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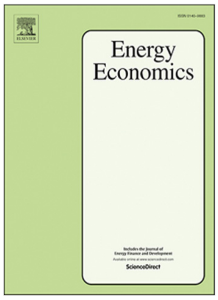

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PII: S0140-9883(22)00113-X
DOI: https://doi.org/10.1016/j.eneco.2022.105939
Reference: ENEECO 105939

To appear in: *Energy Economics*

Received date : 27 May 2021
Revised date : 17 February 2022
Accepted date : 25 February 2022

Please cite this article as: A. Berner, S. Bruns, A. Moneta et al., Do energy efficiency improvements reduce energy use? Empirical evidence on the economy-wide rebound effect in Europe and the United States. *Energy Economics* (2022), doi: https://doi.org/10.1016/j.eneco.2022.105939.

Title page

Do Energy Efficiency Improvements Reduce Energy Use? Empirical Evidence on the Economy-Wide Rebound Effect in Europe and the United States

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Abstract

Increasing energy efficiency is often considered to be one of the main ways of reducing greenhouse gas emissions. However, efficiency gains that reduce the cost of energy services result in energy use rebounding and potential energy use savings being eaten up. Empirical research that quantifies the economy-wide rebound effect while taking the dynamic economic responses to energy efficiency improvements into account is limited. We use a Structural Factor-Augmented Vector Autoregressive model (S-FAVAR) that allows us to track how energy use changes in response to an energy efficiency improvement while accounting for a vast range of potential confounders. We find economy-wide rebound effects of 78% to 101% after two years in France, Germany, Italy, the UK, and the US. This implies that energy efficiency innovations alone may be of limited help in reducing future energy use and emphasizes the importance of tackling carbon emissions directly.

Keywords: Energy efficiency, economy-wide rebound effect, climate change, climate policy, Structural FAVAR, Independent Component Analysis

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Energy Economics: ENEECO-D-21-00659

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1. Introduction

Improving energy efficiency is commonly viewed as one of the key ways to mitigate greenhouse gas emissions (IPCC, 2019; IEA, 2016). In political discussions, energy efficiency is sometimes seen as a panacea for reducing energy consumption while simultaneously reducing the costs of production and thereby ensuring green growth (European Commission, 2019; Ocasio Cortez, 2019; OECD, 2015). However, efficiency gains that reduce the cost of energy services result in some rebound in energy use, so that energy use savings are reduced or even completely eaten up. The rebound effect measures the percentage of potential energy use savings that are not realized due to the responses of economic agents to the energy efficiency gain. In this study, we empirically estimate this rebound effect for four European countries and the United States, finding rebound effects that approach almost 100 % after two years.

The *direct* rebound effect describes the response of consumers and producers who use more energy services as their cost falls (Sorrell and Dimitropoulos, 2008). There are also many follow-on effects across the economy known as *indirect* rebound effects. For example, a cost-saving energy efficiency gain for consumers will redirect saved income to other goods and services that also require energy in their production (Sorrell and Dimitropoulos, 2008). Furthermore, reduced demand for energy may lower the price of energy resulting in further incentives to expand the use of energy services (Gillingham et al., 2016). The new energy-efficient technology might even require more energy to produce than the old technology did (Lange et al., 2021).

While direct rebound effects are comparatively well studied and are estimated to mostly range between 10 % and 30 % in developed countries (Maxwell et al., 2013),[1] fewer empirical studies estimate indirect rebound effects (e.g. Freire-González, 2017; Chitnis et al., 2014; Wang and Nie, 2018), and it is particularly challenging to estimate the *economy-wide* rebound effect, which encompasses both direct and indirect rebound effects. The quantitative literature on the economy-wide rebound effect can be divided into computational, accounting, and fully empirical approaches (Stern, 2020).

Computational approaches, including partial equilibrium methods (e.g. Saunders, 2008) and computable general equilibrium (CGE) models (e.g. Turner, 2009; Koesler, 2013; Rausch and Schwerin,

[1] Some studies find much larger effects for some specific activities. For instance, Moshiri and Aliyev (2017) estimate that the rebound effect of energy efficiency in passenger car transportation is between 63 % and 96 % in Canada.

2018), are most common. These structural models are theoretically consistent and can capture a wide range of mechanisms. The estimated rebound effects from CGE models range from negative effects – indicating that energy use is reduced by more than the efficiency improvement – to "backfire" where energy use increases (Turner, 2009; Colmenares et al., 2020). The accounting approach (Lin and Liu, 2012; Shao et al., 2014; Lin and Du, 2015; Zhang and Lin Lawell, 2017) measures changes in energy efficiency by changes in energy intensity and assumes that rebound is proportional to total factor productivity growth, neither of which is appropriate (Stern, 2020).

Prior to Bruns et al. (2021), only a few studies tried to fully econometrically estimate the economy-wide rebound effect using observed data and statistical methods (Adetutu et al., 2016; Orea et al., 2015; Yan et al., 2019). These earlier studies do not allow GDP and the price of energy to change in response to changes in energy efficiency. Such changes in GDP and the price of energy (and also other relevant time series) may result in further changes in energy use, and ignoring these dependencies will bias estimates of the economy-wide rebound effect.

Recently, Bruns et al. (2021) proposed using a Structural Vector Autoregressive (SVAR) model to estimate the economy-wide rebound effect. SVAR models are the workhorse of macroeconomic time series analysis and consist of a small system of regression equations that model the statistical dependence among the relevant time series (Kilian and Lütkepohl, 2017). In this framework, we can identify exogenous changes in energy efficiency and measure the reaction of energy use to these shocks, taking into account the possibility that this reaction may be mediated by other variables such as the price of energy and GDP. Using this approach, Bruns et al. (2021) estimate that the economy-wide rebound effect for the US is about 100 %.

