Lies, Damned Lies and "Automobile Dependence" - some hyperbolic reflections.

R. E. Brindle,
Chief Research Scientist,
Australian Road Research Board Ltd

Abstract:

Adequate discussion of the trade-offs between mobility and the environment seems to require reliable and informative empirical instruments. An empirically-based hyperbolic relationship between vehicle (or fuel) use and population density is now widely cited as the basis for urban policies such as increases in suburban densities, "neo-traditional neighbourhoods" and ways to encourage non-auto modes of personal travel. In this review paper, the statistical fallacy embodied in the claimed relationship (arising from the creation of non-independent compound variables and erroneous attempts at correlation analysis) are noted and some implications for policies based upon it are discussed. Alternative interpretations of available data suggest that city area and fuel prices might be truer casual factors in fuel use. While there are obvious implications for the reliability of policies based on these various "relationships", there is also cause to reflect on the ways in which data has been used by the wielders of current influence in transport policy development. The dilemma confronting the independent commentator in urban affairs is this: is it productive in the present context to focus on the quality and interpretation of urban data? The paper notes that, while such a preoccupation may not influence policy decisions, it may provide a better chance of affecting what actually happens by shedding light on processes of urban change rather than focussing solely on desired end states.

Contact Author:

R. E. Brindle
Australian Road Research Board Ltd
PO Box 156
NUNAWADING VIC 3131

Telephone: (03) 881-1625
Fax: (03) 887-8104

ATRF94

Disclaimer

This paper is a critique of a theory based on a particular statistical analysis. It is not directed at or against any individuals, and to read the paper in that way would be grossly to misrepresent the author's purpose.

1. INTRODUCTION

When Disraeli, quoting Mark Twain (or was it the other way around?), defined "statistics" as the third kind of "lie" he was probably referring to the persuasive power of lots of numbers. As Daryl Huff (1973) suggested, he might equally as well have been referring to the misuse of the science of mathematical statistics, the process by which we analyse data.

Adequate discussion of the trade-offs between mobility and the environment seems to require reliable and informative empirical instruments. Quantitatively-based contributions to current urban policy discussions are not all reliable and informative, although they may nevertheless be influential. This paper is an attempt to clarify the statistical aspects of the data popularly used to "prove" a relationship between urban structure (specifically, population density) and the extent of use of automobiles in a given city, which has been used to support radical urban development and transport proposals. The graphical presentation of this data, from 32 cities, is now familiar, finding its way into many official documents and secondary sources (Fig. 1). To set the scene for this paper, we need to note the interpretation placed on this graph when it first came to light:

> "The (linear) correlations suggest that strong negative relationships exist between gasoline use or private vehicle use and all the density variables. . .
>
> "The relationship between density and gasoline may be more complex than a purely linear linkage. (Fig. 1) suggest(s) that it may in fact be closer to an exponential relationship particularly under around 30 people per hectare. . It means that in terms of transport energy saved or private car use curtailed, the effects of increasing density can be considerable if they move urban areas into at least the 30/ha range.
>
> "(Fig. 1) suggest(s) that if cities around 10/ha were able to consolidate and move to densities around 30/ha then fuel consumption could be reduced by half or even to around one third of its low density value"
>
> (Newman and Kenworthy 1989, p 47)

Fig. 1 thus invites the conclusion that below 30 persons/ha something significant happens to travel behaviour. We are persuaded to conclude that 30-40 persons/ha is a threshold, and that, moreover, if we can manipulate our cities to reach that density, a change in

