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Oil vulnerability of Australian capital cities: A pilot study using Data Envelopment Analysis (DEA) for vulnerability benchmarking

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Abstract

Skyrocketing oil prices in the mid-2000s have prompted increased academic and policy attention on oil vulnerability. Concerns remain about the continued use of oil due to energy, security and environmental grounds. High per-capita transport energy use remains an issue. Urban transport has been seen as highly oil vulnerable due to urban forms that promote automobile dependence. Due to reduced refinery capacity, risks in main oil supply chains are increasing, suggesting oil vulnerability remains an important research area for transport. Recent studies in Australia have been focused on mapping intra-urban household oil vulnerability by car ownership using journey-to-work data. Yet few studies have looked at the overall fuel use of transport at the metropolitan level. Datasets used in this paper include census, household energy consumption surveys and energy datasets. This paper aims to develop a new methodological framework which integrates a wider range of urban transport data, including average household fuel expenditure at the city level. The intent is to help facilitate policy transfer between cities and to identify best practices to help improve energy efficiency and sustainability in urban transport. The new approach involves the adaptation of data envelopment analysis (DEA) to benchmark the 'efficiency' of cities in causing oil-related impacts and also the resilience thanks to less oil intensive modes (public and active transport). The results show the differences across the largest cities in Australia, with particular vulnerabilities are affected by local conditions of fuel price, socio-economic condition and the usage of sustainable modes. This framework should assist in showing the different levels of oil vulnerability of Australian capital cities. The DEA method has the potential to be expanded to consider more variables and/or applied to a wider set of global cities for comparative purposes.

Keywords: *oil vulnerability, oil resilience, DEA, benchmarking*

1. Background and Introduction

Despite recent decreases in oil prices due to global overproduction and the economic slowdown, cities with high car ownership and car usage should remain vigilant in preventing the potential impacts of sudden oil supply shortfall and oil price increases. Currently, Australia has modest (but declining) domestic crude oil production, alongside plentiful reserves of other energy resources ranging from coal, gas, uranium, solar and wind. However, these are unlikely to help address the 'liquid-fuel problem' in the short-term as the majority of the automobile fleet remains petroleum based. Australia still imports up to 80% of crude oil and about half of its refined petroleum products to meet its liquid fuel demand (Australian Commonwealth Government, Department of Industry and Science, 2015). Figure 1 describes Australia's petroleum energy flows in 2012-13. Most of the petroleum demand in

Australia is used in transport. This makes Australia's transport system highly vulnerable to global oil supply chain disruptions, with the nation exposed to geopolitical, natural disaster and price volatility threats. Recent closures of domestic refineries are leading to higher dependence on imported refined oil products. As Australia has no mandated government strategic liquid fuel stockholding requirement and with limited retail fuel stockholdings, oil supply shortfalls may cause wide ranging effects. Oil fuels are not only used for passenger transport, but also for distribution of vital supplies such as food and pharmaceutical products to end-users (Blackburn, 2013).

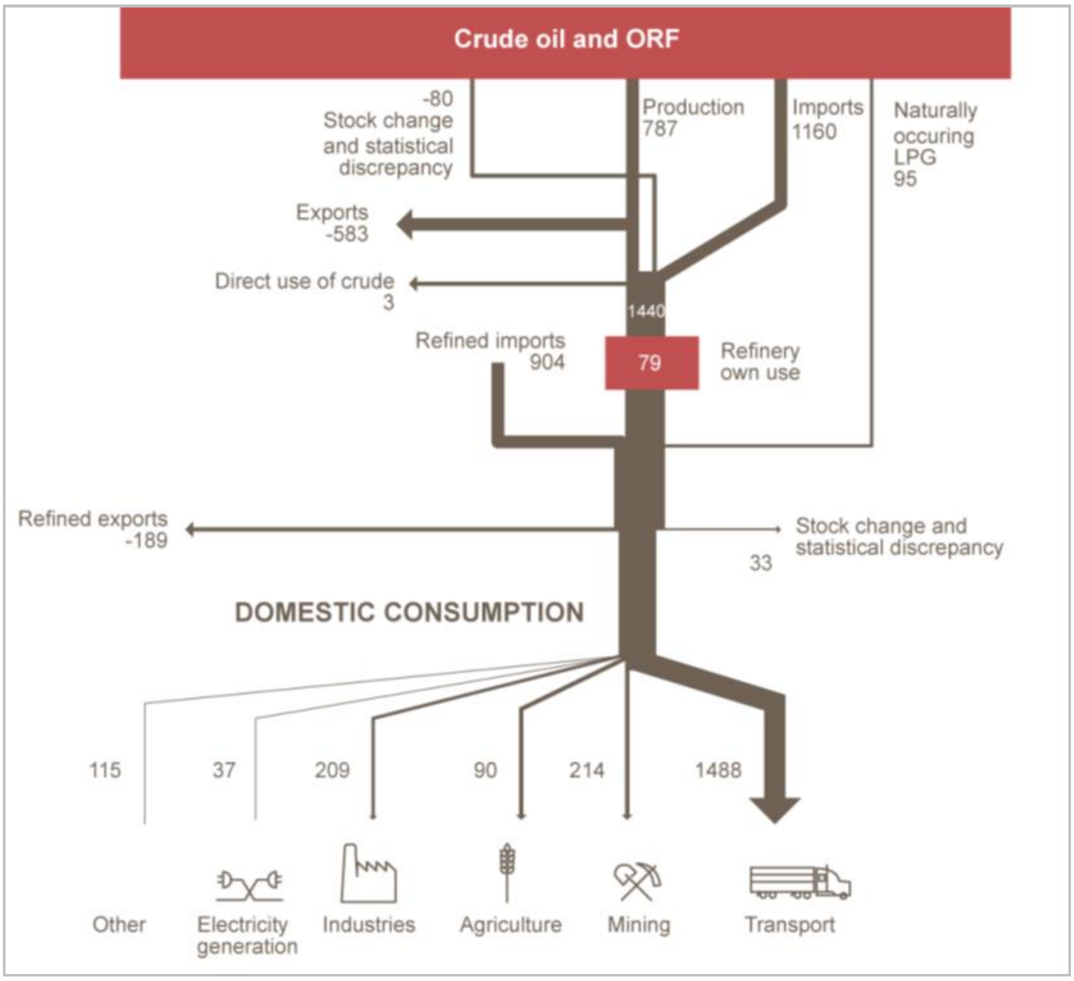

Figure 1: Australia's oil flows (in petajoules), 2012–13
(Bureau of Resources and Energy Economics, 2014)

