, conform with standard economic theory.

Estimates for the rebound effect after 1, 2, 4, and 6 years are presented in Table 1. Estimates of the mixing matrix *B* are presented in Appendix Tables 1 and 2. The estimates of the rebound effect are very similar for the four methods of identification but differ with respect to the data frequencies. 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 the Methods, 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.

We extend the VAR 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 (Figure 4). Table 2 again presents the rebound effect after 1, 2, 4, and 6 years, while estimates of the mixing matrix *B* are presented in Appendix Tables 3 and 4. The estimated rebound effects are very similar to those for the VARs with three variables. This 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.

Discussion

We have produced the first empirical general equilibrium estimate of the size of the economy-wide rebound effect by using SVAR models which are the workhorse of causal inference in macroeconomics and recent advances in machine learning. Causal inference is always difficult in macroeconomics as controlled experiments are impossible and identifying exogenous sources of variation difficult. Our approach is the best that can be done without imposing *a priori* economic theory on the data.

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, as discussed in the Methods, 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 (e.g. van Benthem, 2015; Csereklyei *et al.*, 2016 and theoretical (Lemoine, 2017; Hart, 2018) research 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 and, therefore, greenhouse gas emissions. On the other hand, energy efficiency policies that increase costs, by for example mandating equipment that is more expensive despite being more energy efficient, are likely to reduce energy use by more than the engineering effect.

We can also use our model to understand the drivers of energy use in the U.S. Energy intensity has declined over time in the United States (Figure 2). Based on our three variable SVAR, 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 2 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, as shown in Figure 2, GDP shocks tend to increase GDP by proportionally much more than they increase energy use. This may be because, as we can see, GDP shocks also increase the price of energy, which then restricts the increase in energy use. Finally, increasing energy prices can reduce energy use though they also reduce GDP. However, in Figure 2, they reduce GDP by more than they reduce energy use in the long run.

Methods

Reduced Form and Structural Models

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

$$x_t = \mu + \sum_{i=1}^{p} \Pi_i x_{t-i} + u_t \tag{3}$$

where $u_t = B^{-1}\varepsilon_t$ is a vector of white noise errors that may be correlated across equations, and the other terms are as in Equation (1). As the model assumes it is equally likely that the stochastic component of a technology shock is positive or negative, there will 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.

In addition to the three variable SVAR used in our main analysis, we estimate a five variable SVAR as a sensitivity analysis. This second model includes measures of the structure of the economy and energy quality. We measure energy quantity in joules 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 joules. 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). This five variable and shock framework accounts for the most important other factors:

$$\tilde{x}_t = \tilde{\mu} + \sum_{i=1}^{p} \tilde{\Pi}_i \tilde{x}_{t-i} + \tilde{B}\tilde{\varepsilon}_t \tag{4}$$

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, respectively and $\tilde{\varepsilon}_t = [\tilde{\varepsilon}_{et}, \tilde{\varepsilon}_{pt}, \tilde{\varepsilon}_{yt}, \tilde{\varepsilon}_{st}, \tilde{\varepsilon}_{qt}]'$ is the vector of shocks.

An alternative representation of the structural model to that in Equation (1) is given by:

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

where the diagonal entries of B^{-1} are unity (normalization), $\varepsilon_t = B^{-1}u_t$, and $\mathrm{var}(\varepsilon_t) = I$. Now the effects of shocks on the dependent variables can be independently assessed and each is associated with a particular equation. B^{-1} 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.

Independent Component Analysis (ICA)

SVAR models have more parameters than reduced-form VAR models. The reduced form parameters can be estimated directly from the data using standard regression methods. The structural parameters are then usually 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; Demiralp and Hoover, 2003; Moneta, 2008). This specific approach, although it eschews economic-theoretic assumptions, is based on graph-theoretic conditions (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.

Here, we also use a statistical identification procedure, but one 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 (e.g. Moneta *et al*., 2013; 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.

ICA is based on a theorem, first proved by Comon (1994, Th. 11), 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 B, such that $\varepsilon_t = B^{-1}u_t$, is "almost identifiable." This means that B is identifiable up to a column permutation and the multiplication of each of its diagonal elements by an arbitrary non-zero scalar. In other words, the matrix B 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 (Gourieroux *et al*., 2017: 112). In the ICA literature, several techniques have been developed to estimate the matrices B and B^{-1}, 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 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 B and B^{-1}.

Using three different approaches allows us to explore the robustness of our rebound estimates.

