About the Speaker

Ermanno Affuso

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- Ermanno Affuso is an Associate Professor of Economics and Finance & Chief Scientific Officer of SABRE within the Mitchell College of Business at the University of South Alabama.
- He earned his Ph.D. in Applied Economics from Auburn University, U.S., and a Laurea degree in Civil Environmental Engineering from Bari Polytechnical University, Italy.
- Ermanno is an applied econometrician with primary focus in Empirical Natural Resource Economics within the context of Urban and Regional Science.
- Ermanno's research has been published in several international scholarly journals that include *Energy Economics, Land Economics, Empirical Economics, Urban Studies, and the Journal of Real Estate Finance and Economics*.
  In 2015 and 2017, he received the "Professor of the Year" award from the Mitchell College of Business.
- In 2020, he was granted the Fulbright Specialist Program award by the U.S. Department of State.
- In 2021, he was awarded the Top Professor of Economics by the Mortar Board Honor Society chapter of the University of South Alabama.
- Ermanno is the founder of Quanteras, LLC, a business intelligence firm, and the co-founder and coordinator of the Ph.D. in Business Analytics at the University of South Alabama.
- A blockchain enthusiast, in his spare time, Ermanno also engages in recreational computer coding, ethnic cooking, and traveling.

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A Causal Analysis of Electricity Consumption and Economic Growth in the U.S.

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20 July 2022

Background & Literature

Energy Consumption and Macroeconomic Indicators

- Hamilton (1983): Oil Price Shocks and Economic Growth in the U.S. (prior to 1972)
- Burbridge and Harrison (1984): UK, Germany, Japan, Canada – US & UK similar
- Gisser and Goodwin (1986): Oil price shock and U.S. Aggregate Supply
- Hooker (1996): oil price endogeneity (Granger-causality)
- Brukner et al. (2012): Oil Price, GNP, democratic polity (+)

Literature (cont'd)

Energy Consumption and Economic Growth

Vector Autoregressive Models and Granger Causality

- Kraft and Kraft (1978), Akarca and Long (1980), Yu and Hwang (1984), Absoedra and Baghestani (1991)
- Stern (2000) showed the inconclusiveness of previous studies:
    - multivariate cointegration analysis: energy factor cannot be excluded from the cointegration space
- Belke et al. (2011): Cointegration Analysis of OECD
- Pao et al. (2011) for Russia, Pao and Tsai (2011) for Brazil, Wang et al. (2011) for China, Arouri et al. (2012) for the Middle East and North African economies , Al Mulali and Sab (2012) for the Sub-Saharan African region and Baranzini et al. (2013) for Switzerland
- **Common Consensus: Energy Consumption ↔ Economic Growth (bi-directional)**

Literature (cont'd)

Electricity Consumption and Economic Growth

- Squalli (2007): Electricity ↔ Economic Growth (OPEC): results varies across countries
- Ferguson et al. (2000): over 100 countries - Electricity → Economic Growth strong when compared to primary aggregate energy
- Shiu and Lam (2004): Long-run cointegration relationship Electricity → Economic Growth in China
- Gosh (2002): opposite findings in India
- Wolde-Rufael (2006): inconclusive results in 17 African Countries
- Osman et al. (2016): bi-directional causality in Bahrain, Kuwait, Qatar, Oman, Saudi Arabia and the United Arab Emirates
- Sarwar et al. (2017): 210 countries found bi-directional except for OECD, European, Central Asia, Northern African and Middle Eastern (Electricity → Economic Growth)

Electricity Consumption and Economic Growth in the U.S.
(Panel Vector Autoregressive)
(Disaggregated Information-theoretic Causality Test)

unique contribution

Rationale:
if a bidirectional causality relationship exists between electricity use and economic growth, deregulation of the market for electricity and/or environmental policies that aim to promote energy conservation could affect economic growth

Data

Panel 48 contiguous states (1990 – 2018)