During the period of the historically higher levels of oil prices in 2008 and 2011-2014, concern about 'Peak Oil' and higher fuel costs have sparked debate and attention in Australasian transport policy and research. Higher oil prices have also been a social issue that has attracted widespread attention due to increased fuel expenditure to households. The notion of transport disadvantage has been raised, concerning the lack of transport options at outer or impoverished suburbs or districts of a city due to the impacts of increased fuel price. Research are drawing connections between transport disadvantage and fuel prices, for example, fuel price increases are likely to cause greater impact on those who are forced to drive more due to lack of transport alternatives and with less financial resources (Currie et al., 2010; Dodson et al., 2004; Murray et al., 1998). The term 'oil vulnerability' emerged after a method was developed to use census variables to map small areas of census tracts within a city (Dodson and Sipe, 2007, 2008) (the Vulnerability Assessment for Mortgage, Petrol and Inflation Risks and Expenditure (VAMPIRE) approach). This method remained popular in assessing oil vulnerability due to relative ease and availability of data. It has been adapted by a number of other researchers, within and outside Australasian jurisdictions, showing oil vulnerability mapping results for Melbourne (Fishman and Brennan, 2009), South-East Queensland (Leung et al., 2015), New Zealand (Smith et al., 2012) and North American cities (Akbari and Habib, 2014; Sipe and Dodson, 2013). Oil vulnerability, however, is not the only concept used to denote energy-related transport stress. While the term varies in the European context, with similar terms such as terms such as ‘transport poverty’ (Lucas, 2012) from the UK, ‘energy precarity (*précarité énergétique*)’ from France and ‘energy poverty (*energiearmut*)’ from Germany. Mattioli (2014, 2015) suggests a more compassing term of ‘energy-related economic stress’ instead. Such diversity of terms shows the concern of urban scholars on social disadvantage related to transport, urban form and energy price increases or uncertainty.

In this paper, we use the term ‘oil vulnerability’ as it is the more widely used in the Australasian region to describe energy-related economic stress in transport. In terms of methodology, European researchers have been able to assess the actual energy costs of households due to detailed data collected from statistical authorities in both household travel and energy surveys (Mayer et al., 2014; Motte-Baumvol et al., 2009). Australasian researchers often resort to using proxy variables from the census to depict fuel expenditure, such as car ownership, the mode of journey-to-work (JTW) and commuting distance. Yet detailed investigation on vehicle fuel-efficiency and socio-spatial dimension has also been explored by matching motor vehicle registration data and the Commonwealth Government’s “Green Vehicle Guide” (Li et al., 2015). While this can give reasonable estimates of essential fuel use, the actual fuel cost of motor vehicles for non-work commuting remains inadequately represented. Another issue of oil vulnerability research is the limited focus of geographical extent. Most studies look at a particular city alone, such as the VAMPIRE-inspired studies. Limited work has been done to meaningfully compare the situation of oil vulnerability across different cities. This is possibly due to the difficulty to establish comparable datasets as the typical census data based methods are only internally comparing smaller areas within the same city. To address these research gaps, this research intends to ‘stocktake’ all the available data in Australia and propose to use the city-region as a unit of analysis.

The paper is structured as follows: Section 2 outlines the data available for researchers to conduct transport and energy-expenditure stress research at a city-wide level. Section 3 proposes and reviews the use of data envelope analysis (DEA) as a method to measure vulnerability in other fields, such as hazards and disaster reduction. Section 4 describes the methodology of DEA in measuring oil vulnerability and resilience. Section 5 shows the results and discusses the findings and limitations. Section 6 concludes the paper and outlines some limitations and the possible future research directions.

2. Oil Vulnerability and Energy Transition in Urban Transport of Australian capital cities

Capital city areas are defined by the Australian Bureau of Statistics (ABS) (2010) as the Greater Capital City Statistical Area (GCCSA) classification. The advantage of this is the areas defined for capital cities provide a larger range of available data, including fuel expenditure and price, a variable that has been neglected. The GCCSA area allows a wider range of oil vulnerability variables to be used. It is also possible to aggregate smaller spatial scales to fit in the ABS-defined GCCSA structure. Table 1 lists the data source of the variables used in this paper. The majority of the data used in this study is obtained from the ABS. The *Energy Consumption Survey* data provides fuel expenditure data of each capital that has not been explored in previous oil vulnerability research. Due to privacy and confidentiality concerns, ABS has not been providing this dataset with a geographic scale smaller than the GCCSA. Unless using micro-simulation techniques, as demonstrated by Lovelace and Philips (2014), it would not be possible to estimate fuel expenditure in

Australia at sub-city level in the meantime. It should be noted that State governments have conducted household travel surveys for capital cities. While comparing Australia's diverse household travel surveys may produce a more accurate mode share or fuel use estimation, especially including non-work related trips, the issue of inconsistent methodologies and survey timing would cause some problems for inter-city comparison. The ABS's motor vehicle registration data and the roof-top photovoltaic (PV) installation data are at postcode level which can be aggregated into GCCSA geography. As postcodes are not ABS maintained geographies, some boundaries do not provide an exact fit. For the borders of postcodes that are inconsistent with GCCSA, the differences were approximated by the proportion of area size. Most of the inconsistent areas are located on the outer fringes of GCCSA and the data losses caused by approximation are expected to be small. In addition to conventional governmental datasets, the electrical vehicle (EV) charging point counts are obtained by crowd-sourced information from an online application PlugShare™ that allows users to share the location charging points (Recargo, Inc., 2016).

Using the oil vulnerability conceptual framework proposed by Leung et al. (2015), these variables are classified according to three oil vulnerability components namely exposure, sensitivity and adaptive capacity. The full list of variables is provided in Table 2 for an overall view of the Australian capital cities of all states except the Northern Territory. Darwin is not included because of its small population and being similar to Canberra as a city with a disproportionately larger public service sector and also with higher incomes, social advantage levels and also automobile use. For population density, we used the data of a more recent concept - population-weighted density (PWD), which is measured by aggregating smaller blocks in a city instead of a gross divided population to the total area. The PWD shown in here is obtained from Loader (2013) based on ABS kilometre population grids from the 2011 census. It should be noted the GCCSA often includes a larger area beyond prevailing urban administrative boundaries of Australian capital cities. Therefore, the PWD deemed to be more accurate and appropriate.

A brief observation of the data is provided in the following section based on the oil vulnerability components.

