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## How Large is the Economy-Wide Rebound Effect in Middle Income Countries? Evidence from Iran

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**Abstract**

The issue of whether energy efficiency improvements will lower energy use or not is contentious. We estimate the economy-wide rebound effect for Iran using a structural vector autoregressive model estimated with quarterly data from 1988:3 to 2018:1. The structural shocks are identified by independent component analysis, a statistical identification technique that does not require us to impose restrictions based on economic theory on the model. The results show that in response to an energy efficiency shock energy use falls initially, but returns to near its original level over time. The economy-wide rebound effect in Iran is 84% after 6 years and its confidence interval includes 100% implying that policies that encourage energy efficiency innovation will have limited long-term impact on energy use.

**Keywords:**

Rebound Effect, Energy Efficiency, SVAR, Statistical Identification, ICA, Iran

**JEL Classification:**

C32, O13, Q43

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## 1. Introduction

Improvements in energy efficiency are usually considered an effective way of reducing energy use and so mitigating climate change and improving energy security (Stern, 2017). Energy efficiency has even been considered as a fifth fuel, preferable to new energy supply (Brookes, 1990). However, actual energy savings are usually less than the improvement in efficiency. This gap between potential and actual energy savings is called the rebound effect. Economists and policy makers have debated the size of the rebound effect. Some recent research suggests that the economy-wide rebound is close to 100% in the United States and several European countries, which means that in the long run, energy is not saved (Berner et al., 2020; Bruns et al., 2021). Is the rebound just as large in middle-income countries, such as Iran? We use a Structural Vector Autoregressive (SVAR) model to estimate the economy-wide rebound effect in Iran, finding that, indeed, it is also near 100%.

Energy intensity in Iran increased by 44% from 1990 to 2017, while world energy intensity decreased by 35% over the same period (Figure 1). Energy intensity declined in most high-income countries such as France, Germany, the United States, and the United Kingdom, as shown in Figure 1.

Figure 1 about here

The information given in Figures 2-a and 2-b allows us to investigate energy intensity in more detail. We can see that Iran's primary energy use has increased dramatically from 1988 (third quarter) to 2018 (first quarter). Iran's proved oil and gas reserves were 156 billion barrels and 32 trillion cubic meters in 2018, respectively (BP Statistical Review of World Energy, 2020), which were the fourth and second largest in the world. Oil and natural gas dominate Iran's primary energy consumption mix averaging 50% and 47%, respectively, between 1988 and 2018.

Similarly, there is an upward trend in real GDP. These patterns are not unusual among developing countries (Csereklyei et al., 2016). Therefore, it is of interest to find out whether the dynamics of the economy in response to energy efficiency and other shocks are similar to those in developed economies or differ radically.

Figure 2-a and b about here

Iran's economy must reduce energy consumption and transit to sustainable energy to justify high energy intensity. The first reason is that the limited supply of fossil fuels threatens energy security, critical in sustainable development. The oil and gas export is also one of the primary sources of foreign exchange of the Iranian government. Secondly, the current energy consumption patterns pose a serious threat to the environment. The consumption of fossil fuels is the most significant contributor to CO<sub>2</sub> emissions., leading to worsening economic growth and environmental sustainability. CO<sub>2</sub> emissions in Iran increased from 161 million tonnes in 1988 to 670 million tonnes in 2019 (BP Statistical Review of World Energy, 2020). Iran is now the seventh highest emitter of CO<sub>2</sub> emissions from fossil fuel combustion.

To estimate the economy-wide rebound effect, we apply the approach developed by Bruns et al. (2021) using an SVAR model identified by Independent Component Analysis (ICA). SVAR models are one of the most popular multivariate models that provide an avenue to analyze dynamic phenomena. Our SVAR model models the relationships between energy use, GDP, and the price of energy to study how energy efficiency shocks impact economy-wide energy consumption in Iran. We use ICA – a data-driven approach – to identify the SVAR model. ICA uses the assumptions of independence and the non-Gaussianity of the structural shocks instead of theory-based zero or sign restrictions (Moneta et al., 2013). Data-driven identification avoids unbelievable *a priori* restrictions by letting the data speak, which was the original idea of the VAR approach

(Moneta et al., 2013). We compute the impulse response functions of energy use and the other variables to energy efficiency and other shocks from this SVAR model. We also compute a forecast error variance decomposition to understand how important each shock has been in explaining the evolution of the economy. We estimate the economy-wide rebound effect by comparing the eventual reduction in energy use following an energy efficiency shock to the size of the initial shock.

Four recent Computable General Equilibrium (CGE) studies estimate the economy-wide rebound effect in Iran. Salimian et al. (2018) study rebound effects in energy-intensive industries, Barkhordar (2019) investigates the rebound associated with energy-efficient lighting in households, Khoshkalam Khosroshahi and Sayadi (2020) look at rebounds from energy efficiency improvements associated with four fuels over the economy as a whole, and Rafiei (2021) estimates rebound stemming from efficiency improvements in the use of electricity. The average economy-wide rebound effect obtained in each of these studies is 88%, 44%, 36%, and 112%, respectively. However, the results of these studies are dependent on the chosen parameter values and assumed model structures. Our research instead attempts to estimate the economy-wide rebound effect using econometric methods.