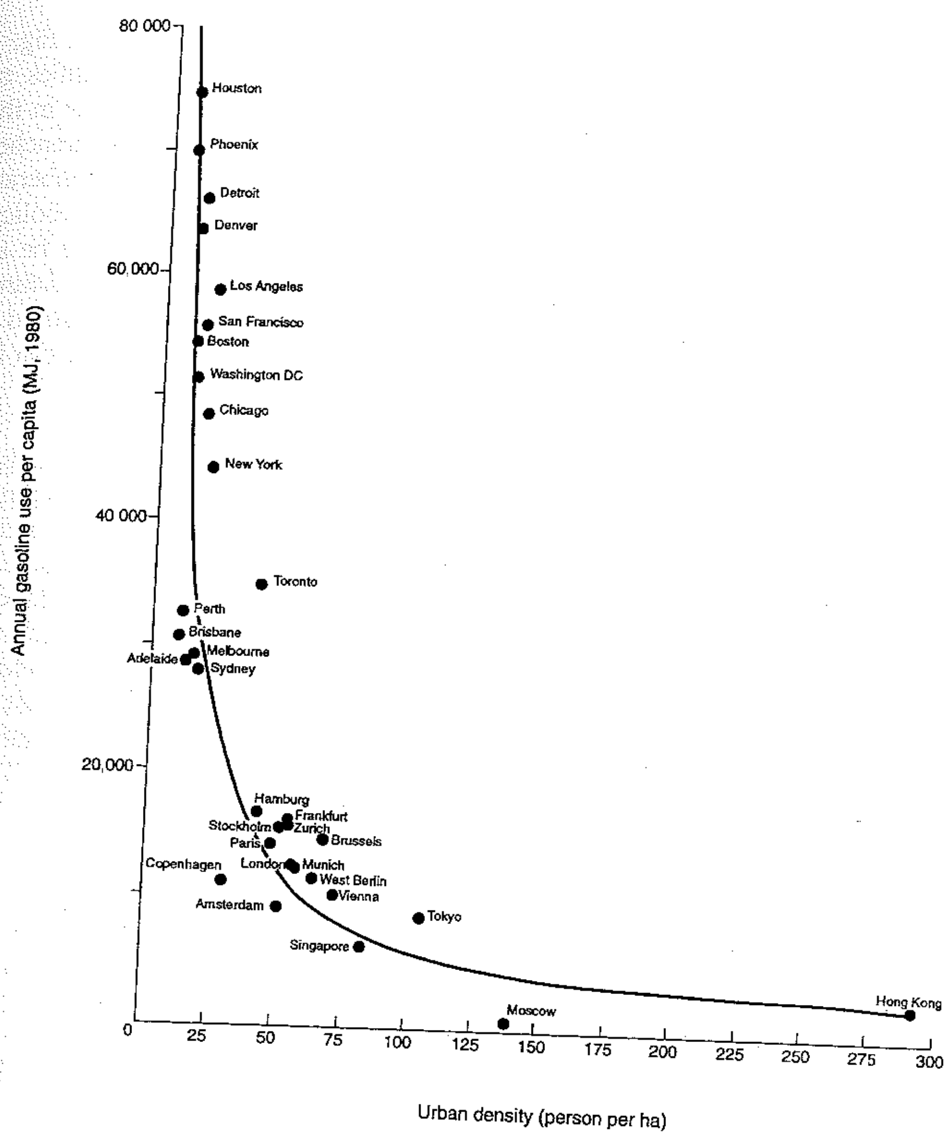

Fig. 1 Gasoline use per capita versus urban density (1980)
(Source: Newman and Kenworthy 1989, p 48)

travel behaviour (away from automobile use) will occur*. Despite the (quite proper) use of the word "suggests" in the above quotes, rather than "proves", the graph is a key item of quantitative evidence in support of the case for increased densities, which features centrally in visions and policies for urban Australia. Students and professionals alike (e.g. Bull 1991; Glazebrook 1992) cite Fig. 1 as an authoritative source in discussions ranging from urban consolidation to traffic calming, and it is known to be presented uncritically in some planning courses. It now is widely accepted as "proof" of a relationship between overall population density of an urban region and the degree of private vehicle use in that region.

* A speaker at the 1992 PTRC gathering in Manchester seriously believed that fig 1 meant that in order to accommodate the projected growth in car use in the UK, "densities would have to halve"! The obvious corollary did not seem to occur to him

However, as this paper will show, it is neither an accident nor is it surprising that Fig. 1 has the shape of a hyperbola - but that fact is due to the unavoidable realities of mathematical statistics rather than to any unique relationship or fundamental law in the urban system. A hyperbola is defined as a conic section consisting of two branches which are asymptotic to two intersecting fixed lines. A hyperbole is a deliberate exaggeration used for effect, although often the user is unaware of being "hyperbolic". Both words come from the Greek for excess or extravagance. There seems to be an abundance of both hyperbolas and hyperbole in current Australian urban futures discussions. By showing the ordinariness of the hyperbolic shape of Fig. 1, perhaps it can be demystified and some of the more extravagant conclusions drawn from it can be moderated.

There are many tempting side issues that we must ignore here. Leave aside, for example, the problem of relying too heavily on cross-sectional data, and the difficulties in defining "density". Do not get distracted here about serious problems with the data on fuel consumption. Accept the assumption that fuel sales are a consistently reliable measure of car travel in a region. Ignore the unexplained differences between the tabulated values of fuel/population (from which Fig. 1 is plotted) and those calculated from the basic data set. For this exercise, be prepared to accept that (contrary to the student's first rule) a demonstrated correlation *can* be taken as a proof of causation. Even assuming out all these difficulties, the central issue is: do these data in fact demonstrate a correlation between fuel use and population density, as claimed?

