Australian National University

How Large is the Economy-wide Rebound Effect?

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Research Question:

- To what degree do energy efficiency improvements result in economy-wide reductions in energy use?

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- To what degree do energy efficiency improvements result in economy-wide reductions in energy use?
- Important, because International Energy Agency et al. expect energy efficiency to contribute significantly to mitigating climate change

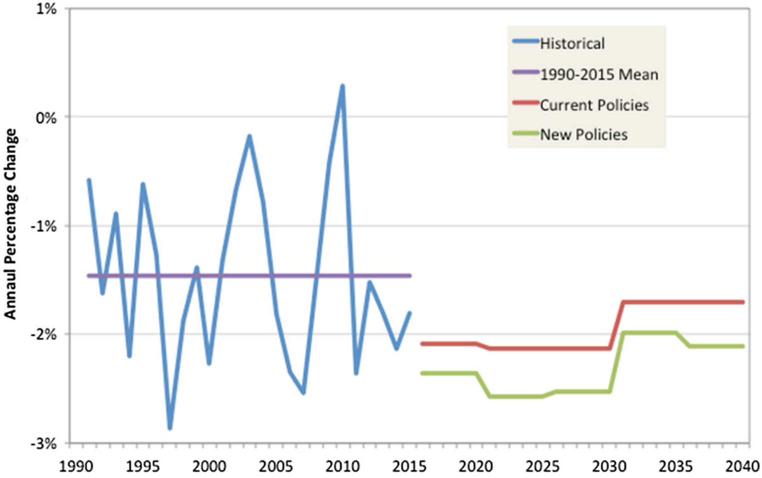


Fig. 1 World Energy Outlook 2016 energy intensity projections vs recent history

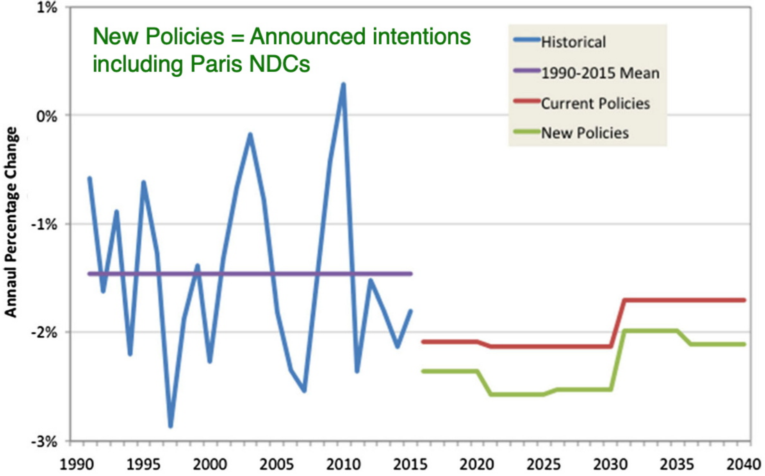
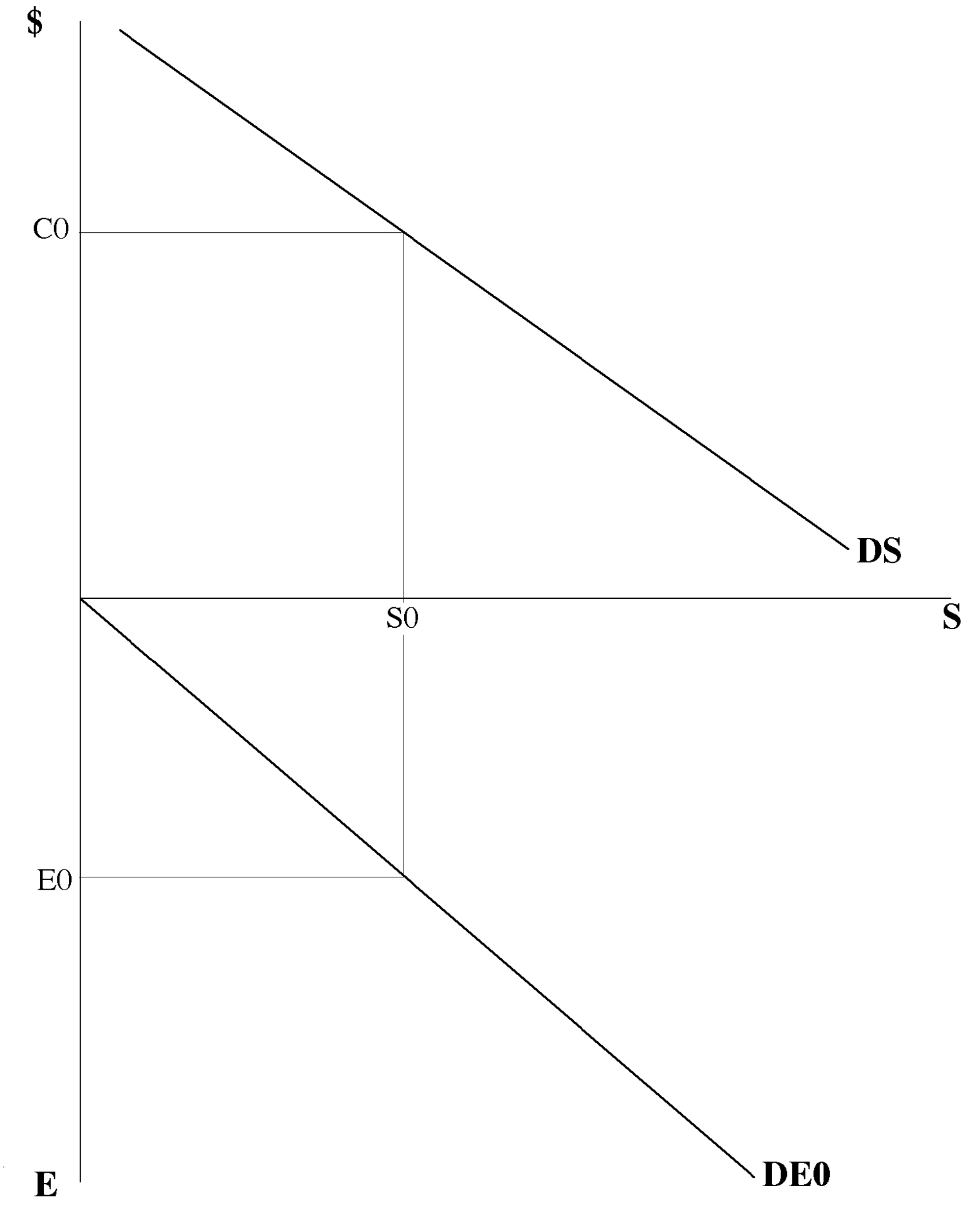
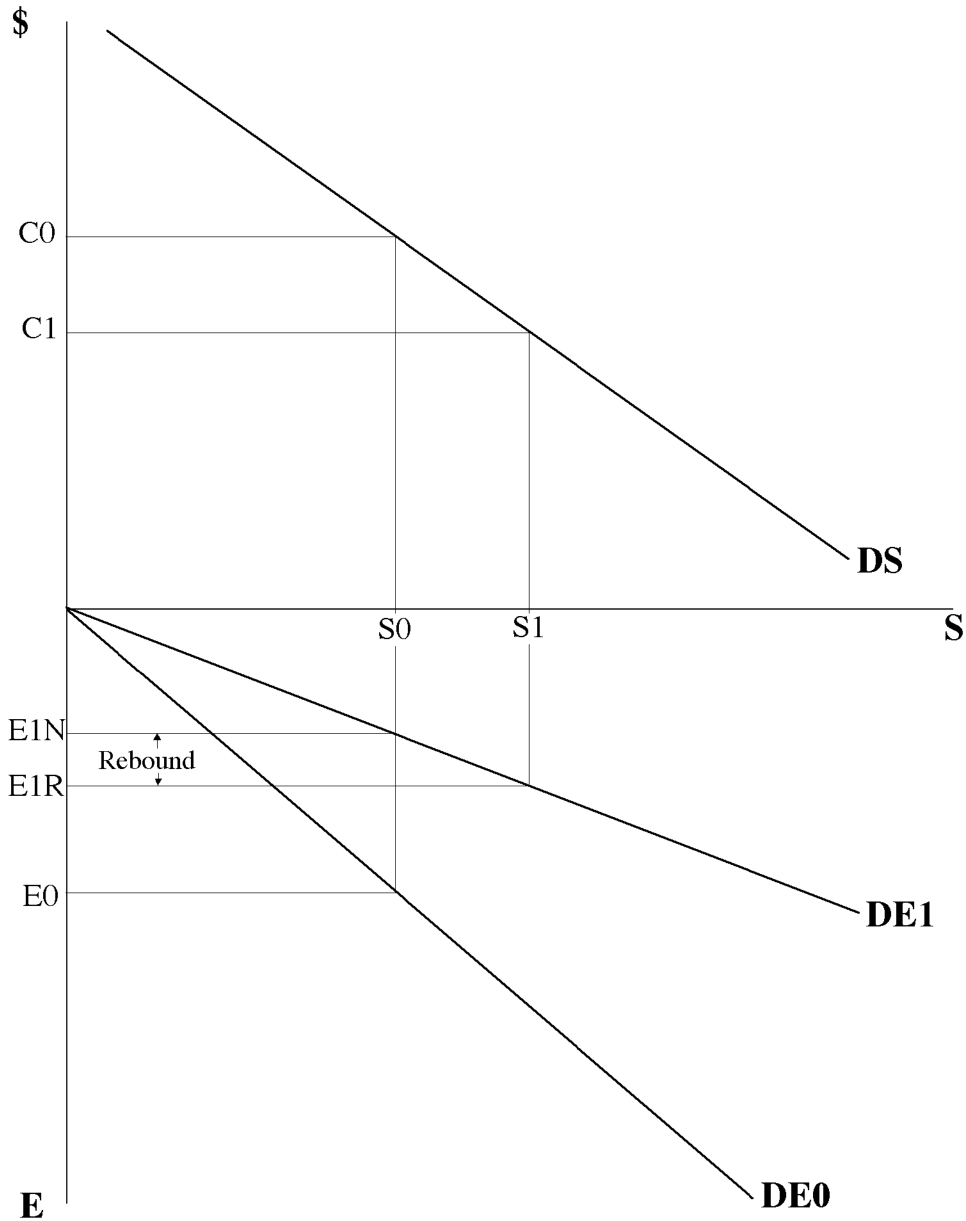