The first method is the distance covariance (dcov) approach (Matteson and Tsay, 2017). This approach minimizes a nonparametric measure of dependence among *n* linear combinations of the observed data (u_t), namely the distance covariance (Székely *et al*., 2007). For example, the distance covariance between, say, u_{1t} and u_{2t} is defined as:

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

$$- E\ |\ u_{1t} - u_{1t}^{*}||u_{2t} - u_{2t}^{**}| - E\ |\ u_{1t} - u_{1t}^{**}||u_{2t} - u_{2t}^{*}| \qquad (6)$$

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}). To estimate the matrices B and B^{-1}, Matteson and Tsay (2011) use this measure of dependence, defining 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 $B(\theta)$ and a vector of structural shocks $\varepsilon_t(\theta) = B(\theta)^{-1}u_t$. Matteson and Tsay (2011) show that the choice of θ that corresponds to $argmin_{\theta}\ \mathfrak{I}(\theta)$ determines a consistent estimator of B and that this mixing matrix is associated with structural shocks $\varepsilon_t(\theta) = B(\theta)^{-1}u_t$ 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 $\varepsilon_t = B^{-1}u_t$ 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 B^{-1} 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. The differential entropy H of x is defined as (Papoulis 1991)

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

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 1991). 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 1999). A potential problem is that estimating mutual information or negentropy would require estimating the probability density function *f(x)* (see Equation (7)). 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 maximizes 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 B; 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 B in $u_t = B\varepsilon_t$ by a matrix DD^{-1} such that D is diagonal (with non-zero diagonal elements) and $D^{-1}\varepsilon_t$ has unit variance. The column indeterminacy is solved by assuring that the diagonal element of BDP (where P is a column permutation matrix) contains the maximum elements of each row of BDP, so that the i^{th} shock maximally impacts on the i^{th}-variable. It is important to notice that this is 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* restrictions needed to achieve SVAR identification.

Lastly, the columns of BDP are normalized such that the diagonal of BDP has 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 these restrictions because we focus on the impacts of positive shocks on variables, except for the impact of energy use, where we want to study effects of its reduction.

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; Hyvärinen *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 B^{-1} and the mixing matrix B. 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: there will be indeed only one permutation that makes B^{-1} and B lower triangular. Since these matrices are estimated with errors, the algorithm searches for the permutation which makes one of these matrices the closest as possible to lower triangular. In comparison with our 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 results 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.

Measurement Error and 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 $i = 0$.

Price shocks might affect the rate of energy efficiency improvements too. Note 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. Hence, changes in energy prices themselves may have little effect on energy efficiency improvements.

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, which is larger and heavier than the previous model, so that the fuel economy of the new model shows less improvement than the engine efficiency improvement. In Austria, for example, the weight and engine capacity of cars increased from 1990 to 2007 as fuel efficiency increased (Meyer and Wessely, 2009). 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. As our approach relies on the rebound taking place over a period of time to measure the size of the rebound, if all the rebound occurred instantaneously we would measure 0% rebound.

The effect on measured rebound depends if the true rebound is greater or smaller than 100%. Assume, for example that the observed shock is 75% of the true energy efficiency shock. If the true rebound is, for example, 50% then the observed rebound is $1 - \frac{0.5}{0.75} = 33\%$. If instead the true rebound is 125%, then 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.

References

Acemoglu, D. (2002) Directed technical change. *Review of Economic Studies* 69: 781–810.

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

Barker, T., A. Dagoumas, and J. Rubin (2009) The macroeconomic rebound effect and the world economy. *Energy Efficiency* 2: 411–427.

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

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

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: 745–767.

Gillingham, K, M. J. Kotchen, D. S. Rapson, and G. Wagner (2013) The rebound effect is overplayed. *Nature* 493: 475–476.

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: 1–17.

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.

Hyvärinen, A. (1999) Independent component analysis by minimization of mutual information. Helsinki University of Technology.

Hyvärinen, A. and E. Oja (1997) A fast fixed-point algorithm for ICA. *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.

Hyvärinen, A., S. Shimizu, and P. O. Hoyer (2008) Causal modelling combining instantaneous and lagged effects: an identifiable model based on non-Gaussianity. In *Proceedings of the 25th international conference on Machine learning* (424-431).

Hyvärinen, A., J. Karhunen, and E. Oja (2001) Independent component analysis. John Wiley & Sons.

King, R. G., C. I. Plosser, J. H. Stock, and M. W. Watson (1991) Stochastic trends and economic fluctuations. *American Economic Review* 81(4): 819–840.