Exposure

Exposure refers to what extent energy-related factors that are able to affect the population of a city. Car ownership, usage and fuel price data are listed in this section. For car ownership, generally the larger the PWD, the lower the car ownership and passenger VKT, which is generally consistent with Newman & Kenworthy et al's (1989; 1999) global observation of cities that lower population density is correlated with higher car VKT per capita. This is not the case for Adelaide which has modest PWD (18.2 persons by km^2) with lowest VKT per capita. This shows higher PWD does not necessarily resulting in less car use. Urban size also shows mixed correlation with VKT per capita. Adelaide and Hobart both are observed with the lowest passenger VKT per capita in Australian cities, while Canberra with similar size, has the highest VKT per capita. Such high VKT in Canberra is possibly due to better socio-economic standing. In contrast, Adelaide and Hobart are relatively disadvantaged due to their weaker economic performance and a higher incidence of older or populations that 'require assistance for core activity' (an indicator of disability), which is a sensitivity variable that is explained in the following section. Another issue that affects oil vulnerability is the variation in fuel prices between the capital cities. Adelaide (141.77 cents per litre (cpl)) and Sydney (142.82cpl) being the lowest while Canberra (146.95cpl) and Brisbane (146.68cpl) being the most expensive. Further work to investigate this disparity of fuel prices might be able to help to understand the underlying factors of oil vulnerability. For the journey-to-work mode share, Adelaide appears to be the city with highest private-owned LOV mode share, followed by Hobart and Canberra. This relates to public transport usage or active travel, which will be covered in the Adaptive Capacity section.

Sensitivity

Sensitivity represents the degree cities are affected by both energy and non-energy drivers. It is often measured by social variables, such as income or socio-economic wellbeing. Canberra has the highest average weekly household disposable income, followed by Sydney, Melbourne and Perth; Hobart has the lowest. Conversely for social disadvantage indicators, it is largely opposite with subtle differences for the rankings in between. Hobart and Adelaide are the most socio-economically disadvantaged capital cities. Yet the level of socio-economic wellbeing alone could not provide an estimate of the potential impact of oil price increase. These sensitivity indicators need to work with other oil vulnerability components in order to estimate oil vulnerability.

Adaptive Capacity

Adaptive capacity represents the ability to adapt to change in a way that makes it better equipped to manage its future exposure and/or sensitivity to oil price influences. The mode share of journey to work by HOV, which is predominately public transport, and activity are compared across the capital cities. Sydney has the highest public transport mode share to work, followed by Melbourne and then Brisbane while Hobart and Canberra are the lowest. This measure is also consistent with the share of public transport VKT. Yet, public transport usage rates do not necessarily show the maximum capacity of the urban transport system in an event of a sudden oil supply shortfall, causing fuel price hikes and a possible upsurge of public transport use (Stone and Mees, 2010). Hence, the consideration that active transport (cycle or walk) is important. Conversely, Hobart and Canberra have a significantly higher share of active mode shares to work. This is probably due to their smaller urban footprint, with shorter commuting distance which makes walking and cycling to work more feasible. Working at home is also tabled for analysis and it should be read in conjunction with the percentage of dwellings having broadband internet connection. It appears despite having the highest penetration of broadband at home, Canberra has the lowest work at home share compared to other capitals. Brisbane has the highest work at home percentage and ranks the second in broadband penetration at home. Still, the relationship between working at home and information communication technology (ICT) remain unclear. This could be related to the nature of jobs as Canberra having very high public sector employment which may not encourage working at home. Moreover, cities with higher time and/or monetary costs of commuting may make working at home more attractive. Despite growing academic attention (Aguiléra et al., 2012; Alizadeh, 2012), further study on working at home and its relation with information communication technology (ICT) is needed to uncover the reasons behind this.

A fresh and comprehensive look at electric vehicles (EV) in Australian capital cities is offered in Table 2. It shows Canberra is having extraordinarily high levels of EVs ownership (4.16 per 1000 persons) while other cities were still under 1 per 1000 persons and with Brisbane being the worst performer (0.06 per 1000 persons). EV ownership does not appear to correlate with the availability of charging points. Perth has the highest EV charging point provision (30.6 per 1 million persons, 56 charging points within the Perth GCCSA area) with initiatives of charger provision by the motoring association and universities since 2012 (Speidel et al., 2012). Yet the EV ownership of Perth in 2015 remains modest (0.29 per 1000 persons). As EV vehicles are still a novelty and are significantly more expensive, perhaps only those with higher incomes can afford them. It should also be noted that Canberra's EV registration number could be boosted by government-owned cars as the Australian Capital Territory (ACT) Government initiated a policy to reduce carbon emissions by acquiring EVs in their fleet (ACT Department of Environment and Sustainable Development, 2012). While EV ownership may not have immediate oil reduction implications, another aspect that might affect electric vehicle uptake is the proliferation of residential photovoltaic solar panels. EVs has been seen as a potential form of electricity storage for solar panels as both could complement each other (Adepetu and Keshav, 2015; CSIRO, 2013). Solar panel registration data from the Australian Government clean energy regulator, the Australian Renewable Energy Agency (AREA) shows Brisbane and Adelaide have the highest uptake of rooftop panels in terms of both dwelling density and capacity. Brisbane's high uptake could be associated with long sun availability; Adelaide has benefited by South Australian government's favourable feed-in tariffs being able to outset of costs of installation. This inter-city comparison offers some insights on the performance of energy transition in Australian capitals. It seems residential solar panel uptake patterns not relate well with EV registration at this moment. As solar panels are still relatively new in Australia, further research in this area would be needed as the beneficial synergetic effect with EVs are currently not well understood (Cao et al., 2015). Due to small uptake numbers at the moment, the impact of EVs and solar panels to reduce oil vulnerability, both numbers are not considered in the subsequent section in which a more detailed estimation of oil vulnerability of Australian capitals. In fact, only small number of the variables listed above could be selected for further analysis by a mathematical modelling tool - DEA.