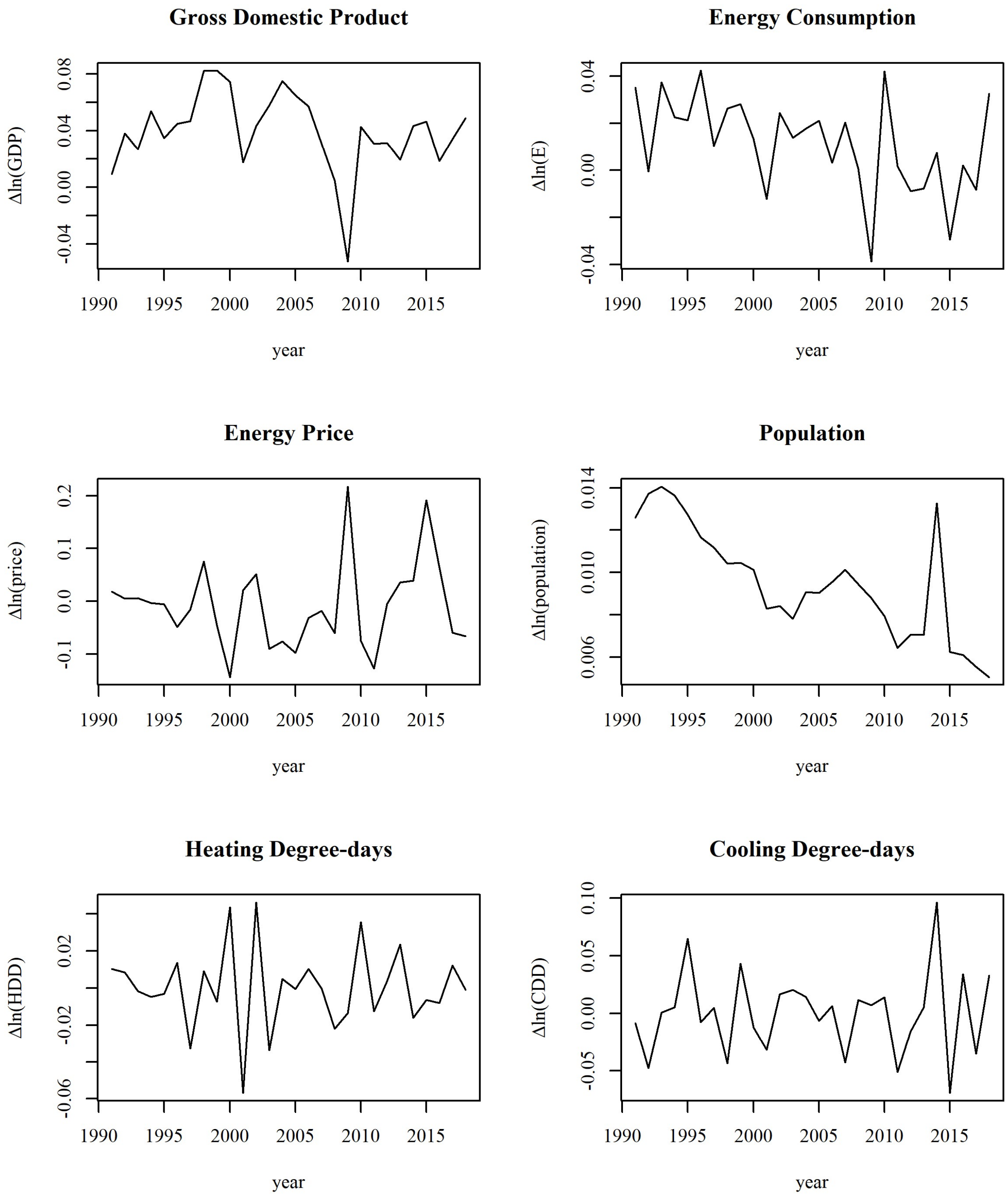
- Energy data: U.S. Energy Information Administration (EIA)
- GDP data for each state: Bureau of Economic Analysis (BEA)
- GDP implicit price deflator and the CPI Energy index for urban consumers: FRED Federal Reserve Bank of Saint Louis.
- cooling and heating degree days (annual basis): National Oceanographic and Atmospheric Administration (NOAA)

Data: Descriptive Statistics

Table 1. Descriptive Statistics.

	Mean	Standard Deviation	Min	Median	Max
GDP	874,422.44	1,468,457.78	29,808	452,919	15,407,539
E	78,410,296.94	69,170,331	1,107,316	56,664,837	477,352,424
Price	15.37	5.53	7.01	14.02	37.18
Population	6,016,066	6,490,348	453,690	4,294,902	39,461,588
Cooling Degree Days	1,109	782	38	893	3,836
Heating Degree Days	1,983	802	33	2,023	4,355
Sample Size	1,392				

Notes: GDP is measured in 2018 Million US$; Electricity is measured in MWh; Price in US$ cents/KWh; Cooling and Heating Degree Days in cumulative Celsius degrees.