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

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. (2017) General equilibrium rebound from improved energy efficiency. *University of Arizona Working Paper* 14-02.

Leon-Ledesma, M. A., P. McAdam, and A. Willman (2010) Identifying the elasticity of substitution with biased technical change. *American Economic Review* 100: 1330–1357.

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 Tsay, R. S. (2011) Dynamic orthogonal components for multivariate time series. *Journal of the American Statistical Association* 106(496): 1450–1463.

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

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 CO_2 emissions. *Energy Policy* 37: 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.

Moneta, A., N. Chlass, D. Entner, and P. Hoyer (2011) Causal search in structural vector autoregressive models. *Journal of Machine Learning Research* 12: 95–114.

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.

Papoulis, A. (1991) *Probability, Random Variables and Stochastic Processes*. McGraw-Hill.

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 Chang*e 80: 1317–1330.

Saunders, H. D. (2014) Recent evidence for large rebound: Elucidating the drivers and their implications for climate change models. *Energy Journal* 36(1): 23–48.

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.

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: 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. (2012) Modeling international trends in energy efficiency. *Energy Economics* 34: 2200–2208.

Stern, D. I. (2017) How accurate are energy intensity projections? *Climatic Change* 143: 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: 357–367.

Székely, G. J., M. L. Rizzo, and N. K. Bakirov (2007) Measuring and testing dependence by correlation of distances. *The 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: 648–666.

Turner, K. (2013) “Rebound” effects from increased energy efficiency: a time to pause and reflect. *Energy Journal* 34(4): 25–43.

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

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

Table 1. 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 interval in brackets. Number of monthly and quarterly observations are 298 and 175, respectively.

Table 2. Rebound Effect (Robustness Analysis)

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 interval in brackets.