Fig. 1 World Energy Outlook 2016 energy intensity projections vs recent history

Direct Rebound Effect

- Innovation increases energy efficiency reducing cost of energy services:
  - Use of energy services increases


$
C0
DS
S0
S
E0
E
DE0


$
C0
C1
DS
S0
S1
S
E1N
Rebound
E1R
E0
DE1
DE0
E

Rebound Effect

$$Rebound = 1 - \frac{Actual\ Saving}{Potential\ Saving}$$

Partial Equilibrium Indirect Rebound Effects

- Changes in use of other energy services

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- Changes in use of other energy services
- Change in consumption of complementary and substitute goods / use of other inputs:
  - Changes in energy use across economy to produce those goods, services, inputs

Partial Equilibrium Indirect Rebound Effects

- Changes in use of other energy services
- Change in consumption of complementary and substitute goods / use of other inputs:
  - Changes in energy use across economy to produce those goods, services, inputs
- Reduction in energy used to produce energy

General Equilibrium Effects

- Changes in prices including price of energy

Intensity vs. Growth Effects

- Most of the rebound effect is a rebound in energy intensity, E/GDP

Intensity vs. Growth Effects

- Most of the rebound effect is a rebound in energy intensity, E/GDP
- But also increase in GDP:
  - Energy efficiency improvement is a TFP increase
  - Capital accumulation
  - Induced technical change?

Backfire or Jevons' Paradox

- Jevons (1865): *The Coal Question*

  "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."

- Backfire: Rebound > 100%

Theory

- Rebound increases with K-E elasticity of substitution in production (Saunders, 1992)

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- Rebound increases with elasticity of substitution between consumption goods (Lemoine, 2019)

Theory

- General equilibrium effects tend to:
  - Increase (decrease) rebound for innovations in energy intensive (extensive) sectors

