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Lynette Molyneaux[1a], Colin Brown[b], Liam Wagner[c], John Foster[a]
a. Energy Economics and Management Group, School of Economics, University of Queensland, Australia
b. School of Agriculture and Food Sciences, University of Queensland, Australia
c. Economics, Griffith Business School, Griffith University, Brisbane, Australia

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Abstract

Carbon constraints will act as a significant fuel shock for electricity generation. This paper seeks to use previous fuel shocks (the 1970s oil price crises and the global surge in energy demand that started in 2003) as the context for analysing the adaptive capacity of electricity generation to large fuel shocks. Resilience is the framework for analysis and the metrics analysed are based on the characteristics of resilience; diversity, spare capacity and organisational structure. This approach differs from current energy resilience research in its pursuit of empirical evidence for the relevance of metrics. The findings indicate that spare capacity is the most important metric for predicting favourable outcomes but diversity also plays a role.

Contents

[1] Corresponding author. Address: Energy Economics and Management Group, University of Queensland, St Lucia, Brisbane, 4072, Australia. Tel: +61 7 334 61003
Email addresses: l.molyneaux@uq.edu.au, j.foster@uq.edu.au, l.wagner@griffith.edu.au, colin.brown@uq.edu.au

1 Introduction

The ability of electricity generators to respond to the changes required for a carbon constrained future is one of the most serious challenges faced by industry and policy makers. In 2013, 23.3 trillion kilowatt hours were generated for billions of consumers around the globe, resulting in 13.4 billion tons of carbon dioxide emissions added to the stock of greenhouse gases which will impact the global climate [1]. The International Energy Agency (IEA) is calling for "*a clear and credible vision of long-term decarbonisation*" to mitigate against the challenges of climate change whilst increasing access to electrification for a further 1.3 billion people. Even a managed transition to decarbonised electricity is going to require significant levels of change. Responding to these changes will require adaptation by generation fleets around the globe. Whilst electricity generation fleets have never had to respond to a change of this magnitude, they have faced significant energy shocks previously. What made electricity generation fleets resilient to significant change in the past is the focus of this paper along with an assessment of metrics used to predict energy resilience.

Energy resilience is generally accepted to be about the adaptive capacity of an energy system to respond to some, unexpected shock. The Global Energy Assessment (GEA) describes resilience as the third 'perspective' of energy security after the perspectives of robustness (protection from predictable events) and sovereignty (protection from non-domestic supply disruption) while resilience is considered the ability to adapt to unpredictable weather events and political instability [2]. Similarly, resilience is described as a country's capacity to deal with disruption in an IEA working paper on energy security [3]. More recent discussion on energy resilience by Roege et al [4] uses a disaster resilience framework to identify four critical components to resilience; namely *plan/prepare, absorb, recover and adapt* [5] while Sharifi and Yamagata propose a similar framework in research on urban energy resilience [6] as that proposed by Roege et al.. Arghandeh el al in their definition of energy resilience for power networks provide a clear divide between the system characteristics of adaptive capacity and organisational structure to monitor and respond [7].

The GEA primarily uses diversity as a metric of energy resilience, although it does consider a multitude of diversities, like fuel diversity for electricity generation, power plant diversity, import route diversity, and overall diversity of primary energy use. Although reference is made throughout the GEA report of the importance of spare capacity, they do not present any meaningful metric of spare capacity. IEA's Measuring Short term Energy Security report (MOSES), identifies 44 metrics to assess energy security including 22 for resilience (10 associated with import point for each fuel into a country; 6 with diversity of supplier; 3 with stock levels of crude oil, petroleum and natural gas; and one each measure flexibility of petroleum refining, natural gas intensity, and volatility of hydro power production). The metrics are assessed through subjective measures for representation of low, medium or high levels of resilience so that country profiles of energy security for risk and resilience can be established [3]. There is no attempt to find empirical evidence for the relevance of including these metrics to measure resilience. Roege et al [4] couple the

National Academy's disaster resilience components of *plan/prepare, absorb, recover and adapt [5]*, with a resilience taxonomy devised for monitoring change and interactions between physical, information and human domains for disaster management [8] to devise a framework for resilience metrics involving 92 different metrics. As with GEA and Moses, the resilience metrics are based on discussion in the literature and on expert opinion rather than empirical evidence. The other discussions on energy resilience by Sharifi and Yamagata and Arghandeh et al did not propose metrics [6, 7].

It is the absence of empirical evidence of the relevance of metrics in predicting desirable outcomes, or resilience, for energy systems that is the motivation for this analysis. Empirical evidence is sought for characteristics that were present in electricity generation fleets in the US which experienced improved outcomes after the 2 large energy 'surprises' experienced over the last 40 years, namely the oil price crises after October 1973 and the surge in global energy demand that raised oil prices from 2003.

Whilst GEA, Moses and Roege et al [4] propose lists of resilience metrics, the framework developed from multiple disciplines in Molyneaux et al [9], to identify the core characteristics of resilience; namely diversity, spare capacity and organisational structure is applied here. ***Diversity*** is generally proposed as the first (and often only) principle for enhancing energy resilience [2, 10, 11] but is also a defining characteristic of energy security [12-15]. ***Spare capacity*** has been identified as a metric for energy resilience but its inclusion is generally not as a primary characteristic. This discounts the importance attributed to spare capacity for energy security by the IEA in its management of the strategic petroleum reserve and by economists' calculations of adequate levels of reserve capacity to guard against energy disruption [16, 17]. ***Structure*** is demonstrated as an important characteristic of energy resilience by the identification of frameworks to facilitate resilience through organisation to *plan/prepare, absorb, recover* and *adapt* [4] and the need to monitor system boundaries to facilitate flexible response to unexpected fault [7]. IEA institutional structures to co-ordinate responses to crises and provide information about risks and dependencies are further evidence of the importance of organisation. Research into Small World Networks, that is networks that are characterized by short path lengths and a few highly connected nodes, shows that structure facilitates the flow of components through the system [18]. In, ecology, system structure presages ecosystems' ability to survive [19, 20] through efficiency and order. In recognition of the importance of structure, a resilience index has been constructed to measure resilience in various stages of transformation to electricity [21]. The inclusion of these key characteristics of diversity, spare capacity and structure therefore reflects research into resilience from multiple disciplines.

