Measuring resilience to energy shocks

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Abstract

Measuring energy security or resilience in energy is, in the main, confined to indicators which are used for comparative purposes or to show trends rather than provide empirical evidence of resilience to unpredicted crises. In this paper, the electricity systems of the individual states within the United States of America are analysed for their response to the 1973-1982 and the 2003-2012 oil price shocks. Empirical evidence is sought for elements which are present in systems that experience reduced volatility from the energy shocks in the form of lower prices. Spare capacity is found to be a reliable indicator of reduced prices through both periods whilst renewable energy is found to be an indicator of reduced prices especially in 1973-1982.

Keywords

Resilience metrics; Energy Security; Electricity; Renewable Energy

1. Introduction

Economic stability is reliant on effective energy systems which in turn need to be resilient to the unexpected. Resilience as a concept has been researched across disciplines and is associated with sustainability and robustness, but it is difficult to measure. Several disciplines have advanced models for the measurement of resilience or the ability to respond to the unpredictable. Portfolio theory (PT), developed for the investment community, measures the risk of an investment portfolio (Markowitz, 1952). The Capital Asset Pricing Model (CAPM) built on Markowitz's theory to optimise a portfolio by diversifying assets based on their risk premiums relative to market performance (Sharpe, 1964). These models are widely used to measure risk (Fama and French, 2004; Hwang et al., 2012).

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In Psychology, the literature on resilience has sought to identify parameters that are associated with positive outcomes through principal component and factor analysis (Ungar, 2012). In Ecology, research has identified the parameters of diversity, redundancy and system integrity as important for resilience, although no model has emerged to predict resilience (Carpenter et al., 2001). Network theorists have focused on the structure of a system, indicating its ability to withstand error, failure or attack (Watts and Strogatz, 1998; Albert et al., 2000). In the field of energy, security is measured by combining relevant indicators which point to risks associated with affordable, available, accessible and acceptable supply of energy (Kruyt et al., 2009). Whilst all of these disciplines deal with risk and survival, there is little consistency between their approaches and, in the main, little evidence of their efficacy.

The questions that need to be answered to gain insight into resilience in energy are: what role diversity, redundancy and structure play in forging resilience; and what predictive models are best suited to provide this insight. In this paper two analytical frameworks will be used to construct models for predicting resilience in electricity systems. Firstly, PT will be assessed for its ability to predict electricity prices in recognition of research proposing PT for risk optimisation (Awerbuch and Berger, 2003; Awerbuch et al., 2008; Bolinger and Wiser, 2008). This will be followed by an assessment of the ability of a Resilience Index (RI) to predict electricity prices, in recognition of research into the potential for national electricity systems to facilitate electricity intensive industry (Molyneaux et al., 2012). To assess the effectiveness of these two methods in predicting good outcomes, their prediction accuracy during periods of large energy shocks will be evaluated.

Analysis of state electricity systems in the United States of America (US) provides data and context to measure resilience as the systems provide evidence of diverse system performances over a 40 year period. The methods of the analysis are outlined in Section 2, the results in Section 3, with section 4 providing discussion around the results. In section 5 the study concludes with policy recommendations on the significant findings.

2. Methods

The primary research tool is multiple linear regression analysis which assumes a linear relationship between the explanatory variables of the PT and RI models and the dependent variable, electricity price.

2.1. Data source

The US Energy Information Agency (EIA) provides detailed energy information in its State Energy Database System (SEDS) 1970-2012[i]. Electricity capacity and generation data by year, state and plant is sourced from the EIA's Form759.

2.2. Price as the dynamic variable

Ecologists argue that fast variables show the dynamics of the underlying structural variables (Carpenter et al., 2001) although stability in variables is not considered a predictor of resilience (Holling, 1973). However ecosystems need to keep functioning despite volatility in elements. Applying these arguments to electricity systems, price represents the fast variable as it reflects the dynamics of the structure. Thus, if price can show levels of stability, despite volatility in structural variables, then this is evidence of resilience in a system such as the electricity supply system.

2.2.1. Which price to measure

Electricity assets are large, expensive, enduring and relatively inflexible. Prices reflect not just changes in current input costs, but decades of infrastructure expenditure. Price is chosen as the dependent variable rather than change in price due to the long-term nature of generation fleets. Measuring change in price fails to incorporate the impacts of prior period performance. Thus, price provides a metric of value associated with the industry, and captures the role of historical and current structural components in influencing that value.

The price of electricity to industry is used as a proxy for wholesale price. Industry price is used in preference to the average price across all consumer classes to exclude the varying costs associated with distribution to residential customers.

Electricity prices in the US 1970-1990 were subject to regulation which reflected the public mood of antipathy to price instability. Although price in any year is a reflection of prior period changes, prices in 1982 do not necessarily reflect the lumpy transition from 1973 to 1982. Figure 1 shows the ratio of industry price in 1982 to the weighted average of industry price 1973-1982. States like Washington and Oregon saw a single sharp increase in price in 1982 due to nuclear power development which is not representative of price 1973-1982. It is therefore more appropriate to measure the weighted average price for industry for the periods analysed.

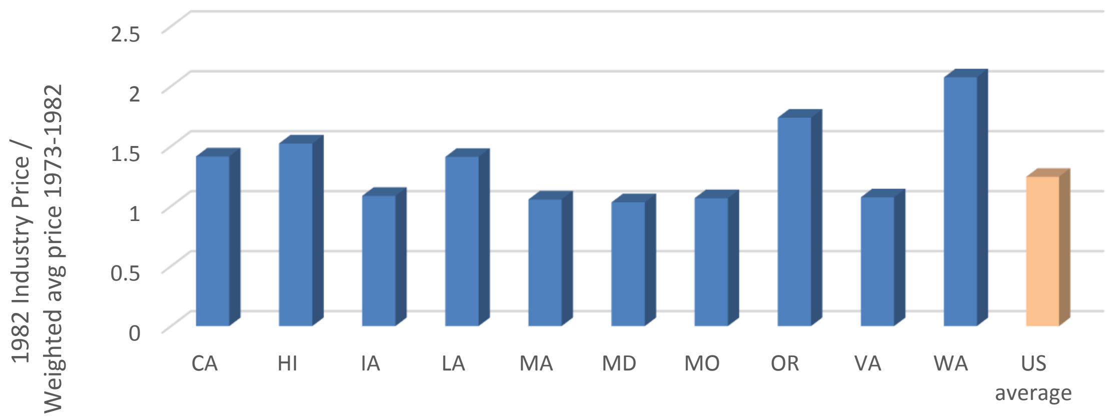

Figure 1: The ratio of the price of electricity to industry in 1982 and the weighted average industry price 1973-1982

Throughout the analysis, real prices are used to differentiate from movements in the general level of prices. Real prices are calculated using nominal prices adjusted for CPI, as detailed in Equation 1:

$$Price_{2012} = Price_n \, X \, \frac{CPI_{2012}}{CPI_n} \tag{1}$$

where

$Price_{2012}$ = Real price (expressed in 2012 dollars)
$Price_n$ = Nominal price in year *n*
CPI_n = Consumer price index in year *n*
CPI_{2012} = Consumer price index in *2012*

2.3. Portfolio Theory as a model for electricity price prediction

PT is premised on volatility in prices indicating risk. Applied to a fleet of electricity generators, the risk associated with each fleet is based on the effects of fuel cost volatility. This risk metric is analysed for its ability to predict electricity price during an energy shock.

2.3.1. Calculating PT risk

PT assumes that the risk of the portfolio is measured by the variance of return of each security and by the covariance of returns between each pair of securities (Dobbins et al., 1994). Applying this model to an electricity system, generation fuel is substituted for security to establish the risk inherent in the system from fuel cost volatility. The five-fuel-source model is shown in Equation 2:

$$V(R) = \sum_{i=1}^{n} P_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} P_i \; P_j \sigma_{ij} \tag{2}$$

Where:

$V(R)$	Variance in price of the generation portfolio
P_i	Proportion of generation from fuel type *i*
σ_i^2	Variance in cost of fuel type *i*
r_{ij}	Covariance in cost between fuel types *i* and *j*
i, j	Fuels: coal (CL), natural gas (NG), uranium (NU), oil (PA), renewable (RE)

2.3.2. PT risk regression model

The PT risk model for regression analysis is specified in Equation 3.

$$ESICDKR_s = \beta_0 + \beta_1 V(R)_s + \varepsilon_s \tag{3}$$

where

$ESICDKR_s$	= Weighted average price to industry in state *s*
β_0	= *ESICDKR* intercept
β_1	= coefficient of $V(R)_s$
$V(R)_s$	= variance in price of generation portfolio for state *s*
ε_s	= random error in *ESICDKR* for state *s*

2.3.3. Disaggregated PT risk regression model

An aggregated PT risk metric may mask the impact of individual metrics, so PT risk is disaggregated into its component metrics to yield insights into which variables exert most influence. Table 1 shows the disaggregated PT risk explanatory variables:

Table 1: Risk metrics as explanatory variables

Risk metric	Regression Variable name	Variable calculation
Coal price	TERM_RISK_CL	$P_{cl}^2\sigma_{cl}^2$
Oil price	TERM_RISK_PA	$P_{pa}^2\sigma_{pa}^2$
NG price	TERM_RISK_NG	$P_{ng}^2\sigma_{ng}^2$
Uranium price	TERM_RISK_NU	$P_{ur}^2\sigma_{ur}^2$
Correlation Coal-oil	TERM_CORR_CLPA	$2P_{cl}P_{pa}r_{clpa}\sigma_{cl}\sigma_{pa}$
Correlation Coal-NG	TERM_CORR_CLNG	$2P_{cl}P_{ng}r_{clng}\sigma_{cl}\sigma_{ng}$
Correlation Coal-uranium	TERM_CORR_CLNU	$2P_{cl}P_{ur}r_{clur}\sigma_{cl}\sigma_{ur}$
Correlation Oil-NG	TERM_CORR_PANG	$2P_{pa}P_{ng}r_{pang}\sigma_{pa}\sigma_{ng}$
Correlation Oil-uranium	TERM_CORR_PANU	$2P_{pa}P_{ur}r_{paur}\sigma_{pa}\sigma_{ur}$
Correlation NG-uranium	TERM_CORR_NGNU	$2P_{ng}P_{ur}r_{ngur}\sigma_{ng}\sigma_{ur}$

Price and correlated price risk for renewables are not present because there is no fuel price or correlated price risk associated with most renewable energy.