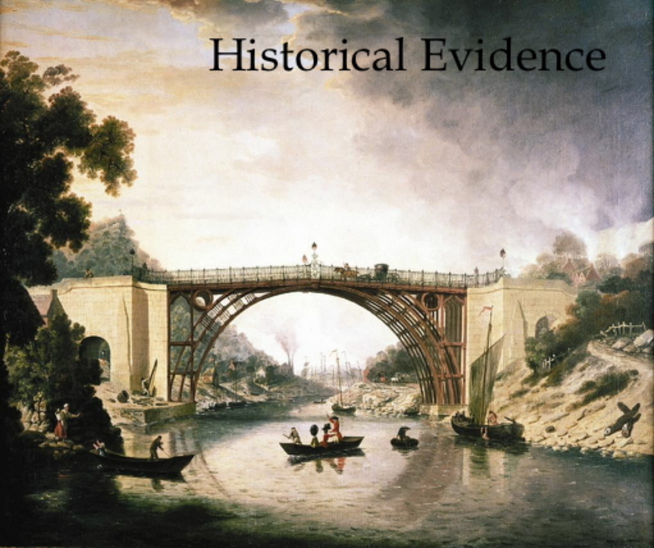
Theory

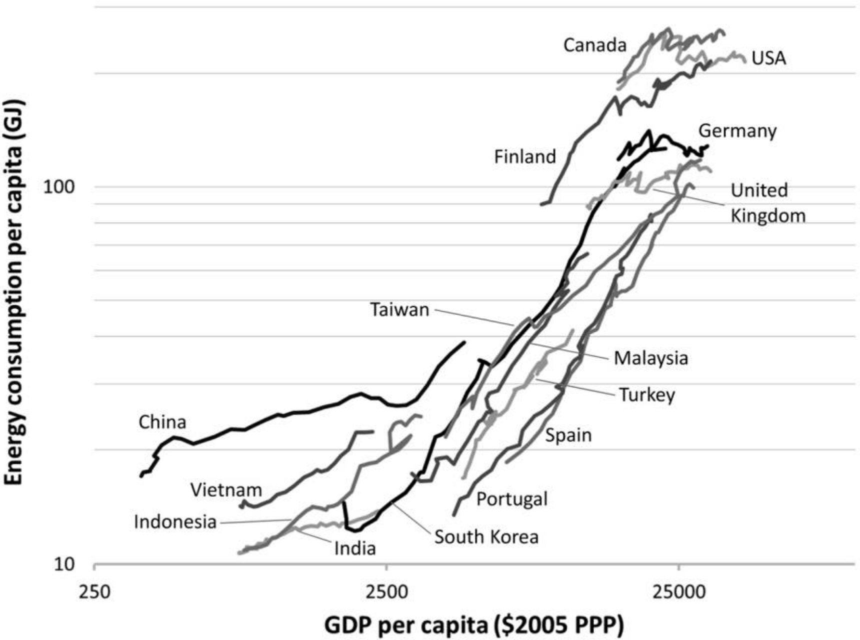
- General equilibrium effects tend to:
  - Increase (decrease) rebound for innovations in energy intensive (extensive) sectors
- Energy production is energy intensive:
  - Reduction in energy use in energy supply sector reduces (R<1) or increases (R>1) rebound

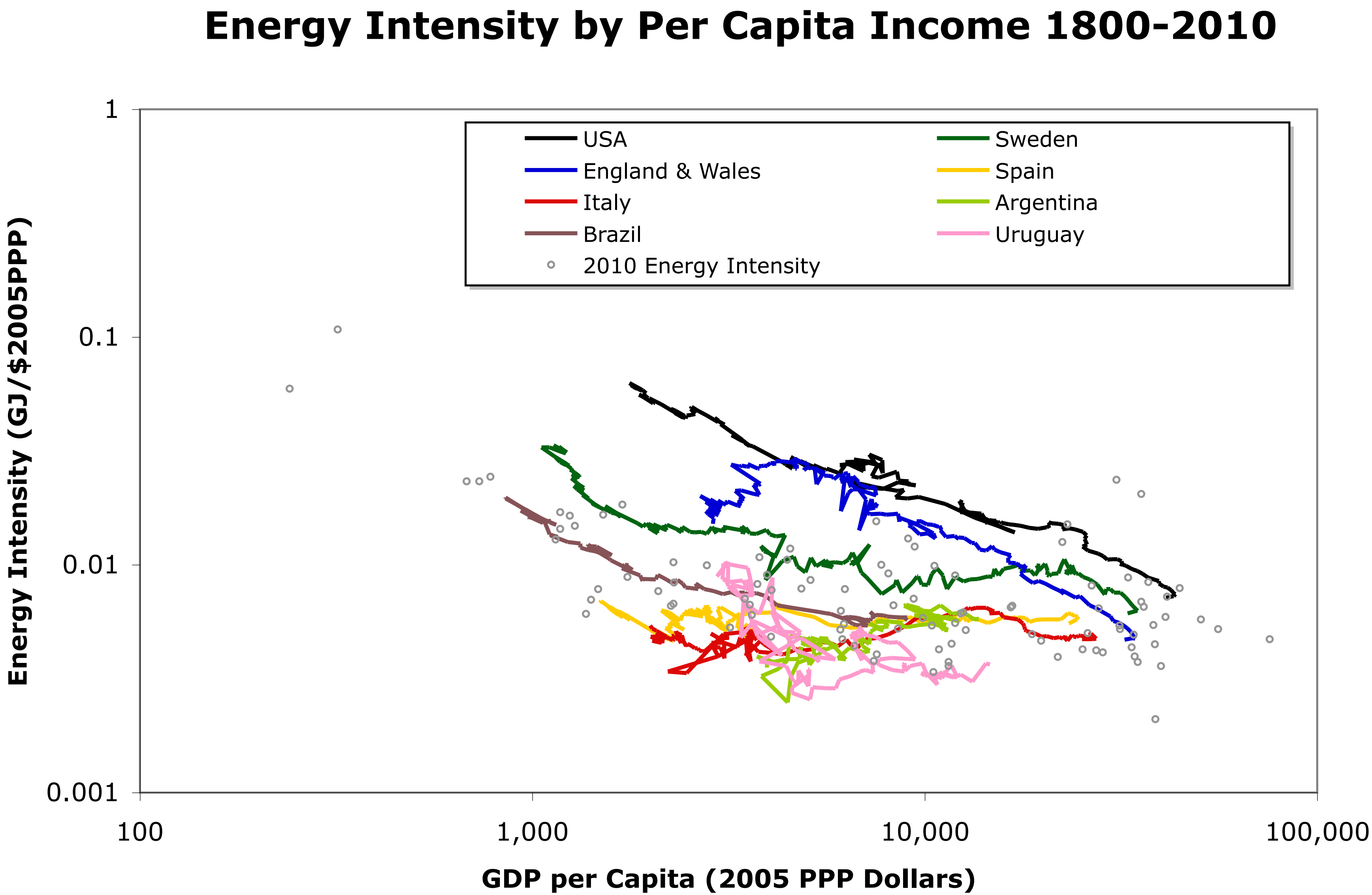
Quantitative Evidence

- Historical evidence
- Analytical approach
- Computational approach
- Econometric approach

Historical Evidence




Energy consumption per capita (GJ)
GDP per capita ($2005 PPP)
100
10
250
2500
25000
Canada
USA
Finland
Germany
United Kingdom
Taiwan
Malaysia
Turkey
Spain
Portugal
China
Vietnam
Indonesia
India
South Korea



Energy Intensity by Per Capita Income 1800-2010
Energy Intensity (GJ/$2005PPP)
1
0.1
0.01
0.001
100
1,000
10,000
100,000
GDP per Capita (2005 PPP Dollars)
USA
England & Wales
Italy
Brazil
2010 Energy Intensity
Sweden
Spain
Argentina
Uruguay

Analytical Approach

- Saunders (2008, *Ener. Econ.*):
  - CES production, energy augmenting technical change, constant energy and capital prices:

$$Y = \left(\gamma\left(K^{\beta}(A_L L)^{1-\beta}\right)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_E E)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

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  - $R = \frac{1}{S_L}\left(S_E + S_L + (\sigma - 1)(1 - \beta)\right)$
  - For $\sigma = 0.67, S_E = 0.1, S_L = 0.63, \beta = 0.3$: $R \cong 79\%$

Analytical Approach

- Lemoine (2019):
  - Elasticity of substitution in consumption is 0.9
  - $\bar{\sigma} = 0.33$
  - $R = 38\%$