2. A LITTLE PRIMER IN CORRELATION

It is in the area of correlation and causation that misused statistics most often become the third and most condemnable "lie". In order to state validly that "A is caused by B", and that "an increase in B will cause a change in A", it is first necessary to demonstrate that A and B do in fact change predictably in relation to one another, and further that the dependency is in fact A on B rather than B on A or on another unknown factor. Here we need to take a little detour into basic statistics. Hang in there, because without this knowledge you will never know why Fig. 1 leads you into error. (If you are familiar with basic statistics, skip the next page or so.)

By calculations on pairs of data (say, A and B) which we will not go into here, you can derive a mathematical expression which best models the way in which A and B vary together. This is called the "regression equation". In simple terms, this can be seen as the equation to the line of best fit to the data if you were to plot it graphically. In simple linear regression, this line of best fit is a straight line and its equation is of the familiar form $y = mx + c$, where y is termed the "dependent variable" (because you calculate it) and x is the "independent variable" (because you feed it in to the equation).

You can also calculate the degree to which the two variable "co-relate" - that is, how close to the line of best fit are the various points. This is done by comparing the variation of the independent variable away from its mean with the variation "explained" by the regression equation. There are two essential measures for you to understand:

Coefficient of determination, r^2 = Variation in the dependent variable (away from its mean) accounted for by the regression equation, divided by the total variation in the dependent variable.

Thus, r^2 is a measure of how much of the variation is "explained" by the calculated relationship. Being a ratio, it takes values between 0 and 1 (1 indicating "perfect correlation").

Correlation coefficient, r = square root of the coefficient of determination

Thus, r takes values between -1 and +1.

For example, the correlation coefficient for the linear regression of fuel use on population density in Fig. 1 was -0.61. This implies that r^2 is 0.37, i.e. that more than 60 per cent of the variation in fuel use is ***not*** *explained by its relationship with density. (Note that you will find neither an equation to the line in Fig. 1 nor a non-linear correlation coefficient in any of the sources which present the graph.)*

It is the nature of correlation (that is, the degree of relationship between variables) that it alone cannot guarantee that a causal relationship exists between the variables, even when a good correlation is demonstrated. The classic example is the high correlation between the numbers of storks nesting on chimneys in a French village, and the number of births in that month. The two may or may not be related (in this case, perhaps through time of year in the cycle of rural work), but clearly a causal relationship is a romantic folk myth despite any calculated correlation. And if you wanted to lower the birth rate, would you simply scare away the birds?

The situation becomes a little more complex with compound variables, that is, variables calculated from products, quotients or other functions of two or more other variables. A simple rule is that attempts to determine a correlation between two compound variables, each of which contains a common variable, will necessarily be risky.

You can test this for yourself. Take any set of random numbers and call them values of a variable C. Work out the values of 1/C and plot 1/C against C. Not surprisingly, you get a perfect hyperbola with a correlation coefficient of -1.

Next, introduce two constants, a and b, and calculate new variables a/C and C/b. All this does is change the scales in your hyperbola, as you will find if you sketch it. The correlation coefficient is still -1.

If instead of the constants a and b you introduce two other random variables, A and B, you can then calculate two sets of compound variables, A/C and C/B. This is the general case that Karl Pearson identified more than 100 years ago as likely to lead to what he called "spurious correlation" - i.e. the possibility of a high calculated correlation which is in fact meaningless because of the dominance of the relationship between a variable (C) and its inverse*.

When we define two new variables, in one of which one of our primary variables is the numerator and in the other is the denominator, we are reflecting the behaviour of a variable against its own inverse and a tendency towards a hyperbola is inevitable.

As C gets larger, 1/C gets smaller (hence the negative sign to the correlation). This effect is greater if the variation in C is significantly greater than that in A or B (i.e. A and B are relatively constant compared with C).

Furthermore, if A and B are themselves related, the "correlation" between A/C and C/B is again inevitably strong. This can be demonstrated by defining:

$$A = kB \qquad (1)$$

where k is constant. Thus,

$$A/C = kB/C \qquad (2)$$

and a plot of A/C against C/B amounts to plotting kB/C against C/B - i.e. a hyperbola with a scale factor introduced, and a correlation coefficient of -1.