Section 2 of the paper reviews the literature on the rebound effect. Our econometric model is described in Section 3. Section 4 is allocated to the data description. The empirical results are presented in Section 5, while Section 6 concludes.

## **2. Literature Review**

The British economist, Jevons, was the first to consider the rebound effect, and in particular the case where there is an eventual increase in energy consumption, known as backfire or Jevons'

paradox (Alcott, 2005), in his book entitled "The Coal Question" in which he asserted that "It is wholly a confusion of ideas to suppose that the economical use of fuel is equivalent to a diminished consumption. The very contrary is the truth" (Jevons, 1865). However, the topic was neglected until Brookes (2000, 1990, 1984, 1978) and Khazzoom (1980) revisited it in the 1970s. The rebound effect has since been studied extensively, with research divided between micro-economic studies covering the direct and indirect rebound effects, and macroeconomic studies of economy-wide effects (Sorrell and Dimitropoulos, 2007). The rebound effect is defined as:

$$R = 1 - \frac{Actual}{Potential}, \quad (1)$$

where "Potential" is the size of the energy efficiency improvement in terms of potentially reduced energy use and "actual" is the actual energy savings (Stern, 2020).

At the microeconomic level, an energy efficiency improvement reduces the cost of energy services due to less fuel being required. For consumers, this results in substitution and income effects. Consumers substitute the now cheaper energy services for the consumption of other goods and services while holding utility constant. The reduction in cost increases consumers' budgets, resulting in increased consumption of all normal goods and services, including the energy service. The change in energy use due to increased consumption of the energy service is called the direct rebound effect. Similarly, for producers, two different effects come into play when the price of energy services falls. The substitution effect results in the now cheaper energy service being substituted for capital, labor, and other materials. As well as this, the firm will want to expand production – the output effect – which requires more inputs including energy (Greening et al., 2000; Jin and Kim, 2019; Sorrell and Dimitropoulos, 2008, 2007; Stern, 2020). There have been several reviews of studies of the direct rebound effect associated with energy services such as

heating, lighting, and transportation (e.g., Greening et al., 2000; Sorrell et al., 2009; Dimitropoulos et al., 2018).<sup>1</sup>

The indirect rebound effect also results from substitution and income or output channels. These increase demand for complementary goods or factors of production and reduce demand for substitute goods or factors. As these include other energy services and all goods require energy to produce them, energy use will change as a result (Lange et al., 2019; Sorrell and Dimitropoulos, 2007). Only a few studies such as Thomas and Azevedo (2013) focus on the indirect rebound effect. Chitnis et al. (2014), Ghosh and Blackhurst (2014), Freire-González and Font Vivanco (2017), Freire-González (2017a), Freire-González (2017b), and Wang and Nie (2018) estimate both direct and indirect rebound effects.

The broader, economy-wide rebound effect includes further chains of effects in addition to these direct and indirect effects. These effects may vary among different energy efficiency improvements (Jin and Kim, 2019; Sorrell and Dimitropoulos, 2008, 2007; Stern, 2020). The economy-wide rebound effect has been estimated using various methods including CGE and energy-input-output models, the economic accounting approach, and econometric models using panel or time series data.

Grepperud and Rasmussen (2004) is an early example of a CGE study of the rebound effect, which examine the effect of increases in the efficiency of the use of electricity and oil in six different sectors in Norway. They conclude that rebound is greater than 100% in some manufacturing

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<sup>1</sup> Recent studies of the direct rebound effect include Lin and Liu (2013), Lin and Li (2014), Wang and Lu (2014), Wang et al. (2014), Zhang et al. (2015), Wang et al. (2016), Stapleton et al. (2016), Lin and Tian (2016), Ruzzenenti and Basosi (2017), Moshiri and Aliyev (2017), Salem and Akbari Tafti (2017), Zhang et al. (2017), Belaïd et al. (2018), Ouyang et al. (2018), Amjadi et al. (2018), Dimitropoulos et al. (2018), Liu et al. (2019), Xin-gang and Pei-ling (2020), Li et al. (2018), and Belaïd et al. (2020).

activities but weak or non-existent in other sectors. Allan et al. (2007) find 30–50% rebound effects for the UK, while Hanley et al. (2009) show that in the short run the rebound effect is 63% for electricity and 54% for other energy in Scotland, but ultimately there is backfire. Broberg et al. (2015) find a rebound effect in Swedish industry of approximately 40–70% due to a 5% increase in energy efficiency. Yu et al. (2015) show that improvements in energy efficiency in production in Georgia, USA results in around 11.5% rebound. Koesler et al. (2016) find that a 10% increase in energy efficiency in German industry results in a global rebound of 46-48%.

CGE studies have also been carried out for some developing economies. Using a 135-sector CGE model, Lu et al. (2017) find that economy-wide rebound effects for various energy sources in China range from 22.1 to 51.2% in the short run and from 0 to 42% in the long run. By contrast, Semboja (1994) indicates that an increase in productivity in the energy sector increases the consumption of energy composite commodities by 3.5% in Kenya while improving the efficiency of energy use reduces energy intensity by 0.54%. Li and Jiang (2016) use energy input-output analysis to find that the economy-wide rebound effect in China is about 1.9%, however, this effect will decrease if energy subsidies are removed. This is not so surprising, as input-output models do not allow for substitution between inputs in each industry.