Using the disaggregated metrics of PT risk as explanatory variables and price as dependent variable, the ordinary least squares regression model is shown in Equation 4.

$$ESICDKR_s = \beta_0 + \beta_1 X_{1s} + \beta_2 X_{2s} + \ldots + \beta_k X_{ks} + \varepsilon_s \qquad (4)$$

where

$ESICDKR_s$ = Weighted average price to industry in state *s*

β_0 = $ESICDKR$ intercept

β_k = coefficients of X_k

X_k = metric *k* of PT risk (detailed in Table 1)

ε_s = random error in $ESICDKR$ for state *s*

2.4. Resilience Index as a model for electricity price prediction

Energy security indices are popular with respect to evaluating the energy security of a country against other countries and over time. Most have focused on the security of oil supply, but others have been constructed to include multitudes of variables including metrics for political risk, long-term sustainability and governance (Kruyt et al., 2009). Thresholds and limits of the metrics used tend to be subjectively applied by nominated experts. An alternate energy security index, the RI, was constructed to measure risk at all levels of the electricity supply process using thresholds and limits of country statistics rather than expert approximations (Molyneaux et al., 2012).

2.4.1. Calculating RI

The individual risks measured by the index included: ENERGY USE (risk of price rises as a result of scarcity; EMISSIONS (risk associated with costs of carbon dioxide (CO_2) emissions); GENERATION EFFICIENCY (risk associated with additional costs from inefficient generation); DISTRIBUTION EFFICIENCY (risk associated with additional costs of inefficient transport of electricity); SPARE CAPACITY (risk associated with price increases because of insufficient capacity); DIVERSITY (risk associated with increased costs from fuel supply constraints); and IMPORTS (risk associated with being reliant on imports of fuel and electricity). The model here is adjusted to reflect constraints in data and the context of the periods.

Firstly, distribution losses are excluded from this analysis. Interstate electricity transfers pre-1990 are estimated by the EIA using, amongst other things, regional loss estimates. Applying regional loss estimates, assumes that distribution losses are constant across multiple states. For this reason, analysing distribution losses is meaningless.

Secondly, CO_2 emissions are excluded from the analysis. Control of CO_2 emissions was not a cost factor during the 1970s and the finalisation of CO_2 emission standards by the Environmental Protection Agency is only expected during 2015/6 (EPA, 2015). For this reason, CO_2 emissions as a potential cost risk are not assessed for impact on price.

Thirdly, the imports metric is an aggregate of imports of fuel for electricity generation and imports of electricity for electricity consumption. Fuel imports are subject to volatility in international, national and local fuel markets whilst imported electricity is dependent on local electricity generation capacity. Reflecting these different structural risks, the imports metric is disaggregated into electricity from imported fuels, and imported electricity.

The RI, as analysed here, is composed of: energy use; generation efficiency; spare capacity; diversity; imports of fuel; and imports of electricity. The individual metrics are normalised, against best and worst thresholds established by best and worst state performance, adjusted for a small margin of error of 5%, and then aggregated into a geometric mean, as shown in Equation 5.

$$x\ index = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{5}$$

The endogenous thresholds are used in preference to subjective predictions of acceptable minima and maxima for each of the metrics. The calculation of the RI is shown in Equation 6.

$$RI = \sqrt[6]{a.b.c.d.e.f} \tag{6}$$

where

a	*non-renewable fuel used per kWh consumed*
b	*1-(energy produced as electricity/energy consumed in generation)*
c	*(maximum electricity capacity - electricity generated)/GDP*
d	*Probability of electricity from a different fuel type*
e	*Proportion of energy generated from imported fuels*
f	*Proportion of electricity consumed from electricity imports or Proportion of electricity exported*

2.4.2. RI regression model

The RI ordinary least squares regression model is specified in Equation 7:

$$ESICDKR_s = \beta_0 + \beta_1 RI_s + \varepsilon_s \tag{7}$$

where

$ESICDKR_s$ = Weighted average price to industry in state *s*
β_0 = $ESICDKR$ intercept
β_1 = coefficient of RI_s
RI_s = RI for state *s*
ε_s = random error in $ESICDKR$ for state *s*

2.4.3. Disaggregated RI regression model

An aggregated RI metric may mask the dynamics of individual metrics, so disaggregating RI may yield insights into which variables exert most influence. Table 2 details the variable calculations.

Table 2: RI metrics as explanatory variables

RI metric	Regression Variable name	Variable calculation
Diversity	DIVERSITY	$=1-\sum_{i=1}^{n} s^2)$
Spare Capacity	SPARECAP_GDP	(maximum kWh possible - kWh generated)/GDP
Loss in generation	LOSSINGEN	1-(BBtu produced as electricity/BBtu

		consumed in generation)
Non-renewable energy used	ENERGYUSED	non-renewable Btu used/kWh consumed
Imports: fuel for generation	IMPORTS_FUEL	kWh from imported fuel / kWh generated
Imports: electricity for consumption	IMPORTS_ELEC	If imports > 0, then kWh imported/kWh consumed, else kWh exported/kWh generated

Adapting Equation 7 to allow for disaggregated metrics of RI, specifies:

$$ESICDKR_s = \beta_0 + \beta_1 X_{1s} + \beta_2 X_{2s} + \ldots + \beta_k X_{ks} + \varepsilon_s \quad (8)$$

where

$ESICDKR_s$ = Weighted average price to industry in state *s*

β_0 = $ESICDKR$ intercept

β_k = coefficients of X_k

X_k = parameter *k* of RI risk (detailed in Table 2)

ε_s = random error in $ESICDKR$ for state *s*

2.5. Periods of analysis

Figure 2 shows the progression of electricity prices in the US 1970-2012.

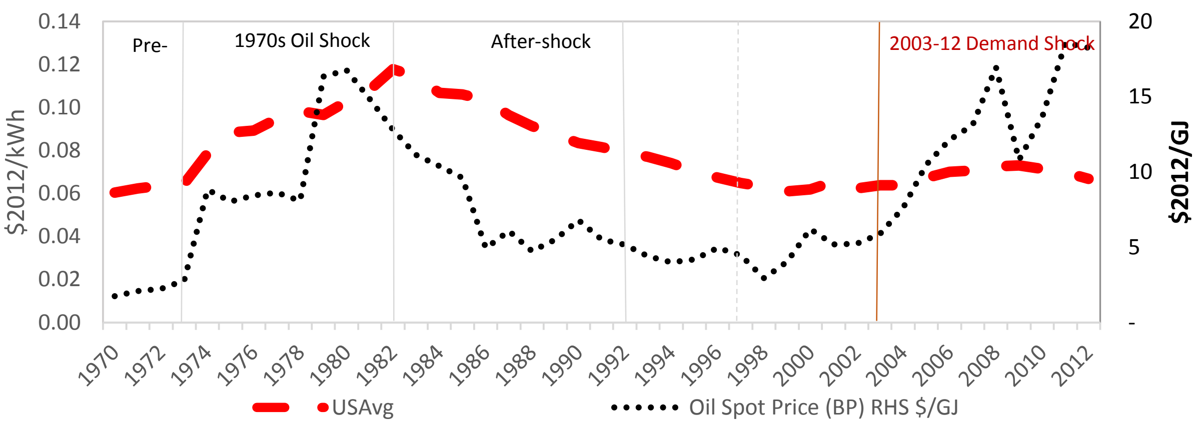

Figure 2: Average US price of electricity to industry and oil spot price, 1970-2012

Prior to 1973, oil prices had been low and stable. Due mainly to US support of Israel during the Yom Kippur war with Egypt, Arab states declared an increase in the posted price of oil and an embargo on the export of oil to most consumer countries in October 1973. This was the start of multiple, large oil price increases until June 1974. Then in late 1978, political disruption in Iran triggered oil prices to escalate dramatically again (Yergin, 1991). Prices peaked in 1980 before starting a slow decline. Electricity prices, being subject to regulatory review and determined by historical costs and profit levels, continued to rise through to 1982 before slowly declining from 1983.

A lengthy period of relatively stable and low oil prices followed. From 2003 a surge in global demand led to oil price increases not seen since the 1970s. The price escalation was interrupted by the 2008 Global Financial Crisis, but surged again after 2009. During 2003-12, electricity prices increased, although not at the levels experienced 1973-1982.

Based on the levels of oil price volatility, the periods analysed are 1973-1982 and 2003-2012.

3. Results

3.1. Analysing the impact of 1970s oil crises on price

3.1.1. Portfolio Theory risk as predictor of price

Figure 3 shows the relationship between PT risk, the composite metric, and price 1973-1982. The majority of states show low PT risk, with varying levels of pricing. Hawaii shows a high level of risk and high price. The fit for risk as a predictor of electricity prices is shown in Table 3. Whilst the composite metric for risk explains only 27.6% of the variation in price, the F statistic of 22.85582 indicates a reasonable overall fit. The coefficient for risk is statistically significant although at 0.0062 is small and most of the price prediction is explained by the average price across the states.

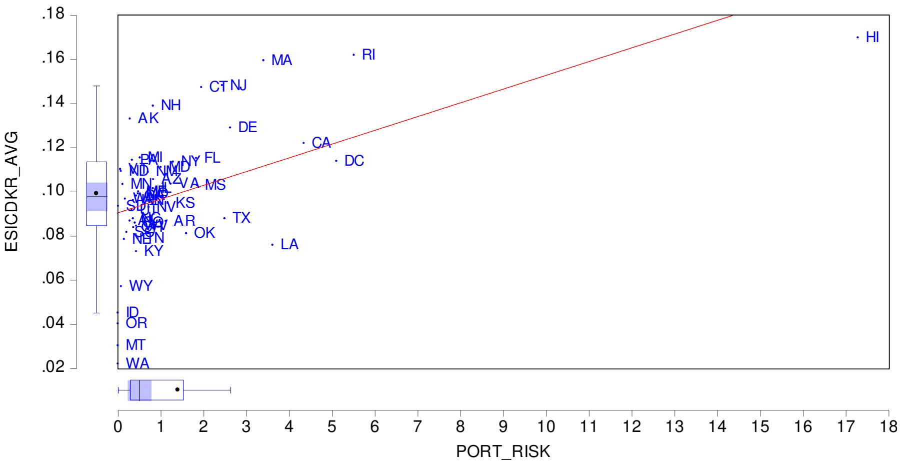

Figure 3: PT risk as predictor of price 1973-1982

Whilst Hawaii may appear to be an outlier, excluding it increases the coefficient from 0.006228 to 0.011527 but does not improve the fit.