Computational Approach

- Turner (2009, *Ener. Econ*), sensitivity analysis of UK CGE model:
  - -13% to 322% rebound
  - Depends on elasticities of substitution

Computational Approach

- Rausch & Schwerin (in press, *IER*) small calibrated dynamic GE model
- Putty-clay assumption
- US data
- Rebound 102%

Econometric Estimates

- Adetutu *et al*. (2016, *Ener J.*):
  - Stochastic frontier model to estimate energy efficiency
  - Partial equilibrium, dynamic panel model to estimate effect on energy use

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  - Short run rebound: 90%. Long-run: -36%

Econometric Estimates

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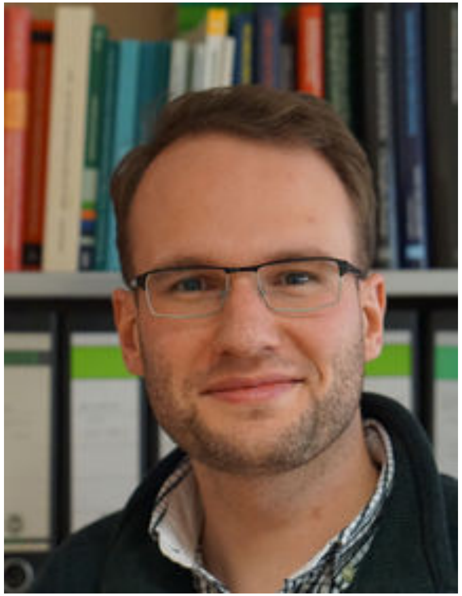
  - Stochastic frontier model to estimate energy efficiency
  - Partial equilibrium, dynamic panel model to estimate effect on energy use
  - Short run rebound: 90%. Long-run: -36%
  - Simple dynamic structure:
    - If E declines in short run, it declines more in long run

Estimating the Rebound Effect

Using structural vector autoregressions to estimate the size of the economy-wide rebound effect