Gross Domestic Product
Δln(GDP)
-0.04
0.00
0.04
0.08
Energy Consumption
Δln(E)
-0.04
0.00
0.04
Energy Price
Δln(price)
-0.1
0.0
0.1
0.2
Population
Δln(population)
0.006
0.010
0.014
Heating Degree-days
Δln(HDD)
-0.06
-0.02
0.02
Cooling Degree-days
Δln(CDD)
-0.05
0.00
0.05
0.10
1990
1995
2000
2005
2010
2015
year

Econometric Model

Strucutural Panel Vector Autoregressive Model

$$(1)\ \Delta E_{it} = -\beta_{12}\Delta y_{it} + \gamma_{11}\Delta E_{it-1} + \gamma_{12}\Delta y_{it-1} + \phi_{11}\Delta p_{it} + \phi_{12}\Delta g_{it} + \phi_{13}\Delta h_{it} + \phi_{14}\Delta c_{it} + \Delta\varepsilon_{it}^{E}$$

$$(2)\ \Delta y_{it} = -\beta_{21}\Delta E_{it} + \gamma_{21}\Delta E_{it-1} + \gamma_{22}\Delta y_{it-1} + \phi_{21}\Delta p_{it} + \phi_{22}\Delta g_{it} + \phi_{23}\Delta h_{it} + \phi_{24}\Delta c_{it} + \Delta\varepsilon_{it}^{y}$$

ΔE_{it} = *energy growth*, Δy_{it} = *income growth*, Δp_{it} = *real price change*, Δg_{it} = *population growth*, Δh_{it} = *HDD*, and Δc_{it} = *CDD*

Econometric Model

Compact Form

$$\boldsymbol{B}\boldsymbol{z}_{it} = \boldsymbol{\Gamma}\boldsymbol{z}_{it-1} + \boldsymbol{\Phi}\boldsymbol{w}_{it} + \boldsymbol{\varepsilon}_{it}$$

B= $\begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix}$, **Γ**=$\begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}$, **Φ**=$\begin{bmatrix} \phi_{11}\phi_{12}\phi_{13}\phi_{14} \\ \phi_{21}\phi_{22}\phi_{23}\phi_{24} \end{bmatrix}$, $\mathbf{z}_{it}$ = $\begin{bmatrix} \Delta E_{it} \\ \Delta y_{it} \end{bmatrix}$, $\mathbf{w}_{it}$ = $\begin{bmatrix} \Delta p_{it} \\ \Delta h_{it} \\ \Delta c_{it} \end{bmatrix}$ and $\boldsymbol{\varepsilon}_{it}$ = $\begin{bmatrix} \Delta \varepsilon_{it}^{E} \\ \Delta \varepsilon_{it}^{y} \end{bmatrix}$

Econometric Model: Reduced Form

Premultiply both sides by $\mathbf{B}^{-1}$

(4) $\boldsymbol{z}_{it} = \boldsymbol{B}^{-1}\boldsymbol{\Gamma}\boldsymbol{z}_{it-1} + \boldsymbol{B}^{-1}\boldsymbol{\Phi}\boldsymbol{w}_{it} + \boldsymbol{B}^{-1}\boldsymbol{\varepsilon}_{it} = \boldsymbol{A}\boldsymbol{z}_{it-1} + \boldsymbol{\Omega}\boldsymbol{w}_{it} + \boldsymbol{e}_{it}$

or in scalar form:

(5) $\Delta E_{it} = \alpha_{11}\Delta E_{it-1} + \alpha_{12}\Delta y_{it-} + \omega_{11}\Delta p_{it} + \omega_{12}\Delta g_{it} + \omega_{13}\Delta h_{it} + \omega_{14}\Delta c_{it} + \Delta e_{it}^{E}$

(6) $\Delta y_{it} = \alpha_{21}\Delta E_{it-1} + \alpha_{22}\Delta y_{it-1} + \omega_{21}\Delta p_{it} + \omega_{22}\Delta g_{it} + \omega_{23}\Delta h_{it} + \omega_{24}\Delta c_{it} + \Delta e_{it}^{y}$


HOUSTON,
WE HAVE
A PROBLEM!
APOLLO 13

Panel VAR: Estimation Issues

- lagged dependent variables are endogenous and correlated with the error terms
- if the variables were not differenced, the individual effects would have been correlated with the lagged dependent variables