Salimian et al. (2018) indicate that the rebound effect from energy efficiency improvements in various energy-intensive industries range from 73-96.3% in Iran. Barkhordar (2019) finds an economy-wide rebound effect of 44% due to the LED Replacement Lamps Program in the household sector of Iran. Khoshkalam Khosroshahi and Sayadi (2020) find that the rebound effect is positive for an increase in the efficiency of the use of different energy sources including gasoline, diesel, natural gas, and electricity in each of 15 production sectors in Iran. The greatest rebound is for gasoline in the transportation sector (28%). Rafiei (2021) finds that increase in electricity



efficiency of 10% leads to an increase in energy consumption of 1.2%, concluding that the rebound effect is 112%.

On the other hand, Turner (2009) finds that rebound critically depends on the assumed values of the parameters in the CGE model. She finds that, depending on the parameters, the economy-wide rebound effect in the UK could take a wide range of values. At one extreme rebound might be negative and at the other it might be greater than 100%. More directly empirical estimates are, therefore, desirable.

The "economic accounting approach" typically compares the growth rate of total factor productivity (TFP) to the growth rate of energy productivity (the inverse of energy intensity) under the assumption that the increase in energy use following an efficiency improvement is proportional to TFP growth and efficiency improvements are equal to changes in energy productivity. Neither of these are good assumptions (Stern, 2020) though some studies, such as Wei et al. (2020), are more sophisticated than this. Several researchers (e.g. Lin and Liu, 2012; Shao et al., 2014; Lin and Du, 2015; Zhang and Lin-Lawell, 2017; Lin and Tan, 2017; Wei et al., 2020) have used these methods to estimate the economy-wide rebound in China.

There are few econometric studies of the economy-wide rebound. Adetutu et al. (2016) use a stochastic frontier analysis to estimate changes in energy efficiency, which they then use in a dynamic panel data analysis to estimate the rebound effect. They apply this to a panel of 55 countries, finding a 90% economy-wide rebound effect in the short run, while in the long run, there is a negative rebound of 36%. Yan et al. (2019) apply the same method to Chinese provinces finding average short-run and long-run rebound effects of 89% and 78%, respectively. These results are due to the specification of the dynamic regression model, which implies that if energy use falls in the short run it must fall by more in the long run. Additionally, these studies do not

allow energy prices and GDP to change in response to changes in energy efficiency. These changes in GDP and energy prices (and other relevant time series) may result in further energy use changes, and ignoring these dependencies will bias the estimated economy-wide rebound effect.

Bruns et al. (2021) use an SVAR identified by Independent Component Analysis (ICA) to estimate the effect of an energy efficiency shock on energy use in the USA. The economy-wide rebound effect is approximately 100% after 4 years. By using Structural Factor-Augmented Vector Autoregression (S-FAVAR) models, Berner et al. (2020) find that economy-wide rebound effects for the UK, Germany, Italy, the U.S., and France as high-income countries are 78%, 93%, 95%, 98%, and 101% after 2 years. We have described the advantages of this approach in the introduction.

### **3. Data**

We use quarterly data for Iran from 1988 (third quarter) to 2018 (first quarter). We chose this sample period according to the availability of reliable data. We seasonally adjust all quarterly observations using the X11 procedure in EViews. All variables are then transformed to logarithms. The following describes the sources of the data. The definitions and summary statistics of the data are presented in Table 1.

Table 1 about here

Energy is represented by primary energy use ( $e$ ), including oil products, natural gas, coal, and primary electricity. To convert the electricity produced into primary energy, energy sources including wind, nuclear, and hydro, which are used to produce electricity in Iran, are divided by the conversion efficiency of fossil fuel generation. We compute the conversion efficiency from annual International Energy Agency data (International Energy Agency, 2020). Data on oil

products, nuclear electricity, hydroelectricity, and wind energy are taken from the economic time series database of the Central Bank of Iran (various years). Furthermore, natural gas consumption is obtained from the gas performance report of the National Iranian Gas Company (various years) and the economic time series database of the Central Bank of Iran (various years). Quarterly coal, geothermal, and solar consumption data are not available. We used annual consumption for these data and assumed that all quarters in a year had equal consumption. We obtain these data from the BP Statistical Review of World Energy (BP, 2020).

We also estimate the price of primary energy ( $p$ ) using multiple sources. The price of Iranian oil products are taken from the statistics of National Iranian Oil Refining and Distribution Company (2018). We obtain the average price of electricity in industrial, household, public, and agriculture sectors from Iran's energy balance sheet published by the Ministry of Energy in Iran. We also obtain the average natural gas price and coal price from the same source. The ratio of the average price of electricity to the conversion efficiency is calculated for the primary electricity price. We convert all these prices to prices per BTU. Finally, we obtain the price of energy by dividing the total cost of energy by total primary energy in BTUs.

Additionally, we use the Divisia Index to compute an energy volume index and derive the energy quality variable,  $q$ , as the ratio of energy volume and BTUs (Stern, 2010). The logarithm of quarterly adjusted real GDP ( $y$ ) and the logarithm of seasonally adjusted industrial production ( $i$ ) are obtained from the economic time series database of the Central Bank of Iran (various years). We use the energy quality and industrial production variables as additional control variables in a robustness analysis.