Collaborators

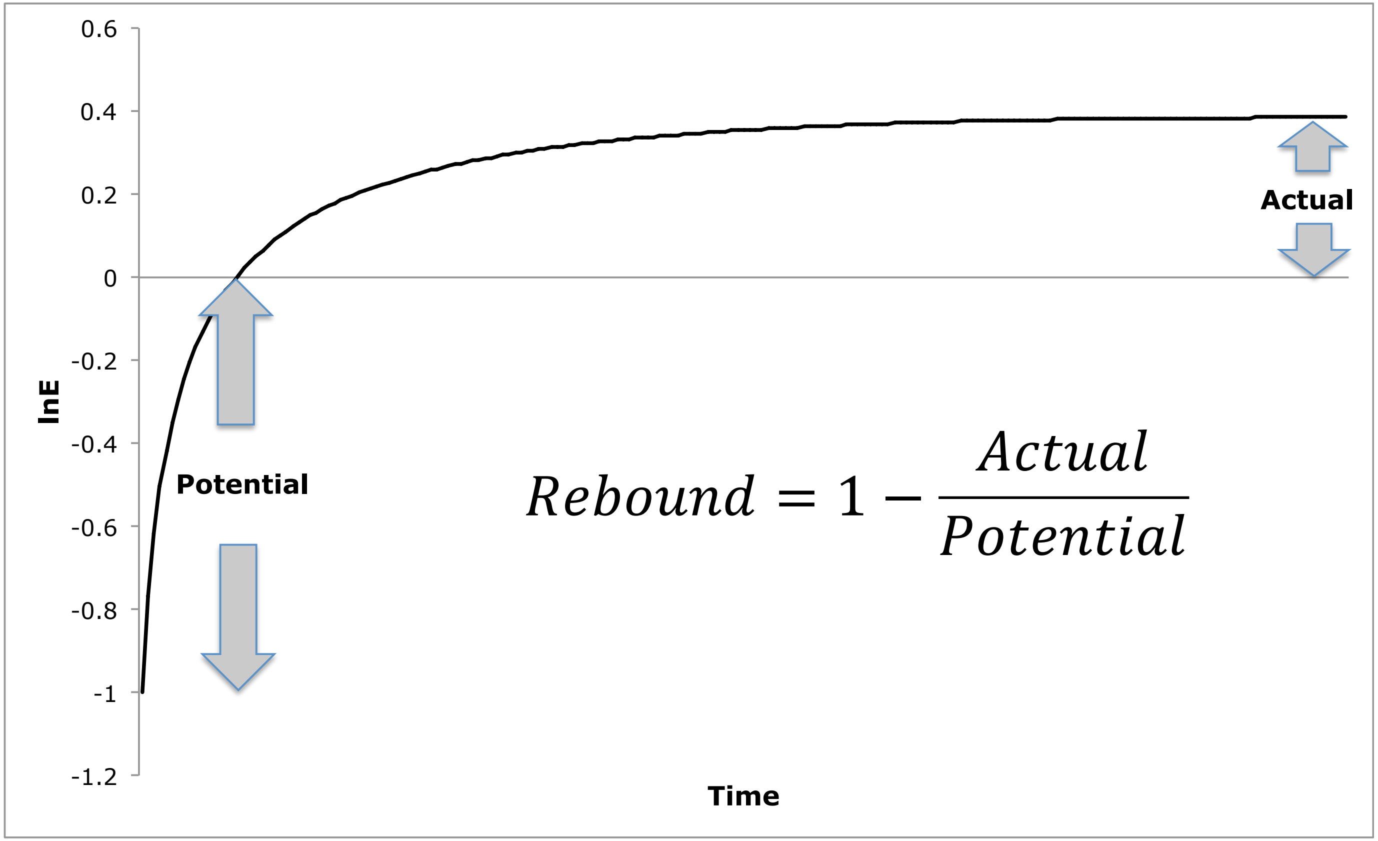


Stephan Bruns *U. Göttingen*	Alessio Moneta *Scuola Superiore Sant'Anna*

Australian Government

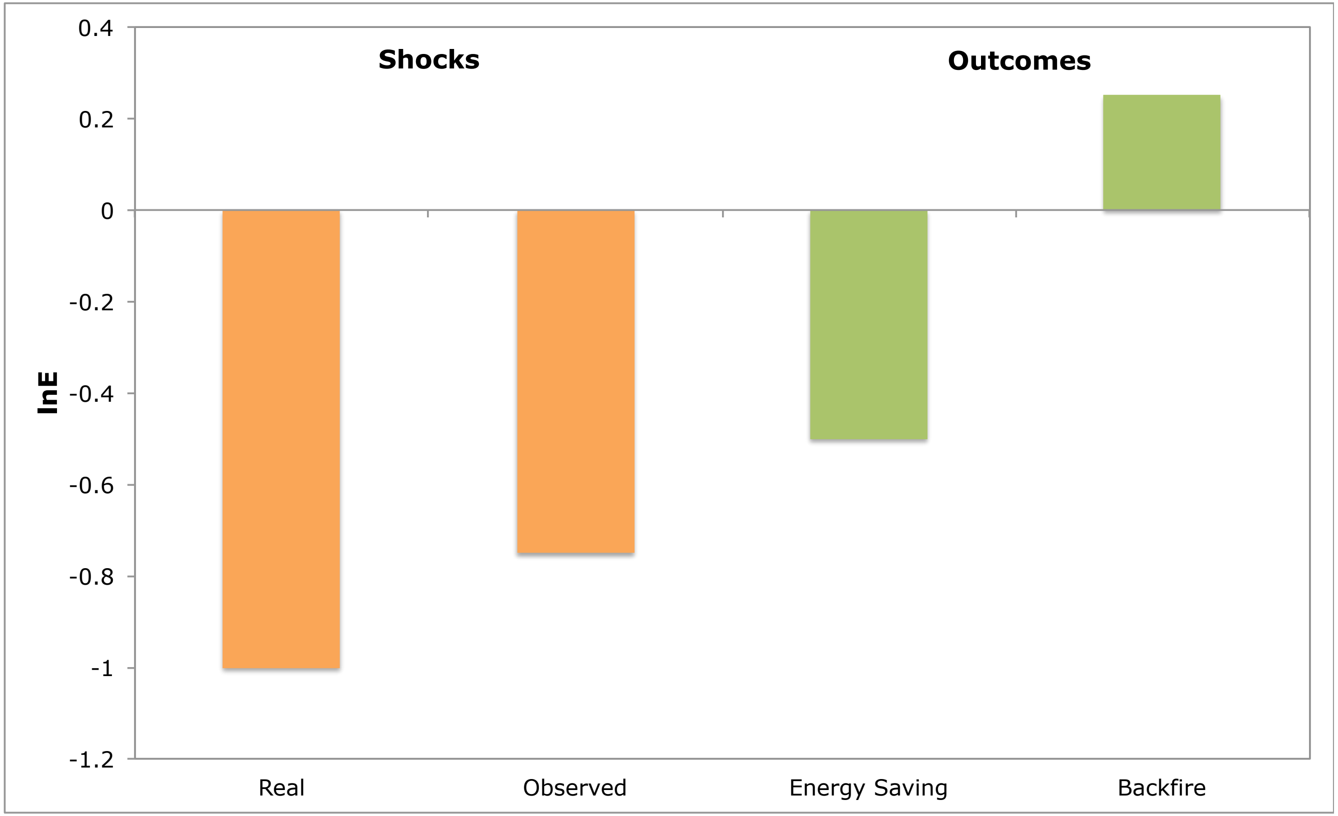
Australian Research Council

Estimating the Rebound Effect



$$Rebound = 1 - \frac{Actual}{Potential}$$

Estimating the Rebound Effect



SVAR Approach

- Reduced form VAR:

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

$$x_t = [\ln E_t, \ln Y_t, \ln P_t]'$$

- Structural VAR:

$$x_t = \sum_{i=1}^{p} \Pi_i x_{t-i} + B\varepsilon_t \,; VAR(\varepsilon_t) = I; u_t = B\varepsilon_t$$

- Identify B empirically using Independent Component Analysis

Advantages of the SVAR Approach

	Analytical Approach	CGE	Partial Equilibrium Econometric	SVAR
Empirical	✗	✗	☺	☺
General equilibrium	✗	☺	✗	☺
Exogeneity of shocks	☺	☺	✗	☺

Identifying the Mixing Matrix, B

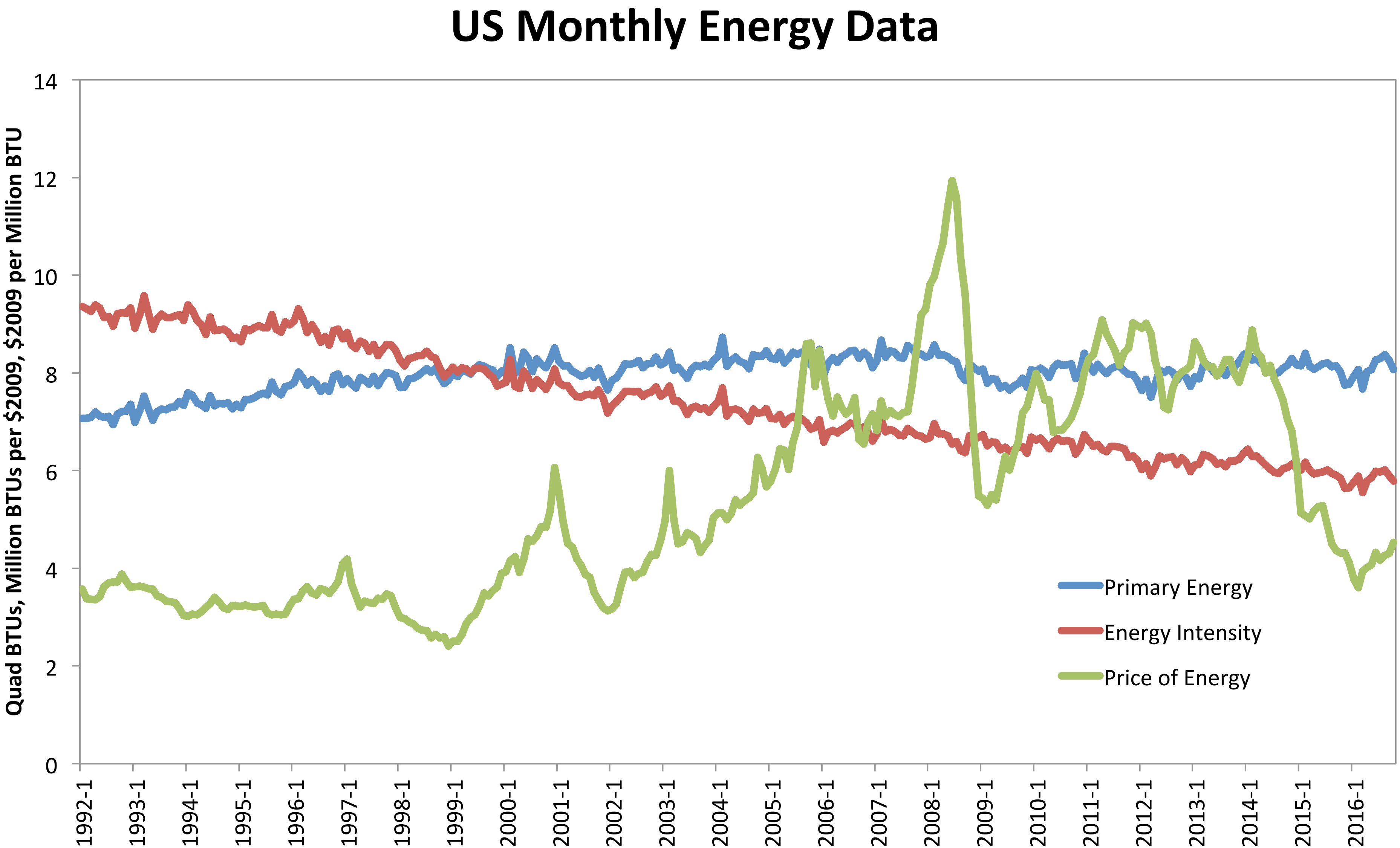
- # parameters in B > # parameters in $\text{var}(u_t)$
- Traditional approach: Impose restrictions on B
- Sign restriction approach
- Independent Component Analysis: Places conditions on ε_t