3.1.1.1. Which risk variables are statistically significant as predictors of price

The disaggregated risk variables explain 31.3% of the variation in prices which is an improvement on the fit for the composite metric at 27.6%. However, t-tests on the coefficients indicate that many of the variables are not statistically significant. Excluding the statistically insignificant variables, the remaining significant variables of TERM_RISK_PA and TERM_CORR_CLPA explain 34.9% of variation in price.

Table 3: Regression analysis of PT variables as predictors of price

	PT	**PT disaggregated variables**	**PT stat-signfcnt variables**
Dependent variable *(Weighted average price 1973-82)*		ESICDKR_AVG	
Mean of dependent variable		0.099258	
Std Deviation of dependent variable		0.030340	
Regression		Least squares	
Observations		51	
Fit: R2	0.290219	0.450202	0.374694
Fit: Adj R2	0.275733	0.312752	0.348639
Fit: F-stat	22.85582 *(0.000045)*	3.275397 *(0.003547)*	14.38118 *(0.000013)*
Intercept *(Prob)* VIF	0.090559 *(0.0000)* 1.3	0.086081 *(0.0000)* 3.9	0.089083 *(0.0000)* 1.4
Coefficients			
Single metric*(Prob)* VIF	0.006228 *(0.0000)* 1.3		
Term_risk_CL*(Prob)* VIF		0.002573 *(0.9351)* 2.4	
Term_risk_NG*(Prob)* VIF		-0.013746 *(0.2417)* 2.5	
Term_risk_NU*(Prob)* VIF		0.516463 *(0.4130)* 1.8	
Term_risk_PA*(Prob)* VIF		0.006285 *(0.0001)* 1.3	0.006719 *(0.0000)* 1.1
Term_corr_CLNG*(Prob)* VIF		0.026603 *(0.4898)* 2.2	
Term_corr_CLNU *(Prob)* VIF		-0.037847 *(0.9193)* 1.6	
Term_corr_CLPA *(Prob)* VIF		0.057980 *(0.0698)* 1.5	0.074380 *(0.0105)* 1.3
Term_corr_NGNU *(Prob)* VIF		-0.526896 *(0.2240)* 2.0	
Term_corr_PANG *(Prob)* VIF		0.028852 *(0.0521)* 2.1	
Term_corr_PANU *(Prob)* VIF		0.152748 *(0.4619)* 2.4	

Jarque_Bera stat *(heteroskedasticity, exists if > 5.99)*	2.195632	4.508548	3.773523
Matrix condition index *(multicollinearity, exists if > 15)*	3.4423	503.7042	22.2756

The intercept reflects the average price across the states, with the coefficient for TERM_CORR_CLPA of 0.074 with 99% confidence of statistical significance predicting a strong impact on price. The graphical representation of the fit and residuals in Figure 4 shows low economic significance. The PT risk model predicts none of the benefit experienced by the hydro states of Idaho, Montana, Oregon and Washington in the form of very low electricity prices and price stability.

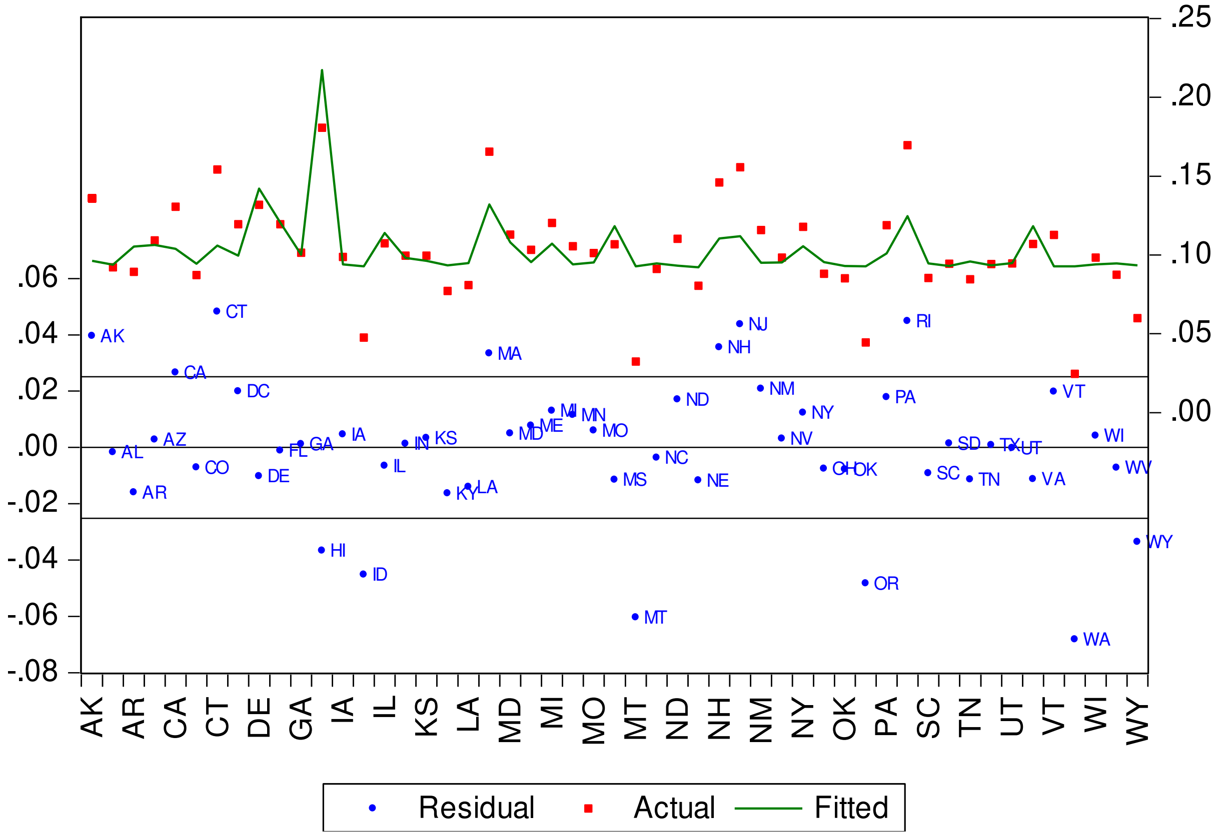

Figure 4: Fit and residual analysis of statistically significant parameters of PT risk as predictors of price

3.1.2. Resilience Index as predictor of price

Figure 5 shows the relationship between RI, the composite metric, and price. Lower prices are associated with higher levels of resilience.

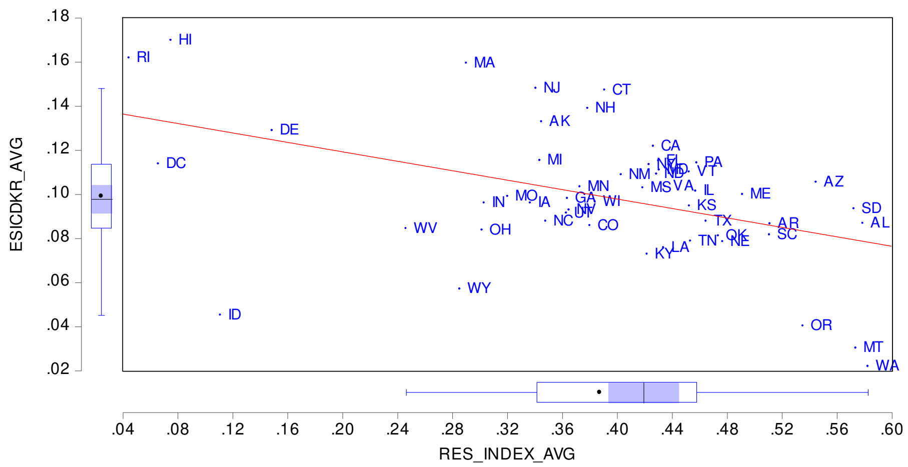

Figure 5: RI as predictor of price 1973-82

The fit for the RI as a predictor of price is shown in Table 4. The composite RI explains 18.6% of the variation in price, although the RI coefficient of -0.107047 with 99% confidence of statistical significance provides evidence of a sizeable negative relationship with price.

3.1.2.1. Which RI variables are statistically significant as predictors of price

The disaggregated variables of resilience explain 64.1% of the variation in prices. However, hypothesis tests on the coefficients indicate that many of the variables are not statistically significant. When the statistically insignificant variables are excluded from the model, the remaining LOSSINGEN, SPARECAP_GDP and IMPORTS_FUEL explain 63.4% of variation in price.

LOSSINGEN, however, masks the different efficiencies associated with different fuel types and technologies. If LOSSINGEN is disaggregated into the percentage of generation from each fuel source (P_i in Equation 2), greater visibility of each fuel's impact on price can be achieved. Including the percentage of all fuel types in regression analysis however could result in collinearity between the fuel percentage variables. Thus, in recognition of the dominance of CL in electricity generation, CLPERC is excluded as an explanatory variable.

The explanatory variables that are included in the adjusted model, are NGPERC, NUPERC, PAPERC, REPERC, DIVERSITY, SPARECAP_GDP, IMPORTS_FUEL and IMPORTS_ELEC. These variables explain 74.8% of the variation in price. The coefficients for NGPERC, NUPERC and IMPORTS_FUEL are very small and the hypothesis tests on the coefficients indicate a high probability that the coefficients are not statistically significant, so they are excluded from the model.