In this study, we extend the work of Bruns et al. (2021) in two directions. First, while the SVAR approach provides powerful tools for estimating the responses of an economic system to exogenous forces, the presence of unobserved confounders may bias these estimates (Bernanke et al., 2005; Bai and Ng, 2013; Favero et al., 2005). Accounting for unobserved confounders in macroeconomic time series analysis is non-trivial, as the number of potential confounders is very large, while the number of available observations is small. We use a Structural Factor-Augmented Vector Autoregressive (S-FAVAR) model that, like SVAR models, estimates the relationship among several variables over time, but also augments the core model with the principal components of a rich set of potential confounders (Bernanke et al., 2005). Specifically, our core model includes three variables:

energy use, the real price of energy, and GDP. We obtain the additional factors from a set of 41 to 56 (depending on the country considered) economic time series. This approach helps to comprehensively mitigate the threat of omitted-variable biases and to reduce the potential bias due to economic agents anticipating energy efficiency improvements (nonfundamental shocks). Second, while Bruns et al. (2021) estimate a rebound effect of roughly 100 % for the US, it is important to investigate whether the economy-wide rebound effect is similarly large in other major polluting countries, or whether the dynamics differ due to differences in industrial structure, reactions to the financial crisis, or countries' energy mixes, among other factors. Here, we use the S-FAVAR approach to estimate economy-wide rebound effects in France, Germany, Italy, the UK, in addtiion to the US.

Our analysis relies on the notion that changes in the economic system can be traced back to independent impulses, commonly referred to as "shocks" in the econometrics literature (Kilian and Lütkepohl, 2017). We identify an energy efficiency shock by applying Independent Component Analysis (ICA) to the residuals of a reduced-form Factor-Augmented Vector Autoregressive (FAVAR) model. ICA finds the least dependent linear combinations of the residuals, which correspond to an estimate of the independent shocks that jointly affect the observed variables. Based on this, we can estimate the response over time of economy-wide energy use to an energy efficiency shock.

We find that the economy-wide rebound effect narrowly ranges between 78 % and 101 % after two years in France, Germany, Italy, the UK, and the US despite differences in their industrial structure and energy mix and despite considering a large set of time series to reduce the risk of bias due to omitted variables and anticipated shocks. This implies that policies to encourage energy efficiency improvements may not be effective in reducing energy use in the long run, which would be at odds with common green growth strategies.

The remainder of the paper is organized as follows. Section 2 presents our empirical strategy by explaining the different components of the S-FAVAR model and introducing the dataset. Empirical results are discussed in Section 3. Finally, Section 4 summarizes and concludes.

2. Empirical Approach

2.1. The Economy-Wide Rebound Effect

We estimate the economy-wide rebound effect by identifying an energy efficiency shock, that is, an independent and exogenous shock to economy-wide energy use that cannot be explained by any other variable considered in the S-FAVAR model outlined in the subsequent sections, and by tracing the dynamic response of energy use to this shock. Using the subscript i to denote the number of periods since the energy efficiency improvement, the economy-wide rebound effect is given by:

$$R_i = 1 - \frac{\text{Actual}}{\text{Potential}} = 1 - \frac{\Delta\hat{e}_i}{\varepsilon_{e_1}} \tag{1}$$

where ε_{e_1} is the contemporaneous response of energy use to the energy efficiency shock, which represents the potential "engineering" change in energy use, and $\Delta\hat{e}_i$ is the actual change in energy use (Bruns et al., 2021). Notice that ε_{e_1} is by construction a negative number, while $\Delta\hat{e}_i$ measures the response of energy use to the energy efficiency shock after i periods and can be any real number.

2.2. Structural Factor-Augmented Vector Autoregressive (S-FAVAR) model

It would be desirable to consider all variables that potentially influence economy-wide energy use and, therefore, potentially confound the estimate of the economy-wide rebound effect. However, the analysis of intertemporal dependencies in a "data-rich" environment is problematic using standard multivariate autoregression models, as the number of parameters to be estimated may rapidly exceed the available observations. Augmenting a classical SVAR model with a small number of factors obtained from a large set of time series provides a remedy.

To characterize the effect of an energy efficiency shock on energy use, we assume that the state of the economy is represented by a vector C_t, whose entries are both observed and latent variables. As we are interested in estimating the response of energy use to an energy efficiency shock, we include the following three core observable series: energy use, E_t, GDP, Y_t, and the price of energy, P_t. Moreover, we incorporate several latent factors, F_t, in the vector C_t that summarize the information in a large set of macroeconomic indicators (see Section 2.3 for the estimation of these factors). The dynamics of the common components are modeled by the following reduced-form FAVAR model:

$$C_t = \Phi(L)C_{t-1} + u_t$$

where

$$C_t = \begin{bmatrix} E_t \\ Y_t \\ P_t \\ F_t \end{bmatrix} \quad (2)$$

and $\phi(L)$ is a conformable lag polynomial of finite order. The error term, u_t, is assumed to be i.i.d. with mean zero and covariance matrix Σ_u.

2.3. Factor augmentation

The factor model reduces a large matrix of time series data into a few latent factors. The following equation relates the unobserved common factors, collected in the $r \times 1$ vector F_t, and the vector of m observed core variables W_t (in our case time series data on the price of energy, energy use and GDP, so that $m = 3$) to an $N \times 1$ vector of (observed) "informational" variables Z_t (in our case 41 to 56 time series, depending on the country analyzed):

$$Z_t = \Lambda^f F_t + DW_t + \zeta_t, \quad (3)$$

where Λ^f is an $N \times r$ matrix of factor loadings, D is a $N \times m$ diagonal matrix, and ζ_t is a $N \times 1$ vector of idiosyncratic residuals. Hence, changes in Z_t are driven by the latent factors, F_t, the observable time series, W_t, and idiosyncratic noise. We can collect the individual vectors for each time period into the $T \times N$ data matrix, $Z = (Z_1, Z_2, \ldots, Z_T)'$, the $T \times m$ matrix of observables, $W = (W_1, W_2, \ldots, W_T)'$, and the $T \times r$ matrix of latent factors, $F = (F_1, F_2, \ldots, F_T)'$. We estimate D, Λ^f, and F in two steps (Hwang, 2009):

1. Regress Z_t on W_t, and compute the least squares estimates, $\hat{D}$, and the residuals, $\hat{U}_t = Z_t - \hat{D}W_t$;
2. Estimate the first $K - r$ principal components of $\hat{U}_t$ which represent the estimated latent factors.