Independent Component Analysis

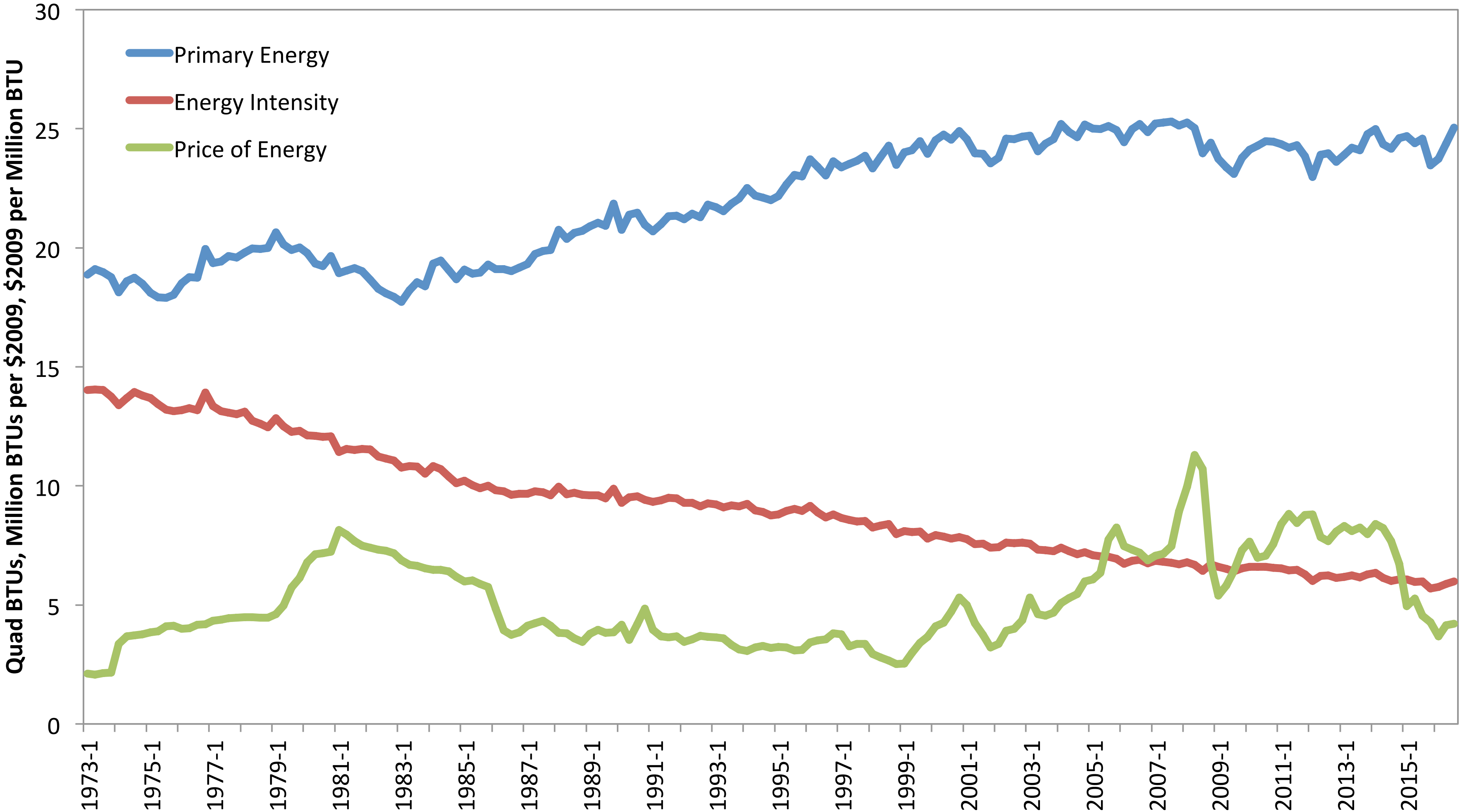
- From machine learning literature
- Assume elements of ε_t are independent and non-Gaussian
- ICA algorithms find linear combinations of u_t that are maximally independent according to various criteria:
  - Distance covariance
  - Maximum likelihood
  - Negentropy maximization (FastICA)
  - LINear non-Gaussian Acyclic Model

Data

- Estimate with US monthly data, 1992:1-2016:10; Quarterly data, 1973:1-2016:3
- Primary energy use and prices from US EIA
- Price = Energy cost / BTU
- Deseasonalized using X11 procedure
- Monthly GDP data from Macroeconomic Advisors, quarterly from BEA


US Monthly Energy Data
Quad BTUs, Million BTUs per $2009, $2009 per Million BTU
14
12
10
8
6
4
2
0
1992-1
1993-1
1994-1
1995-1
1996-1
1997-1
1998-1
1999-1
2000-1
2001-1
2002-1
2003-1
2004-1
2005-1
2006-1
2007-1
2008-1
2009-1
2010-1
2011-1
2012-1
2013-1
2014-1
2015-1
2016-1
Primary Energy
Energy Intensity
Price of Energy