Note that these comments hold true even if A, B and C represent functions rather than simple variables

You can do your own tests on all this. An illustrative selection of random numbers and manipulations on them are shown in Table 1 It would be a bold person who could discern a relationship between any two of A, B and C from their scatter diagrams. In fact, the r squared values for A on C and B on C are 0.010 and 0.000 respectively. Clearly, here are three variables that have no connection with each other.

Yet, when you plot C/B against A/C you find that this data produces a marked trend towards a hyperbola. The plot of C/B against A/C from the random data in Table 1 is shown in Fig. 2. Curve fitting to this data showed that the best fit came (surprise!) from a power model:

$$C/B = 1.5016(A/C)^{-0.9929} \qquad (3)$$

The r squared value is 0.64 (and so r = -0.80, compared with the -0.61 quoted for the "32 cities" data behind Fig. 1). Thus we have created an apparently stunning relationship between three sets of random numbers! If A, B and C happened to represent three quite unrelated variables, such as beer sales, the number of cats and total population, respectively, in a zone we will apparently have "proven" that cat ownership rates are

* Compare with the exposure of a similar statistical flaw in "Smeed's Law" by Andreassen (1991).

Table 1: Random values of three variables, and two compound variables calculated from them.

A	B	C	A/C	C/B
53	99	50	1.06	0.50
59	98	84	0.70	0.86
66	47	1	51.80	0.03
7	15	78	0.09	5.33
71	66	86	0.82	1.30
34	63	6	6.09	0.09
75	74	11	6.81	0.15
78	96	95	0.82	0.99
74	52	94	0.79	1.81
24	15	9	2.50	0.64
93	92	5	18.63	0.05
79	36	45	1.76	1.26
51	16	55	0.93	3.50
58	49	16	3.69	0.32
69	7	41	1.66	5.96
14	22	44	0.32	2.01
69	31	73	0.94	2.36
53	1	65	0.82	44.19
71	76	89	0.80	1.16
64	18	98	0.65	5.58

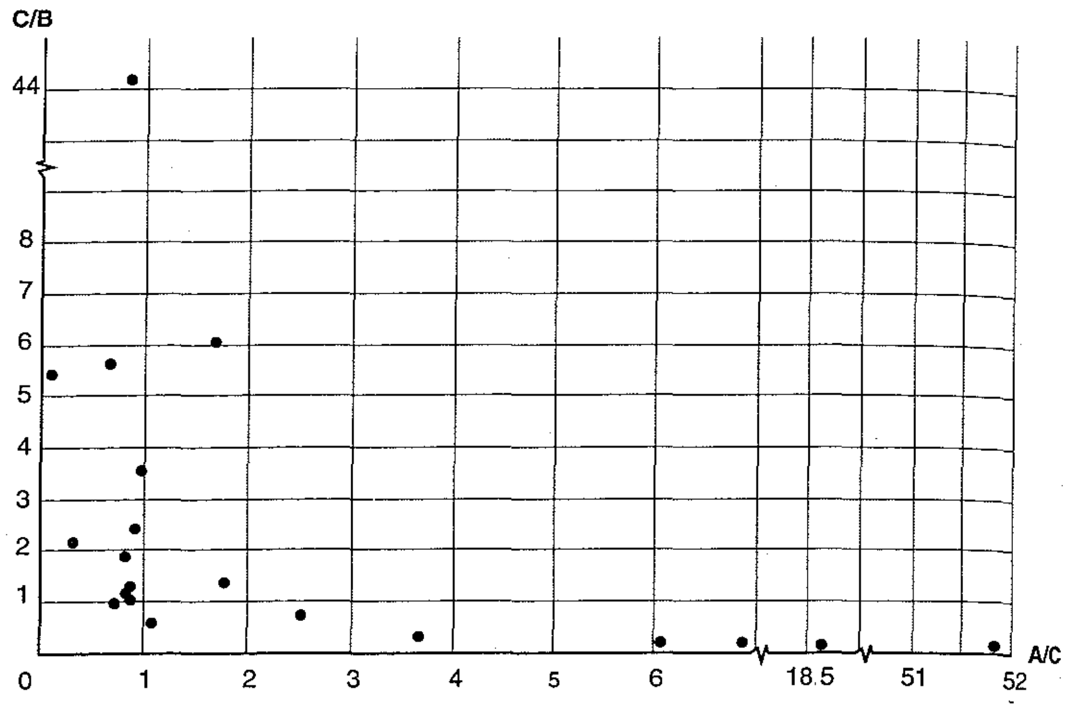

Fig. 2 Plot of C/B vs A/C from random numbers in Table 1

strongly negatively related to beer consumption - more strongly, in fact, than automobile dependency is related to population density! That may be true, but this form of statistics does not in fact prove any such thing (Be warned, in any case, that correlation - even non-spurious correlation - is never *proof* of a causative relationship.)