Table 4: Regression analysis of RI variables as predictors of price

	RI	**RI disagg. variables**	**RI Stat-signfcnt variables**	**RI adj W-FuelPerc variables**	**RI adj Stat-signfcnt variables**
Dependent variable *(Weighted average price 1973-82)*			ESICDKR_AVG		
Mean of dependent variable			0.099258		
Std Deviation of dependent variable			0.030340		
Regression			Least squares		
Observations			51		
Fit: R2	0.202505	0.683774	0.656080	0.788649	0.780384
Fit: Adj R2	0.186230	0.640653	0.634128	0.748392	0.755982
Fit: F-stat	12.44239 *(0.000922)*	15.85687 *(0.000000)*	29.88660 *(0.000000)*	19.59019 *(0.000000)*	31.98066 *(0.000000)*
Intercept *(Prob)* VIF	0.140695 *(0.0000)* 10.4	0.41508 *(0.0022)* 25.0	0.038134 *(0.0036)* 23.5	0.110369 *(0.0000)* 21.4	0.112084 *(0.0000)* 18.9
Coefficients					
Single metric *(Prob)*	-0.107047 *(0.0009)*				
EnergyUsed *(Prob)* VIF		0.001058 *(0.2273)* 19.0			
Lossingen *(Prob)* VIF		0.093598 *(0.0030)* 56.2	0.124238 *(0.0000)* 26.4		
Imports_elec *(Prob)* VIF		0.002524 *(0.8917)* 3.9		-0.028637 *(0.0084)* 1.8	-0.026225 *(0.0098)* 1.6
Imports_fuel *(Prob)* VIF		0.031783 *(0.0010)* 3.6	0.026594 *(0.0023)* 3.0	0.009373 *(0.3274)* 5.7	
Diversity *(Prob)* VIF		0.018865 *(0.1690)* 6.1		0.025875 *(0.0385)* 7.1	0.028178 *(0.0074)* 5.0
Sparecap_gdp *(Prob)* VIF		-0.122260 *(0.0000)* 9.9	-0.100925 *(0.0001)* 7.6	-0.097249 *(0.0003)* 11.6	-0.095639 *(0.0003)* 11.5
NGperc				-0.003205	

(Prob) VIF				*(0.8014)* 2.1	
NUperc *(Prob)* VIF				0.003753 *(0.8105)* 2.3	
PAperc *(Prob)* VIF				0.055855 *(0.0000)* 3.1	0.061970 *(0.0000)* 2.4
REPerc *(Prob)* VIF				-0.059217 *(0.0000)* 2.3	-0.061539 *(0.0000)* 1.8
Jarque_Bera stat *(heteroskedasticity exists if >5.99)*	4.96	0.69	1.79	1.22	1.65
Condition index *(multicollinearity exists if >15)*	9.1	168.0	12.9	5.3	14.2

The explanatory variables of PAPERC, REPERC, DIVERSITY, SPARECAP_GDP AND IMPORTS_ELEC, explain 75.6% of the variation in price, as detailed in Table 4 with a good overall fit. The coefficients on fuel percentages provide a useful indication of how the price of electricity from different fuel sources varies from the intercept (which reflects the average price associated with CLPERC, NGPERC and NUPERC). The coefficients for PAPERC and REPERC, at +0.061970 and -0.061539 respectively with 100% confidence of statistical significance, show the additional price associated with electricity

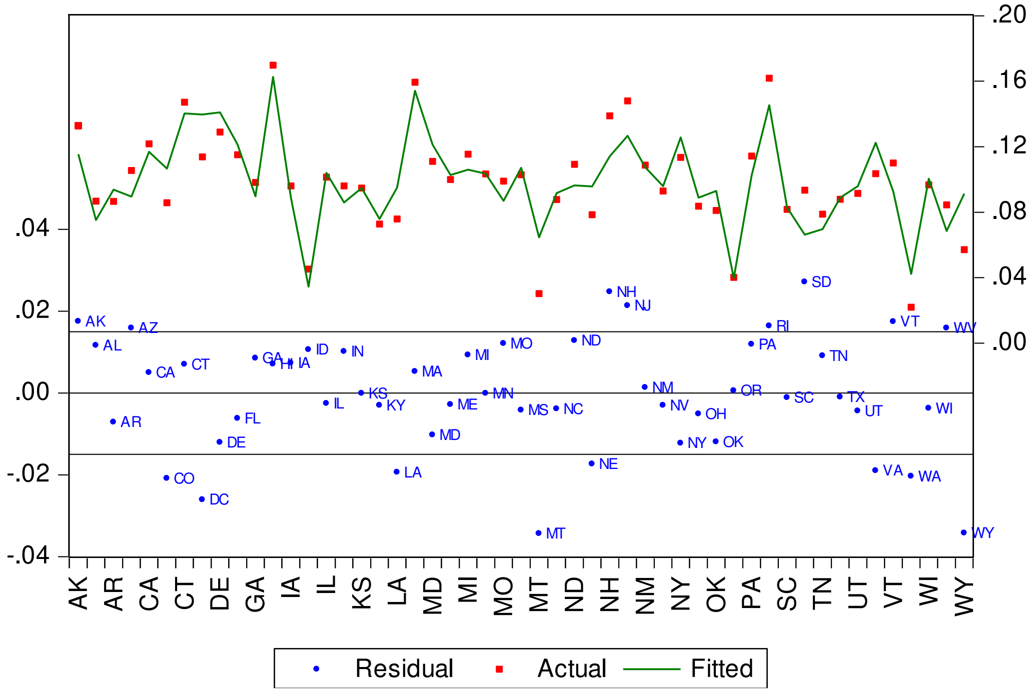

Figure 6: Fit and residual analysis of statistically significant variables of RI as predictors of price

from PAPERC and the discount associated with electricity from REPERC. The coefficient for SPARECAP_GDP at -0.095639 with nearly 100% confidence of significance highlights the potential for spare capacity to exert downward pressure on price. The coefficient for IMPORTS_ELEC at -0.026 with 99% confidence of significance shows modest downward pressure on price. Against expectations, the coefficient for DIVERSITY at +0.028 with 99% confidence of significance shows evidence of upward pressure on price. Figure 6 shows the fit and residual analysis of the statistically significant RI variables on price.

For completeness, alternative calculations for diversity shown in Table 5 were also analysed using single linear regression. However they showed no improved relationship between alternative measures of diversity and price.

Table 5: Alternative measures of diversity analysed

Measure of diversity	Calculation	
Shannon's diversity index	$-\sum_{i=1}^{s} p_i \ln p_i$	p_i = proportion of entity from ith type s = total number of entities
Simpson's Equitable diversity index	$E = \frac{1}{\sum_{i=1}^{s} p_i^2} \, x \, \frac{1}{s}$	p_i = proportion of entity from ith type s = total number of entities
Hunter-Gaston index (Simpsons index sampling without replacement)	$\frac{\sum_{i=1}^{s} n_i(n_i - 1)}{s(s-1)}$	n_i= number of entities from ith type s = total number of entities

3.1.2.2. Considering multi-collinearity

Analysis of the coefficients indicates the possibility of collinearity between SPARECAP_GDP and the intercept. Variance Inflation Factor (VIF), a measure of the inflation of a coefficient estimate due to collinearity, for SPARECAP_GDP is 11.5 and for the intercept is 18.9. Collinearity is not considered to indicate mis-specification but rather the potential for unstable estimated regression coefficients. Acceptable levels of collinearity are based on rules of thumb, generally up to a VIF of 10 (Chatterjee and Hadi, 2006).

Whilst the VIF for SPARECAP_GDP is higher than the usual threshold, there is little other evidence that collinearity is a problem in the model. Firstly, the adjusted R^2 is not unusually high and increases by only 0.079 when SPARECAP_GDP is added to the model. Secondly, when SPARECAP_GDP is removed from the model, the other variable coefficients adjust marginally and the coefficient for IMPORTS_ELEC reduces in statistical significance but the signs do not change. Thirdly, the standard errors for SPARECAP_GDP and the other variables are small which does not point to collinearity. Fourthly, a correlation matrix reveals that there is some correlation between SPARECAP-GDP and CLPERC but it is only 0.431 while the correlation between SPARECAP_GDP and CLPERC-NGPERC-NUPERC combined is 0.553. Fifth, the coefficient covariance matrix indicates little covariance between any of the coefficients or the intercept. Finally, Belsley et al propose that decomposition of the coefficient-variance matrix to establish the sensitivity of the estimated standard errors of regression coefficients to small changes in the data, can diagnose potential collinearity problems. This sensitivity is measured by the condition number of the matrix which is the largest condition index, calculated as follows:

$$I = \sqrt{Eigenvalue_{max}/Eigenvalue_{min}} \qquad (9)$$

They find that the joint condition of high variance-decomposition proportions for two or more coefficients associated with a high condition number signals the presence of degrading collinearity. Condition numbers of 15 indicate some level of collinearity but over 30 indicate serious and degrading collinearity (Belsley et al., 2005). In this model, the condition number is 14.2, which points to acceptable levels of collinearity.

In conclusion, it is to be expected that there will be some relationship between SPARECAP_GPD and CLPERC-NGPERC-NUPERC because they are the major sources of large generation. Although there is some evidence of collinearity between SPARECAP_GDP and CLPERC, it is unlikely to diminish the results as presented in Table 4.

3.1.3. Comparing PT and RI variables as predictors of price

TERM_RISK_PA predicts small impact on price but TERM_CORR_CLPA predicts large impact on price. However, TERM_RISK_PA and TERM_CORR_CLPA explain only 34.9% of the variation in price. By contrast, the RI parameters of PAPERC and REPERC, SPARECAP_GDP, DIVERSITY and IMPORTS_ELEC explain 75.6% of the variation in price. DIVERSITY and PAPERC exert upward pressure on price whilst REPERC, SPARECAP_GDP and IMPORTS_ELEC exert downward pressure on price. The results, summarised in Figure 7, suggest that the RI variables are better at predicting price over the longer term than the PT variables.