Hence, the factor estimates can be specified as $\hat{F} = \hat{U}'\Lambda^f$, where $\hat{U} = (\hat{U}_1, \ldots, \hat{U}_T)'$ and the columns of Λ^f are the eigenvectors corresponding to the largest eigenvalues of $\hat{U}'\hat{U}$. This ensures that the loading matrix has orthonormal columns and can be identified.[2] The resulting factors, F_t, are included in the reduced-form FAVAR (2), which can be estimated using OLS, before identifying the structural representation.

2.4. Identification

After estimating the factors, the model in Equation (2) can be treated as a standard VAR. As the residuals, u_t, might be correlated across equations, we rewrite these innovations as a linear combination of the underlying orthogonal structural disturbances, η_t. Rewriting Equation (2) results in the following structural model:

$$\begin{bmatrix} F_t \\ W_t \end{bmatrix} = \phi(L) \begin{bmatrix} F_{t-1} \\ W_{t-1} \end{bmatrix} + B\eta_t \tag{4}$$

where η_t has mean zero with covariance matrix $\Sigma = I$. The non-singular mixing matrix, B, contemporaneously transmits the effects of the shocks to the dependent variables and specifies the relations between the shocks and the reduced-form innovations, $u_t = B\eta_t$ with $\Sigma_u = BB'$.

We estimate the matrix B and so identify the shocks, using two different search methods. These use unsupervised statistical learning typical of machine learning research that fall within the class of Independent Component Analysis (Comon, 1994). Both methods rely on two key assumptions about the statistical properties of the vector of shocks: the shocks are assumed to be mutually statistically independent and are distributed according to a (not necessarily specified) non-Gaussian distribution, with at most one exception. The latter assumption can be easily checked indirectly by testing whether we can reject the Gaussianity of the reduced-form innovations, u_t. The former assumption cannot be tested but is in tune with the idea of finding the primitive exogenous forces that drive the dynamics of the system, each of which is denoted by a particular economic characteristic not shared with the other shocks.

The two ICA approaches we apply are distance covariance (dcov) (Matteson and Tsay, 2011) and non-Gaussian Maximum Likelihood (nGML) (Lanne et al., 2017), which have been recently

[2] See Kilian and Lütkepohl (2017) Table 16.1 or Bai and Ng (2013) for alternative sets of identification conditions for factors and factor loadings.

studied in the econometric literature in the context of SVAR models (Herwartz, 2018). Herwartz et al. (2021) show that distance covariance is the most robust of various approaches to data-based identification of SVARs, though nGML performs better if the shocks are actually t-distributed and homoskedastic. To test the robustness of our results, we also compute the Choleski decomposition of the residual variance matrix, which gives similar results (see Table E.7 for a comparison of the different rebound estimates).

ICA determines neither the sign nor the economic meaning of the shocks *a priori*. The columns of the mixing matrix should be reordered and if necessary their sign changed to make them easier to interpret economically (Gouriéroux et al., 2017; Moneta and Pallante, 2020).[3] We solve this indeterminacy by assuming that, of the three empirically identified shocks, the energy efficiency improvement should have the largest (in absolute value) contemporaneous effect on energy use. This shock represents exogenous changes in energy use that are not explained by any of the other variables considered in the model and, thus, we attribute them to changes in energy efficiency. The effect of this shock on energy use is by definition negative, as we are interested in studying the effect of improvements in energy efficiency.

In our analysis, we extensively use the R package `svars`, which implements independence-based identification (Lange et al., 2019).

2.5. Estimating the economy-wide rebound effect

The rebound effect is defined as the percentage of potential energy savings that are not realized (see Equation (1)). This can be estimated using the impulse-response function of energy with respect to the energy efficiency shock.

Figure 1 shows an illustrative impulse-response function of energy use with respect to an energy-specific shock. The initial or potential savings (ε_{e_1}), indicated by the fall in energy use at time 0, decrease over time and energy use even exceeds, in this particular illustration, the pre-shock level leading to negative actual savings ($\Delta\hat{\varepsilon}_i$) and, therefore, to backfire.

[3] In the language of matrix analysis, ICA identifies the impact matrix up to the right multiplication of a signed permutation matrix, i.e. a matrix containing exactly one entry in each row and column equal to +1 or -1 and all other entries equal to 0. ICA leaves undetermined also the scale of the shocks, but these are typically normalized to have unit variance.

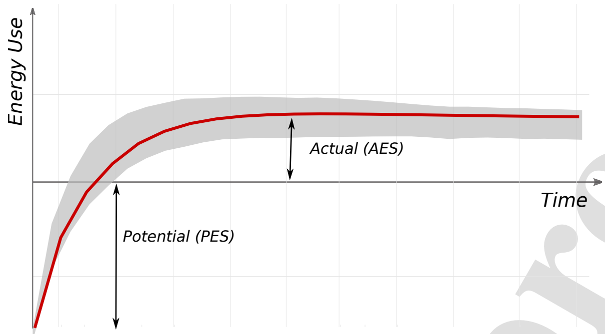

Figure 1: **Illustration of potential energy savings (PES) and actual energy savings (AES)** depicting an illustrative impulse-response function of energy use with respect to the energy efficiency shock (red curve) and its confidence interval (gray area).