Whilst discussions on measuring energy resilience point to metrics, none suggest a dependent variable, which might be used to gauge the performance of the metrics proposed. In the absence of an applicable model, attention is turned to early discussions on resilience for further insight. Ecologists have argued that fast variables of the system show the dynamics of the underlying structural variables [22]. Applying this argument to electricity generation, price represents the fast variable as it reflects the dynamics of the structure transforming fuel source to electrical energy. Thus, if price can show levels of stability, despite volatility in structural components, then there is evidence of resilience in electricity generation.

Thus the model proposed here is to establish the statistical significance of the metrics of diversity, spare capacity and system structure in predicting price outcomes during periods of significant oil price volatility as the context for measuring resilience of electricity generation to fuel shock. State electricity systems in the United States of America (US) provide data to describe diverse system responses to energy shocks. The state electricity systems operate in consistent frameworks in terms of their macro-economies, monetary systems, governance, legislature, labour and industry institutional structures eliminating the need to control for non-energy structural variation. After describing the methods and their rationale in section 2, the results are presented in section 3 and discussed in section 4. Conclusions on the measurement of resilience are drawn at the end of the paper.

2 Method

A multiple linear regression analysis[i] is used to examine the relationship between the resilience metrics as explanatory variables and electricity price as the dependent variable. The primary data is drawn from the US Energy Information Agency (EIA) State Energy Database System (SEDS) 1970-2012. Electricity capacity and generation data by year, state and plant is sourced from the EIA's Form759.

The regression model[ii] takes the form:

$$ESICDKR_s = \beta_0 + \beta_1 X_{1s} + \beta_2 X_{2s} + \ldots + \beta_k X_{ks} + \varepsilon_s \qquad \text{Equation 1}$$

Where

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

β_0 = $ESICDKR$ intercept

β_k = coefficients of X_k

X_k = variable *k* of Resilience metric

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

The type and length of the disturbance needs to be defined, to establish the electricity

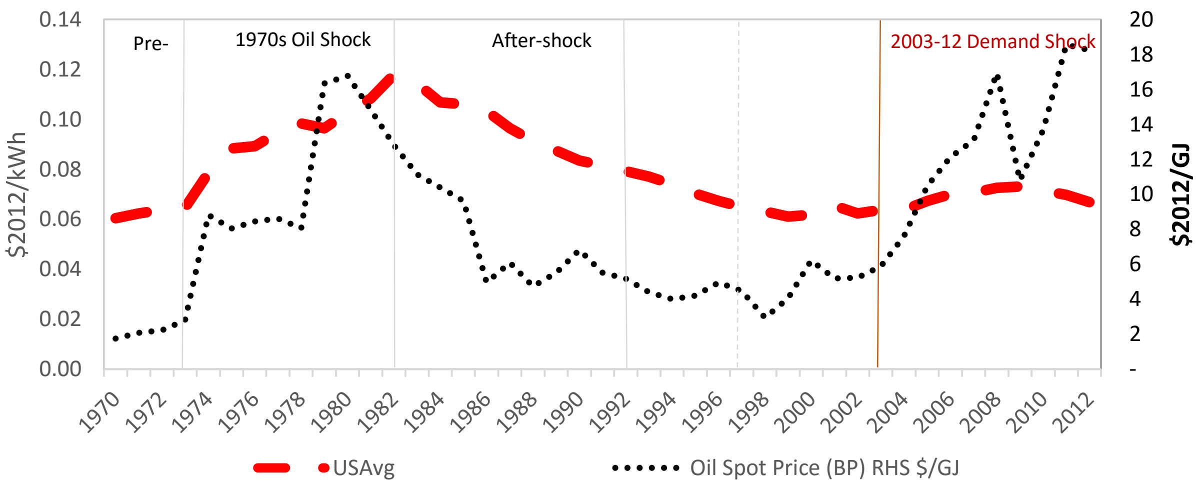

Figure 1: Price of electricity to industry 1970-2012 and oil spot prices

generators' response to an exogenous shock. Estimations of correlation calculated over longer periods smooth out the 'noise' of shorter period variability. Although oil is not currently a dominant source of fuel for electricity generation, in the early 1970s eastern states in the US were in the process of transitioning to oil as a fuel source for generation due to its reduced emissions of pollutants. The oil crises, starting in 1973, and the ensuing legislation which required electricity generation to be fuelled by coal [23], reduced dependence on oil for electricity. However, as shown in Figure 1, electricity prices increased in tandem with oil price rises 1973-82, and to a lesser extent 2003-12, so there would appear to be linkage between oil and electricity prices through fuel price correlations.

2.1 Dependent variable: electricity industry price

If price of electricity is representative of the capacity of the fleet to adjust to change, it can be considered to be predictive of energy resilience. Economic models which use price as a dependent variable tend to measure change in price when assessing the impact of independent variables on price. However, due to the nature of generation assets, historic and structural factors need to be taken into account if price is to represent the adaptive capacity of the fleet. The price of electricity to industry is chosen as the most appropriate measure of price to eliminate network costs and regulatory inconsistencies. In addition, the weighted average price of electricity over the period of analysis is chosen in preference to either change in price over the periods or point estimates of price at any stage during or after the periods of analysis[iii]. This is because weighted average price provides more information about the state of the system during the energy shock than do other measures. Throughout the analysis, real prices are used to differentiate from movements in the general level of prices.

2.2 Explanatory variables: Resilience characteristics

Table 1 summarises the resilience characteristics included in the analysis and the calculations that determine their metrics.

Table 1: Resilience characteristics as explanatory variables

Resilience Characteristic	**Regression Variable name**	**Metric calculation**
Diversity	*diversity*	Proportion of electricity generated from each fuel source
Spare Capacity	*sparecap_gdp*	kWh/$GDP
Structure: Generational Efficiency	*lossingen*	Proportion of energy lost in transformation
Structure: Imports - electricity for consumption	*imports_elec*	Proportion of electricity imported/exported
Structure: Imports – energy for electricity generation	*imports_fuel*	Proportion of electricity generated from imported fuel sources

2.3 Calculating diversity

For electricity generation, as Figure 1 shows, electricity price shocks have been delivered through fuel shocks; contagion contracted through interconnected fuel systems. If immunity to contagion is sought, generation fleets must be able to shift to alternative fuel sources which offer protection. Diversity should therefore be a measure of possible alternatives, rather than a subjective measure of fuel type preferences. For the purposes of this analysis, a common metric detailed in Equation 2 is applied. In the ecology literature, the metric is known as Simpson's Diversity Index while in market concentration studies it is known as the Herfindahl Index and takes the form:

$$D = 1 - \sum_i p_i^2 \qquad \text{Equation 2}$$

Where p_i is the proportion of all elements from category i.