Panel VAR: Solutions

- error terms of (5) and (6) and the past values (with lags greater than 2 in this case) of the *E* and *y* processes are orthogonal with respect to the current specification (Holtz-Eakin, et al. , 1988)

- lagged values of E and y from 3 to T (after accounting for differencing the variables) are good candidates as instruments that could identify the model

- Arellano and Bond (1991) proposed a GMM procedure to estimate (5) and (6)

- **Panel VAR consists of pairing a single equation dynamic panel model à la Arellano and Bond (1991) with a Vector Autoregressive model à la Sims (1980)**

Panel VAR: Estimation Issues and Solutions (cont'd)

- The number of instruments grows quadratically with T (Greene, 2008: p. 344)
- In long-panel studies like in the current case proliferation of instruments may overfit the endogenous variables, therefore failing to remove the endogenous component (Roodman, 2009)
- Solution: the matrix of instruments is collapsed according to Roodman (2009:138)
- Forward Orthogonal Transformation (FOD) is used in lieu of first differencing (Arellano and Bover, 1995)
- FOD = subtracting the average of all available future observations from the contemporaneous value. Advantage: gain one additional observation.

Parametric Granger-causality test

- Wald statistics: test H_0: No Causality - parameters associated with the past values of the driving processes (e.g., $\Delta\log(E)_{it-1}$ and $\Delta\log(Y)_{it-1}$) and driven ($\Delta\log(Y)_{it}$) or ($\Delta\log(E)_{it}$) are concurrently equal to zero.

Formally:

- $W = \boldsymbol{r}(\mathrm{A}i)'\Sigma\boldsymbol{r}(\mathrm{A}i) \sim x^2(2)$:

- where **r** is a 2x2 matrix whose columns are linear continuous functions of the elements of the column $\mathbf{A}_i$ in (4) and **Σ** is the estimated asymptotic covariance matrix of **A**

Nonparametric Granger-causality test

Transfer Entropy (Schreiber, 2000)

- The Transfer Entropy (TE) is a measure of information transfer between nonlinear dynamic stochastic processes
- Chavez et al. (2003) – **Neuroscience**: to identify Granger causality among electroencephalography signals in different areas of human brains
- Verdes (2005) – **Atmosphere Science**: to identify couplings and information transfer between total solar irradiance, greenhouse gases and the mean temperature of the planet in the past four centuries
- Mokhov and Smirnov (2006) – **Climatology**: to test for causality between El Nino Southern Oscillation and Northern Atlantic Oscillation events in the second half of the 19th century
- Diks and Panchenko (2006) – **Finance**: causality between stock returns and trading volumes
- Affuso (2019) – **Economics**: test for causality between Climate Change and change in consumers behavior
- Hlaváčková-Schindler et al. (2006): Extensive Survey

Transfer Entropy

- $TE_{X\to Y} = \iiint \left\{ f(Y_{t+1}, Y_t, X_t) \ln \frac{f(Y_{t+1}|Y_t, X_t)}{f(Y_{t+1}|Y_t)} \right\} dY_{t+1} \mathrm{d}Y_t \mathrm{d}X_t =$
  $\mathcal{E}(Y_{t+1}|Y_t, X_t) - \mathcal{E}(Y_{t+1}|Y_t)$
  $= \mathcal{E}(Y_{t+1}, Y_t, X_t) + \mathcal{E}(Y_t) - \mathcal{E}(Y_t, X_t) - \mathcal{E}(Y_{t+1}, Y_t)$
- f(·) are conditional probability densities and $\mathcal{E}$ (·) are Shannon entropies and mutual information that can be used to measure the functional dependence of two stochastic processes (Granger and Lin, 1991)
- By using theorem 4 in Granger and Lin (1991:375), the asymptotic TE statistics reduces to
- $TE_{X\to Y} = \frac{1}{T} \sum_{t=1}^{T} \left(\hat{f}(Y_{t+1}, Y_t, X_t) + \hat{f}(Y_t) - \hat{f}(Y_t, X_t) - \hat{f}(Y_{t+1}, Y_t) \right)$

Transfer Entropy (cont'd)

- $TE_{X \to Y} = \frac{1}{T} \sum_{t=1}^{T} \left(\hat{f}(Y_{t+1}, Y_t, X_t) + \hat{f}(Y_t) - \hat{f}(Y_t, X_t) - \hat{f}(Y_{t+1}, Y_t) \right)$
- where $\hat{f}(\cdot)$ are univariate and multivariate kernel density estimates
- Diks and Fang (2017) suggest using the plug-in density estimator based on the standard multivariate Gaussian kernel function
- Kernel Density Estimates can be easily computed using the Compositional Data Analysis library available in the R statistical programming ecosystem (Tsagris, 2022)