The estimation of the rebound effect based on an S-FAVAR model addresses the omitted variables problem that is common in SVAR analysis by including the information from a large set of variables. Furthermore, the S-FAVAR model allows us to tackle a related but subtler problem, which is typical of standard (small scale) SVAR models and may bias the estimation of the rebound effect. In SVAR analysis, structural shocks are identified from a linear transformation of VAR prediction errors (i.e. reduced-form residuals). But it is conceivable that these prediction errors do not accurately capture the true prediction errors of the economic agents, because the latter rely on a larger information set than that contained in the econometric model. This creates a mismatch between the (true) data generating process shocks and the shocks of the SVAR model, which has been studied in the literature on so-called *nonfundamental shocks* (Kilian and Lütkepohl, 2017; Alessi et al., 2011).[4] In such a case, the shocks identified using an SVAR model may in fact be anticipated by the economic agents. This would bias the estimates of the energy efficiency shock and the rebound effect. This problem, and, more generally, the problem of nonfundamental shocks, can be ameliorated in S-FAVAR analysis because the information set is much larger than in a standard SVAR analysis, and so it is more likely that it mirrors the information set that economic agents use to predict or anticipate energy efficiency improvements.

However, there are two remaining caveats. First, the model does not capture rebound that may

[4]The name is due to the fact that the moving average representation of the VAR prediction errors is called the fundamental representation. Nonfundamental shocks are shocks that cannot be recovered from this representation.

happen contemporaneously with the efficiency improvement. [5] Bruns et al. (2021), however, explain that the error due to this effect is smaller the closer the true rebound effect is to 100 %. Second, our rebound estimate describes only the response that can be attributed to energy-specific efficiency improvements. The reason is that we assume that our energy efficiency shock is orthogonal to other the shocks. Therefore, if labor- or capital-augmenting innovations are captured in the GDP shock (or other shocks) and if these innovations are correlated with improvements in energy efficiency, then these energy efficiency improvements will not be captured in the energy efficiency shock.

2.6. Data

The main variables in our model are energy use, the price of energy, and economic output, measured by GDP. For the US, the data used in this article is the same as the data described in Bruns et al. (2021) but captures a shorter time period. Compared to the US, monthly time series data at the country level are still quite sparse for Europe. Therefore, we restrict our analysis to France, Germany, Italy, and the UK, as monthly data for these countries are available from January 2008 to September 2019, providing 141 observations. All data series were log-transformed and deseasonalized using the `seasonal` package in R with the X-11 adjustment procedure.

Energy use: We measure energy use by gross inland consumption (GIC), which covers the amount of energy that is needed to satisfy the total energy use of a country. Eurostat provides monthly energy data from January 2008 onwards for crude oil (without natural gas liquids), natural gas, and solid fuels. [6] Monthly primary electricity data can only be constructed from 2010 onwards. We derive the primary electricity time series using data on the electricity generation mix (IEA, 2021b) and the energy conversion efficiency of fossil-fuel fired electricity generation. (IEA, 2021a). [7] All series are converted from the original energy units to tonne(s) of oil equivalent (toe) and aggregated for each country. [8]

Our main analysis uses only the fossil fuel series, as this allows for a longer time series and is the variable of interest if we are concerned about the consequences of the rebound effect for climate

[5] This is discussed in the literature as the “embodied-energy” and “redesign” effects (Lange et al., 2021).
[6] Including data on hard, coke oven and brown coal, peat, oil shale, and oil sands, patent fuels and brown coal briquettes.
[7] For details see AppendixG.
[8] We use conversion factors from the IEA energy unit converter: https://www.iea.org/classicstats/resources/unitconverter/

change. However, we also carry out a robustness check using the time series that include primary electricity (see AppendixG).

The energy mix is quite diverse: While Germany still obtains a large share of its primary energy from solid fuels (42.6 %) followed by the US with 21 %, in France, Italy, and the UK that share is below 10 %. [9] The share of energy contributed by primary electricity is lowest in Germany (12 %) and the US (16 %) and highest in France (45.7 %), where nuclear energy is very important. Natural gas is the most important energy carrier in Italy and the UK (46 % and 44 %, respectively), but is less important in the US (27 %), Germany (25 %) and France (23 %). Globally, oil is the greatest source of energy. This is reflected here by shares varying from 23 % (Germany) to 37.5 % (Italy).

Energy prices: Monthly energy prices for European countries are not available for all energy carriers. We derive the price of crude oil using the monthly mean of the weekly series provided in the European Commission's Oil Bulletin (European Commission, 2020). For the other three energy sources, prices are provided on a quarterly basis by the IEA (IEA, 2020). To approximate the monthly evolution, we use Eurostat's harmonized consumer prices indices (HICP) which measure the changes over time in the prices of consumer goods and services acquired by households (Eurostat, 2020). The indices are available for the three different energy carriers (solid, liquid, gaseous fuels and electricity). To obtain a monthly energy price series for the primary energy carriers, we multiply the monthly HICP for each energy carrier with the level of the quarterly end-use energy prices for industry for the first quarter of 2010 and divide by the average HICP in that quarter. To compute the mean price of energy, we multiply the price series for the different energy carriers with their gross inland consumption and sum over energy carriers. Finally, we divide this cost series by the total gross inland consumption of energy.

Gross Domestic Product: As monthly GDP data is not available for European countries, we construct monthly real GDP using the encompassing methods proposed by Mönch and Uhlig (2005) and Bernanke et al. (1997). We create a monthly economic activity time series by combining the available quarterly GDP series and appropriate historical monthly time series (the approach is explained in detail in Appendix AppendixA).