For completeness, alternative calculations for diversity shown in Table 2 were also analysed.

Table 2: Alternative measures of diversity analysed

Measure of diversity	Calculation	
Shannon's diversity index	$-\sum_{i=1}^{n} p_i \ln p_i$	p_i= proportion of entity from i th type n= total number of entities
Simpson's Equitable diversity index	$\frac{1}{\sum_{i=1}^{n} p_i^2} x \frac{1}{n}$	p_i= proportion of entity from i th type n= total number of entities
Hunter-Gaston index (Simpsons index sampling without replacement)	$\frac{\sum_{i=1}^{s} s_i(s_i - 1)}{n(n-1)}$	s_i= number of entities from i th type n= total number of entities
Portfolio Theory	$V(R) = \sum_{i=1}^{n} P_i^2 \sigma_i^2 + 2\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} P_i P_j \sigma_{ij}$	V(R) = Variance in price of the generation portfolio P_i = Proportion of generation from fuel type i in the portfolio σ_i^2 = Variance in cost of fuel type i *to* the portfolio σ_{ij} = Covariance in cost between fuel types i and j i = Fuel types: Coal (CL), Natural Gas (NG), Uranium (UR), Oil (PA), Renewable (RE)

2.4 Calculating spare capacity

Spare capacity is the difference between the amount of electricity generated in a year, and the amount of electricity that could be generated at full capacity, normalised by applying total spare electricity available for use in the economic activity of each state. Equation 3 shows detail.

$$sparecap\_GDP = \left(\sum_{i=1}^{n} (((GW_i * hours) * CF_i) - GWh_i) \right) / GDPR \qquad \text{Equation 3}$$

Where:

$sparecap\_GDP$	Potential energy available for use in economy
GW_i	Installed capacity in millions of kilowatts using fuel type i
$hours$	8760 hours is generally assumed in estimations of total annual capacity
CF_i	Capacity factor: Maximum proportion of total generation possible from installed plant for fuel type i [iv]
GWh_i	Electricity generated in millions of kilowatts from fuel type i
$GDPR$	Real gross domestic product in $2012 millions
i	Fuel types: Coal (CL), Natural Gas (NG), Uranium (NU), Petroleum(PA), Hydro (HY)

2.5 Measuring structure

In recognition of Ulanowicz's view of resilience, that efficiency and order define the structure of the system, structure is included here as 3 separate metrics: (a) the efficiency of generation; (b) imports of fuel for generation; and (c) imports of electricity.

Efficiency of generation

Efficiency of generation provides a proxy for the effectiveness of the fleet structure, and is calculated as the percentage of energy lost in generation for each state as detailed in Equation 4.

$$lossingen = 1 - (TWh * 3412)/TEEIB \qquad \text{Equation 4}$$

where:

$lossingen$	Proportion of energy lost in transformation to electricity
TWh	Total electricity generated in billions of kWh
$TEEIB$	Energy consumed in production of electricity in billions of Btu's

The metric for generation efficiency, *lossingen*, is an aggregation of the conversion efficiency of the state fleet. Different fuels and technologies have different efficiency in conversion of fuel source into electricity. To gain further insight into the role that different fuel types play in the determination of price, *lossingen* can be disaggregated into the percentage of generation from each fuel source. The percentage of generation from each fuel source is calculated as shown in Equation 5.

$$Perc_i = \frac{\sum_{i=1}^{n} GWh_i}{GWh} \qquad \text{Equation 5}$$

Where

$Perc_i$	Percentage of generation from each fuel type i
i	fuel type: CL, NG, PA, NU, Renewable Energy (RE)

To include the small contribution of biomass, wind and solar in system performance, electricity generated from these fuels is aggregated with hydro-electricity to provide a measure of generation that is independent from fuel markets.

Regression analysis of the resilience characteristics is conducted with the aggregated metric for generation efficiency, *lossingen,* and the disaggregated metrics for generation efficiency of *clperc*, *ngperc*, *nuperc*, *paperc* and *reperc*. Both the aggregate and the disaggregated metrics are compared in regression analysis to provide an insight into the role that diversity plays in conjunction with *lossingen* as distinct from the role that diversity plays when coupled with the fuel percentages that are elements of the diversity metric itself.

Imports of fuel for generation

Generation reliance on imports of fuel from ex-state, will have implications for the fleet's performance. Imports of fuel for electricity generation is calculated where the total consumption of each fuel is greater than the total production of that fuel in-state. The proportion of fuel imported for state consumption is applied to electricity generation for each fuel type and each state as shown in equation 6.

$$imports\_fuel = \left(\sum_{i=1}^{n} \phi_i(((TCB_i - PRB_i)/TCB_i) * GWh_i) \right) / GWh \qquad \text{Equation 6}$$

where:

$imports\_fuel$	Proportion of electricity generated from imported fuels
ϕ_i	Imports indicator for fuel type i If $PRB_i - TCB_i < 0$, then ϕ_i = 1, else ϕ_i = 0
PRB_i	Energy produced in BBtu from fuel source i
TCB_i	Energy consumed in BBtu from fuel source i
GWh_i	Electricity generated in GWh from fuel source i
i	Fuel types: CL, NG, PA

Imports of electricity

Where generation is not available in-state or surplus to requirement in-state, transfers of electricity will measure that aspect of structure. Net electricity transfers from both inter-state and international sources are calculated by SEDS and the metric is calculated for each state as the proportion of total electricity consumed that is imported, or the proportion of total electricity generated that is exported.

$$imports\_elec = \left(\psi * \frac{ELNIP + ELISP}{ESTCP} \right) + \left(\theta * \frac{(ELNIP + ELISP)}{TTEGP} \right) \qquad \text{Equation 7}$$

where:

$imports\_elec$	Proportion of electricity imported/exported
ψ	Net import indicator: If $ELNIP + ELISP < 0$, then ψ = 1, else ψ = 0
θ	Net export indicator: If $ELNIP + ELISP > 0$, then θ = -1, else θ = 0

$ELNIP$	Net imports of electricity into US in GWh
$ELISP$	Net interstate sales of electricity in GWh[v]
$ESTCP$	Total electricity consumed in GWh
$TTEGP$	Total electricity generated in GWh

For clarity rather than accuracy, generation efficiency will be referred to as the metric for structure. The metrics for fuel imports and electricity imports will be referred to as the metrics for imports.

