Quantification of Economy-wide Rebound Effects using FAVAR Models

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Project ReCap

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GEFÖRDERT VOM



Energy Efficiency Policy

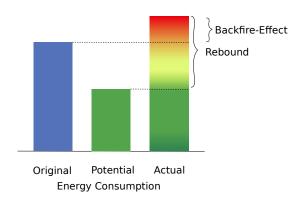
- Save energy and money



Berner, Bruns, Moneta, Stern 26/08/2019 3 / 16

 $^{^{1}}$ Source: Synthesis report on the evaluation of national notifications related to Article 14 of the Energy Efficiency Directive

Rebound Effect

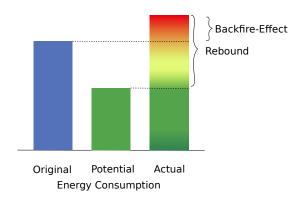


2

Rebound Effect =
$$1 - \frac{\text{Actual change in Energy Consumption}}{\text{Potential change}}$$

 $^{^{2}\}mathrm{Own}$ representation based on Madlener & Alcott (2011)

Rebound Effect



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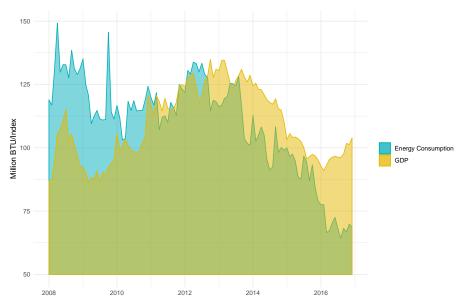
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Simultaneity Challenge

Decrease in Energy Consumption in the UK



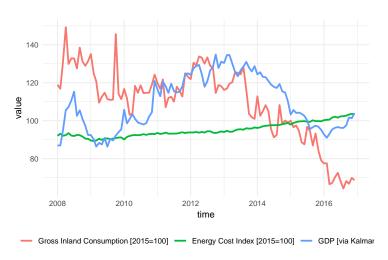
What about Causality?



- 1. "Ex ante" via Partial/Computable General Equilibrium Models e.g. Turner (2013); Koesler (2013)
- 2. "Ex post" via econometric general equilibrium model
 - Partial equilibrium econometric estimates do not credibly identify causal effect, e.g. Saunders (2013); Orea, Llorca, and Filippini (2015)
 - ▶ Our approach: Structural Vector Autoregressive (SVAR) model
 - Empirical identification with minimum number of assumptions

Idea: Isolate energy efficiency impact on energy consumption:

$$E = f$$
 (Energy Efficiency, Price, GDP, X) (1)



SVAR Model

$$A_0 x_t = A_0 \xi_t + \sum_{i=1}^p A_0 \Pi_i x_{t-i} + \eta_t$$
 (2)

- x_t is the vector of the three variables
- Π captures lag cross-correlations between energy use, GDP and the energy price, where u_t is a noise/shock process
- $\eta_t = A_0 u_t$ and $var(\eta_t) = 1$
- A_0 captures contemporaneous effects of the endogenous variables on each other o **Identification problem**

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Identification Problem

Data-driven Independent Component Analysis (ICA) techniques to estimate $\it A_{\rm 0}$



³Source: https://www.deichstube.de

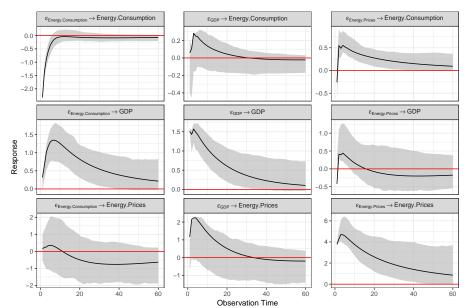
- Monthly data from January 2008 to December 2016
- Gross inland energy consumption: Quantity of energy necessary to satisfy inland consumption of the country
- Harmonized consumer price indices (Solid and liquid fuels, electricity and gas)
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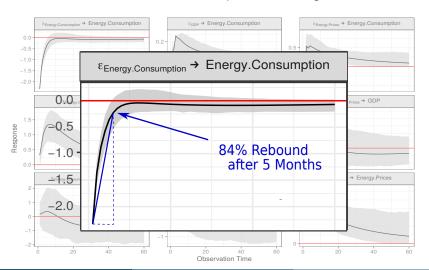
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Impulse Response Analysis - Germany