Diagnostics

- Time dummies are included to prevent contemporaneous correlation across individual states (Roodman, 2009)
- moment selection criteria (MMSC – Andrew and Lu, 2001) to select optimal number of past lags to use as instruments to ensure minimum information loss (J-statistics) and optimal number of past lags as regressors
- Panel VAR stability analysis (eigenvalues of the matrix of endogenous parameters)

MMSC Test

Optimal Number of Past Lags (Regressors)

MMSC-BIC(1 lag) = -981.9;
MMSC-BIC(2 lags) = -955.3;
MMSC-BIC(3 lags) = -928.8;
MMSC-BIC(4 lags) = -902.3;
MMSC-BIC(5 lags) = -875.8.

Optimal # Instrumental Variables Lags: 27

Table 2. MMSC Test.

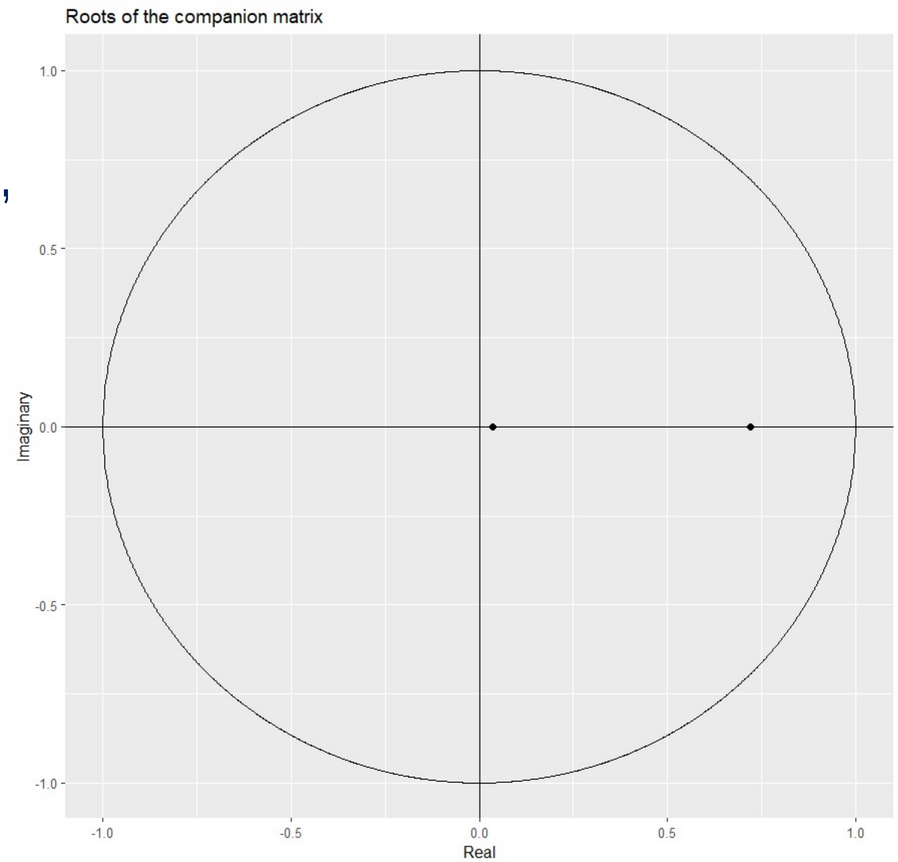
Lags	BIC	HQIC
1	-236.5	-136.5
2	-265.2	-153
3	-293.8	-169.6
4	-322.5	-186.1
5	-351.2	-202.7
6	-379.9	-219.2
7	-408.5	-235.7
8	-437.2	-252.3
9	-465.9	-268.8
10	-494.5	-285.4
11	-523.2	-301.9
12	-551.9	-318.5
13	-580.5	-335
14	-609.2	-351.6
15	-637.9	-368.1
16	-666.5	-384.6
17	-695.2	-401.2
18	-723.9	-417.7
19	-752.5	-434.3
20	-781.2	-450.8
21	-809.9	-467.4
22	-838.5	-483.9
23	-867.2	-500.4
24	-895.9	-517
25	-924.5	-533.5
26	-953.2	-550.1
27	-981.9	-566.6

Notes: BIC = Bayesian Information Criterion; Hanna and Quinn Information Criterion.