3 Results

3.1 Impact of 1970s oil crises on price

The results of the first regression (A in Table 3) indicates that the resilience metrics explain 63.7% of the variation in prices. 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, (B in Table 3), *lossingen*, *sparecap_gdp* and *imports_fuel* explain 63.4% of variation in price.

If *lossingen* is disaggregated into the percentage of generation from each fuel source, each fuel's impact on price becomes visible. Including the percentage of all fuel types in regression analysis could result in collinearity between the variables. Thus, in recognition of the dominance of CL in electricity generation, *clperc* is excluded as an explanatory variable. These variables explain 74.8% of the variation in price (C in Table 3). 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 significant, and so they are excluded from the model.

Table 3: Regression analysis of Resilience metrics as predictors of price during oil crises 1973-82

	Resilience metrics	**Resilience Statistically-significant metrics**	**Resilience adj With FuelPerc metrics**	**Resilience adj Statistically significant metrics**
Regression version	A	B	C	D
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	0.673002	0.656080	0.788649	0.780384
Fit: Adj R2	0.636669	0.634128	0.748392	0.755982
Fit: F-stat	18.52308 *(0.000000)*	29.88660 *(0.000000)*	19.59019 *(0.000000)*	31.98066 *(0.000000)*
Intercept	0.039054	0.038134	0.110369	0.112084

(Prob) VIF	*(0.0034)* 24.39	*(0.0036)* 23.5	*(0.0000)* 21.4	*(0.0000)* 18.9
Coefficients				
Diversity *(Prob)* VIF	0.012840 *(0.3148)* 5.33		0.025875 *(0.0385)* 7.1	0.028178 *(0.0074)* 5.0
Sparecap_gdp *(Prob)* VIF	-0.117718 *(0.0001)* 9.72	-0.100925 *(0.0001)* 7.6	-0.097249 *(0.0003)* 11.6	-0.095639 *(0.0003)* 11.5
Imports_elec *(Prob)* VIF	-0.014713 *(0.2248)* 1.63		-0.028637 *(0.0084)* 1.8	-0.026225 *(0.0098)* 1.6
Imports_fuel *(Prob)* VIF	0.030130 *(0.0016)* 3.53	0.026594 *(0.0023)* 3.0	0.009373 *(0.3274)* 5.7	
Lossingen *(Prob)* VIF	0.119521 *(0.0000)* 27.73	0.124238 *(0.0000)* 26.4		
NGperc *(Prob)* VIF			-0.003205 *(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)*	0.957445	1.79	1.22	1.65
Condition index *(multicollinearity problem if >15)*	15.06	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 D in Table 3. 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*, show that price increases by 0.6c/kWh for every 10% of generation from oil and decreases by 0.6c/kWh for every 10% of generation from renewable sources of energy. The coefficient for *sparecap_gdp* shows that for every 100Wh of spare capacity for use in the economy, price decreases by 1c/kWh. The coefficient for *imports_elec* shows that for every 10% of electricity imported, price decreases by 0.3c/kWh but conversely for every 10% of electricity exported, price increases by 0.3c/kWh. Against expectations, the coefficient for *diversity* shows that for every 10% probability that electricity will be from a different energy type, price increases by 0.3c/kWh.[vi]

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. The adjusted R^2 is not unusually high, the standard errors for *sparecap_gdp* and the other variables are small, correlation between *sparecap_gdp* and *clperc-ngperc-nuperc* at 0.553 is not high, and there is little evidence of covariance between any of the coefficients or the intercept. The matrix condition number from Equation 13 of 14.2, points to acceptable levels of collinearity. Although there is some evidence of collinearity between *sparecap_gdp* and *clperc*, it is unlikely to diminish the results as presented in Table 3.

3.2 Impact of oil demand growth 2003-12 on price

US average electricity prices for industry remained at pre-1973 price levels from 1997-2002. However, in 2003 oil prices started rising again. In Table 4, the results of the regression analysis of resilience metrics as predictors of price during oil demand growth for 2003-12 are presented.[vii, viii]

As detailed in D in Table 4, the statistically significant disaggregated resilience metrics, with fuel percentages substituted for *lossingen*, explain 72.4% of the variation in price. The coefficients for the fuel percentages indicate 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 after 2008 when unconventional sources increased supply. The coefficient for *Sparecap_gdp* indicates that for every 100Wh of spare capacity for use in the economy, price decreases by 0.5c.kWh.

Table 4: Regression analysis of resilience metrics as predictors of price during oil demand growth 2003-12

	Resilience metrics	**Resilience Statistically significant metrics**	**Resilience adj with FuelPerc metrics**	**Resilience adj Statistically significant metrics**
Regression version	A	B	C	D
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	0.317875	0.299996	0.759040	0.746856
Fit: Adj R2	0.240360	0.254344	0.712023	0.724354
Fit: F-stat	4.100856	6.571302	16.14408	33.19111
Intercept *(Prob)* VIF	0.047875 *(0.0188)* 40.57	0.064859 *(0.0000)* 10.8	0.061477 *(0.0000)* 16.5	0.060518 *(0.0000)* 6.8
Coefficients				

Diversity *(Prob)* VIF	0.036815 *(0.0312)* 8.02	0.036069 *(0.0313)* 7.88	0.002676 *(0.8439)* 14.1	
Sparecap_gdp *(Prob)* VIF	-0.067378 *(0.0023)* 4.42	-0.064977 *(0.0015)* 3.9	-0.060671 *(0.0001)* 5.1	-0.054312 *(0.0000)* 4.1
Imports_elec *(Prob)* VIF	0.005104 *(0.6943)* 1.58		-0.009316 *(0.3096)* 2.1	
Imports_fuel *(Prob)* VIF	0.015826 *(0.2112)* 4.55	0.020372 *(0.0489)* 3.0	0.000820 *(0.9204)* 5.1	
Lossingen *(Prob)* VIF	0.031371 *(0.3009)* 36.52			
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 *(heteroskedasticity exists if >5.99)*	11.48	9.56	2.96	4.22
Condition index *(multicollinearity problem if >15)*	15.69	8.0	14.5	9.1

4 Discussion

"*Resilience, as a property of a system, must transition from just a buzzword to an operational paradigm for system management*" [25]. The findings of this study imply that at least part of that operational paradigm needs to be based on empirical evidence of metrics which articulate resilience. If greater stability in prices is evidence of energy resilience when a major fuel source is undergoing unexpected change, the analysis reported in Section 3 provides evidence that the metrics used for spare capacity and structure (the proportion of electricity generated from each fuel type) play an important role in predicting resilience. However the metrics for diversity and imports do not.