Figure 2 presents the data series for energy intensity and the price of energy. Note that the data for

[9] The percentage numbers here report shares of the energy use data in November 2019, see G.23

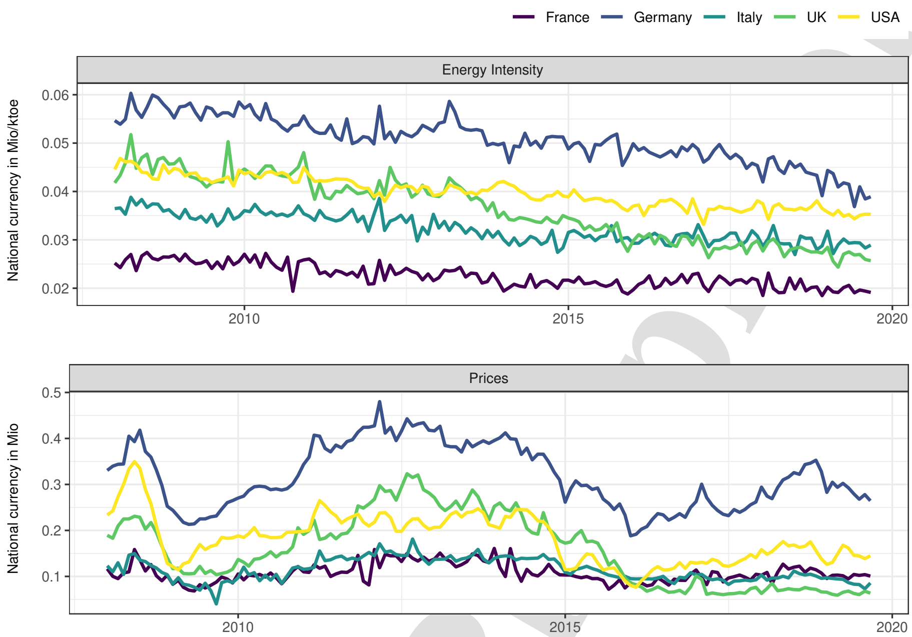

Figure 2: **Time series data for the countries included in the analysis.**

energy consumption in the US also includes energy from renewables, biomass, and nuclear power generation, which are not included in the European data.

Finally, we extract the latent factors from a large matrix of time series from the Main Economic Indicator (MEI) database (OECD, 2020). This data set covers the labor market, national accounts, retail sales, production, construction, prices, finance, international trade, and the balance of payments. The latent factors are intended to summarize the main sources of variation in the data panel and hence can be interpreted as the common driving forces behind the various economic variables. AppendixA discusses the sources of the data in detail.

3. Results

3.1. Reduced-form FAVAR

Using the Akaike information criterion and maximum lag lengths of 6 and 12, we select lag lengths of $p = 2$ for France, the UK, and the US, $p = 3$ for Italy, and $p = 4$ for Germany (see Table E.6 in the Appendix for details).

We statistically evaluate the number of Gaussian components among the reduced-form residual series using component-wise normality tests (Shapiro-Wilk, Shapiro-Francia, Jarque-Bera). [10] The test results indicate that we cannot reject the presence of more than one Gaussian component (see Table D.5 in the Appendix). However, these tests perform poorly in small samples, especially if the distributions of the samples are close to normality (Gouriéroux et al., 2017; Maxand, 2020). Maxand (2020) shows that at least the unique identification of the non-Gaussian shocks can be guaranteed irrespective of the distributions of the remaining shocks. We are particularly interested in the energy efficiency shock, and the normality of the reduced-form residuals of the energy use equation can be rejected for all countries except France. Furthermore, in the case of multiple Gaussian reduced-form residuals, the ICA methods will still deliver orthogonal shocks, since they orthogonalize the residuals as in a standard principal component analysis. However, the residuals are only identified up to an orthogonal transformation, which may dramatically increase the variance of the estimates (Hyvärinen and Oja, 2000). Additionally, we tested the robustness of the identified shocks by comparing the result of the independence-based identification strategies with the results of a Choleski decomposition. The results are similar for the energy efficiency shock (see Appendix E.7).

3.2. Factor augmentation to account for potential confounders

The first two factors explain from 45.78 % (UK) to 62.82 % (US) of the variance of the informational variables in each country dataset (see Table 1). We include these two factors in the S-FAVAR model to ensure a balance between the variance explained and degrees of freedom lost. Increasing the number of included factors to three adds roughly 10 % to the explained variance (see Table 1). A robustness check of the estimated rebound effect with three factors included can be found in the Appendix (Figure E.17).

The two estimated factors are presented in Figure 3. The identification of the estimated factors is only possible up to a change of sign. [11] The factors fluctuate strongly during the financial crisis

[10] We also compared the component-wise tests with a boostrappping test, based on fourth order blind identification (FOBI) as explained in the Appendix.

[11] This is demonstrated by Factor 1 peaking during the financial crisis in 2008/2009 for Germany, Italy, and the UK and collapsing in France and the US.

Table 1: Explained variance in the set of country-specific time series

Factor #	1	2	3	4	5	6	7	8	9	10
France	33.22	13.49	11.31	7.69	6.46	6.17	5.56	5.07	4.82	4.08
Germany	35.59	19.54	12.09	8.89	8.39	5.73	4.36	4.17	4.06	3.60
Italy	37.34	15.04	10.27	8.80	6.97	6.06	5.65	5.43	4.21	3.64
UK	23.78	22.00	11.70	9.88	7.23	6.11	5.81	5.32	4.55	4.11
USA	43.33	19.49	12.80	9.16	8.29	6.57	5.05	4.41	3.72	3.44

Notes: Each row shows the variance in the country-specific set of time series explained by the respective factor (in %).

that started in 2008, which shows that they enlarge the information set by adding the impact of the financial crisis.

We present the factor loadings for Germany (Panel a) and the UK (Panel b) in Figure 4 to investigate what the latent factors might represent. The higher the absolute value of a factor loading, the higher the correlation between that factor and the respective time series. For both Germany and the UK, one factor seems to load mainly on different producer price indices and the other on exchange rates, the unemployment level, exports, industrial production, and expectations. This means that one factor mostly represents real changes in the economy while the other mostly represents changes in prices. The factor loadings for the other countries are similar to the German example and can be found in the Appendix (Figure E.15).