## 4. Methods

The SVAR model can be written as:

$$\Gamma_0 X_t = \mu + \sum_{i=1}^p \Gamma_i X_{t-i} + \varepsilon_t, \quad (2)$$

where  $X_t$  is a  $k$  dimensional vector of endogenous variables,  $\Gamma_0$  and  $\Gamma_i$  with  $i = 1, \dots, p$  are  $k \times k$  matrices of coefficients,  $\mu$  is a vector of intercept parameters, and  $\varepsilon_t$  is the  $k \times 1$  vector of structural shocks (Kilian and Lütkepohl, 2017). It is assumed that the covariance matrix of the structural shocks,  $\Sigma_\varepsilon = E(\varepsilon_t \varepsilon_t^T)$ , is diagonal (Lütkepohl, 2005). Endogeneity of the  $X_t$  vector means that we cannot estimate Equation (2) employing Ordinary Least Squares (OLS). Instead, we first estimate the reduced form VAR model, which we can find by multiplying Equation (2) by the inverse of  $\Gamma_0$ :

$$\begin{aligned} X_t &= \Gamma_0^{-1} \mu + \sum_{i=1}^p \Gamma_0^{-1} \Gamma_i X_{t-i} + \Gamma_0^{-1} \varepsilon_t \\ &= a + \sum_{i=1}^p A_i X_{t-i} + u_t, \end{aligned} \quad (3)$$

where  $u_t$  is the vector of reduced-form residuals. These residuals are serially uncorrelated with  $E(u_t) = 0$ .  $\text{Cov}(u_t) = \Sigma_u$  can be non-diagonal (Moneta et al., 2013). The instantaneous impact of the structural shocks is given by  $\Gamma_0^{-1}$  and the structural shocks are linear transformations of the reduced-form errors,  $\varepsilon_t = \Gamma_0 u_t$ . Though OLS provides consistent estimates of the reduced-form parameters ( $a$ ,  $A_i$ , and  $u_t$ ), recovering the structural form requires additional information.

Theory-based approaches and statistically-based identification strategies have been suggested to solve this problem. Theory-based restrictions include two main types of restrictions, zero restrictions (Blanchard and Quah, 1989; Sims, 1980) and sign restrictions (Faust, 1998; Uhlig, 2005). This type of identification has been frequently used, but strongly depends on *a priori*

assumptions derived from economic theory, which might be too restrictive in many cases (Moneta et al., 2013).

In contrast, statistically-based identification procedures allow the data to speak. There are two main types of statistical identification. The first one builds upon the statistical distribution of the reduced-form model residuals. These heteroskedasticity-based approaches, therefore, depend on background knowledge just as the theory-based approach does (Moneta et al., 2013). Alternatively, SVAR models can be identified using Independent Component Analysis (ICA), which assumes that the structural shocks are non-Gaussian (Comon, 1994). There are several ICA algorithms, including distance covariance (dcov), non-Gaussian maximum likelihood (ngml), Cramér-von Mises statistic (CvM), and the fastICA algorithm (Herwartz et al., 2019; Hyvärinen and Oja, 2000; Maxand, 2020). Following Bruns et al. (2021), we adopt ICA, as this approach allows the recovery of a unique instantaneous impact matrix (up to a column permutation and sign) without imposing restrictions based on economic theory. Furthermore, the assumption of non-Gaussianity is not unexpected in macroeconometrics.

We employ the distance covariance approach proposed by Matteson and Tsay (2017), as this algorithm has been used in recent SVAR analyses (e.g., Bruns et al., 2021; Herwartz and Plödt, 2016). An estimate of the instantaneous impact matrix,  $\hat{\Gamma}_0^{-1}$ , is obtained by minimizing distance covariance (Székely et al., 2007) following Herwartz et al. (2019) and Maxand (2020).

The scale indeterminacy of the estimated instantaneous impact matrix,  $\hat{\Gamma}_0^{-1}$ , is addressed by post-multiplying the  $\Gamma_0^{-1}$  estimated by ICA by a matrix,  $DD^{-1}$ , where  $D$  is a diagonal matrix and  $D^{-1}\varepsilon_t$  has unit variance. The rescaled matrix is then  $\Gamma_0^{-1}D$ , and the rescaled structural shocks are given by  $D^{-1}\varepsilon_t$ . The column indeterminacy is addressed by finding a column permutation of  $\Gamma_0^{-1}$  where the  $i$ th shock has the greatest impact on the  $i$ th variable (Herwartz and Plödt, 2016). This

is a further *a priori* identifying assumption in addition to the assumptions of non-Gaussianity and independence of the shocks. Finally, we multiply each column of  $\Gamma_0^{-1}D$  by 1 or -1 so that the diagonal entries of  $\Gamma_0^{-1}D$  are greater than zero, except for the entry corresponding to energy use, which we set as negative to represent the effect of a reduction in energy use. The structural shock to energy use represents an exogenous change in energy use while controlling for other factors that explain changes in energy use. We interpret this shock as an energy efficiency shock.