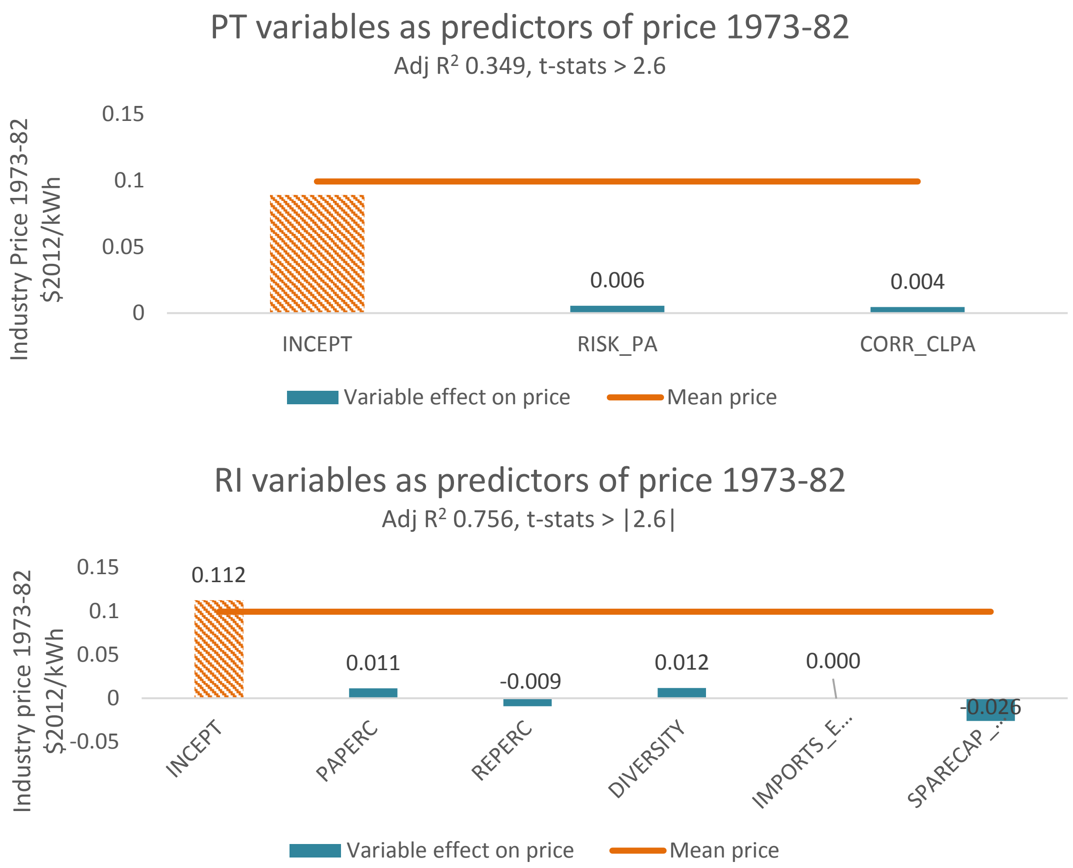

Figure 7: Summary of PT risk and RI variables as predictors of price

In theory, electricity from coal, natural gas and nuclear should have offered security from price volatility in the oil markets. PT indicates that correlation between oil and coal prices explains an increase in the price of electricity generated from coal, but fails to identify the benefits associated with diversification towards renewable energy. The improved fit of the RI suggests that the RI variables are more representative of the illiquid nature of the fleet and show the effect of the slow-moving structural variables on price. Types of fuels used, which dictate technologies used and fuel import networks, are structural variables that change slowly over time, whereas price variance and correlations are designed to measure short-term marginal benefits from switching between substitutes.

3.2. Analysing the impact of oil demand growth 2003-12 on price

US average electricity prices for industry remained at pre-1973 price levels from 1997 to 2002. However, in 2003 oil prices started rising again. In this period, prices in Hawaii were more than 3 standard deviations higher than the rest of the country, as can be seen in Figure 8. Hawaii is therefore excluded as an outlier.

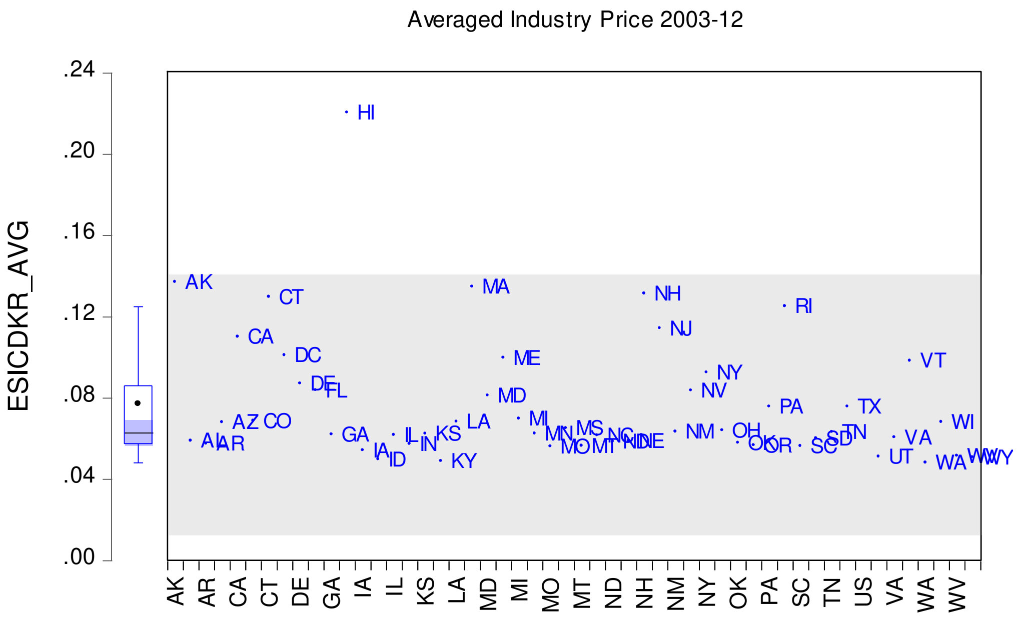

Figure 8: Prices to industry 2003-12

3.2.1. Portfolio Theory variables as predictors of price

As detailed in Table 6, PT risk explains only 7.4% of the variation in price, but disaggregating PT into its component metrics, shows the statistically significant independent variables explaining 63.1% of the variation in price. The coefficient for TERM_RISK_NU at 10.27375 with 94% confidence of significance shows a strong influence on variation in price. The negative coefficient TERM_CORR_NGNU with nearly 100% confidence of significance, appears to contradict the positive coefficient for TERM_RISK_NG.

The results are sufficiently unexpected to justify additional analysis. Checking for collinearity, VIFs range from 1.1 to 3.0 which are not high. However the matrix condition number of 6582 suggests serious collinearity (Belsley et al., 2005). Using fuel price variance multiple times within the calculation of PT risk, reiterates the same relationship with electricity price, so the existence of collinearity makes sense. Variables associated with variance decomposition proportions of greater than 0.5 include TERM_RISK_NU, TERM_CORR_CLNU, TERM_CORR_CLPA, TERM_CORR_NGNU and TERM_CORR_CLNG. The condition number reduces to 3.7 when these variables are excluded. Whilst collinearity does not predict mis-specification of the model, very high levels indicate that the coefficients are extremely sensitive to small changes in variable values and are therefore unreliable (Chatterjee and Hadi, 2006). Considering that the composite metric, PT risk, is not a good predictor of price and that it is inadvisable to rely on the coefficients of the disaggregated PT explanatory variables, it is suggested that only the explanatory variables TERM_RISK_NG and TERM_RISK_PA be included for analysis. The Jarque-Bera stat however indicates heteroskedasticity which is only reduced under the test threshold of 5.99 when Alaska, New Hampshire, Connecticut, Massachusetts, California and Vermont are excluded. With the remaining 43 states, TERM_RISK_NG and TERM_RISK_PA show small increases in coefficients and explain 63% of the variation in price. Excluding so many states from the analysis however complicates comparison with RI, so the 43 state model is excluded.

Table 6: Regression analysis of PT risk variables as predictors of price

	PT	**PT disaggregated variables**	**PT stat-signfcnt variables**	**PT stat-signfcnt variables wout collinear**	**PT stat-signfcnt variables wout collin&hetskd**
Dependent variable *(Weighted average price 2003-12)*			ESICDKR_AVG		
Mean of dependent variable			0.073919		0.066128
Std Deviation of dependent variable			0.024989		0.015926
Regression			Least squares		Least squares
Observations			50		43
Fit: R2	0.093072	0.711348	0.683802	0.284068	0.649446
Fit: Adj R2	0.074178	0.637335	0.631102	0.253603	0.631918

Fit: F-stat	4.925941 *(0.031216)*	9.611076 *(0.000000)*	12.97545 *(0.000000)*	9.324360 *(0.000389)*	37.05251 *(0.000000)*
Intercept *(Prob)* VIF	0.071842 *(0.0000)* 1.1	0.064818 *(0.0000)* 3.4	0.063650 *(0.0000)* 2.6	0.067418 *(0.0000)* 1.2	0.060546 *(0.0000)* 1.2
Coefficients *(Prob)* VIF					
Single metric *(Prob)* VIF	0.002741 *(0.0312)* 1.3				
Term_risk_CL *(Prob)* VIF		-0.058358 *(0.351)* 2.9			
Term_risk_NG *(Prob)* VIF		-0.013908 *(0.0000)* 1.5	0.013798 *(0.0000)* 1.4	0.015214 *(0.0000)* 1.2	0.013362 *(0.0000)* 1.2
Term_risk_NU *(Prob)* VIF		8.823021 *(0.1113)* 3.2	10.27375 *(0.0590)* 3.0		
Term_risk_PA *(Prob)* VIF		0.001315 *(0.1817)* 1.5	0.002065 *(0.0168)* 1.1	0.001922 *(0.1051)* 1.0	0.002136 *(0.0002)* 1.0
Term_corr_CLNG *(Prob)* VIF		0.112245 *(0.0277)* 3.4	0.158853 *(0.0003)* 2.3		
Term_corr_CLNU *(Prob)* VIF		-1.253339 *(0.0649)* 3.2	-1.373458 *(0.0191)* 2.3		
Term_corr_CLPA *(Prob)* VIF		0.334788 *(0.0021)* 2.0	0.355043 *(0.0002)* 1.4		
Term_corr_NGNU *(Prob)* VIF		-0.696605 *(0.0203)* 4.2	-0.947696 *(0.0001)* 2.4		
Term_corr_PANG *(Prob)* VIF		0.031776 *(0.1955)* 1.9			
Term_corr_PANU *(Prob)* VIF		1.540874 *(0.1888)* 3.3			
Jarque_Bera stat *(heteroskedasticity. exists if >5.99)*	16.49	4.14	15.00	29.07	4.85
Matrix condition *(collinearity, exists if >15)*	3.4	6800	6582	3.7	3.8

TERM_RISK_NG and TERM_RISK_PA as explanatory variables explain 25% of the variation in price. The regression results in Table 6 show that TERM_RISK_NG exerts upward pressure on price with nearly 100% confidence of statistical significance and TERM_RISK_PA exerts small upward pressure on price with 89% confidence of statistical significance. The F-stat indicates a good overall fit.

Figure 9 shows the fit and residual analysis of the statistically significant PT variables as predictors of price.