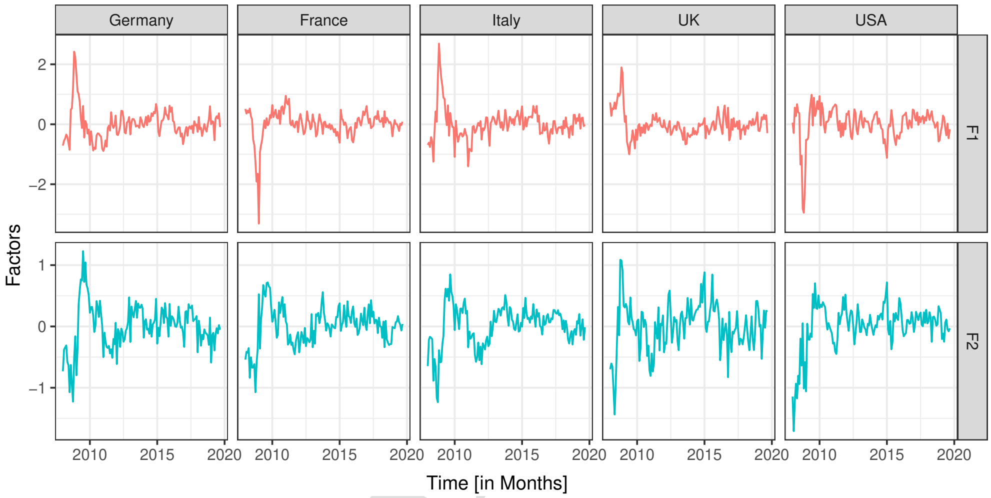

Figure 3: **Estimated latent factors.** The factors with the highest explanatory power, factor 1 (in red) and factor 2 (in blue), are depicted for each country.

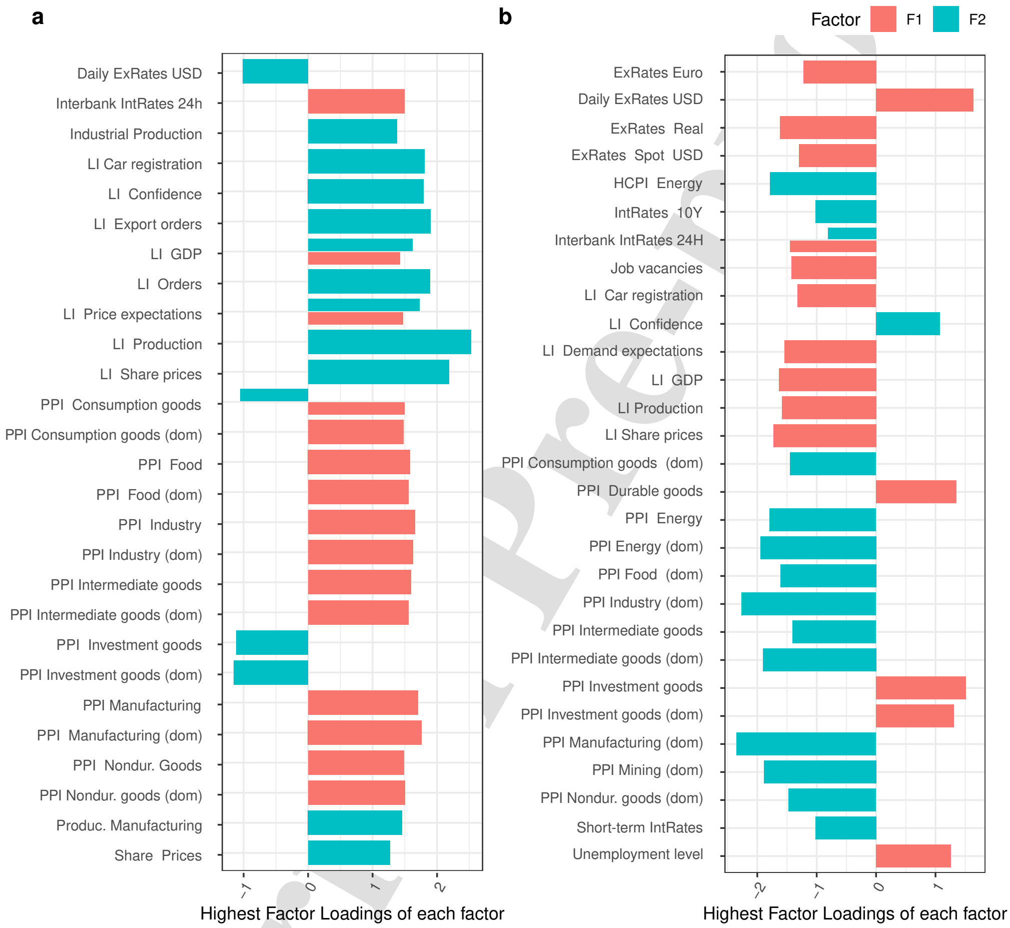

Figure 4: **Example factor loadings.** The 15 highest factor loadings for the first two factors for (**a**) Germany and the (**b**) UK. "ExRates" stands for exchange rates, "IntRates" for interest rates, "LI" for leading indicator, "PPI" for producer price index, and "HCPI" for harmonized consumer price index.

3.3. Identifying energy efficiency shocks

As described in the methods section, we identify the energy efficiency shock using the criterion that this shock should have the largest contemporaneous effect on energy use. As our focus is on estimating the economy-wide rebound effect, identification of the energy efficiency shock is sufficient. The shocks associated with GDP and the price of energy, as well as the overall economic plausibility of the estimated S-FAVAR model are discussed in AppendixC.