We measure the rebound effect using the impulse response function of energy use with respect to the energy efficiency shock. The rebound effect is given by

$$R_i = 1 - \frac{\Delta e_i}{\Delta \hat{e}} = 1 - \frac{\text{Actual}}{\text{Potential}}, \quad (4)$$

where the subscript  $i$  indicates the number of periods since the energy efficiency improvement (Bruns et al., 2021).  $\Delta \hat{e}$  is the potential proportional change in energy use, and  $\Delta e_i$  is the actual proportional change in energy use. The potential proportional change in energy use is equal to the energy efficiency shock.<sup>1</sup>

We also conduct a robustness check by including the quality of energy and industrial production as further control variables (Bruns et al., 2021). Moreover, we explore robustness with regards to outliers in the price series. The analysis is conducted in R (R Core Team, 2019) and mainly relies on the the R package ‘svars’ (Lange et al., 2021).

## 5. Empirical Results

### 5.1. Lag Length and Gaussianity

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<sup>1</sup> Equation (1) defined the rebound effect in terms of the potential and actual energy savings rather than changes in energy use. The signs of these terms are the opposite of the actual and potential change in energy use. As a result, the rebound formula is the same.

Following the recommendation of Kilian and Lütkepohl (2017), we use the Akaike Information Criterion (AIC) to select the optimal lag length for the VAR with a maximum lag length of four (Schwartz, 1989). This approach results in a lag length of four. In order to apply ICA, at most one of the shocks can be Gaussian (Comon, 1994). Because the structural shocks are linear combinations of the reduced-form residuals, we can indirectly test the non-Gaussianity of the structural shocks by applying the Jarque-Bera (JB) test of normality to the reduced-form residuals. Table 2 indicates that the null hypothesis of Gaussianity can be rejected for the residuals of GDP and the price of energy at the 1% level of significance. We infer from this that not more than one of the structural shocks is Gaussian.

Table 2 about here

## 5.2. Identifying the SVAR Model

Our main SVAR model includes the logarithms of primary energy use ( $e$ ), real GDP ( $y$ ), and the price of primary energy ( $p$ ). Robustness of the estimated rebound to alternative model specifications is discussed in Section 5.4. We compute 90% confidence intervals for the impulse response functions using a wild bootstrap with 1000 iterations.

The estimated instantaneous impact matrix is reported in Table 2. We label the first shock as the energy efficiency shock because it has the largest and only statistically significant instantaneous effect on energy use. The instantaneous effects of this shock on both GDP and energy price are not statistically significant, as the confidence intervals of these effects include zero.

We label the second shock as the GDP shock because it has the largest instantaneous effect on GDP. As expected from economic theory, the second shock has a positive effect on all variables,

but only its instantaneous effect on GDP is statistically significant according to the confidence intervals. We consider the third shock to be an energy price shock because it has a large positive and statistically significant effect on the price of energy. Its effect on energy consumption is negative, and its effect on GDP is positive, though based on the confidence intervals these latter effects are not statistically significant.

Table 3 about here

We also conduct a variance decomposition of the forecast errors to show the relative contributions of the shocks to the total variability of each endogenous variable (Iwayemi and Fowowe, 2011). This analysis supports the labeling based on the largest contemporaneous effect. Looking at Figure 3, we can see that more than 75% of the prediction mean squared error of energy use can be explained through the energy efficiency shock at first. However, this contribution dramatically decreases over time to reach around 10% after 30 periods. The shocks labeled as GDP shock and energy price shock also account for a substantial portion of the respective prediction mean squared error.

Figure 3 about here

### **5.3. Impulse Response Functions**

Figure 4 presents the impulse response functions. Each shock is one standard deviation of the structural shocks. The effects of the energy efficiency shock are displayed in the first column of Figure 4. This shock initially results in an over 2% decrease in energy use. Over time, the impact of the shock reduces dramatically which is consistent with the findings of Berner et al. (2020) and Bruns et al. (2021) about high-income countries. The energy efficiency shock initially has a positive effect on both the price of energy and GDP though these soon become negative. The



second column of Figure 4 shows the effects of the GDP shock. This shock's effects on GDP and energy consumption are positive and statistically significant. The energy price response to the GDP shock is mostly not statistically significant. The GDP shock's effect on energy consumption is similar in size to the GDP shocks's effect on GDP. This helps explain why energy intensity has risen over time in Iran (Figure 1). By contrast, though Bruns et al. (2021) also found that the GDP shock had a positive effect on energy use, this was smaller than its effect on GDP itself. As a result, energy intensity declined in the US over time.

The third column of Figure 4 reveals the effects of the energy price shock. This shock has a negative contemporaneous effect on energy use is, but in the long run the effect becomes positive though not statistically significant. Furthermore, the price shock's effects on the price of energy and GDP are not statistically significant in the long run.

Figure 4 about here

#### **5.4. The Rebound Effect**

Table 4 reports the estimated rebound effect after various intervals of time. After one year there is 69% rebound, while in years 4 and 6, the rebound effect is 81% and 84%, respectively. While the point estimates obtained for Iran tend to be smaller compared to those found for the U.S. by Bruns et al. (2021) and for various other high-income countries (France, Germany, Italy, U.K.) by Berner et al (2019) , the confidence interval for the Iranian rebound effect includes 100% after four years, suggesting that economy-wide rebound effects are large in both middle- and high-income countries. Additionally, our findings is similar to results of Salimian et al. (2018) which obtain that the rebound effect range from 73-96.3% among various energy-intensive industries in Iran.