4.1 The role of diversity in resilience

The metric of diversity shows no consistent role in the models. In the regression analysis of the 1973-82 period, the diversity metric predicts increased prices with and without the disaggregated structure metric (fuel percentages), whilst the analysis of the 2003-12 period predicts increased prices without the disaggregated structure metrics, but no price outcome with the aggregated structure metric.

Electricity prices for states with generation from a dominant fuel source and states with mixed portfolios appear in Table 5. Across the decades, the price of electricity for states with a mixed portfolio is higher than the US average. However, during the first oil price shock period of 1973-1982, the price of electricity in states with mixed generation fleets increased by only 46% compared with the US average of 55%. While the price increase for mixed generation fleet states was lower than states with NG generation (59%) and oil generation (67%), it was higher than states with predominantly coal generation (34%) while states with high levels of hydro experienced no increase in price. Washington and Oregon's nuclear programs resulted in price rises in 1982 but thereafter trended downwards. Thus states with mixed portfolios experienced smaller increase in price than states reliant largely on oil or NG, which is perhaps evidence that diversification away from oil and NG reduced their exposure to potential price increases had they been reliant only on either oil and/or NG.

Table 5: Weighted average electricity prices by fuel source 1970-2012

$2012/kWh	1970-72 Wtd-Avg	1973-82 Wtd-Avg	1983-92 Wtd-Avg	1993-02 Wtd-Avg	2003-12 Wtd-Avg	1970-2012 Wtd-Avg.
			$2012/kWh			
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:						
CL	0.070	0.094	0.088	0.061	0.062	0.073
NG	0.059	0.094	0.128	0.115	0.120	0.104
NU	n/a	0.105	0.120	0.098	0.099	0.087
PA	0.088	0.147	0.130	0.112	0.160	0.137
RE (HYDRO)	0.049	0.046	0.062	0.051	0.053	0.052

During the oil price surge 2003-2012, average US price rose only 11%. *States with mixed generation fleets* showed price decreases in 2003-12. This decrease reflects historically high price mixed portfolio states like Connecticut and Massachusetts shifting from mixed to predominantly NG generation and historically low priced states like Alabama, Arkansas and Oklahoma shifting to mixed portfolios. If the states that shift between mixed and NG groups are excluded from the average price calculation, the price for states that were mixed in 1993-02 and 2003-12 remained stable at 0.075 in 1993-02 and 0.078 in 2003-12. Lower priced NG enabled Connecticut and Massachusetts to shift away from coal and oil, and Oklahoma and Alabama to shift back to NG. *States with NG fleets* showed price rises in concert with oil price from 2003, but then stabilised in 2009 as NG from unconventional sources boosted supply. The overall effect of this volatility for fleets reliant on NG was that weighted average price increased by a small amount over the period 2003-12. Outside of the coal-oil-NG nexus, *states with nuclear fleets* experienced higher prices than coal and hydro fleets despite low fuel requirement and mature technology. *States with hydro fleets* experienced small absolute increases in price 2003-12. The weighted average price 1970-2012 shows a significant discount for industries doing business in states with high levels of hydro-electricity.

An important discussion about diversifying between fuels for electricity generation is whether shifting between fuels like coal, oil and NG serves as diversification, or merely as variation. Complex systems theorists have considered the difference between variation and diversity [26]. 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. As a consequence of the interconnection between oil, NG and coal prices, the only fuel sources that offered