Table 1: Data source for variables used

<table>
<tr><th>Provider</th><th>Data Source</th><th>Variable</th><th>Remarks/Reference</th></tr>
<tr><td rowspan="6">Australian Bureau of Statistics (ABS)</td><td rowspan="5">Census 2011</td><td>Usual Resident Population (persons)</td><td></td></tr>
<tr><td>Population-Weighted Density (persons/km)</td><td>Figures from Loader (2013), based on ABS's (2014) Population Grid data</td></tr>
<tr><td>Mode Share to Work
- LOV (Low Occupancy Vehicles)
- Public Transport modes
- Non-Motorised (Walking or cycling)
- Work at home</td><td></td></tr>
<tr><td>Disability (Core assistant needed for activities)</td><td></td></tr>
<tr><td>Motor vehicle numbers in each dwelling</td><td></td></tr>
<tr><td>Socio-Economic Indexes for Areas (SEIFA) (Derived from Census 2011 data)</td><td>Index of Relative Socio-economic Advantage and Disadvantage (IRSAD)</td><td>The Decile 1 (Most disadvantaged) is used</td></tr>
<tr><td rowspan="2">Australian Bureau of Statistics (ABS)</td><td>Motor Vehicle Survey 2014</td><td>Vehicles registered by fuel type
- Petrol
- Diesel
- Dual-fuel (LPG)
- Electric
- Other</td><td>Postcode-level data aggregated into GCCSA</td></tr>
<tr><td>Energy Consumption Survey 2012</td><td>Total and Disposable Household Income and Fuel Expenditure</td><td>Weekly</td></tr>
</table>

Table 1: Data Source for Variables (Continued)

Provider	Data Source	Variable	Remarks/Reference
Bureau of Infrastructure, Transport and Regional Economics (BITRE)	Traffic and congestion cost trends for Australian capital cities (IS-074)	VKT of different modes	
Australian Institute of Petroleum (AIP)	Weekly Price Update 2011-2012	Metropolitan Average Retail Fuel Price	6 weekly average sample points approx. every 2-months to reduce fluctuation effects
Compiled by the Australian Photovoltaic Institute (APVI) Original data from the Australian Renewable Energy Agency (AREA)	Photovoltaic (PV) Installations Mapping data 2016 March	PV installation density and capacity	Postcode-level data aggregated into GCCSA
Plugshare.com	Crowd-sourced data, 2016 May	Locations and counts for EV charging points	

Table 2: Descriptive statistics and oil vulnerability data of Australian capital cities, [ ] brackets denote ranking, 1 is highest and 7 for the smallest

	Sydney	Melbourne	Brisbane	Adelaide	Perth	Hobart	Canberra
Usual Resident Population (persons)	4,391,674 [1]	3,999,981 [2]	2,065,998 [3]	1,225,235 [5]	1,728,865 [4]	211,656 [7]	356,586 [6]
Population-Weighted Density (persons/km)	34.40 [1]	24.90 [2]	18.10 [4]	18.20 [3]	17.60 [5]	12.00 [7]	15.70 [6]
Exposure							
Registered Vehicles per capita (per 1000 persons)	692.16 [7]	806.08 [5]	844.58 [3]	902.75 [2]	920.66 [1]	792.34 [6]	833.81 [4]
Dwellings with more than 2 vehicles (%)	41.23 [1]	46.43 [4]	48.44 [3]	45.14 [6]	50.37 [1]	44.75 [7]	49.41 [2]
Proportion of method to work is only by private low occupancy vehicles only (LOVs) (%)*	67.04 [7]	74.64 [6]	75.42 [5]	81.34 [1]	78.50 [4]	81.19 [2]	80.92 [3]
Total annual VKT of private vehicles (car and motorcycles) (billions km)	31.22 [1]	30.62 [2]	14.67 [3]	8.19 [5]	12.98 [4]	1.46 [7]	3.06 [6]
Metropolitan Average Retail Fuel Prices (cents per litre, cpl)	142.82 [6]	142.87 [5]	146.68 [3]	141.77 [7]	143.65 [4]	150.28 [1]	146.95 [2]
Mean weekly expenditure for vehicle fuel (AU$)	61.17 [5]	63.89 [2]	62.54 [4]	51.71 [7]	64.04 [1]	52.98 [6]	63.44 [3]
Sensitivity							
Average weekly disposable household income (AU$)	1,727.52 [2]	1,715.6 [3]	1,538.6 [5]	1,413.84 [6]	1,690.15 [4]	1,360.24 [7]	1,971.09 [1]
Proportion of population, core activity needs assistance (%)	4.38 [4]	4.48 [3]	4.18 [5]	5.37 [2]	3.56 [6]	5.44 [1]	3.35 [7]
Proportion of population with lowest SEIFA decile (%)	8.55 [3]	6.52 [5]	7.74 [4]	11.03 [2]	3.14 [6]	17.11 [1]	0.56 [7]

Table 2 (continued): Descriptive statistics and oil vulnerability data of Australian capital cities, [ ] brackets denote ranking, 1 is highest and 7 for the smallest

	Sydney	Melbourne	Brisbane	Adelaide	Perth	Hobart	Canberra
Adaptive Capacity							
Proportion of method to work is by at least one trip by public transport # (%)	19.47 [1]	13.09 [2]	11.68 [3]	8.38 [5]	9.49 [4]	5.69 [7]	6.80 [6]
Proportion of method to work is by active transport (%)	5.41 [3]	4.80 [4]	4.67 [5]	4.13 [6]	3.89 [7]	7.37 [2]	7.43 [1]
Proportion of work at home (%)	4.41 [2]	4.14 [3]	4.56 [1]	3.68 [6]	3.92 [5]	4.09 [4]	3.08 [7]
Proportion of dwellings with broadband connection (%)	65.62 [3]	63.87 [4]	66.94 [2]	60.40 [6]	63.62 [5]	56.96 [7]	70.48 [1]
Electric vehicle registered (per 1000 persons)	0.12 [6]	0.39 [3]	0.06 [7]	0.13 [5]	0.29 [4]	0.61 [2]	4.16 [1]
Electric vehicle charging points (per 1 million persons)	7.74 [5]	9.75 [4]	7.74 [5]	5.71 [6]	30.66 [1]	28.35 [2]	16.83 [3]
Solar panel installation density (per 100 dwellings)	8.55 [7]	10.76 [5]	28.26 [1]	25.63 [2]	22.41 [3]	10.29 [6]	11.97 [4]
Solar panel installation capacity (kW per capita)	96.00 [7]	133.15 [6]	348.58 [2]	360.63 [1]	253.81 [3]	148.06 [5]	158.25 [4]

* Private LOV refers to low occupancy vehicles including car as drivers/passengers, motorcycle, truck.

Public transport includes rail, tram/light rail, bus, ferry and taxi. Transfer using more than one mode including Private LOVs are included in this category.

3. Using Data Envelopment Analysis (DEA) to Measure Oil Vulnerability and Resilience

To address the shortcomings of previous oil vulnerability assessment in Australian research, an inter-city oil vulnerability benchmarking method is developed. In this section, the concept of DEA is briefly outlined, followed by a review of DEA methods. The DEA method was originally developed by Charnes, Cooper and Rhodes (1978) (hence is often referred to as the CCR model). DEA is a method to measure the relative efficiency of an organisation, often referred as a Decision Making Unit (DMU) in the DEA literature. The analysis method is based on a mathematical linear programming method to estimate relative efficiency based on a mathematically derived weighted ratio of outputs to inputs with the following simplified equation:

$$Efficiency = \frac{sum \quad of \quad weighted \quad outputs}{sum \quad of \quad weighted \quad inputs}$$

This can be visualised as a diagram in Figure 2, for example, the DMUs that are using the least input to produce the most output are the best amongst the peers, which can be seen as located on the ‘best practice frontier’. The CCR is also assuming the return of scale is constant.