Table 4 about here

Finally, we conduct a robustness check by extending our model to include the logarithms of energy quality ( $q$ ) and industrial production ( $i$ ) as control variables to reduce potential omitted-variable biases. We apply the previously discussed identification method to estimate the model for the vector of  $X_t = (e_t, y_t, p_t, q_t, i_t)$ . We report the estimated rebound effects for this model in Table 4. Though the estimated rebound effect tends to be larger and reaches roughly 100% after four years, the confidence intervals of the main analysis and robustness analysis overlap, indicating the robustness of our main findings.<sup>1</sup>

Table 5 about here

## 6. Conclusions

We analyze whether increases in energy efficiency lead to decreasing energy consumption at the macroeconomic level in Iran, using data from 1988 (third quarter) to 2018 (first quarter). Following Bruns et al. (2021), we identify a Structural Vector Autoregressive (SVAR) model by using Independent Component Analysis (ICA) to estimate the size of the economy-wide rebound effect. The results reveal that improvements in energy efficiency initially lead to considerably decreased energy consumption but energy use rebounds quite fast. The estimated economy-wide rebound effect is large and reaches 84% after 6 years and the confidence intervals include 100%.

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<sup>1</sup> We also estimated models with dummies for the periods 2010-2 and 2011-1 to account for a major energy price reform program. These two periods show a large outlier in the reduced-form residuals of the energy price equation. The estimated rebound effect tends to be roughly 10% smaller than in our main model, but the confidence intervals become very large and, for example, range from -55% to 139% after six years. This is to be expected when we remove some of the most important variation in the data by using dummy variables.

These results are remarkably similar to those obtained with the same approach for the United States (Bruns et al., 2021), and various European countries (Berner et al., 2020), despite the huge differences between these economies. This suggests that large economy-wide rebound effects occur not only in high-income countries, but might be widespread. One of the main differences with the U.S. results is that the GDP shock in Iran tends to have similar long-run effects on energy use and GDP whereas in the U.S. the effect on energy use was smaller. This helps explain why energy intensity has risen in Iran while it has fallen over time in the U.S. It could be tempting for policy-makers to think that this increase in energy intensity can be reversed by energy efficiency policies but based on our research this does not seem to be generally the case.

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Table 1. Definitions of variables and summary statistics

Variable	Definition	Mean	Std. Dev.	Min	Max	Obs
$e_t$	Primary energy use (Billion BTU)	2,071,971	717,083	957,924	3,248,125	119
$y_t$	Real GDP (Billion Rial)	1,140,939	368,238	520,381	1,849,889	119
$p_t$	Price of primary energy (Rial per BTU)	25,579	12,951.	9,911	61,468	119
$q_t$	Energy quality	0.876	0.064	0.733	0.997	119
$i_t$	Industrial production (Billion Rial)	182,229	91,390	49,774	349,917	119

Table 2: Normality tests on the residuals of the VAR

Residuals	JB statistic	$p$ -value (JB)
$u_{et}$	1.3924	0.4245
$u_{yt}$	16.679	0.0035
$u_{pt}$	1608.5	< 2.2e-16

Note: JB denotes Jarque-Bera test for normality.  $u_{et}$ ,  $u_{yt}$  and  $u_{pt}$  are the reduced-form residuals of energy, GDP, and the price of energy.

Table 3: Estimated instantaneous impact matrices for the first model

Variables	$\varepsilon_e$	$\varepsilon_y$	$\varepsilon_p$
$e_t$	-2.71	0.44	-0.14
	[-2.73, -2.33]	[-0.78, 1.37]	[-0.64, 0.13]
$y_t$	-0.05	4.88	0.42
	[-2.2, 1.61]	[4.21, 4.88]	[-0.18, 1.42]
$p_t$	1.07	1.16	12.37
	[-1.38, 2.12]	[-1.48, 2.64]	[12.07, 12.46]

Note: 90% confidence interval in brackets using wild bootstrap.

Table 4: Rebound effect

1 year	2 years	4 years	6 years
0.69	0.75	0.81	0.84
[0.39,0.91]	[0.41, 0.99]	[0.4,1.07]	[0.32,1.1]

Note: 90% confidence intervals in brackets using wild bootstrap.

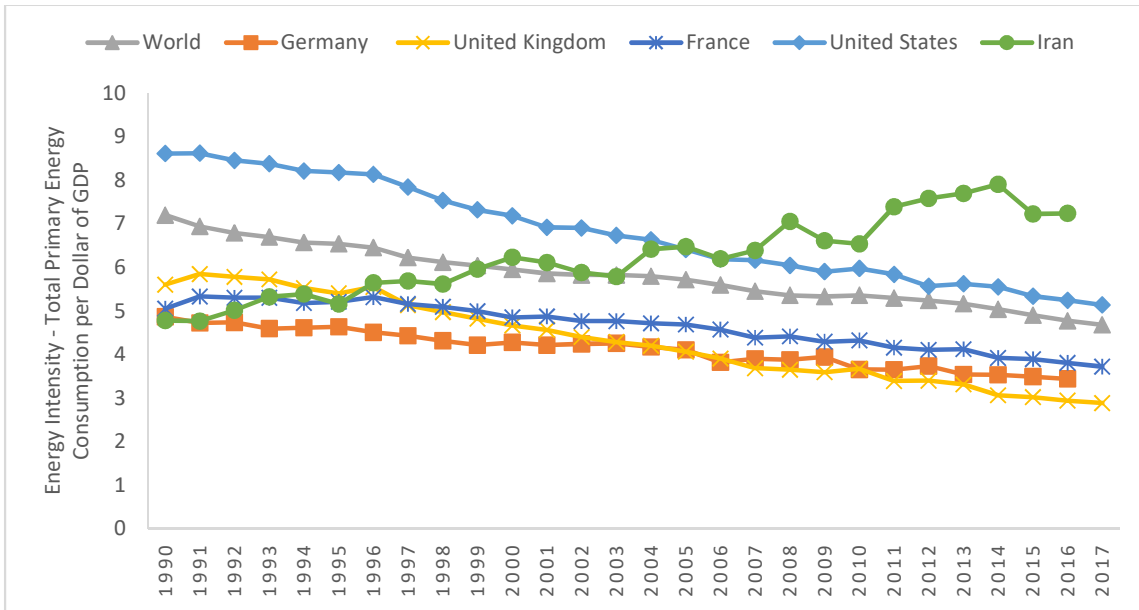
Table 5: Rebound effect (Robustness check)