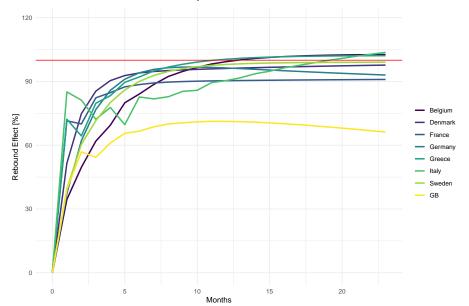


Rebound Effect

$$R = 1 - \frac{\Delta e_i}{\Delta \hat{e}} = 1 - \frac{\text{actual change}}{\text{potential change}}$$
 (3)



Rebound Effects in Europe



- Extreme rebound effect might have omitted variables
- Evidence that large data sets include relevant information (Stock & Watson, 2016, 2005; Bernanke, Boivin, & Eliasz, 2005)
- Idea: Use a small set of estimated factors to summarize large amount of information about the economy
 - ightarrow Large monthly macroeconomic data set by OECD (MEI)
 - 1. Core variables of interest Y_t and latent Factors F_t drive the common dynamics of the large informational dataset:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t$$

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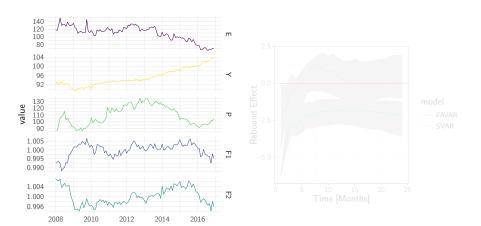
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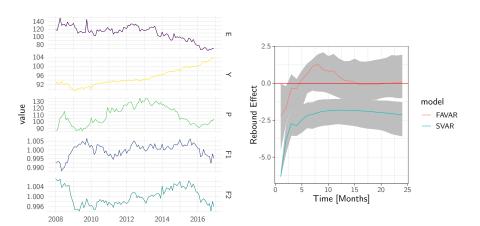
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Factor Estimation for the UK



Factor Estimation for the UK



Conclusion

- Rebound effect shockingly consistent
- Approx. 100 % rebound effect in all analyzed countries after 1 year
- Future work:
 - Apply the FAVAR to all EU countries
 - Quality of Energy: Exergy/Divisia Index
 - Sectoral analysis in order to understand drivers of the rebound effect

Thank you for your attention!

Literature I

- Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *Quarterly Journal of Economics*, 120(1), 387–422.
- Koesler, S. (2013). Catching the rebound: economy-wide implications of an efficiency shock in the provision of transport services by households. *ZEW discussion papers*.
- Lange, A., Dalheimer, B., Herwartz, H., & Maxand, S. (2018). svars:

 Data-driven identification of svar models [Computer software manual]. Retrieved from

 https://CRAN.R-project.org/package=svars (R package version 1.2.1)
- Lanne, M., Meitz, M., & Saikkonen, P. (2017, feb). Identification and estimation of non-Gaussian structural vector autoregressions. *Journal of Econometrics*, 196(2), 288–304.

Literature II

- Matteson, D. S., & Tsay, R. S. (2017). Independent Component Analysis via Distance Covariance. *Journal of the American Statistical Association*, 112(518), 623–637.
- McCracken, M. W., & Ng, S. (2016). Fred-md: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, 34(4), 574–589.
- Orea, L., Llorca, M., & Filippini, M. (2015). A new approach to measuring the rebound effect associated to energy efficiency improvements: An application to the US residential energy demand. *Energy Economics*, 49, 599–609. doi: 10.1016/J.ENECO.2015.03.016
- Saunders, H. D. (2013). Historical evidence for energy efficiency rebound in 30 US sectors and a toolkit for rebound analysts. *Technological Forecasting and Social Change*, 80(7), 1317–1330. doi: 10.1016/J.TECHFORE.2012.12.007

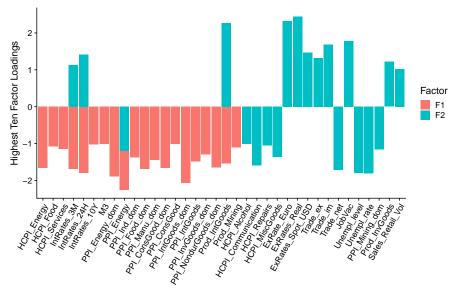
Literature III

- Stock, J. H., & Watson, M. W. (2005). An empirical comparison of methods for forecasting using many predictors. *Manuscript, Princeton University*.
- Stock, J. H., & Watson, M. W. (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In *Handbook of macroeconomics* (Vol. 2, pp. 415–525). Elsevier.
- Turner, K. (2013). "Rebound" effects from increased energy efficiency: A time to pause and reflect. *Energy Journal*, *34*(4), 25–42. doi: 10.5547/01956574.34.4.2