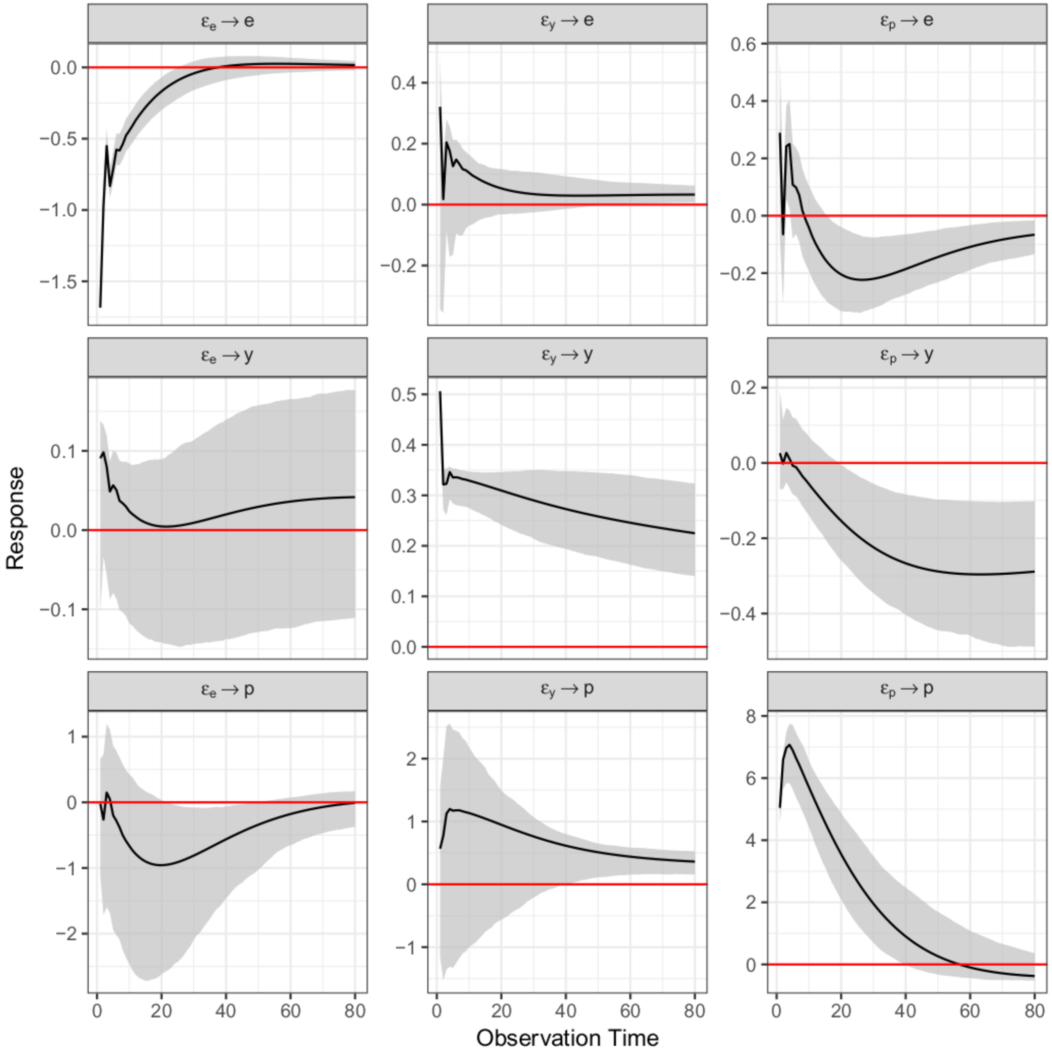
US Quarterly Energy Data



B for monthly data

	ε_e	ε_y	ε_p
Distance covariance			
Energy	-1.685	0.321	0.289
GDP	0.091	0.506	0.026
Energy price	-0.020	0.566	5.042
Non-Gaussian Maximum Likelihood			
Energy	-1.500	-0.660	0.466
GDP	-0.210	0.455	0.031
Energy price	0.145	0.515	4.814

Impulse Response Functions



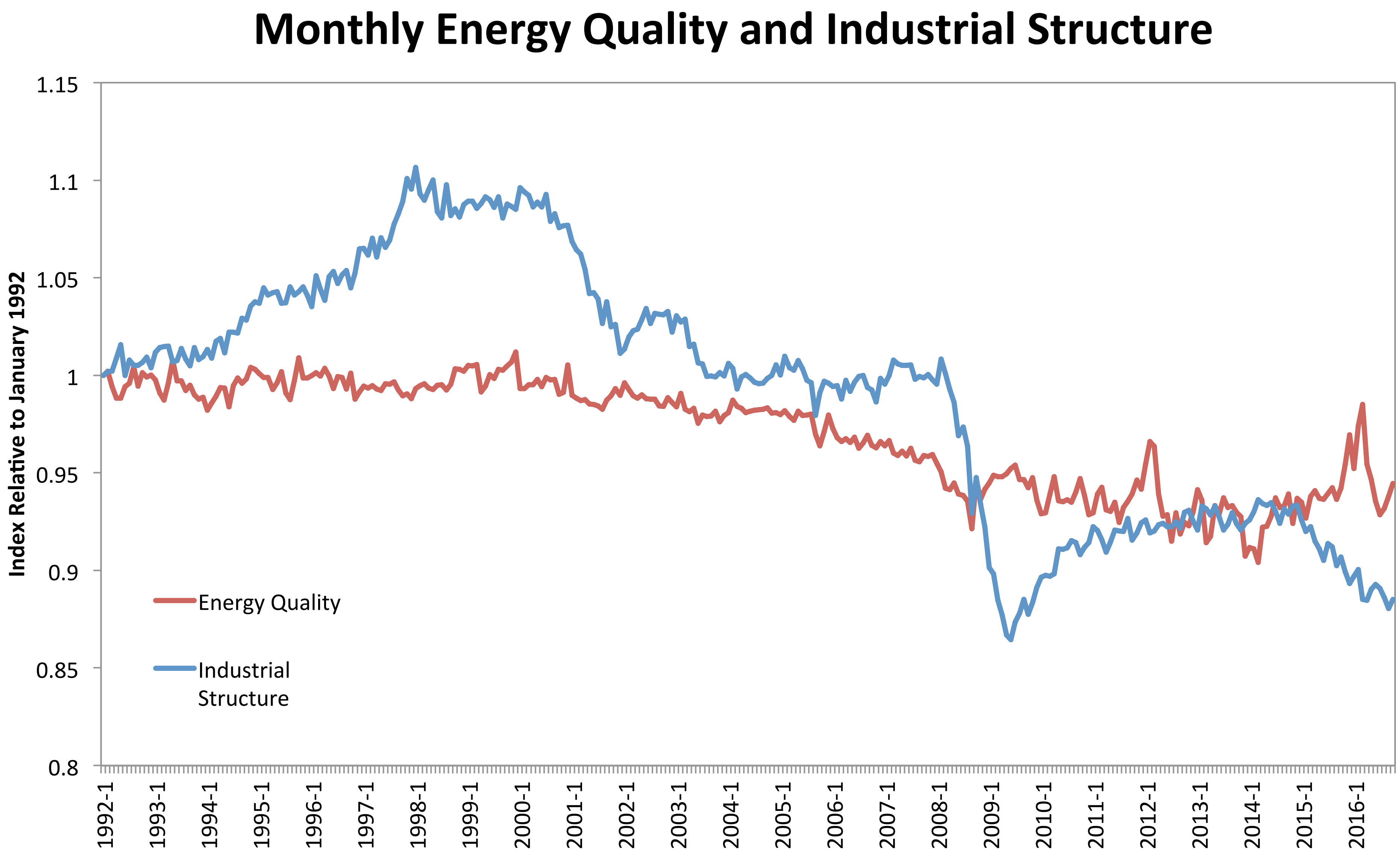
Rebound effect

Model	1	2	3	4	5	6
Frequency	Monthly	Monthly	Quarterly	Quarterly	Quarterly	Quarterly
Method	Dcov	Ngml	Dcov	Ngml	Dcov	Ngml
Period	1992-2016	1992-2016	1973-2016	1973-2016	1992-2016	1992-2016
1 year	0.78	0.76	0.61	0.61	0.58	0.45
	[0.61,0.88]	[0.62,0.89]	[0.34,0.68]	[0.35,0.63]	[0.35,0.81]	[0.34,0.8]
2 years	0.94	0.91	0.9	0.9	0.91	0.77
	[0.76,1.04]	[0.76,1.04]	[0.57,1.03]	[0.6,0.97]	[0.58,1.2]	[0.58,1.14]
4 years	1.01	0.99	1.16	1.17	1.09	1.01
	[0.91,1.1]	[0.9,1.09]	[0.81,1.38]	[0.84,1.32]	[0.8,1.35]	[0.8,1.31]
6 years	1.01	0.99	1.23	1.24	1.07	1.03
	[0.95,1.08]	[0.94,1.06]	[0.94,1.47]	[0.96,1.45]	[0.87,1.3]	[0.88,1.28]

Notes: 0.90 confidence interval in brackets.