Stability Analysis

eigenvalues of the endogenous parameters' matrix lie inside the unit circle [0.721, 0.036]'

The model is stable



Results (1/2)

Table 3. Panel VAR: Results.		
	$\Delta\log(E)$	$\Delta\log(GDP)$
$\Delta\log(GDP)_{t-1}$	0.1760*** (0.0132)	0.6667*** (0.0039)
$\Delta\log(E)_{t-1}$	0.0904*** (0.0045)	0.1949*** (0.0044)
$\Delta\log(P)$	-0.0914*** (0.0071)	-0.2017*** (0.0046)
$\Delta\log(CDD)^a$	-0.0277 (0.0193)	0.0280** (0.0088)
$\Delta\log(HDD)^b$	0.0232 (0.0119)	-0.0100*** (0.0029)
$\Delta\log(Population)$	0.0502*** (0.0046)	0.1552*** (0.0047)

Notes: ***99%, **95%, *90% confidence interval; standard error in parentheses; Sample size = 1,296; Number of Istruments = 170; [a]CDD = Cooling Degree Days; [b]HDD = Heating Degree Days.

Results (2/2)

Table 3. Panel VAR: Results.		
	Δlog(E)	Δlog(GDP)
2007	0.0235* (0.0109)	0.0015 (0.0054)
2008	0.0112 (0.0099)	-0.0276*** (0.0066)
2009	-0.0194 (0.0119)	-0.0187* (0.0086)
2010	0.0582*** (0.0087)	0.0183** (0.0059)
2011	0.0320* (0.0129)	0.0180** (0.006)
2012	-0.0341* (0.0147)	0.0288** (0.0089)
2013	0.0212* (0.0098)	0.0201* (0.0096)

Notes: ***99%, **95%, *90% confidence interval; standard error in parentheses; Sample size = 1,296; Number of Istruments = 170; [a]CDD = Cooling Degree Days; [b]HDD = Heating Degree Days.

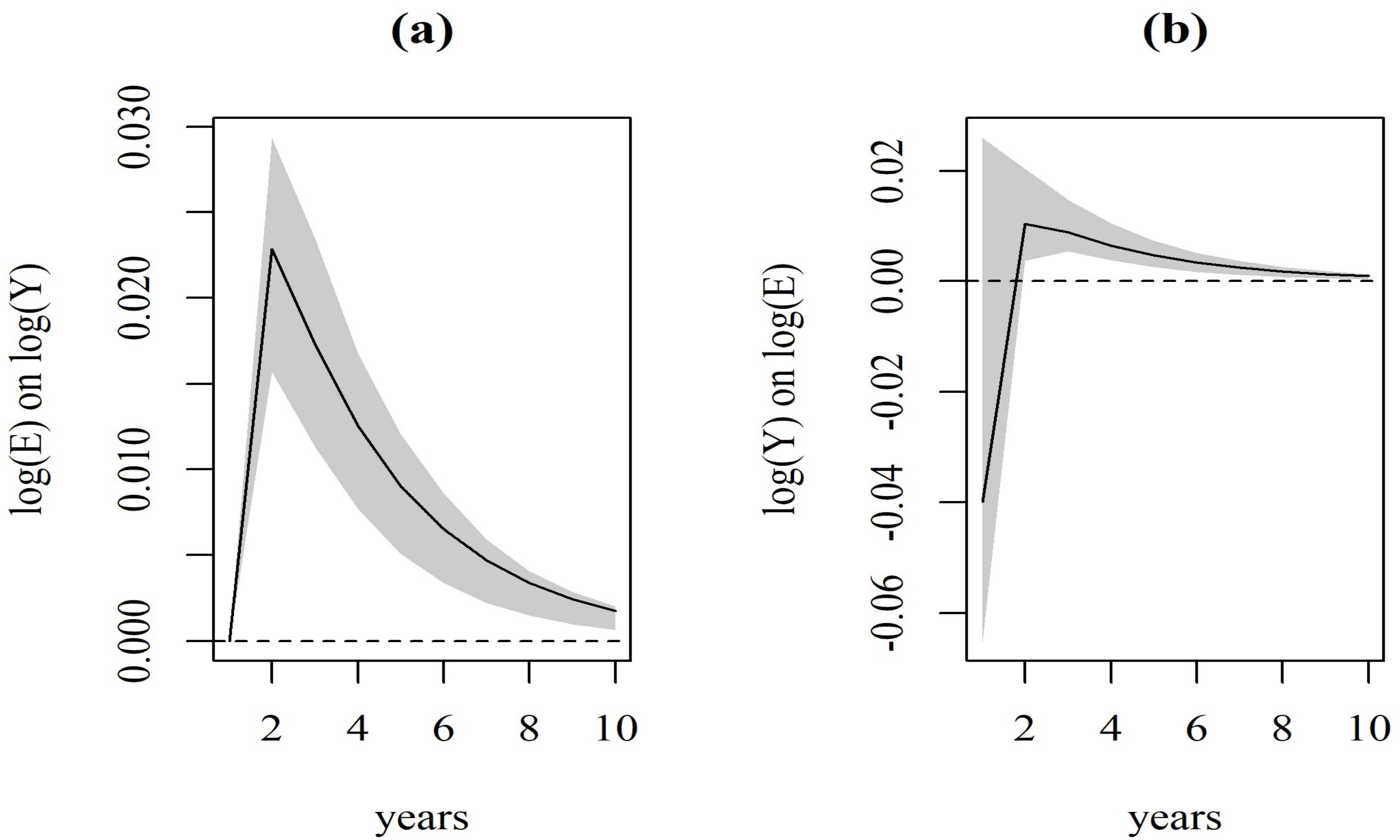
Granger Causality (Parametric)