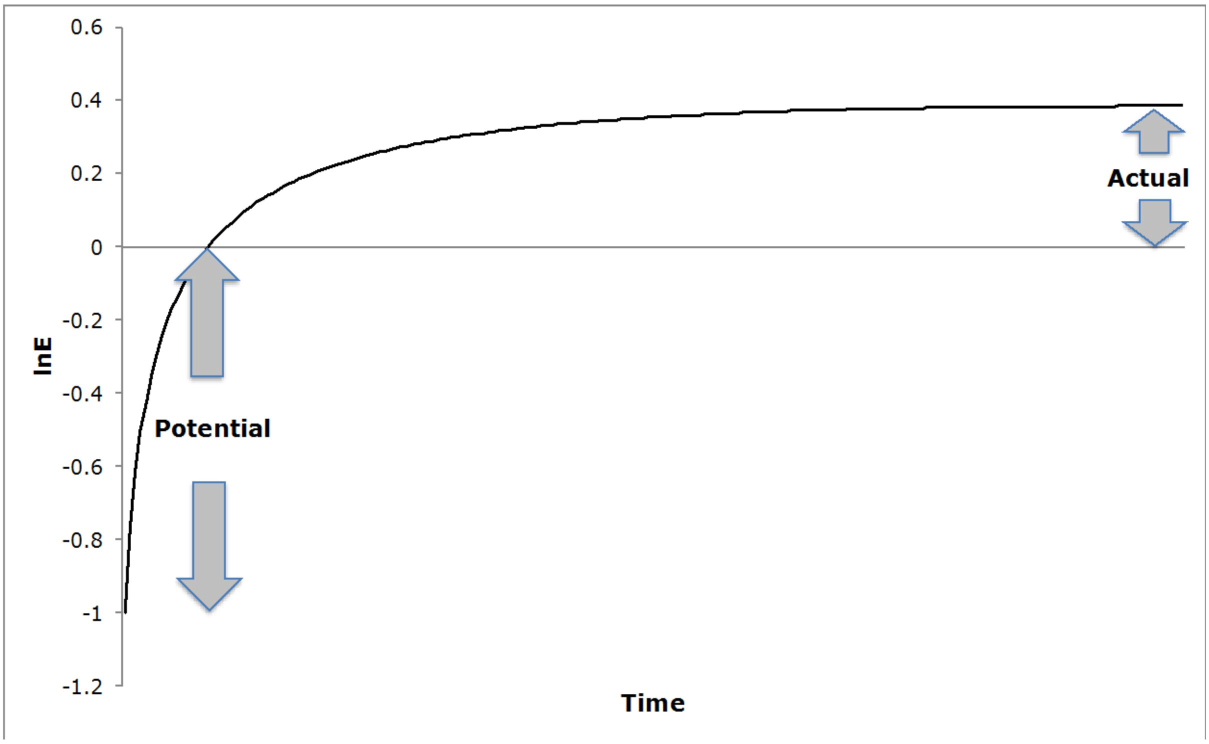
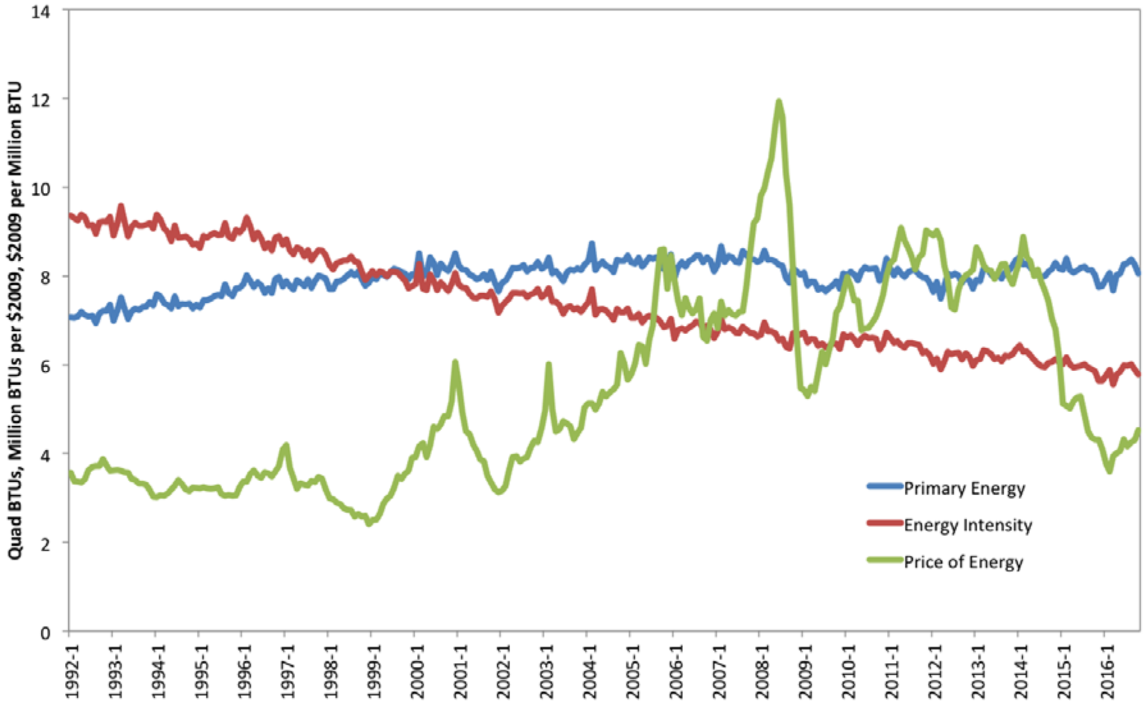


Figure 1. The Rebound Effect

a.



b.