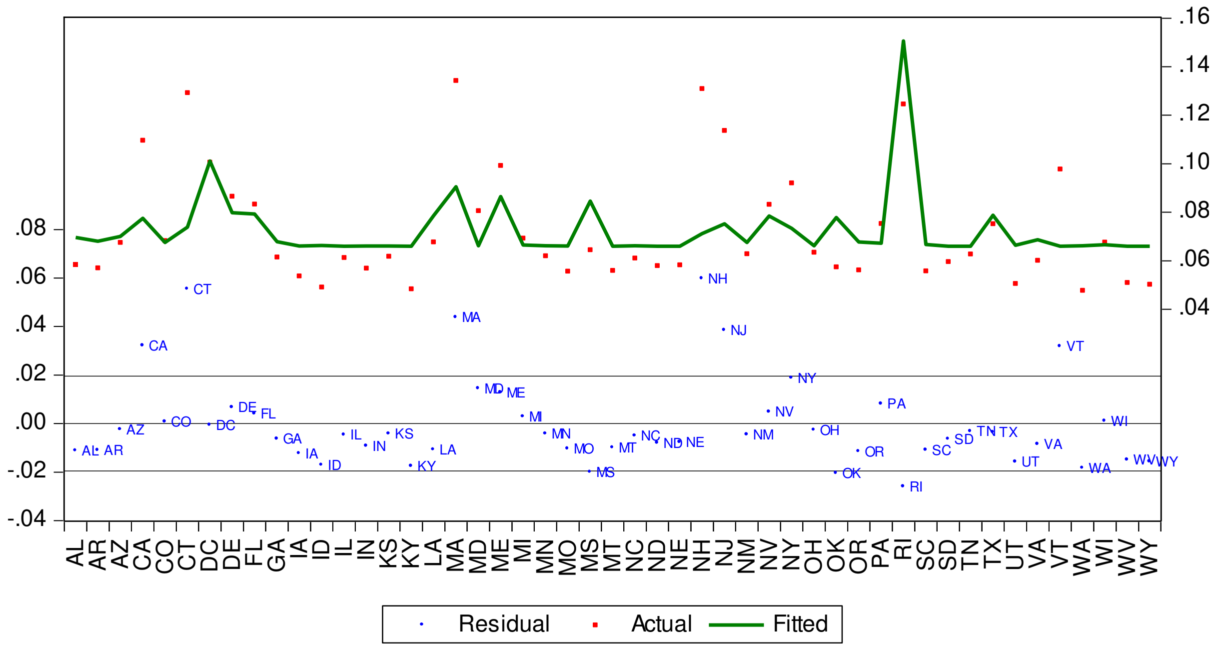

Figure 9: Fit and residual analysis of statistically significant PT variables as predictors of price 2003-12 (excluding HI)

3.2.2. Resilience Index variables as predictors of price

As detailed in Table 7, the composite RI explains only 3.2% of the variation in price. However, the statistically significant disaggregated RI variables, with fuel percentages substituted for LOSSINGEN, explain 72.4% of the variation in price. The coefficients for the fuel percentages indicate, with more than 99% confidence of statistical significance, that the price of electricity from: NG is higher than the average by 8c/kWh; nuclear is higher by 5c/kWh; and oil is higher by 5c/kWh. The increased price associated with electricity from NG is surprising in view of the large reduction in NG prices as a result of supply from unconventional sources, but confirms the finding in the PT risk analysis that NG price risk was associated with higher prices.

Table 7: Regression analysis of RI variables as predictors of price

	RI	RI disagg. variables	RI Stat-signfcnt variables	RI adj W.FuelPerc variables	RI adj Stat-signfcnt variables
Dependent variable *(Weighted average price 2003-12)*			ESICDKR_AVG		
Mean of dependent variable			0.073919		
Std Deviation of dependent variable			0.024989		
Regression			Least squares		
Observations			50		
Fit: R2	0.051388	0.317928	0.299996	0.759040	0.746856
Fit: Adj R2	0.031625	0.222755	0.254344	0.712023	0.724354
Fit: F-stat	2.600228	3.340530	6.571302	16.14408	33.19111
Intercept *(Prob)* VIF	0.094399 *(0.0000)* 14.3	0.047730 *(0.0215)* 41.2	0.064859 *(0.0000)* 10.8	0.061477 *(0.0000)* 16.5	0.060518 *(0.0000)* 6.8
Coefficients *(Prob)* VIF					
Single metric *(Prob)* VIF	-0.049933 *(0.1134)* 14.3				
EnergyUsed *(Prob)* VIF		9.07E-05 *(0.9541)* 34.9			
Lossingen *(Prob)* VIF		0.029599 *(0.4959)* 73.8			
Imports_elec *(Prob)* VIF		0.006380 *(0.8046)* 6.1		-0.009316 *(0.3096)* 2.1	
Imports_fuel *(Prob)* VIF		0.015927 *(0.2179)* 4.6	0.020372 *(0.0489)* 3.0	0.000820 *(0.9204)* 5.1	
Diversity *(Prob)* VIF		0.037361 *(0.0584)* 10.6		0.002676 *(0.8439)* 14.1	
Sparecap_gdp *(Prob)* VIF		-0.067451 *(0.0026)* 4.4	-0.064977 *(0.0015)* 3.9	-0.060671 *(0.0001)* 5.1	-0.054312 *(0.0000)* 4.1
NGperc *(Prob)* VIF				0.087292 *(0.0000)* 2.7	0.085848 *(0.0000)* 2.0
NUperc *(Prob)* VIF				0.047065 *(0.0022)* 3.7	0.049304 *(0.0000)* 2.1
PAperc *(Prob)* VIF				0.054862 *(0.0048)* 1.7	0.047133 *(0.0025)* 1.2
REPerc *(Prob)* VIF				-0.007822 *(0.5133)* 2.3	
Jarque_Bera stat	13.86	11.57	9.56	2.96	4.22

(heteroskedasticity exists if >5.99)					
Condition index *(multicollinearity exists if >15)*	10.4	187.5	8.0	14.5	9.1

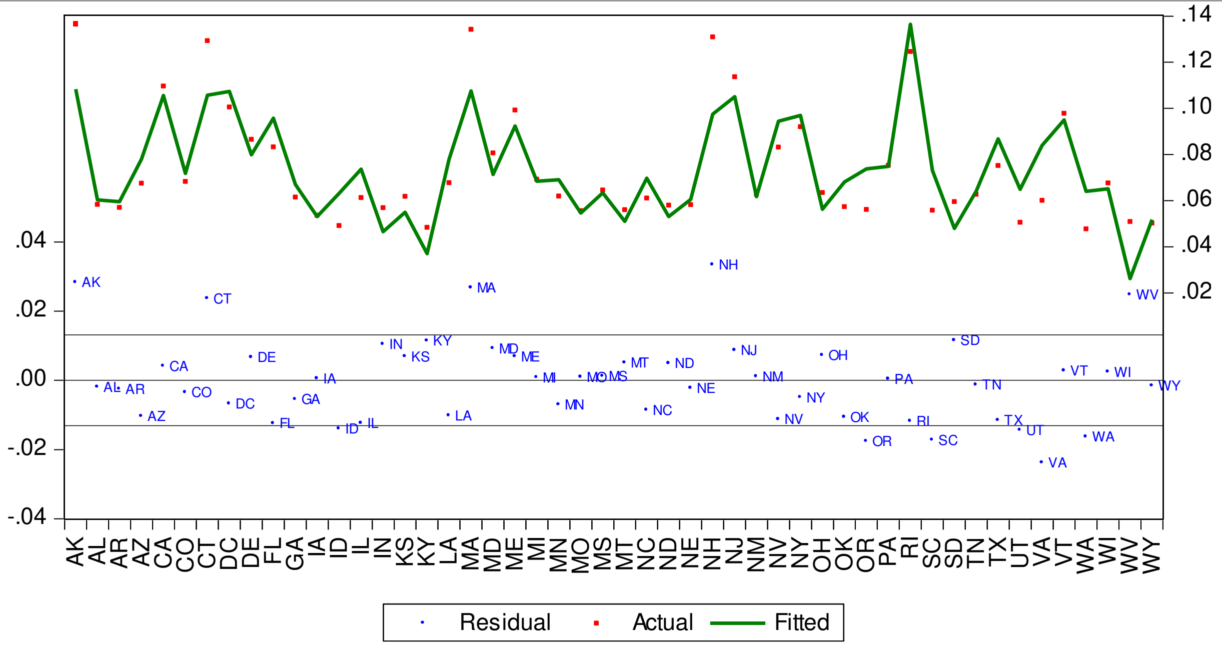

Figure 10: Fit and residual analysis of statistically significant variables of RI on price (excluding HI)

SPARECAP_GDP with a coefficient of -0.054 and 100% statistical significance is again found to provide downward pressure on price. The fit and residual analysis is shown in Figure 10.

Assessment of collinearity shows that there is some relationship between SPARECAP_GDP and the intercept, with a VIF of 4.1 for SPARECAP_GDP. The condition number of 9.1 points to acceptable levels of collinearity in the model.

3.2.3. Comparing PT and RI as predictors of price

The PT statistically significant variables of TERM_RISK_NG and TERM_RISK_PA explain 25% of the variation in price. If multicollinearity and heteroskedasticity is ignored, PT risk variables explain 63% of the variation in price. The RI variables of NGPERC, NUPERC, PAPERC and SPARECAP_GDP explain 72% of the variation in price. SPARECAP_GDP is a consistent predictor of lower prices. The fit of the model with the statistically significant RI variables shows more robust prediction of variation in prices than does the model with the statistically significant PT variables.

3.3. Other regression analysis matters

Prior period price is excluded as an explanatory variable from the models. In analysing the models, where prior period price was included in the models, the absolute fit improved but the size and number of the statistically significant coefficients decreased. This suggested that prior period price masks the relationship between price and the structural variables. It is proposed then that the disaggregated metrics of PT and RI adequately identify the dynamics of the electricity system structure.

Alternative functional forms were considered for regression analysis. In particular, log-linear models were considered for both PT and RI variables and found to provide no improved relationship information.

4. Discussion

4.1. Is risk, as calculated by PT, an adequate predictor of resilience?

Using fuel price volatility and price correlations as predictors of an electricity system's response to energy shock does not appear to provide an adequate model for the calculation of resilience in the electricity system for 1973-1982 nor for 2003-2012. There is evidence of structural problems in the model, specifically significant levels of multicollinearity, which degrades the results. Regression analysis shows that the coefficients for a few variables of PT risk indicate higher prices but do not predict the low-risk, low-cost effect of renewable sources of generation on price.

4.2. Is the RI an adequate predictor of resilience?

The original variables of the RI are slightly better at predicting stable electricity prices during an energy shock than the PT variables. However, when the metric for energy efficiency, LOSSINGEN, is disaggregated into its component fuel source percentages, fuel source and SPARECAP_GDP show a reasonable ability to predict electricity prices during energy shocks. This empirical analysis indicates that spare capacity and the type of fuel used play an important role in resilience, but diversity, imports and energy efficiency do not.