Hypothesis 1: $H_0 \rightarrow \alpha_{11} = \alpha_{12} = 0$, i.e., electrical energy consumption growth does not Granger-cause economic growth in the United States between 1990 and 2018. This hypothesis was rejected with 1% alpha-level (W=189.1 > 9.21 — $\chi^2_{0.01\%}$ with 2 degrees of freedom).

BIDIRECTIONAL CAUSALITY

Hypothesis 2: $H_0 \rightarrow \alpha_{21} = \alpha_{22} = 0$, i.e., economic growth does not Granger-cause electricity use in the United States between 1990 and 2018. This hypothesis was rejected with 1% alpha-level (W=10.23 > 9.21 — $\chi^2_{0.01\%}$ with 2 degrees of freedom).

Impulse Response Functions



Impulse Response Functions (Cont'd)

Table 4. Variance Decomposition.		
	$\Delta \ln(E)$	$\Delta \ln(Y)$
$\Delta \ln(Y)$	9.87%	90.13%
$\Delta \ln(E)$	88.16%	11.84%

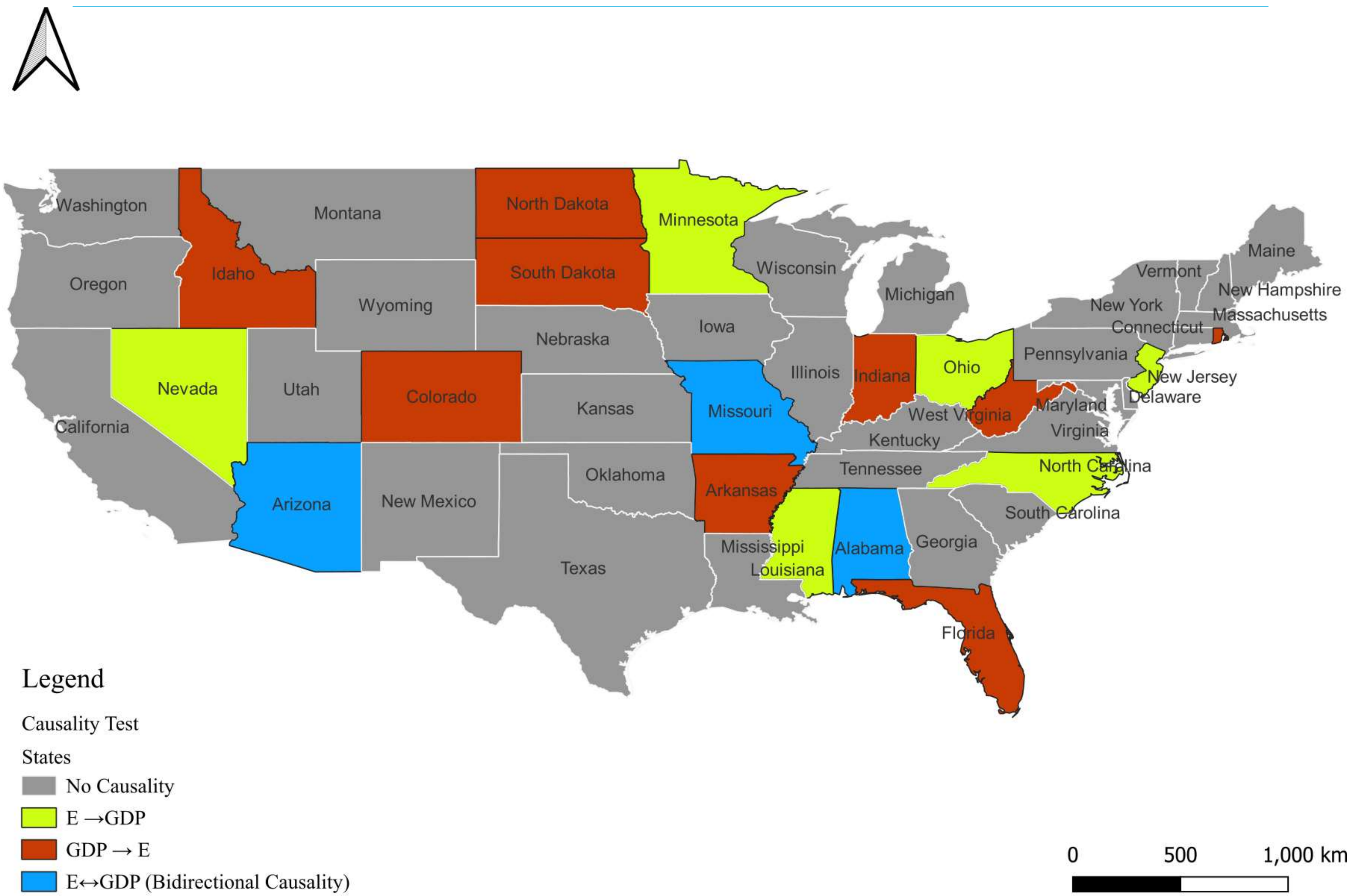
Notes: Percent of variation in the column variable explained by the row variable 10 periods ahead.

- **E→Y: Short-run ~ 2.3 p.p. – Long-run (cumulative) ~ 8 p.p.**
- **Y→E: Short-run ~ 0.5 p.p. – Long-run (cumulative) ~ 1.6 p.p.**

Granger Causality (Transfer Entropy)

- High-resolution (TE computed state-by-state)
- Optimal bandwidth for multivariate kernel estimation based on sample size, process dimensionality and variance of the data (Silverman, 1986:87 and Scott, 1992:152)
- bootstrap simulation of the non-Granger causality based on 999 surrogate datasets of the driving process
- surrogate datasets fast-discrete Fourier transform of the driving process (Kantz and Schreiber, 1997:96-99)
- surrogate datasets have the same mean and power spectrum of the original driving process, thereby preserving the dependence structure of the null hypothesis of non-Granger causality
- p-value for the one-sided test is computed as $\hat{p} = (1 + \sum_{i=1}^{B} \mathbf{1}(TE_i \geq \widehat{TE}))/(\frac{1}{B} + 1)$ - Diks and Fang (2017:7)