The advantage of DEA is that it is completely ‘data-driven’ and does not require prior knowledge or assumption of the relationship between the inputs and outputs. It can also generate ‘slack’ values to predict how optimal efficiency be achieved by adjusting the combination of inputs. Therefore, DEA has been widely used in operations research, management and economic fields with evolving variations (Seiford, 1996). For transport, there is a wide range of DEA applications worldwide, including public transport (Chiou et al., 2012; Hilmola, 2011; Lan et al., 2014; Pina and Torres, 2001; Sampaio et al., 2008), ports or airport operations (Tongzon, 2001; Yoshida and Fujimoto, 2004) and even property value uplifting effects from public transport (Yen et al., 2014). There are also innovative uses of adapting DEA to measure undesirable outputs such as pollution or CO_2 emissions (Daraio et al., 2016; Ha et al., 2011; Lin et al., 2015; Song et al., 2015). This demonstrates DEA is highly adaptive to different situations, a strength as it offers a wide range of variants available for researchers (Chen, 2004; Cook and Seiford, 2009).

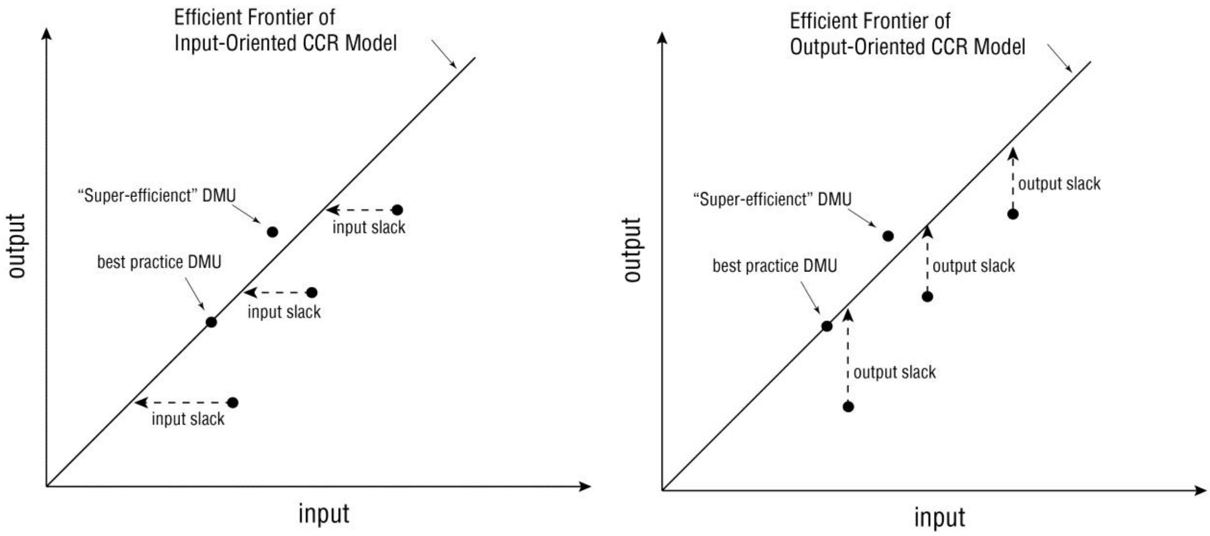

Figure 2: The basic concept of DEA and the CCR input and output oriented models

In the field of vulnerability research, vulnerability indices were typically based on mean-adjusted ranking, or expert-adjusted weights to determine vulnerability scores as a reference measure of the level, or the risk of a potential impact (Cutter et al., 2008; Dwyer et al., 2004; Esty et al., 2005). However, it is often difficult to ascertain the weights to be given on the indices. To address this, there is a growing trend to treat 'vulnerability' as the 'efficiency of baseline factors in causing damage' in hazards reduction and vulnerability literature. Whereas the exposure to impacts or background levels can be seen as inputs and the resultant damage or loss as outputs. A societal system, such as a city, can be seen as a DMU. The types of hazards or disasters used this way to assess vulnerability include floods (Rygel et al., 2006; Wei et al., 2004), droughts (Yuan et al., 2015), exposure to pollutants (Ratick and Osleeb, 2013) and war (Benini, 2015). Conversely, DMUs with higher levels of resilience or adaptive capacity could reduce the propensity of loss from hazards or negative effects can be assessed by DEA. Examples of DEA-based resilience studies such as coastal hazards resilience at country level (Zou and Wei, 2009) and earthquake resilience (Üstün, 2016). This paper incorporate both vulnerable and resilience analysis by DEA benchmarking. The following section describes the methodology used in this study.

4. Methodology

This study attempts to adapt DEA approaches from the hazards or vulnerability literature to urban transport oil vulnerability assessment. Two DEA models are used in this paper to measure oil vulnerability and resilience, respectively, as illustrated in Figure 3. The first DEA model (OV-DEA) measures oil vulnerability, which includes city-wide and household exposure and sensitivity components. The capital city area population and mean weekly household income are seen as inputs, whereas VKT and fuel expenditure are treated as outputs. A more vulnerable city is more ‘efficient’ in having fewer inputs (population and income) to produce more outputs (total VKT of private vehicles and fuel expenditure). The second DEA model (OR-DEA) takes account of resilience to oil price increases. The input is a combined measure of household fuel stress, calculated by the percentage of weekly household fuel expenditure to weekly household income. The output is the mode share of less oil-intensive modes, including public and active transport. This measures how efficient a city adapting to fuel stress by not driving.