Factor Estimation

- Approach: Two-step procedure (Stock & Watson, 2005)
 - 1. Common components, C_t , are estimated using the first principal components of X_t
 - $ightarrow \hat{F}_t$ is space covered by C_t that is not covered by Y_t
 - 2. FAVAR-equation is estimated by standard methods, with \hat{F}_t
- Data: Large monthly macroeconomic data set by OECD (MEI) comparable to McCracken and Ng (2016)
 - ★ Money and Credit
 - ★ Consumption, orders, and inventories
 - ★ Import/Export
 - ★ Labour Market
 - ★ Output and Income
 - ★ Prices
 - * Stock Market

Factor Loadings



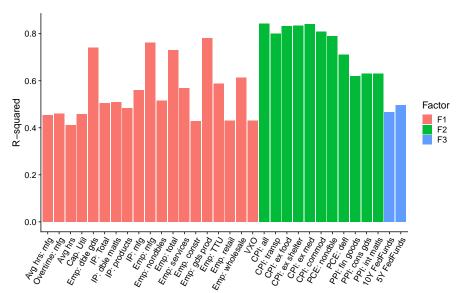
Independent Component Analysis

Data-driven Independent Component Analysis (ICA) techniques to estimate A_0

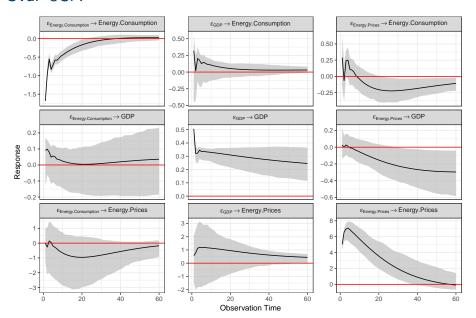
- Idea: Searching for the linear combinations of the observed data (u_t) that are minimally dependent
- Assumptions on elements of η_t :
 - 1. Independent mutually and cross-sectionally
 - 2. Non-Gaussian with at maximum one exception
 - \rightarrow Invertible matrix A_0^{-1} is "almost identifiable"
- Two techniques applied by using svars-Package (Lange et al., 2018):
 - 1. Distance covariance approach (Matteson & Tsay, 2017)
 - 2. Non-Gaussian Maximum Likelihood Estimator (Lanne et al., 2017)

Factor Analysis

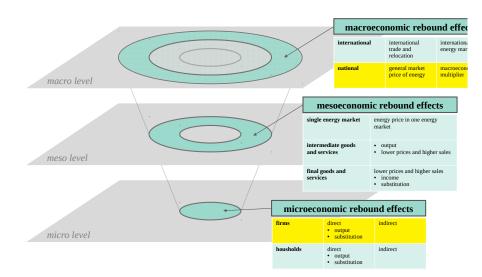
 $R^2 s > 0.4$ of regressing each variable in X_t on the three factors



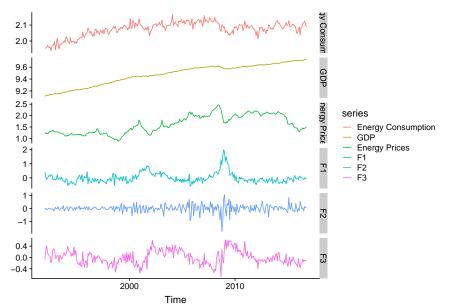
Svar USA



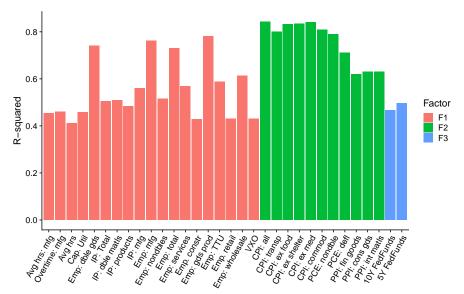
Svar USA



Factor Analysis - Preliminary Results



Factor Analysis - Preliminary Results



Rebound effect after 5 months

	Country	X1month	X3 months	X6months	X12months	CI_90
1	Belgi	49.58	69.41	88.58	100.16	[89.05 11
2	Germa	62.12	85.83	95.68	96.04	[86.9 106
3	Denma	74.80	90.40	94.68	96.31	[95.08 10
4	Greec	64.37	83.30	94.93	100.89	[89.11 10
5	Franc	70.01	84.74	89.29	90.44	[86.75 97
6	Italy	81.22	77.78	81.80	91.76	[79.15 10
7	Swede	60.42	80.12	92.82	98.31	[78.16 10
8	Unite	56.86	61.01	68.65	71.08	[55.09 82