The identified contemporaneous effects of the shocks (elements of the B matrix) are presented in Table 2. For all countries, the energy efficiency shock has a large contemporaneous effect on energy use compared to its effects on GDP and the price of energy, except for the US where its effect on energy use is similar in magnitude to its effect on the price of energy. The effect of this shock on energy use is negative by construction, and in all countries the confidence intervals do not overlap zero. By contrast, the confidence intervals of the contemporaneous effects of the energy efficiency shock on GDP and the price of energy always overlap zero, except for the effect on GDP in France where zero is marginally excluded.

We confirm the identification of the energy efficiency shock by inspecting the forecast error variance decompositions (FEVD) shown in Figure 5. FEVDs are a measure of the impacts of the shocks on each of the modeled variables. FEVDs show how much of the variance of the forecast error of each variable (the prediction mean squared error of the model variables) at various time horizons is accounted for by the different shocks. If a shock accounts for most of the forecast error variance of a specific variable, x, at most time horizons, this provides good evidence that the shock should be labeled as the x-shock.

The panels show for each country the percentage of the forecast error variance of energy use explained by the different shocks in the months following a shock of each type. If the forecast error variance of energy use can be largely explained by the shock that we identified as the energy efficiency shock, then this would be a strong sign that the identification is correct. For all forecast horizons in Germany, for example, about 75 % of the forecast error variance of energy use is explained by the shock that we identified as the energy efficiency shock (top left plot in Figure 5). For all countries and at all time steps considered, the forecast error variance of energy use is mostly explained by the identified energy efficiency shock.

The FEVDs for the other variables, shown in Figure B.8 of the Appendix, and the discussion of the

Table 2: Contemporaneous effects of the energy efficiency shock

	Germany	France	Italy	UK	US
e_t	-3.41	-5.25	-4.53	-4.02	-1.8
	(-3.7, -1.32)	(-6.05, -1.85)	(-4.61, -3.51)	(-4.51, -1.46)	(-2.01, -0.68)
y_t	0.03	-0.17	-0.03	0.03	-0.01
	(-0.16, 0.14)	(-0.23, -0.02)	(-0.13, 0.08)	(-0.11, 0.11)	(-0.22, 0.17)
p_t	1.47	3.88	-1.28	-0.23	1.76
	(-0.92, 3.4)	(-0.48, 5.88)	(-3.08, 2.04)	(-3.43, 3.58)	(-0.91, 3.43)

Notes: Contemporaneous effects of the energy efficiency shock on energy use (e_t), GDP (y_t), and the price of energy (p_t). 95 % confidence intervals in parentheses using a wild bootstrap.

economic plausibility of the estimated impulse response functions (provided in AppendixC) further strengthen our identification of the energy efficiency shock.

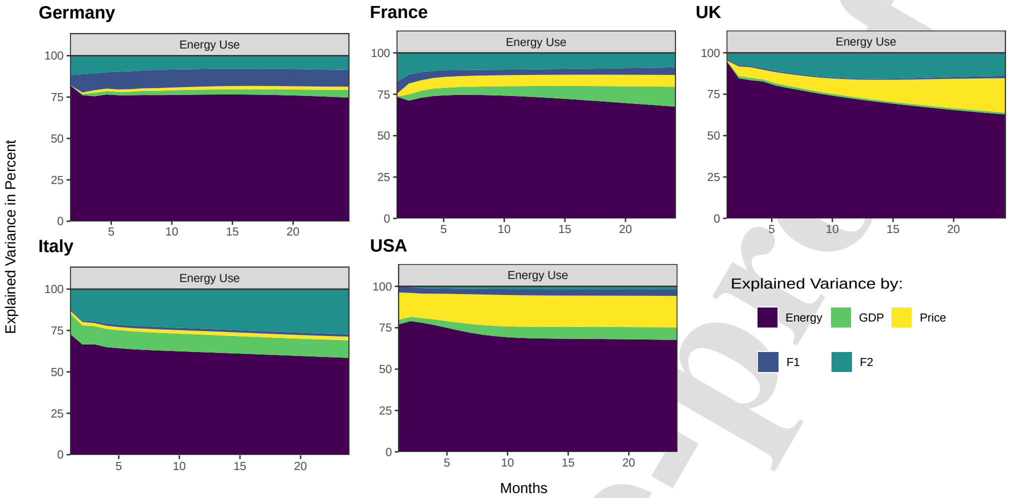

Figure 5: **Forecast error variance decomposition for energy use.** The decomposition shows the percentage (y axis) of the i-months (x axis) ahead forecast error variance which is explained by the five different shocks (indicated by the five different colours).

3.4. Economy-wide rebound effect

The impulse response function of energy use with respect to an energy-efficiency shock shows the same tendency in all countries: after an immediate reduction in energy use due to increased efficiency, energy use rebounds towards its original level (Figure 6, left panel). The impulse-response curves of the US and France seem to rebound faster than those of the other countries. However, the differences are subtle and the confidence intervals are overlapping. Figure 6 (right panel) shows that after 24 months the estimated rebound effect ranges between 78 % and 101 % for all countries with all confidence intervals overlapping 100 %. In general, estimates for the rebound effect are consistent across countries and identification methods (compare Table E.7 in the Appendix).

To analyze the influence and importance of confounders, we compare the FAVAR rebound estimates with those of the SVAR model proposed by Bruns et al. (2021) (see Figure E.19 in the Appendix). The analysis shows that controlling for these confounders does not fundamentally change the results. This result suggests that simple models that do not include the latent factors could be sufficient to estimate the rebound effect at the economy-wide level. However, this result does not necessarily generalize to other countries.