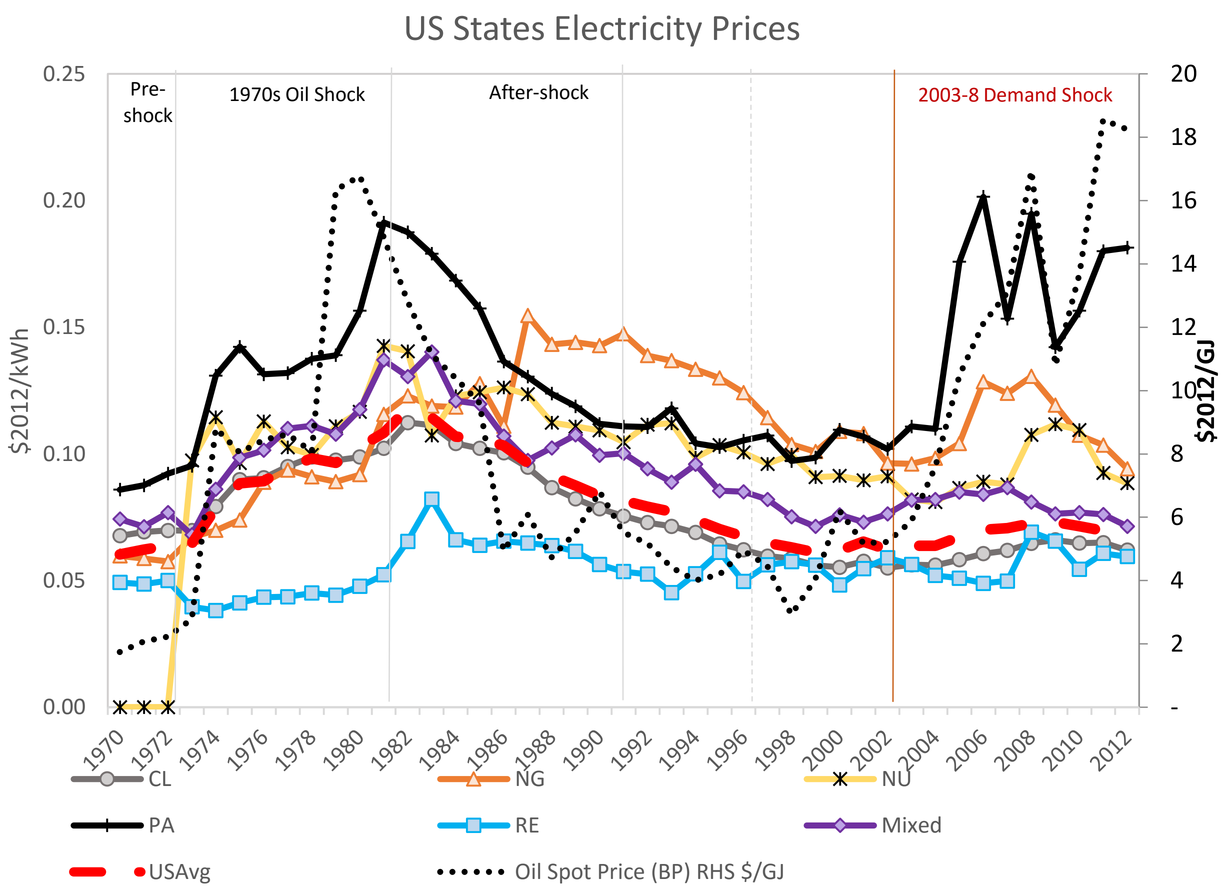

Figure 2: Price of electricity from major fuel sources and price of oil 1970-2012

diversification, rather than variation, were uranium and hydro. Reduced policy intervention *in 2003-12*, enabled a technology break-through which decreased NG prices. Potential for substitution between NG and coal, removed upward pressure on coal prices. The net effect of the arrival of unconventional NG on the market was to halt the impact of rising energy prices. Notwithstanding the benefits associated with substitution in 2003-12, hydro-electricity provided the lowest priced electricity across both periods as shown in Figure 2.

A finding that hydro-electricity provides the cheapest form of electricity is not surprising but it was its complete independence from the fleet effect that was important for resilience. Whilst coal, NG and uranium were sensitive to oil prices at varying levels across both periods, hydro was independent. Rainfall is hydro's major risk but a reasonably severe drought struck in 1977 [27] with little consequence for electricity price in hydro states. Independence from oil provided hydro states with greater resilience than oil, NG, coal or uranium during the 2 energy shocks analysed.

Introducing solar, wind, geothermal or marine power sources to fleets to reduce CO_2 emissions would bring greater independence from fuel price contagion as they are individually independent from all other fuel sources. As solar and wind technology costs have decreased, there is potential for greater resilience in electricity generation as a result of increased independence between fuels. This improved resilience will be negated by a reduction in spare capacity, due to the intermittency and variability of both solar and wind power. However, it can ultimately be resolved by judicious deployment of storage technologies.

The conclusion drawn from these analyses is that the impact of oil crises on state generator fleets was determined mostly by the individual performance of the fuel systems within each state and region, and by policy decisions which drove perceptions of potential constraints. The metric used for diversity (including the alternative diversity metrics analysed and detailed in section 1.2.4) provides insufficient information about benefits. However, the disaggregation of the structure metric, generation efficiency, into fuel percentages, provides evidence of the price differentials that result from varied responses by individual fuel systems and the power plants dependent on those fuel systems. Thus there is evidence of the potential benefits from diversification; it is just not articulated by the metrics traditionally applied to represent diversity.

Whilst states with diversified portfolios were protected from oil/NG price escalation in 1973-82, the higher than average price paid by states with mixed portfolios indicates that states suffered a penalty for diversifying away from fuels that were less sensitive to oil price. A metric of diversity therefore needs to reflect distance, or independence, not from each other but from a dominant fuel source as discussed by Sterling [28]. Analysis of the correlation between oil, NG, coal and uranium provides evidence of the quixotic nature of relationships between fossil fuel prices. Independence can be influenced by perception as well as technology. The price of uranium provides a good example. Uranium is not technologically compatible with coal, NG or oil consuming technologies, but its price escalated after 2007 [1] due to perceptions of potential scarcity [29]. Thus nuclear power was perceived to be related to the surge in demand for energy, then evidenced by the increase in oil prices, through its potential to substitute for oil in a future constrained from using oil. Because of these complex and fluctuating perceptions of, and actual, interconnection between fuel types, a metric that articulates the benefits associated with diversification, will prove challenging to construct.

4.2 The role of spare capacity in resilience

As a metric of resilience, spare capacity, as calculated here, 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 generators. An examination of the spare capacity of these systems during the crises produces a narrative of how spare capacity within all fuel systems influenced electricity prices.

1973-82

When the embargo of oil started in October 1973, the Texas Railroad Commission had recently removed all restrictions on US oil production eliminating adaptive capacity [30]. 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 [31] which reduced spare capacity. Residential and small business consumers were given priority access to NG forcing generators onto alternative fuels [32]. The Energy Supply and Environmental Coordination Act [33] and the Powerplant and Industrial Fuel Use Act [23], forced states that had traditionally relied on in-state low-cost 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 [34]. 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 [35] after the Nixon Wage-Price controls expired in April 1974 [30] as shown in Figure 3. Analysts claimed that the age of cheap energy was over [36]. A lack of transport capacity limited non-Appalachian producers from resolving the perceived supply-demand imbalance. Although production from the Great Plains region 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.

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

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.