1 year	2 years	4 years	6 years
0.58	0.91	1.03	1.02
[0.43,0.89]	[0.7,1.38]	[0.76,1.67]	[0.7,1.73]

Note: 90% confidence intervals in brackets using wild bootstrap.

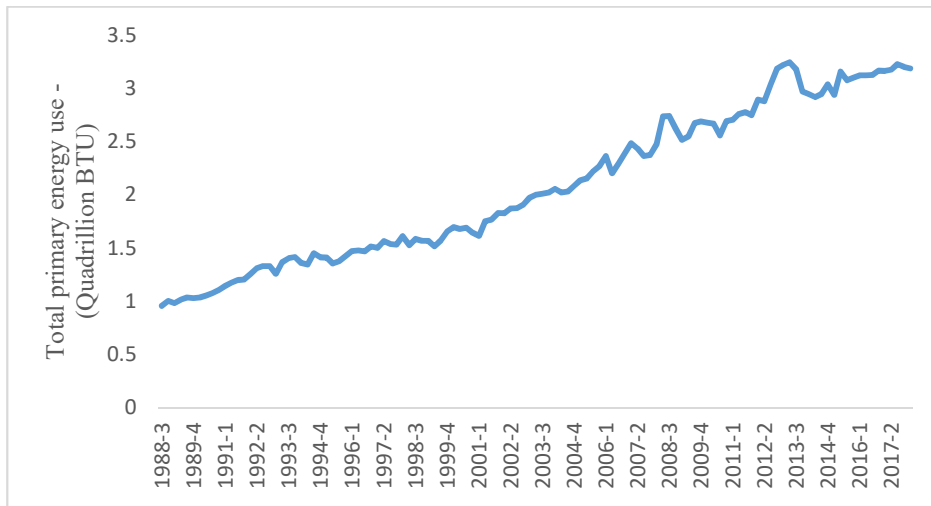


Figure 1: Energy intensity



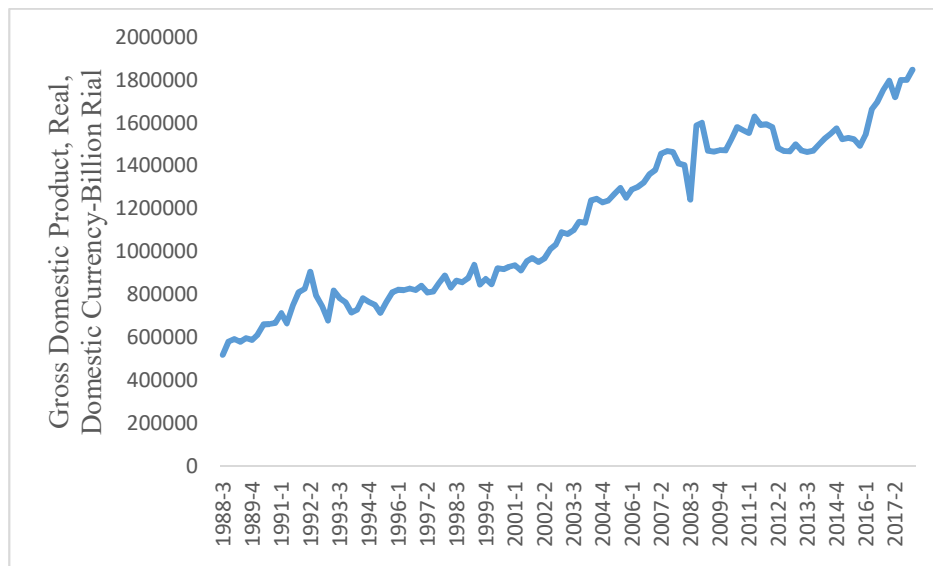
Source: World Development Indicators (WDI), 2019.