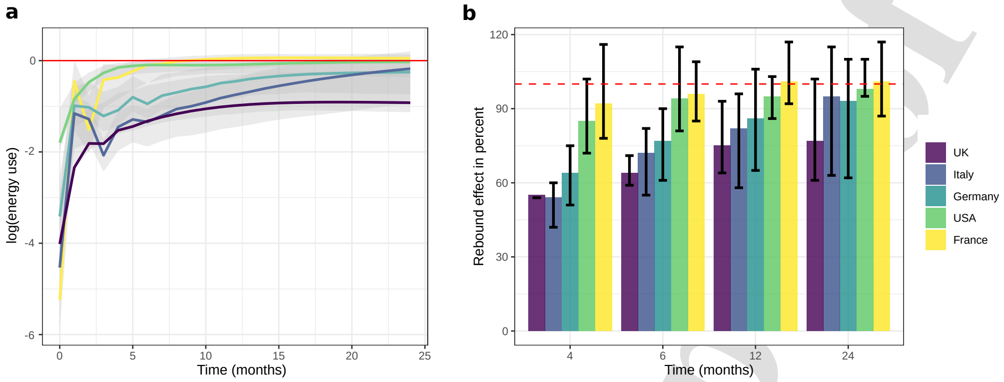

Figure 6: **Impulse response functions of energy use with respect to an energy efficiency shock (a) and estimated rebound effects (b)**. Shaded areas represent 90 % confidence intervals in the left panel. Error bars represent 90 % confidence intervals in the right panel. Confidence intervals based on wild bootstrapping.

As our data sample starts in 2008, the global financial crisis might influence our results. We repeat our analysis using samples starting in 2009 and 2010 (instead of 2008) and find that the estimated rebound for all countries but the UK is consistent across the different sample periods (see Figure E.16 in the Appendix). For the UK, the sample starting in 2009 leads to a higher estimated rebound.

4. Discussion and Conclusions

We use a Structural Factor Augmented Vector Autoregressive (S-FAVAR) model to quantify the economy-wide effect of energy efficiency improvements on energy use. Our methodology improves on past research by being able to separate the effect of energy efficiency improvements on energy use from the effects of other factors that might influence energy use, such as economic growth, exogenous changes in the price of energy, and a multitude of other potentially confounding factors. Our approach also allows GDP and the price of energy to evolve in response to the energy efficiency impulse and, in turn, energy use to respond again to the evolution of GDP and the price of energy.

Our analysis extends in two main ways the work of Bruns et al. (2021) who use U.S. data to provide the first SVAR-based quantification of the economy-wide rebound effect. First, we augment the SVAR with factors obtained from a rich panel of time series to address the potentially large number of confounders. Addressing potential omitted-variable biases is crucial to improving and ensuring the reliability of the estimated economy-wide rebound effect. Furthermore, augmenting the model with factors from a rich macroeconomic data set better reflects the information available to economic agents in the real world. This makes it less likely that the identified energy efficiency shocks are events that can be systematically anticipated by economic agents, which would bias the estimate of the economy-wide rebound effect. Rather, the shocks can be interpreted as genuine innovations, whose rebound effect can be reliably estimated. Second, we apply the improved estimation approach to both the U.S. and four European countries – France, Italy, Germany and the UK – to explore how similar the economy-wide rebound effect is across large, high-income countries.

We find that the economy-wide rebound effect is between 78 and 101 % across our sample of countries, which differ in industrial structure and energy mix. This finding is fairly consistent with Bruns et al. (2021), who find an economy-wide rebound effect of about 100 % for the US using an SVAR despite considering here a large set of time series to mitigate the risk of bias due to omitted variables and anticipated shocks (S-FAVAR). This implies that energy efficiency improvements that save energy by adopting more efficient cost-reducing technology will have limited long-run impact on aggregate energy consumption. These results are congruent with the growing evidence in recent studies that suggest that economy-wide rebound effects are large (Brockway et al., 2021; Saunders et al., 2021; Stern, 2020).

Our analysis identifies exogenous changes in energy use as changes in energy efficiency, as they can be neither explained by the core variables nor by the additional factors. We interpret these exogenous changes to largely represent cost-reducing improvements in energy efficiency. It should be emphasized that Fullerton and Ta (2020) show in a theoretical model that energy efficiency mandates that raise the cost of energy services can have a negative rebound effect resulting in more energy being saved than mandated. On the other hand, they find that in the face of binding energy efficiency mandates cost-reducing innovations should have an especially large rebound effect.

We conclude by emphasizing that even though cost-reducing energy efficiency innovations might enhance welfare, by providing more energy services to consumers and producers for a given cost, the magnitude of the estimated rebound-effect means that they will not significantly reduce energy use in the long run. However, a tightening cap on carbon emissions or an equivalent carbon tax policy would reduce fossil fuel use regardless of the rebound effect. In fact, improving energy efficiency would help reduce the welfare cost of such a policy.

Supplementary material

The supplementary material contains the Online Appendix as well as data and code to reproduce all findings reported in this article. Additionally, all replication files can be found at: `https://gitlab.gwdg.de/berner7/rep_enecon`.

5. Acknowledgements

We thank participants of the IAEE Conference (2019), the ESEE Conference (2019) and seminars at the Chairs of Statistics and Econometrics in Göttingen for helpful comments. We are also grateful to Harald Uhlig, Emmanuel Mönch, Hannes Rohloff, and Alexander Lange for sharing their code with us.

Funding: The research leading to this article has been funded by the Federal Ministry of Education and Research (BMBF) [Funding code: 01UT170].

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Energy Economics: ENEECO-D-21-00659

Do Energy Efficiency Improvements Reduce Energy Use? Empirical Evidence on the Economy-Wide Rebound Effect in Europe and the United States

Highlights

- We estimate and compare the economy-wide rebound effect in 5 industrialized countries
- We use a structural FAVAR model to identify the energy efficiency shock
- The economy-wide rebound effect is between 78 and 101% after 2 years
- We consistently find large rebound effects despite differences between the countries

Energy Economics: ENEECO-D-21-00659

Do Energy Efficiency Improvements Reduce Energy Use? Empirical Evidence on the Economy-Wide Rebound Effect in Europe and the United States

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