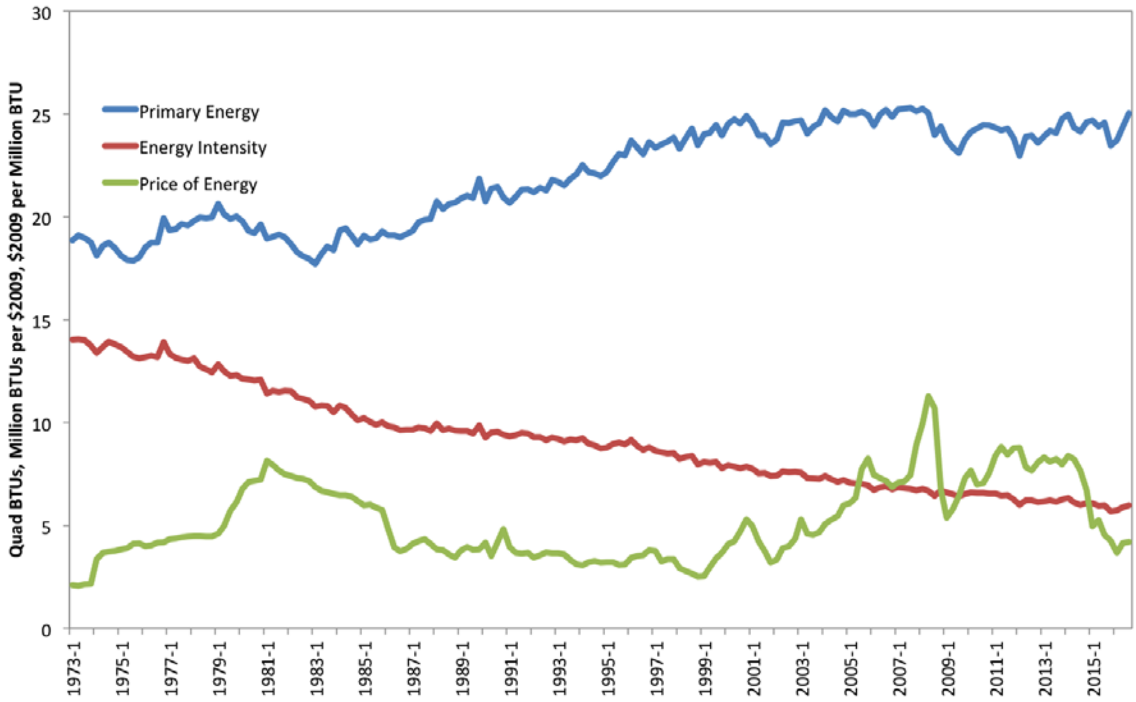


Figure 2. Main Variables: Energy intensity is shown instead of GDP. Data have been deseasonalized. See Appendix for data sources. **a.** Monthly U.S. data **b.** Quarterly data.