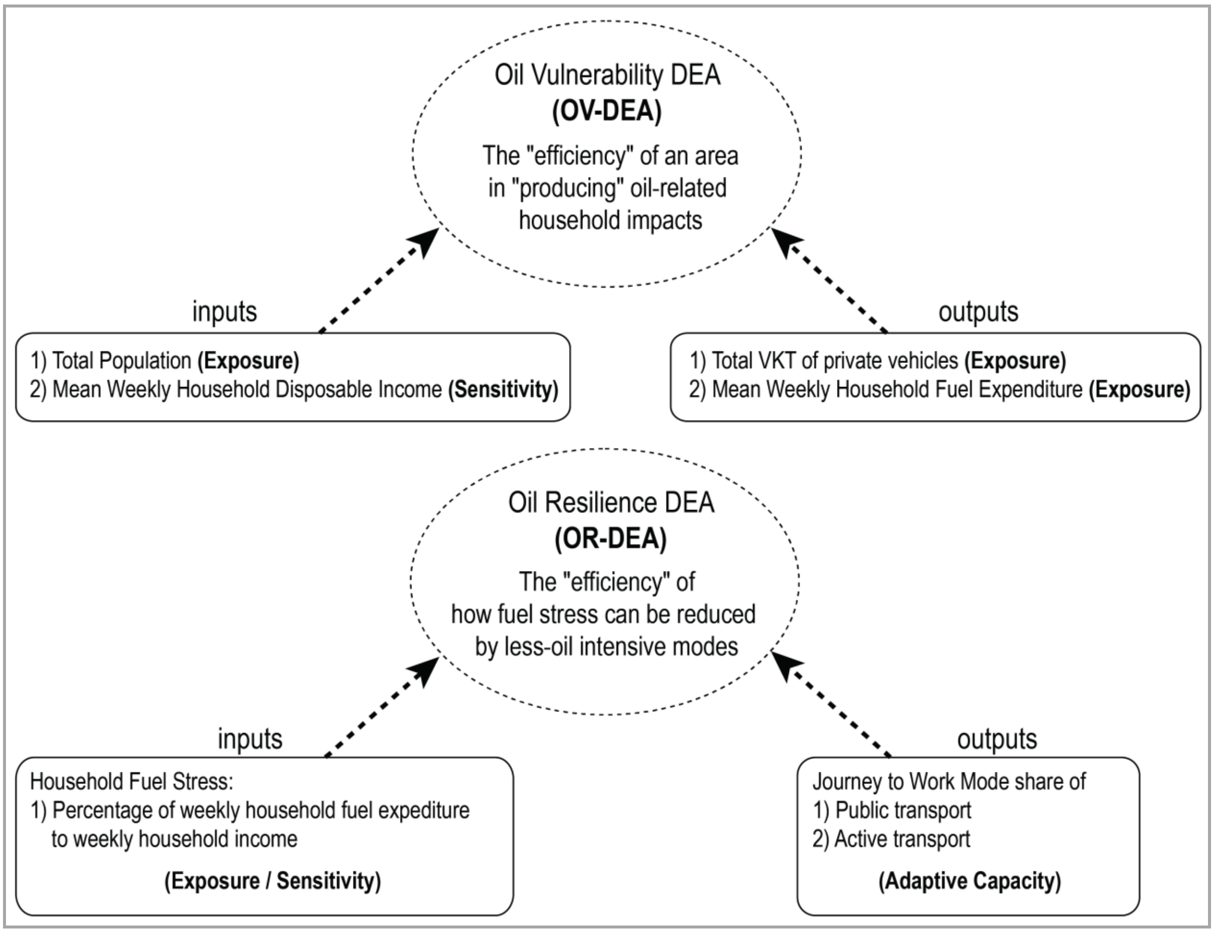

Figure 3: Conceptual DEA model for assessing oil vulnerability and resilience in urban transport

This research appears to be the first in using DEA method to evaluate oil vulnerability and resilience. The proposed DEA structure progresses from previous oil vulnerability assessments (e.g.: the VAMPIRE approach) that used subjective ranking method (i.e.: equal weighting for all variables). The proposed DEA models incorporate not only exposure components, also sensitivity and adaptive capacity. This is an advancement to prevailing oil vulnerability methods, as it considers household fuel expenditure and adaptive capacity at city level. The classical input-oriented CCR DEA model is applied for the OV-DEA. The mathematical equation is as follows:

[CCR-I] $$Min\ \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$\text{s.t. } \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_o x_{io} \quad i = 1,2\cdots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \quad r = 1,2 \cdots, s$$

$$\lambda_j \geq 0 \qquad j = 1,2,\cdots,n$$

Suppose we have a set of n DMUs. Each DMU$_j$ ($j = 1,...n$), produces s different outputs y_{rj} ($r = 1,...,s$) utilising m different inputs x_{ij} ($i = 1,...,m$). Where θ is the vulnerability score, ε is the non-Archimedean infinitesimal, x_{io} and y_{ro} refers to the i^{th} input and r^{th} output of the city; s_i^-, s_r^+ are the input and output slack value. Slack refers to which the excess input or missing output that exists after the proportional change in the input or the outputs to reach the efficiency frontier. In other words, it is the difference of input levels between the inferior performer and the best performer. The purpose of slacks analysis is to predict how optimal efficiency can be achieved by adjusting the combination of inputs. λ_j refers to the weight given to the DMU$_j$ in an effort to 'outperform' DMU$_o$. This weight is used to determine the relative efficiency based on the inputs and outputs values. The classical CCR model limits the efficiency value to be under 1 (or 100%). Likewise, the output-oriented model can be formulated for the OR-DEA as follows:

[CCR-O] $$Max\ \theta + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

s.t. $$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io} \quad i = 1,2 \cdots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \theta y_{ro} \quad r = 1,2 \cdots, s$$

$$\lambda_j \geq 0 \qquad j = 1,2,\cdots,n$$

This restriction can be relaxed to allow comparison of scores beyond 1 (i.e.: beyond the efficiency frontier) by the following condition:

$$s_i^-,\ s_r^+ \geq 0$$

$$\lambda_j \geq 0 \quad j \neq 0 \quad j = 1,2,\cdots,n$$

This relaxed model is known as super-efficiency model which permits more precise ranking of the DMUs while the inefficient DMUs remains the same as classical DEA model (Andersen and Petersen, 1993; Wu et al., 2014; Zhu, 2001). Table 3 shows the basic descriptive statistics of the variables used in the DEA models. Table 4 shows the correlation coefficients among input and output variables. Note that the correlation coefficients between input and output variables of the OV-DEA are positive, while the OR-DEA are negative. To test the relevance of the selected input and output variables, regression analyses are further conducted and Table 5 presents the results. The variables for OV-DEA are statistically significant, but not for OR-DEA. As the aim of this study is to use DEA to create a vulnerability and resilience index, not to identify the actual efficiency of a DMU in typical DEA studies. Hence, a negative correlation and non-significant relationship between inputs and outputs are acceptable.