4.3. The role of diversity in resilience

Diversity does not play a consistent role in the models. During 1973-1982, regression analysis indicates that diversity led to increased prices whilst during 2003-2012, there is little evidence from regression analysis that diversity plays any role in prices. Greater stability in prices is associated with renewable energy more than with any combinations of fuel types especially during 1973-82.

Table 8 shows prices for states with generation from a single dominant fuel source and states with mixed portfolios over the decades. Across the decades, the price of electricity for states with a mixed portfolio is higher than the US average. The price of electricity 1973-1982 increased by 34% for predominantly coal fired generation, 59% for natural gas generation and 67% for oil generation. States with high levels of hydro experienced no increase in prices. However, Washington and Oregon's nuclear programs resulted in electricity prices rising after 1982.

Table 8: Price of electricity by fuel source 1970-2012

$2012/kWh	1970-2 Wtd-Avg	1973-82 Wtd-Avg	1983-92 Wtd-Avg	1993-02 Wtd-Avg	2003-12 Wtd-Avg	1970-12 Wtd-Avg.
US average	0.064	0.099	0.091	0.065	0.069	0.079
States with mixed generation portfolios	0.074	0.108	0.111	0.084	0.077	0.100
States with > 50% generation from:						
Coal	0.070	0.094	0.088	0.061	0.062	0.073
Natural gas	0.059	0.094	0.128	0.115	0.120	0.104
Nuclear	n/a	0.105	0.120	0.098	0.099	0.087
Oil	0.088	0.147	0.130	0.112	0.160	0.137
Renewables	0.049	0.046	0.062	0.051	0.053	0.052

During the oil price surge 2003-2012, the average electricity price across all the states rose only 6 %. Coal prices and electricity prices from coal generation remained low. There is no evidence that declining NG price as a result of technological advances in unconventional production was passed through to electricity price. Outside of the coal-oil-NG fuel nexus, electricity from nuclear sources remained more expensive than that from coal and renewable sources despite its exceedingly low fuel requirements and mature technology. Electricity prices in states with high levels of renewable energy experienced small absolute increases in price from 2003-2012. Unlike 1973-82, states with mixed generation portfolios showed price decreases in 2003-2012. However, this decrease reflects historically high price mixed portfolio states like California and Massachusetts shifting from mixed to predominantly NG generation and historically low price coal generation states like Arkansas shifting to mixed portfolios.

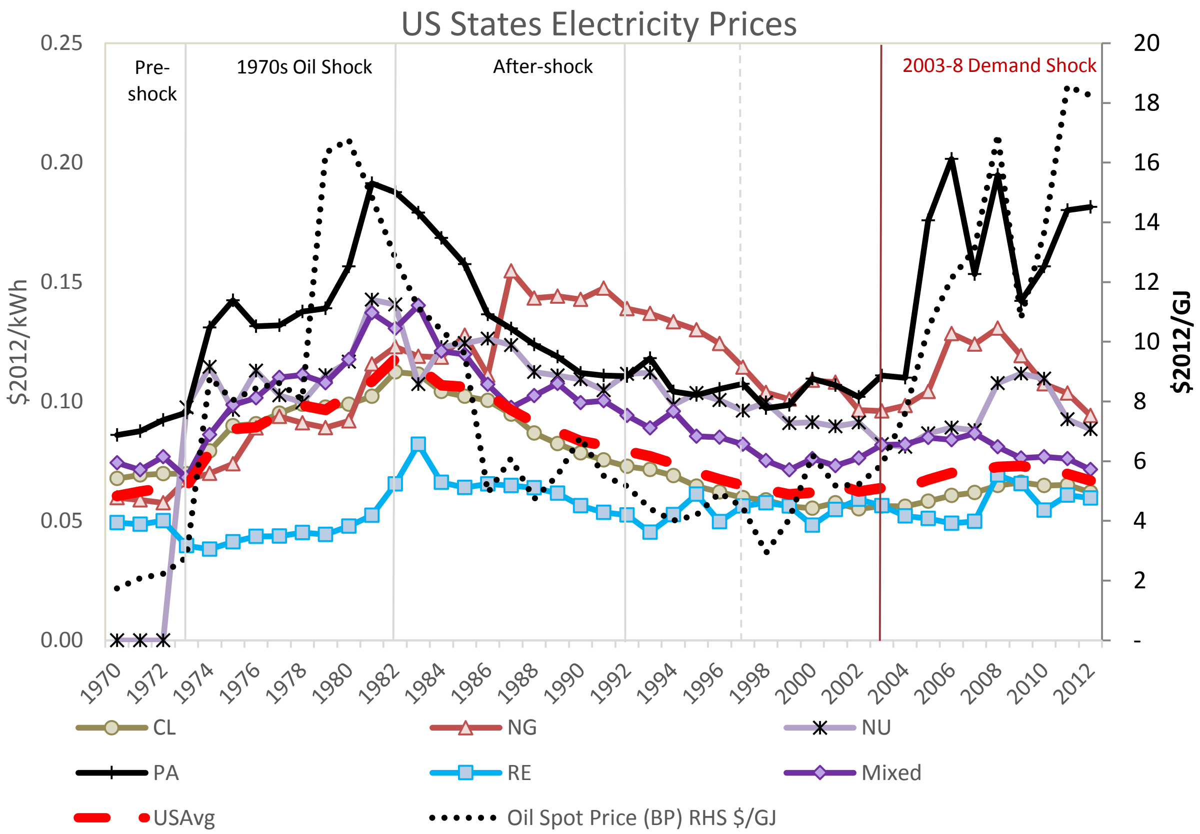

Figure 11: Average price of electricity to industry in states with dominant fuel source, and oil spot price

The weighted average price 1970-2012 shows a significant discount for industries doing business in states with high levels of renewables. The pattern of prices among states is also evident in Figure 11 which shows the progression of prices 1970-2012 for states with a dominant fuel source, and states with mixed generation portfolios.

The conclusion drawn from these analyses is that the impact of an oil crisis on the US electricity systems is determined mostly by the individual performance of the fuel systems within each state and region, and by policy decisions which drive perceptions of fuel constraints. The calculation of diversity shows no role in price stabilisation, so it follows that the PT risk model will not be effective in predicting stable prices. Equally, the diversity metric within the RI will not measure resilience.

The over-riding question is whether diversifying between fuels like coal, oil and gas serves as diversification, or merely as variation. Complex systems theorists have considered the difference between variation and diversity (Page, 2011). In this view, variation is difference within a type whereas diversity is difference of type. Whilst variation assists with adaptation by encouraging the establishment of niches, its effectiveness is limited to being able to respond to minor changes in the environment. By comparison, diversity creates synergies and overlap that facilitate robustness to major changes. In the 1970s, shifts within fossil fuel types could have facilitated adaptation but the combination of policies pursued by the US federal government reduced the systems' ability to adapt. The only fuel sources that offered diversification, rather than variation, were uranium and renewable (mainly hydro) systems. Reduced policy intervention in 2003-12, enabled generation to shift between fossil fuel types thus limiting the impact of rising oil prices on electricity systems. Notwithstanding the benefits associated with substitution in 2003-12, renewable energy provided the lowest priced electricity across both periods.

4.4. The role of spare capacity in diversity

As a metric of resilience, spare capacity as calculated in the RI is consistently associated with lower electricity prices. However, a requirement for spare capacity should not stop at electricity generation capacity. The requirement for spare capacity needs to extend to the inherent capacity within each fuel system which supplies electricity systems. An examination of these systems' spare capacity during the crises produces a narrative of how spare capacity within all fuel systems influenced electricity prices.

4.4.1. 1973-82

When the Arab embargo of oil started in October 1973, the Texas Railroad Commission had recently removed all restrictions on US oil production removing capacity to adapt to the supply shock (Yergin, 1991). This coincided with utilities transitioning to oil-and NG generation to prepare for sulphur emissions standards. Therefore, oil price escalation, facilitated by a lack of US spare capacity, increased generation costs and caused electricity prices to rise across the eastern states.

After 1973 NG production declined across the US. The Federal Power Commission's (FPC) regulatory power over NG interstate sales and prices halted exploration (NaturalGas.org, 2015) and reduced spare capacity. Residential and small business consumers were given priority access to NG forcing generators onto alternative fuels (Woodmansee, 1972). The Energy Supply and Environmental Coordination Act (US Government, 1974) and the Powerplant and Industrial Fuel Use Act (US Government, 1978), forced states that had traditionally relied on in-state affordable NG, like Louisiana, Oklahoma and Texas, to fuel electricity generation with relatively higher priced ex-state coal. The shift to coal generation caused electricity prices in the NG-rich states to increase.

The Appalachian coal region, the largest coal producing region in the US, struggled to meet demand in 1973 (Westerstrom, 1973). The Federal Environment Agency, in the Energy Supply and Environmental Coordination Act, legislated to prohibit the use of oil and NG in the generation of electricity (US Government, 1974). The perception that demand for coal would soar resulted in the coal price rising across the Appalachian states from an average of $10/ton to $20/ton between 1973 and 1974 (Westerstrom, 1974) as shown in Figure 12. This could happen as the Nixon Wage-Price controls expired in April 1974 (Yergin, 1991). Analysts claimed that the age of cheap energy was over

(Fiscor, 2012). A lack of transport network capacity limited non-Appalachian producers from resolving the perceived supply-demand imbalance. Although production from the Great Plains region gradually increased, high transport costs to demand centres and lower heat value meant that coal prices in the Great Plains region did not rise as fast as eastern coal prices. A combination of a lack of spare capacity in coal production in the eastern coal region coupled with a lack of spare capacity in the transport network to the eastern demand centres, served to facilitate increases in the price of electricity from coal