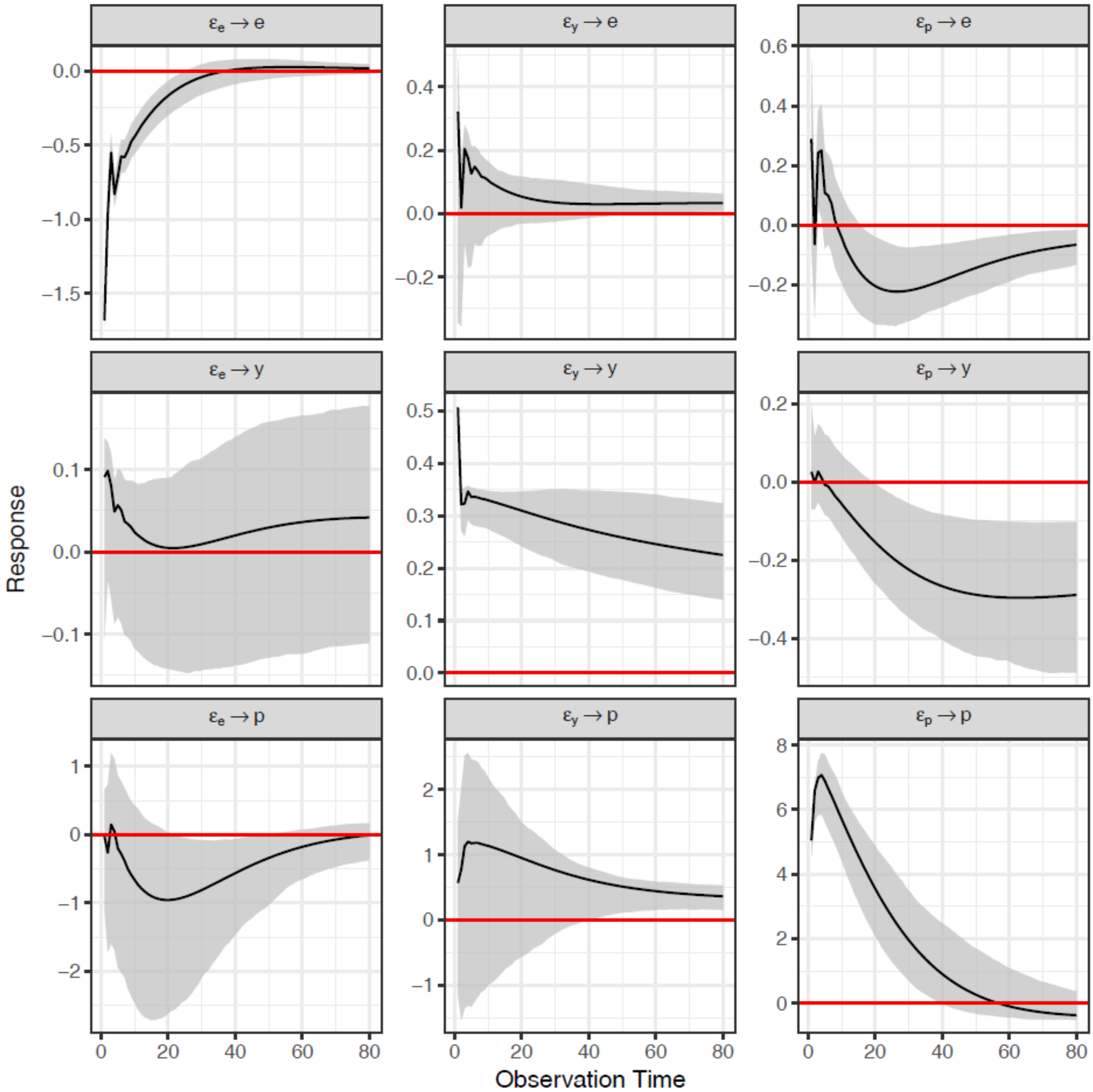
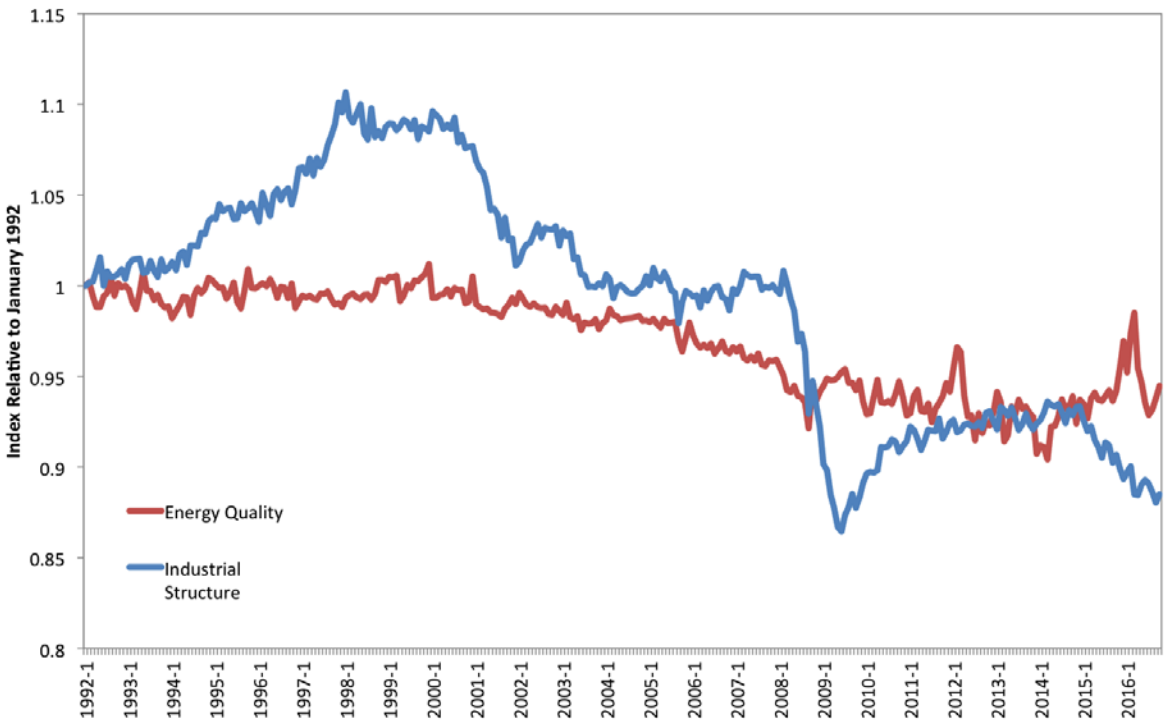


Figure 3. Impulse Response Functions for Monthly Data: SVAR estimated using distance covariance method. Grey shading is a 90% confidence interval computed using the wild bootstrap with 1000 iterations. All variables are in natural logarithms.

a.



b.