Figure 2-a: Total primary energy use in Iran



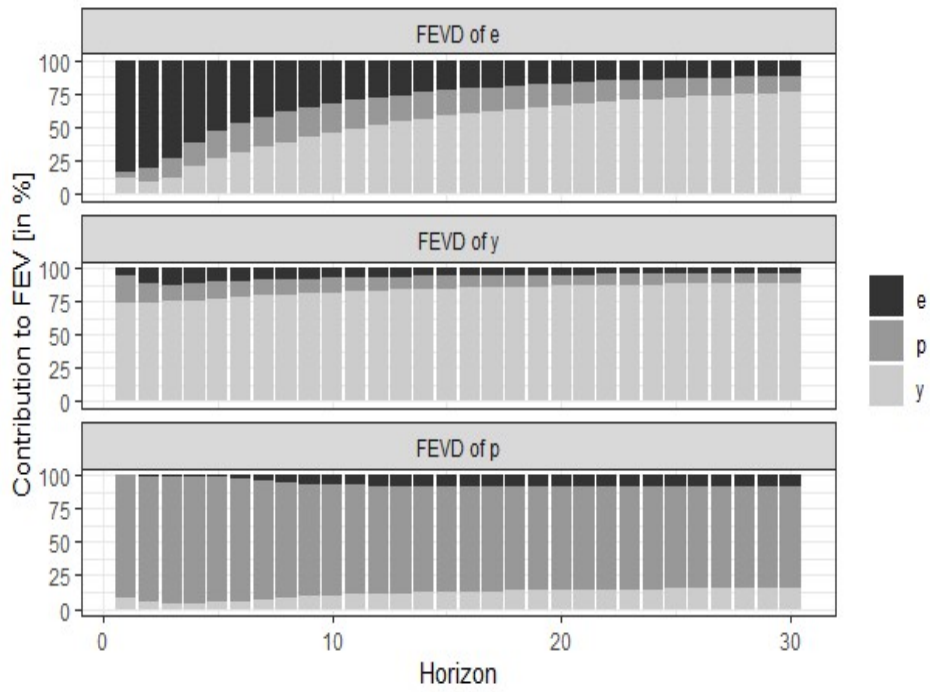
Source: Gas handling management performance report published by National Iranian Gas Company (NIGC) and data reported by Central Bank of Iran (CBI).

Figure 2-b: Real Gross Domestic Product- Billion Rial (constant 2011-Billion Rial)

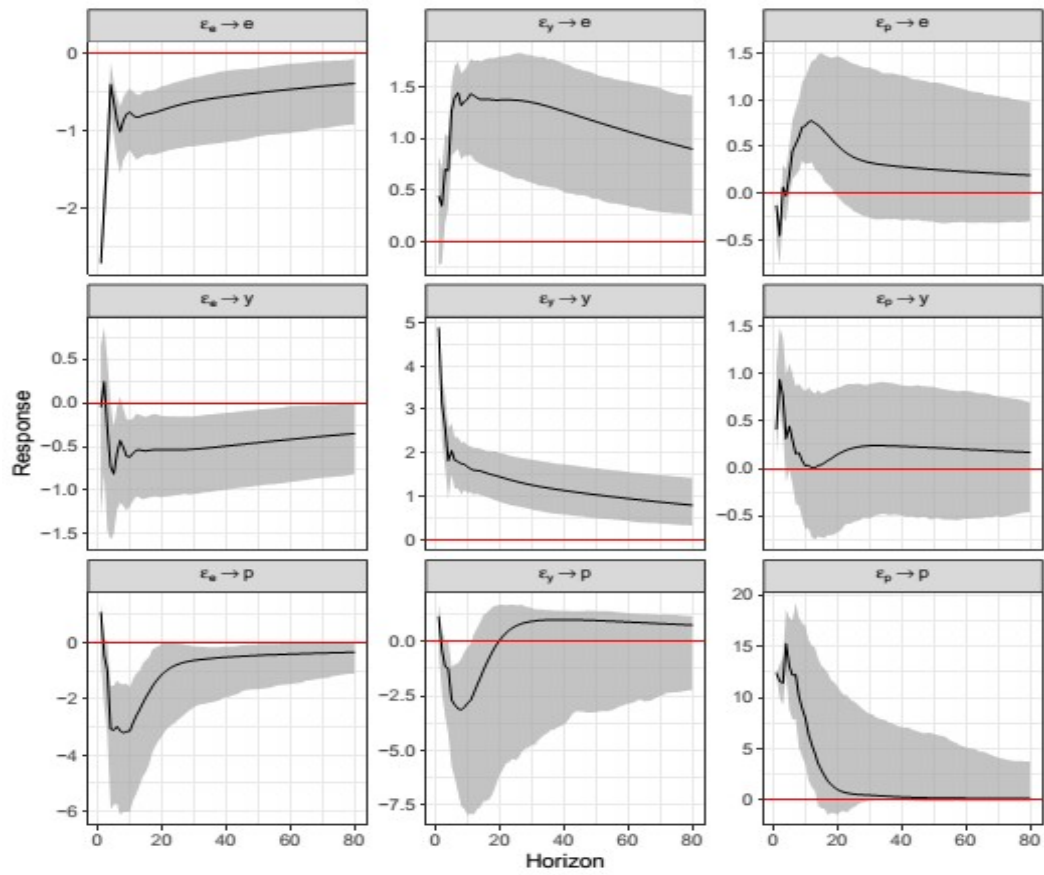


Source: Central Bank of Iran (CBI)

Figure 3: Forecast error variance decomposition for 30 periods



**Figure 4:** Impulse response functions with 90% confidence bounds



Note: The shaded area represents 90% confidence intervals using wild bootstrap. The first column presents the effect of the energy efficiency shock on energy use, GDP and the price of energy. Analogously, the second and third columns present the GDP and energy price shock, respectively.