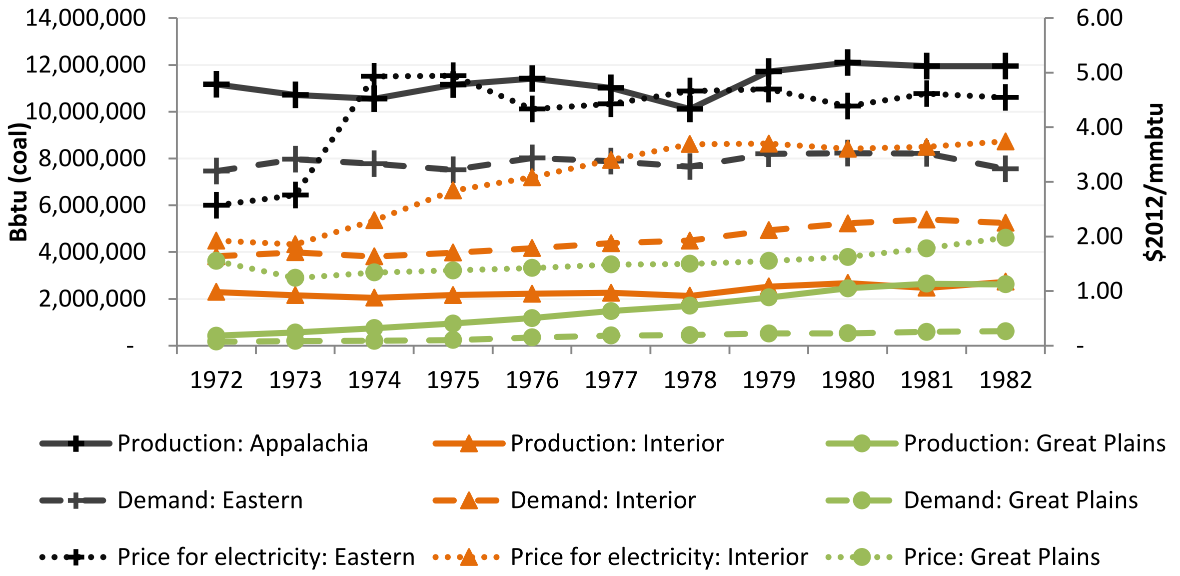

Figure 12: Coal system regional responses 1972-1982

The conclusion drawn about 1973-1982 is that the crisis was heightened and spread to electricity systems by a lack of spare capacity in oil, NG, coal and coal-transport systems.

4.4.2. 2003-12

After more than a decade of low stable prices, growth in demand from China and India, the US-led invasion of Iraq and declining US production, caused oil prices to escalate from 2003. High oil prices facilitated investment in technology to release tight shale oil onto the US market, although production increased only after 2008 with US production levels recovering to pre-2003 levels after 2010. Access to tight shale oil released spare capacity for the oil system.

Prices for NG in the US were relatively high in 2003 reflecting declining US production levels. As with tight shale oil, technology increased access to tight shale gas with production increasing after 2006. A surplus in supply led to the price halving after 2008, and falling further after 2011. Access to new reserves provided the NG system with spare capacity.

Coal prices increased only marginally from 2003-12. The lack of correlation with oil prices may have been as a result of perceived concerns over coal as a strategic source for energy in a carbon constrained world. It could also have been as a result of competition from cheaper NG. Figures 13 and 14 show the fuel prices for electricity generation between the 2 different periods.

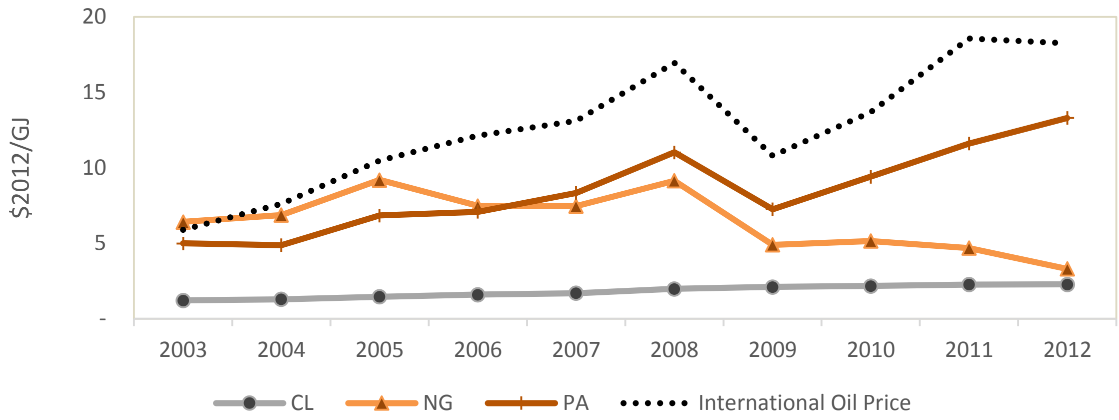

Figure 13: Fuel prices for electricity generation: 2003-12

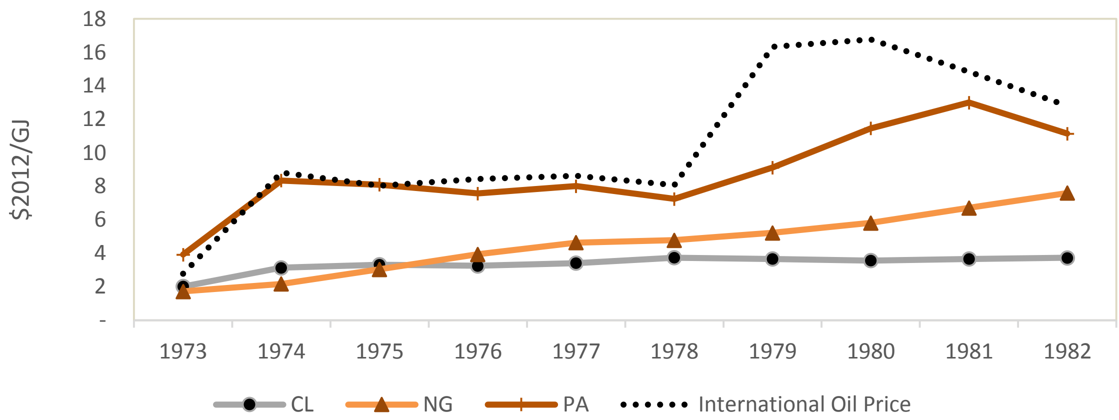

Figure 14: Fuel prices for electricity generation: 1973-82

The difference between the 1970s and the 2000s was the existence of spare capacity in coal and the emergence of spare capacity in NG and oil in 2003-2012.

5. Conclusions and policy implications

Each fuel system is a complex web of structural variables, interconnected with other fuel systems through the ability of fuels to serve as substitutes. The price of each fuel reflects the dynamic structure of each fuel system. Where structural imbalances in supply or demand occur, price adjusts to reduce the pressure of the imbalance. If substitution is possible, substitute fuel systems will supply into the constrained system to reduce pressure. This will increase the pressure in the substituting fuel system, causing both systems to reach a new extended equilibrium. Where policy interventions constrain the response of either system, the pressure from the original structural problem will shift to another, more responsive, substitute system.

In 1973-1982, the consequences of historic policy interventions in the wake of the Natural Gas Act of 1938, the curtailment plans associated with NG regulation, the Energy Supply and Environmental Coordination Act of 1974 and the Power Plant and Industrial Fuel Use Act of 1978, reduced the ability of the NG systems to respond to the imbalance in the oil market. This shifted fuel supply imbalances to the coal industry and from there spread price increases to the electricity industry. The energy policy interventions which sought to control inflation and increase energy security shifted the contagion to all fuel systems, failing to isolate and contain it.

By contrast, in 2003-12 energy policy interventions were limited to judicious drawdowns of oil from the strategic petroleum reserve in 2005 after Hurricane Katrina and 2011 after civil unrest in Libya. Prices in the oil and NG systems relieved the structural imbalances by stimulating technological advances. In effect, the lack of policy intervention ensured that the systems responded effectively to the energy shock. The price of uranium escalated in 2007 not due to scarcity but due to perceptions of increased demand and a potential scarcity of supply, which resulted in prices of electricity in states with predominantly nuclear power increasing unexpectedly.

This is not the first study to identify that policy mechanisms in the 1970s exacerbated the energy crises but it is the first to highlight that a lack of spare capacity within fuel systems constrains responses that can isolate and contain the original problem. Whether the lack of spare capacity was caused by legislation, or the lack of capacity resulted in legislation, the underlying trigger is that a fuel source is in some way constrained. Fuels that have to be found, extracted, transported and financed will always be vulnerable to constraints, structural imbalances and price volatility. Although spare capacity is crucial to isolate contagion, network structure also plays a role in the spread or control of contagion. Restrictions placed on NG interstate sales and the lack of capacity in coal transport facilitated the rise of all fuel prices in the 1970s, whilst transport of NG and coal in the 2000s facilitated the flow of fuels from areas with capacity to areas of structural imbalance, averting general fuel price rises.

A preferable policy intervention is to increase the proportion of generation from fuel sources that are not substitutes and are not subject to systemic contagion; fuel sources that show diversity rather than variation. In the 1970s, there was investment in nuclear generation which was a diverse alternative but it was expensive, subject to the availability of uranium and safety costs. In 2003-2012 oil price contagion spread to uranium, perhaps identifying that uranium, like NG, offers variation rather than diversity. Most renewable energy, however, is subject to system constraints that are independent of fossil fuel system constraints making them an excellent counter to systemic contagion. Geographic limitations of hydro-electricity, and the immaturity of other renewable technologies, eliminated wide-spread roll out of renewable energy options during and after 1973-1982, but that is no longer the case in 2015. The 2003-2012 technological advances in oil and NG production and effective fuel transport networks served to provide access to spare capacity to avert structural imbalances and avoid the consequences of the 1973-82 crises. The technology breakthrough that stopped high-price contagion was however due more to luck, than good strategy. If energy policy is to address resilience in energy it needs to ensure that critical fuel systems have adequate spare capacity to respond to unexpected threats and that truly diverse fuel sources are readily available at sufficient scale to contain any threat of systemic contagion.

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Notes

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[i] The estimations of net interstate electricity transfers 1970-1989, as calculated by EIA SEDS, involve total energy estimates that are considered by the International Energy Agency (IEA) to be inappropriate (TAYLOR, Y. 22 January 2014 2014. *RE: Historic Data.* Type to MOLYNEAUX, L.). An alternative method has been devised in this paper to calculate net interstate transfers 1970-1989. States are separated into Western Interconnection and Eastern Interconnection to reflect the larger transmission distances in the former. Generation, plus net international electricity flows, less consumption, calculates interstate transfers. The totals provide the average electricity loss percentage for each interconnection area. The interconnection area electricity loss percentage is applied to each applicable state to calculate net interstate transfer. Equation A details the calculation:

$$\text{NET INTERSTATE TRANSFERS} = \text{GENERATION} + \text{NET INTERNATIONAL TRANSFERS} - \text{CONSUMPTION} - (\text{ESTIMATED INTERCONNECTION LOSS PERCENTAGE} * \text{GENERATION}) \quad \text{(A)}$$

Equation A calculates net interstate transfer estimates that appear consistent with data reported 1990-2012.