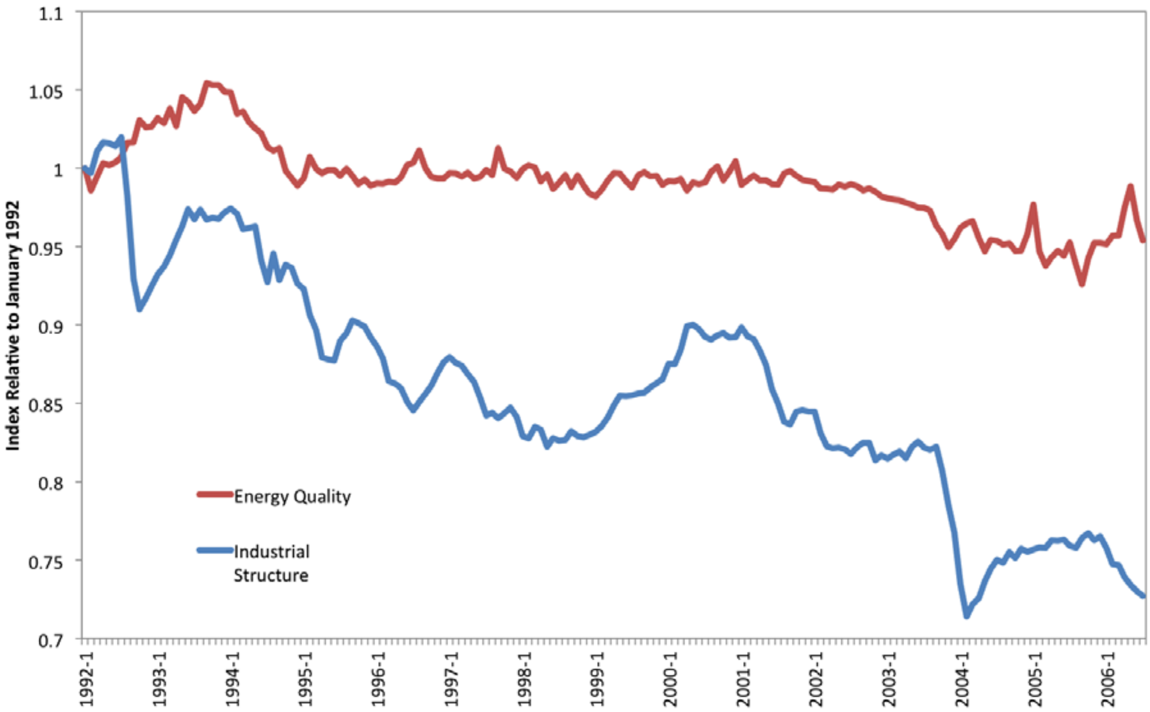


Figure 4. Additional Variables: Data have been deseasonalized. See Appendix for data sources. Energy quality is the ratio of a volume index of energy use to total joules. Industrial structure is the ratio of industrial production to GDP. See Methods for more details. **a.** Monthly U.S. data **b.** Quarterly data.

Appendix

Data

We estimate models for the United States using monthly and quarterly data. Identifying restrictions are generally more plausible the more frequent the data is (Kilian, 2009) but it is also possible that estimates using monthly data will focus on the short run and underestimate the long-run effects.

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 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 (for primary electricity) 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. To obtain the energy quality index we compute a Divisia energy volume index and divide this by total BTUs.

GDP: Macroeconomic Advisors 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 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.

Additional Econometric Results

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. The estimated reduced-form residuals are linear combinations of the structural shocks. According to the central limit theorem, the structural shocks tend to be non-Gaussian if the reduced-form residuals are non-Gaussian. 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. We use the R package svars to estimate the dcov and ngml models.

The contemporaneous effect on GDP of an improvement in energy efficiency should be positive due to the increase in TFP this represents and the effect on energy prices should be negative due to the reduction in demand for energy. However, we expect the contemporaneous effect of energy efficiency improvements on GDP and energy prices to be small as the transmission of these effects is likely to take some time. In the long run too, the effect on GDP should be small as energy costs are a small share of GDP. The contemporaneous effect on energy use should be large. As the column sign is not identified, we chose the effect on energy use to be negative. While our focus is on the energy efficiency shock and partial identification of the SVAR would be sufficient to estimate the rebound effect, we also discuss the GDP and energy price shocks to ensure that the estimated SVAR is generally consistent with economic theory. We expect the contemporaneous effect of a positive energy price shock on energy use and GDP to be small, especially in monthly data. The effect should be negative on both energy use and GDP. We also do not expect a strong contemporaneous effect of a positive GDP shock on energy use and energy prices, but these effects should be positive.