Table 3: Descriptive Statistics of the inputs and outputs for the DEA models used

Variables			Minimum	Maximum	Mean	Standard Deviation
OV-DEA	Input	Population	211,656.00	43,91,674.00	1,997,142.14	1,648,084.00
		Weekly Disposable Income ($)	1360.24	1971.09	1690.15	210.02
	Output	VKT of private vehicles (billion)	1.46	31.22	14.60	12.13
		Weekly Fuel Expenditure ($)	51.71	64.04	59.97	5.31
OR-DEA	Input	Fuel Stress (%)	2.65	3.41	3.08	0.26
	Output	Public Transport Mode Share (%)	6.64	22.60	12.84	5.45
		Active Transport Mode Share (%)	3.89	7.43	5.39	1.46

Table 4: Correlation coefficients among input and output variables of the DEA models

OV-DEA

Variable	Inputs		Outputs	
	Population	Weekly Income	Total VKT of Private Vehicles	Weekly Fuel Expenditure
Population	1			
Weekly Income	0.23	1		
Total VKT of Private Vehicles	0.99	0.25	1	
Weekly Fuel Expenditure	0.44	0.80	0.47	1

OR-DEA

Variable	Input	Outputs	
	Household Fuel Stress	Public Transport (PT) Mode Share to Work	Active Transport Mode Share to Work
Household Fuel Stress	1		
PT Mode Share	-0.1	1	
Active Transport Mode Share	-0.23	-0.44	1

Table 5: Regression results for input and output variables

OV-DEA

Dependent variables	Independent variables	
	Population	Weekly Income
Total VKT of Private Vehicles	0.99 (32.75)	0.03 (0.96) R^2 =0.997
Weekly Fuel Expenditure	0.27 (0.97)	0.73 (2.61) R^2 =0.701

Table 5 (Continued): Regression results for input and output variables

OR-DEA	
Dependent variables	**Independent variables**
	Household Fuel Stress
PT Mode Share to Work	-0.10 (-0.23) R^2 =0.01
Active Transport Mode Share to Work	-0.23 (-0.52) R^2 =0.051

5. Results and Discussion

The two DEA models outlined in Section 4 are used to evaluate the city-level oil vulnerability and resilience. For a classical CCR DEA assessment, a value of 1 means it is the most 'efficient' and is located at the 'efficiency frontier'. To allow more meaningful benchmarking, the super-efficiency model is used in both models. The results of OV-DEA in measuring oil vulnerability is shown in Table 6.

Table 6: Oil Vulnerability Scores calculated from OV-DEA Model (1 is the most vulnerable; 7 the least vulnerable)

Ranking	Capital Cities	Classical CCR Oil Vulnerability (CRS)	Super-efficient Oil Vulnerability (CRS)
1	Hobart	1	1.407
2	Canberra	1	1.187
3	Melbourne	1	1.073
4	Brisbane	1	1.066
5	Sydney	1	1.013
6	Perth	0.990	0.990
7	Adelaide	0.926	0.926
	Average	0.988	1.094

The result shows most cities are quite close to the 'efficient' frontier of oil vulnerability. It can be said Hobart, Canberra, Melbourne, Brisbane and Sydney, with the oil vulnerable score of 1 in the classical CCR OV-DEA model, are the more oil vulnerable capitals. Conversely, Adelaide achieved the lowest score and it is the least oil vulnerable as it has on average the lowest fuel expenditure and VKT in relation to its population size. The results show Hobart (1.407) and Canberra (1.187) are the most oil vulnerable capitals. For the case of Hobart, this is because of high fuel prices and high private car VKT in relation to its lower income levels and smaller population. For the case of Canberra, it is attributed to very high private car VKT, despite Canberra's relatively higher income levels that can cushion the impact. Adelaide has the lowest fuel price among the capital cities, whereas Hobart and Canberra has the highest (Table 2). Fuel price in the capital cities could be an external factor explaining oil vulnerability and this could be considered in future studies. The ability to use less oil-intensive modes, such as public or active transport, are also examined in the OR-DEA model and the results are shown in Table 7.

Table 7: Oil resilience calculated from OR-DEA Model (1 is the most resilient; 7 the least resilient)

Ranking	Capital Cities	Classical CCR Oil Resilience (CRS)	Super-efficient Oil Resilience (CRS)
1	Sydney	1	1.498
2	Canberra	1	1.233
3	Hobart	0.821	0.821
4	Melbourne	0.764	0.764
5	Brisbane	0.668	0.668
6	Adelaide	0.599	0.599
7	Perth	0.598	0.598
	Average	0.788	0.883

Sydney and Canberra are seen as ‘best practice’ cities in terms of oil resilience with resilience values above 1. It could be useful if both OV-DEA and OR-DEA can be plotted together for comparing both vulnerability and resilience of the capital cities analysed. As shown in Figure 4, the mean value of the score of both DEA models is used as cut-off levels to create four quadrants. Most Australian capitals fall into the quadrant of “Less Vulnerable; Less Resilient”. For the worst case, Adelaide has the lowest OR-DEA efficiency value, which means the city is the least able to utilise public or active transport to reduce oil-related fuel cost impacts and it is also the least oil vulnerable according to the OV-DEA. Melbourne is straddling nearer the mean value of both DEA scores. Hobart is the most vulnerable and close to mean level resilience, whereas Canberra is quite vulnerable but also the most resilient. Sydney is the only city that is less vulnerable and more resilient, which means the capital will be least impacted by higher oil prices in Australia. Fortunately, no cities are falls into the quadrant of ‘More Vulnerable; Less Resilient’ which is an undesirable position. In order to understand how each can improve its efficient, Table 8 demonstrates the slack analysis from OR-DEA model. The slack analysis shows how much each city needs to improve to become more resilient (or the efficiency in using public transport or active transport in relation to fuel stress). For example, it assumes Melbourne can be as oil resilient as its closest peer, Sydney, if it can improve its active transport mode share by 31.94% (i.e., Increasing from its current active transport mode share from 4.79% to 5.41%, to reach the level of Sydney’s). The slack analysis shows except for Hobart, all other non-optimum cities could gain resilience by improving active transport mode share so as to reach the efficiency of the best performer. It should be noted the two input slack values cannot be separated to create the overall improvement. Hence for Hobart, it has to improve both the public transport and active transport as specified in Table 8 in order to be as ‘resilient’ as Canberra. Larger capital cities such as Melbourne and Brisbane had to improve from 30-40% in active transport to reach ‘best practice'. However, for Adelaide and Perth, even more drastic measures of up to 70% active transport mode share improvements are needed to reach the resilience levels of Sydney or Canberra. These sets of analysis show the importance of evaluating the oil vulnerability and resilience performance for the cities at the same time. It would facilitate the urban transport or land use policy makers to address oil vulnerability of the Australian capital cities evaluated. The proposed DEA models offer an objective and data-driven benchmark ranking method of oil vulnerability and resilience for Australian capital cities. This DEA approach could be useful for Federal level policy makers to determine the priority of public transport infrastructure of Australian cities in relation to oil vulnerability. This method can also be used in conjunction with the other intra-city mapping approaches, if a smaller level data are available.