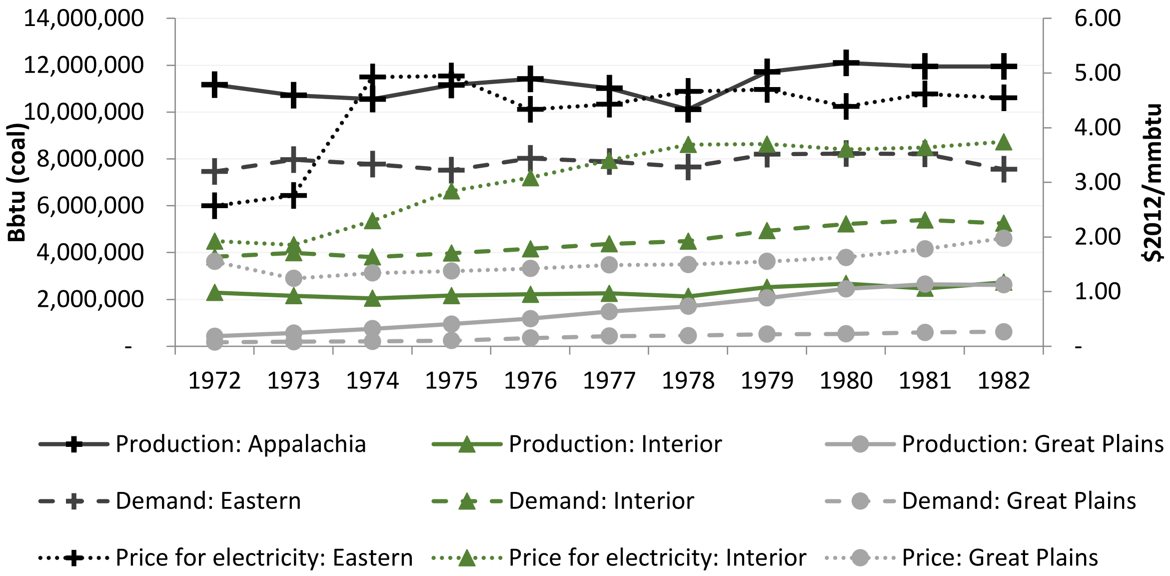

Figure 3: Coal system regional responses 1972-1982

From 2000, NG prices for electricity generation started rising reflecting declining US NG production levels. By 2008 NG price had more than doubled from 2002. As with tight shale oil, technology provided 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 large amounts of spare capacity.

Coal prices increased gradually over 2003-12 and ended 92% higher in 2012 over 2002. The reduced 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. More likely, it was the result of competition from cheaper NG. Figures 4 and 5 show the fuel prices for electricity generation between the 2 different periods.

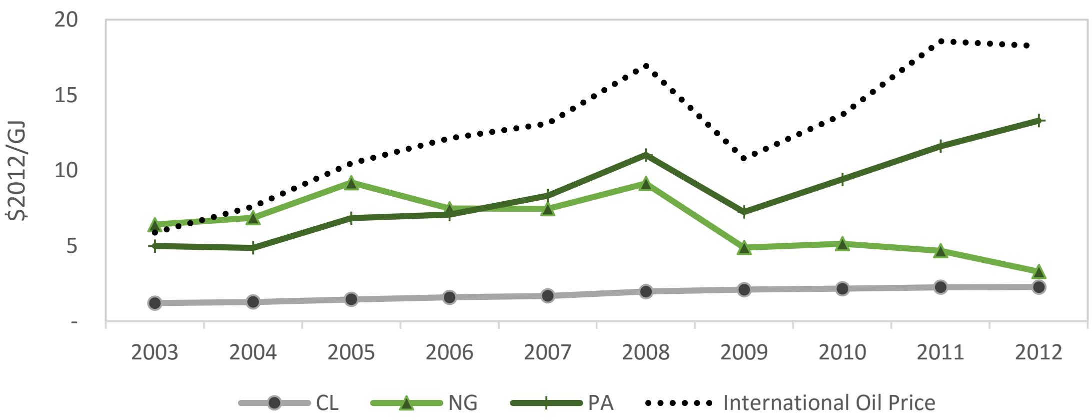

Figure 4: Fuel prices for electricity generation: 2003-12

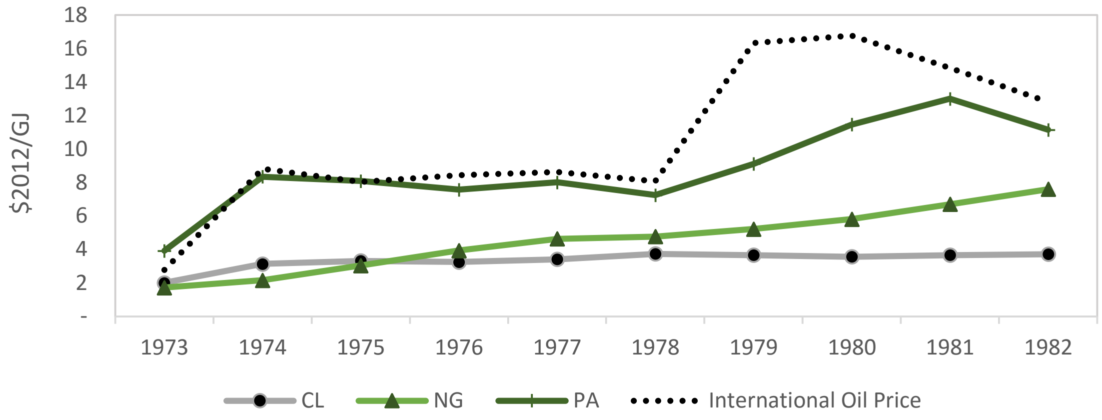

Figure 5: Fuel prices for electricity generation: 1973-82

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 from 2009-12.

The metric for spare capacity in the generation fleet provides evidence of improved resilience from spare capacity. However due to the interconnected nature of the energy systems, spare capacity in each of the fuel systems and the fuel transport networks also play a role in electricity resilience. A comprehensive understanding of the role of spare capacity in electricity generation resilience requires the inclusion of metrics for the fuel systems' and fuel networks' spare capacity. This has not been pursued here due to a lack of adequate data.

As metrics for energy resilience are dominated by diversity calculations [2, 3, 10], the finding here that the metric for spare capacity is more significant than the metric for diversity is important. It reflects what other disciplines have suggested namely that diversity and spare capacity should jointly be considered to be the characteristics of resilience [37].

4.3 The role of structure in resilience

Whilst the disaggregated metric for structure, the percentage of generation from each fuel type, serves as good predictor of price, the metrics for imports (both fuel and electricity) that are also intended to measure structure, do not provide statistically significant evidence of price benefits. Interconnected fuel markets and electricity generators make it unlikely that imports will provide information about resilience. Hawaii's electricity price reflects the consequences of an isolated system. It is therefore not surprising that fuel and electricity price are influenced by their fuel systems more than by state borders which dictate their level of imports.