Appendix Table 1 shows the B 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 energy efficiency shock. This shock has the largest contemporaneous effect on energy use and comparably small effects on GDP and energy prices as expected from economic theory. While the signs of the contemporaneous effect on GDP and energy price are in line with theory if dcov is used, applying ngml and FastICA result in a positive sign for the effect on energy prices and a negative sign for the effect on GDP. However, these effects are small compared to the effect on energy use, and bootstrapped confidence intervals. We, therefore, conclude that the energy efficiency shock conforms with economic theory.

Applying LiNGAM, we estimate the causal order as $y \rightarrow e \rightarrow p$ assuming a recursive causal structure.[1] 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.

[1] Note that the mixing matrix reported in Table S2 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 then

Regarding the GDP shock, the bootstrapped confidence intervals again suggest that only the contemporaneous effect on GDP is statistically significant, except for LiNGAM where the effect on energy prices is also significant. The signs are consistent with theory if Distance Covariance is applied. 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.

Appendix Table 2 shows the B 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 are not statistically significant. For quarterly data, the energy efficiency shock identified by LiNGAM is also more consistent with economic theory. Moreover, the signs are consistent with economic theory for all approaches except for distance covariance. LiNGAM suggests the same contemporaneous causal structure as for monthly data ($y \rightarrow e \rightarrow p$).[2]

Regarding the GDP shock, it is again only the contemporaneous effect on GDP that is statistically significant, except for LiNGAM where all effects are statistically significant. For all methods, the price shock is only statistically significant for the contemporaneous effect on prices.

The B matrices for monthly and quarterly data for the five variable SVAR can be found in Appendix Tables 3 and 4. Labeling shocks by the largest 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.

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.

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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->e->p output of LiNGAM is satisfactorily stable.

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

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 $s \rightarrow q \rightarrow y \rightarrow e \rightarrow$ 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).

References

Kilian, L. (2009) Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review* 99: 1053–1069.

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

McCracken, M. and S. Ng (2015) FRED-MD: A Monthly Database for Macroeconomic Research, *Federal Reserve Bank of St. Louis Working Paper* 2015-012B.

Schwert, G. W. (1989). Tests for unit roots: A Monte Carlo investigation. *Journal of Business and Economic Statistics* 2: 147–159.

Appendix Table 1. Mixing Matrices, B, for SVARs with Three Variables: Monthly Data

	ε_e	ε_y	ε_p
Distance covariance			
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			
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]	[-4.97, -4.07]
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: LiNGAM (Causal structure y → e → p): 95.4 % bootstrap stability; 100% initial conditions stability. 90% confidence intervals in brackets using wild bootstrap with 1000 iterations.

Appendix Table 2. Mixing Matrices, B, for SVARs with Three Variables: Quarterly Data

	ε_e	ε_y	ε_p
Distance covariance			
e_t	-1.55 [-1.63, -1.45]	0.51 [-0.40, 0.54]	0.05 [-0.46, 0.45]
y_t	0.16 [-0.24, 0.18]	0.71 [0.63, 0.72]	0.03 [-0.23, 0.18]
p_t	0.05 [-2.47, 2.36]	-0.52 [-2.29, 2.58]	8.59 [7.51, 8.59]
Non-Gaussian Maximum Likelihood			
e_t	-1.55 [-1.62, -1.51]	0.42 [-0.32, 0.40]	0.14 [-0.23, 0.25]
y_t	0.15 [-0.21, 0.12]	0.72 [0.64, 0.73]	0.07 [-0.16, 0.14]
p_t	-0.05 [-1.20, 1.24]	-0.74 [-1.61, 1.63]	8.85 [7.79, 9.30]
FastICA			
e_t	-1.53 [-1.59, -1.52]	0.41 [-0.32, 0.40]	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 [-1.31, 1.34]	8.33 [8.17, 8.37]
LiNGAM			
e_t	-2.05 [-2.28, -1.82]	0.52 [0.23, 0.80]	0.00
y_t	0.00	1.30 [1.17, 1.43]	0.00
p_t	-1.90 [-3.94, 0.22]	0.731 [1.17, 1.43]	15.25 [13.81, 16.75]

Notes: LiNGAM (Causal structure y → e → p): 91.8 % bootstrap stability; 100% initial conditions stability. 90% confidence intervals in brackets using wild bootstrap with 1000 iterations.

Appendix Table 3. Mixing Matrices, *B*, for SVARs with five variables: 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 → s → q → e → p) 64.5% bootstrap stability, 58% initial conditions stability.

Appendix Table 4. Mixing Matrices, B, for SVARs with five variables: 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: (Causal structure: q → y → s → e → p) 38.7% bootstrap-stable; 73% initial conditions stable.