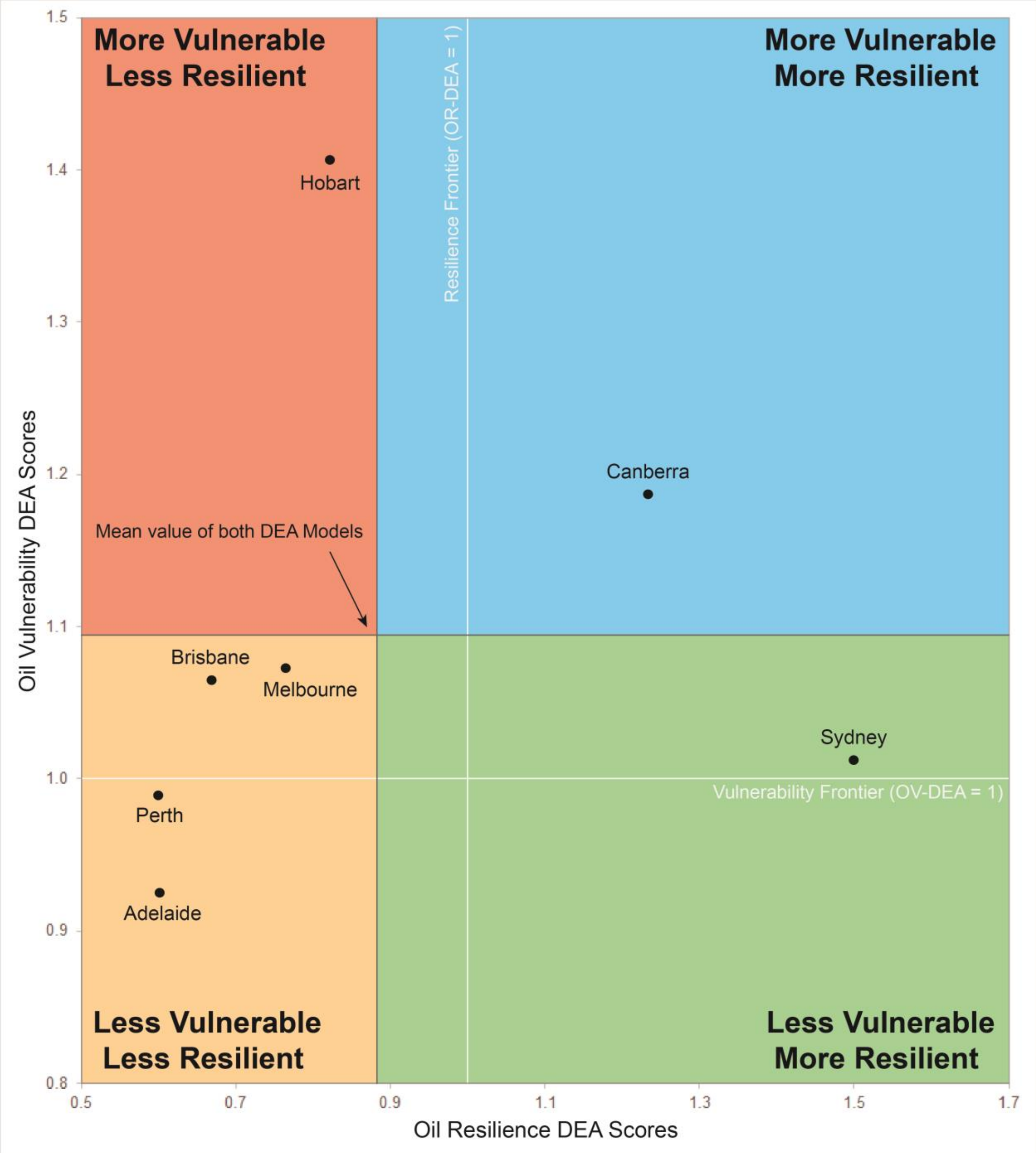

Figure 4: Cross analysis of OV-DEA and OR-DEA scores of the Australian capital cities

Table 8: Slack values (Improvements strategies) for the transport mode share of capital cities to be as good as the 'peers'

Code	Capital City	Best Practice Peers	Public Transport	Active Transport
1	**Sydney**	-	0%	0%
2	**Melbourne**	Sydney, Canberra	0%	31.94%
3	**Brisbane**	Sydney, Canberra	0%	39.07%
4	**Adelaide**	Sydney, Canberra	0%	72.55%
5	**Perth**	Sydney, Canberra	0%	75.35%
6	**Hobart**	Canberra	18.54%	0.71%
7	**Canberra**	-	0%	0%

6. Concluding Remarks and Further Research

Inter-city assessment is useful to provide insights on how cities perform in terms of oil vulnerability and transport energy sustainability. This study proposes two DEA models to measure oil vulnerability (OV-DEA) and oil resilience (OR-DEA). These models adopting a new set of data regarding oil vulnerability and energy transition looking at all major Australian capital cities. The data itself shows exposure, sensitivity and adaptive capacity differs greatly amongst the capitals. Generally speaking, larger cities appear to be better in coping with oil vulnerability due to better public transport systems and driving being less prevalent. However, as oil prices and living standards differ greatly, the actual propensity of the impact caused by higher oil prices also are mixed and complicated. By the use of DEA modelling, it is possible to consider the interplay of factors in a data-driven and objective way. Moreover, slack analysis provides further improvement strategies to understand how to be more resilient.

Further research would be needed to understand this aspect in greater detail. Many DEA studies also incorporate second stage analysis, using Tobit regression models to investigate the contribution of external factors (Chiou et al., 2012; Chiou and Chen, 2006; Hilmola, 2011; Pina and Torres, 2001). It is worthy to add more cities in the proposed DEA approach to examine model applicability. For example, cities beyond Australia in the Asia Pacific region can be included in further analysis. Aggregated city data is widely available in many urban jurisdictions. Alternatively, using sub-city scales of larger areas (e.g.: Statistical Area 4 (SA4) of ABS's census geography) with State conducted household travel survey with fuel expenditure data with DEA is also feasible if data availability permits. Using DEA in the traditional way, that is, to measure efficiency can also be conducted with the same datasets presented in this paper. For instance, to measure efficiency of public transport or electric vehicle uptake using the same set of data presented here. There are many ways to make use of the DEA method and hence, there is ample opportunity for further research. It is also hoped this approach can be applied to transport infrastructure priority and fund allocation at a higher governmental level, for instance, at Federal government level.

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