The nature of the metrics for structure, percentage of generation from each fuel type, may be acting in concert to predict benefits from diversity. Reliance on generation from specific fuels is in turn reliant on the structure of the fuel systems that supply generators. This suggests that diversity and spare capacity are, in effect, the metrics of structure. But how does that relate to the concept of efficiency or organisational structure in adaptive capacity?

In line with the perception that structure is important for resilience, the analysis conducted above sought to find a relationship between the proxy for structure, efficiency in resource use, and improved price outcomes. However, in considering the research into the benefits associated with Small World Networks, it is the speed with which the communication or pulse is able to negotiate the structure that is important, rather than the structure per se. Thus, the focus on efficiency in energy use may be inconsistent with the concept that the efficiency with which the energy system is able to respond to the change is the important predictor of adaptive capacity.

The most effective mechanism for energy systems to respond to change is the price. Sharp increases in price due to supply constraints reduce demand and allow for a dynamic adjustment to the disruption in supply. If the price mechanism responds only slowly to supply constraints, it is inefficient in its ability to transmit information to consumers about the supply constraint and does not facilitate adaptation. Prices in energy systems in the 1970s were established through a combination of bilateral agreements between producing countries/states/companies and consuming countries/states/companies as well as some form of regulatory tariff setting. Under these structures, price adjustments were slow, which meant that the efficiency with which the systems were able to adapt to change was impaired. Nowhere is this more evident than in pricing electricity generation. Because of the nature of electricity price setting, the electricity price for industry across all states adjusted slowly to input price variations, severely restricting generators from adapting to the changed fuel costs. Whilst the proxy for structure used here, the proportions of generation from each fuel source, provided valuable information with respect to the influence of each fuel type on in-state price, it provided little information about the efficiency with which information was transmitted to consumers about the need to adapt.

The inclusion of electricity price as the dependent variable, in this analysis as the proxy measure of resilience, accurately reflects its importance in showing the ability of the underlying fleet structure to respond to change. The fact that electricity price in most states was at elevated levels across the whole period 1973-82 demonstrated the lack of resilience in both the generation fleet and the supplying fuel systems. The time needed for electricity tariffs to signal to consumers that adaptation was required meant that the system was constrained from adapting. This was the case for all electricity generation across all states in the period 1973-82. Whilst wholesale electricity prices are now established in a wholesale market in many states, end user prices are still mostly negotiated based on annual price setting arrangements. This means that electricity systems today continue to reduce adaptive capacity by inefficient tariff setting mechanisms.

5 Conclusions

The interconnection between fuel systems throughout the US affects the ability of the state based electricity generators to respond to energy shocks. Each fuel system represents a complex interconnection of structural variables, with the price that emerges from each system reflecting its dynamic nature. Where imbalances in supply or demand occur, price adjusts to reduce the pressure of the imbalance. If substitution is possible, substitute fuel systems supply into the constrained system to reduce pressure. This increases 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 shifts to another, more responsive, substitute system. In 1973-82, policy actions taken to secure energy supply, eliminated NG system response to the imbalance in the oil market. This shifted fuel supply imbalances to the coal industry and from there spread price increases to electricity. The energy policy interventions which sought to control inflation and improve energy security shifted the contagion to all fuel systems. 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 stimulated technological advances which increased spare capacity and reduced prices.

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, supply-demand imbalances and price volatility. Although spare capacity in fuel is crucial to defend against 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 energy prices in the 1970s, whilst fuel transport networks in the 2000s facilitated the flow of fuels from areas with capacity to areas of structural imbalance, averting general energy price rises.

Whilst the metric used to represent diversity provides little evidence of any benefits, analysis of fuel generation proportions indicates that fleets using fuels more independent of oil price lowers price, counteracting energy price contagion. This is particularly noticeable with hydro-electricity. Geography has limited development of hydro-electricity, and until recently technological immaturity and cost has limited the use of other renewable fuels for electricity. Maturity of renewable technologies provides the opportunity for further diversification, if coupled with storage to enhance spare capacity. Shifting to fuels independent of carbon constraints will lessen the potential for contagion to electricity generators from costs associated with CO_2 emissions.

This study provides empirical evidence for the inclusion of spare capacity and structure, as a proxy for diversification, as metrics of resilience but it remains a first step on the path to providing quantifiable evidence for metrics of energy resilience.

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

[ii] Dummy variables were included for the major Independent System Operators to assess the possibility for spatial correlation between states which share power pools. In both periods, the dummy variables for all except the New England ISO (NEISO) show no evidence of significance. The NEISO shows a small positive, statistically significant coefficient for both periods, indicating some clustering of prices. Whilst the coefficients for the other statistically significant variables adjusted slightly to accommodate the inclusion of the dummy variable for NEISO, there was little change to the model and results.

[iii] Where prior period price was included in the models, the absolute fit improved but the size and number of the statistically significant coefficients decreased suggesting that prior period price masks the relationship between price and resilience metrics. In the study, the disaggregated resilience metrics were considered to adequately identify the dynamics of electricity generation structure.

[iv] Maximum generation capacity is defined as maximum percentage possible from fuel/technology after consideration of maintenance requirements. Maximum percentage possible from PA, NG and CL is 85% and NU is 90%. HY is calculated to be the maximum percentage generated over prior 10 years. Other renewables are assumed to be operating at maximum due to low marginal cost.

[v] 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 ([24] Taylor Y. Historic Data. In: Molyneaux L, editor.: EIA; 2014.). 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:

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

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

[vi] The alternative measures for diversity (Table 2) showed no improved relationship with price. Portfolio price risk explained 29% of the variation in price across the states. The coefficient for portfolio risk was statistically significant but economically insignificant at 0.006228. In addition, when portfolio risk was included with other resilience metrics in multiple regression, hypothesis tests on the coefficient indicated a high probability that the coefficient is not significant.

[vii] In this period, electricity prices in Hawaii were more than 3 standard deviations higher than the rest of the country. Hawaii is therefore excluded as an outlier.

[viii] There is some relationship between *sparecap_gdp* and the intercept, with a VIF of 4.1 for *sparecap_gdp,* indicating collinearity. The condition number of 9.1, however, points to acceptable levels of collinearity. Alternative diversity metrics provided no greater explanation of change in price. Portfolio price risk explained 7% of the variation in price. The coefficient for portfolio risk was statistically significant but economically insignificant at 0.002741.