Control Variables

- Energy mix and industrial structure are major factors affecting energy intensity
- Control using:
  - Energy mix: energy quality
  - Industrial structure: industrial production



Monthly Energy Quality and Industrial Structure
Index Relative to January 1992
1.15
1.1
1.05
1
0.95
0.9
0.85
0.8
Energy Quality
Industrial Structure
1992-1
1993-1
1994-1
1995-1
1996-1
1997-1
1998-1
1999-1
2000-1
2001-1
2002-1
2003-1
2004-1
2005-1
2006-1
2007-1
2008-1
2009-1
2010-1
2011-1
2012-1
2013-1
2014-1
2015-1
2016-1

Rebound Effect: 5 Variable VAR

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.

Conclusions and Policy Implications

- No consensus, but economy-wide rebound could be high

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- Energy efficiency innovation probably of limited value in climate mitigation
  - Especially with existing binding efficiency mandates (Fullerton & Ta)

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- No consensus, but economy-wide rebound could be high
- Energy efficiency innovation probably of limited value in climate mitigation
  - Especially with existing binding efficiency mandates (Fullerton & Ta)
- Increasing costly mandates can have large effects (Fullerton & Ta)

More information:

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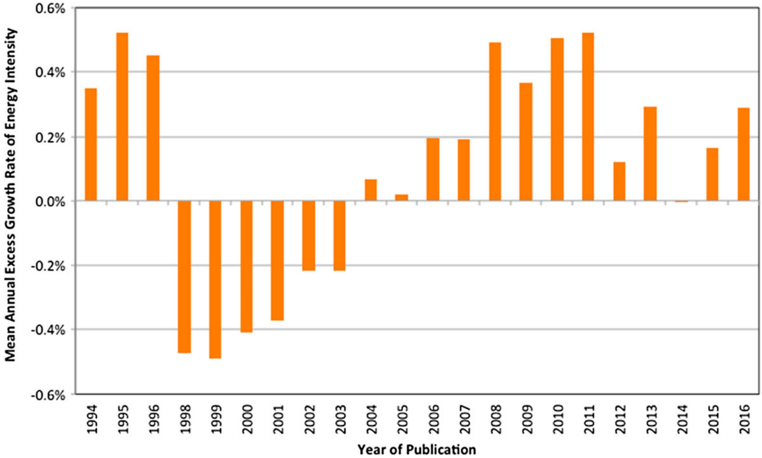


Fig. 2 Energy intensity projection errors. The *dates* refer to the publication date of the *WEO*. The percentage error is the mean annual difference between the percentage rate of change in actual energy intensity and projected energy intensity from the base year of the respective *WEO* through 2015 for *WEO-1998* forward. *Positive values*, therefore, indicate that energy intensity declined by less than expected and so the level of energy intensity was higher than projected in 2015 (2010 from *WEO-1994* to *WEO-1996*). Because the base year of *WEO-2015* is 2013 and of *WEO-2016* is 2014, it is possible to compute a projection error for these two latest reports

Independent Component Analysis

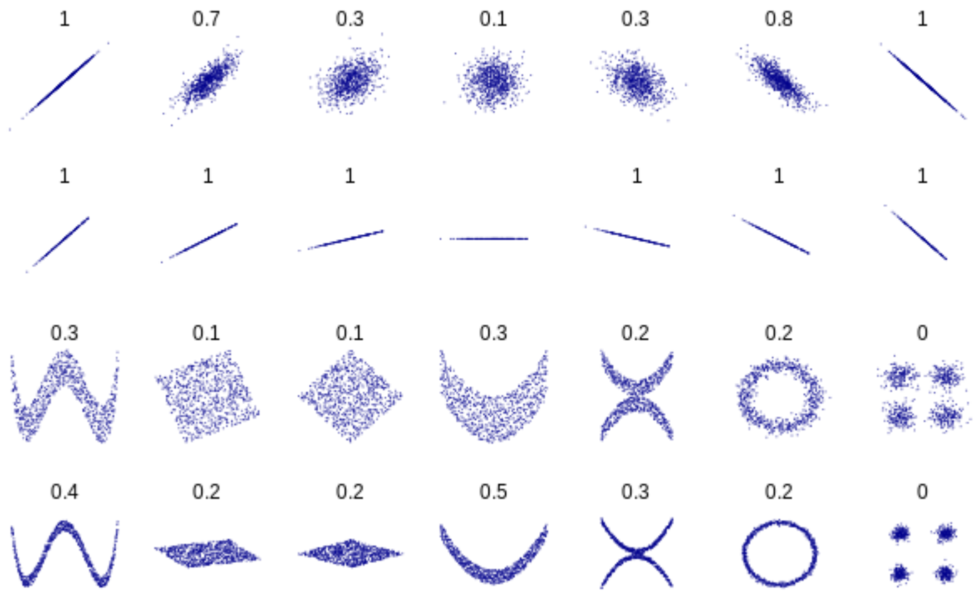
- Identifying the mixing matrix

$$u_t = B\varepsilon_t$$

- If all elements of ε_t are mutually independent and non-Gaussian (with a maximum of one exception), then B is identifiable up to a column permutation and sign (Comon, 1994)
- Label shocks by the variable they impact most

Distance Covariance

Distance covariance (Székely, 2007) can measure linear and nonlinear dependence of random variables



Distance Covariance

- Matteson and Tsay (2017)
- Minimize $dCOV\left(\varepsilon(\theta)\right)$
- θ vector of rotation angles of Givens rotation matrices
- $B(\theta) = DQ(\theta)$; D Choleski factor of $\hat{\Sigma}_u$, Q product of Givens rotation matrices
- $\hat{\varepsilon}_t(\theta)$=$B(\theta)^{-1}\hat{u}_t$

Non-Gaussian Maximum Likelihood

- Lanne *et al*. (2017)
- ML assuming mutual independence of shocks and specific distributions for each
- At most one can be Gaussian
- We assume t-distribution

B for quarterly data

	ε_e	ε_y	ε_p
Distance covariance			
Energy	-1.549	0.511	0.052
GDP	0.163	0.706	0.028
Energy price	0.051	-0.524	8.585
Non-Gaussian Maximum Likelihood			
Energy	-1.550	0.421	0.140
GDP	0.155	0.725	0.072
Energy price	-0.048	-0.743	8.848