TE Causality test: Results



Conclusions

- The study analyzed the causality relationship between Electricity Consumption and Economic Growth in the U.S.
- Panel VAR was used to study the macroeconomic dynamics
- Results at the aggregate level supports bi-directional causality between Electricity consumption and Economic growth in the U.S. between 1990 and 2018
- A higher resolution non-parametric causality test showed that bidirectional causality exists in three states; energy-economic growth causality in six states; economic growth-energy growth in nine states; and no causality was detected in the remaining 30 states
- A contemporaneous shock in Electricity consumption could lead to 2.3 percentage points growth in the short-run and 8 percentage points growth in the long-run
- A contemporaneous shock in economic growth could lead to 0.5 percentage points in consumption growth in the short-run and 1.6 in the long-run

Conclusions (cont'd)

- The study did not include Carbon Emissions (data might not be available)
- Electrical energy conversion costs (from different sources – price transmission may affect the results)

Policy Recommendations

- Policy makers should incentivize the use of electrical energy (especially in states where E→Y is significant)
- Electrical energy deregulation may reduce the price of electricity towards competitive level, thereby boosting consumption to favor economic growth
- Public and Private R&D institutions should invest in projects that allow electrical energy storage more efficiently
- Subsidized wide adoption of efficient storage devices and economies of scale may reduce the cost of electricity storage in the future

Thank You

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