3. THE "AUTOMOBILE DEPENDENCY" VS. DENSITY RELATIONSHIP

What has this to do with Fig. 1? Simply that the data on density and fuel consumption (which is presented as a proxy for vehicle travel and, by implication, "automobile dependence") are obtained from the primary data in Table 2 by dividing F by P, and P by A*.

Fig. 1 is therefore a plot of two compound variables which are calculated from three primary variables. The variable P (population) is common to both compound variables.

The cautions about spurious correlation sounded above obviously apply to the data in Fig. 1 and Table 2.

* In fact, I discovered some unexplained differences for 19 cities between the values of F/P calculated in this way, and those listed in the source book which are plotted in Fig. 1. There may be a simple reason for this, of which I am unaware; the differences are not germaine to the discussion here.

Table 2: Data on fuel use, population and area for 30 of the 32 Cities* (1980)

	P Population	A Area, in hectares	F Motor spirit, in joules $x10^{15}$	F/P (Calculated) $x10^{9}$	P/A (Calculated)
Adelaide	931886	72221	27.66	29.69	12.9
Amsterdam	716900	14122	5.08	7.09	50.8
Boston	2678473	221880	149.70	55.89	12.1
Brisbane	1028527	100718	34.46	33.50	10.2
Brussels	997293	14800	14.70	14.74	67.4
Chicago	6779799	387951	342.72	50.55	17.5
Copenhagen	1739880	57179	19.32	11.11	30.4
Detroit	3809327	270336	266.79	70.04	14.1
Denver	1352070	113613	68.06	50.34	11.9
Frankfurt	631287	11695	10.16	16.09	54.0
Hamburg	1645095	39433	27.43	16.67	41.7
Houston	2412664	271696	191.90	79.54	8.9
London	6713200	119321	83.42	12.43	56.3
Los Angeles	9479436	473278	437.24	46.13	20.0
Melbourne	2722817	165961	82.56	30.32	16.4
Munich	1298941	22842	16.07	12.37	56.9
New York	15590274	726324	789.30	50.63	21.5
Paris	10094000	209392	142.23	14.09	48.2
Perth	898918	83545	30.94	34.42	10.8
Phoenix	1409279	165991	88.32	62.67	8.5
San Francisco	3190690	206045	179.97	56.41	15.5
Singapore	2413945	28997	14.38	5.96	83.2
Stockholm	647214	12613	10.08	15.57	51.3
Sydney	3204696	182559	92.65	28.91	17.6
Tokyo	11597211	110900	113.51	9.79	104.6
Toronto	2137395	53970	74.41	34.81	39.6
Vienna	1531346	21242	15.25	9.96	72.1
Washington	2763105	208933	153.11	55.41	13.2
West Berlin	2001000	31486	22.67	11.33	63.6
Zurich	780502	14544	12.26	15.71	53.7

* Omitting Hong Kong and Moscow, for obvious reasons.

Source: Newman and Kenworthy (1989)

Furthermore, if you plot F (fuel consumption) against A (gross area) from Table 2, you get a good fit to a straight line:

$$\text{Fuel use} = 0.001006(\text{gross area}) - 30.77 \qquad (4)$$

with an r squared of 0.95, where fuel use is in joules $x10^{15}$ and gross area is in hectares.

If the graph is forced through the origin, on the logic that a negative fuel use is meaningless, you get:

$$\text{Fuel use} = 0.00091(\text{gross area}) \qquad (5)$$

with an r squared of 0.93.

Thus, we can say with some confidence that there is a linear relationship between F and A in the 32 cities data (the larger the city area, the more fuel is used, regardless of density or other characteristic) and therefore we have a condition in the data which exemplifies eq. (2):

$$F = kA \qquad \text{(approx)} \qquad (6)$$

Therefore:

$$F/P = kA/P \qquad \text{(approx)} \qquad (7)$$

Therefore, a plot of F/P against P/A amounts to a plot of P/A against its inverse, with a scale factor. A hyperbola is inevitable. The better the fit of F versus A to a straight line, the closer to a hyperbola the plot of F/P versus P/A will get.

Note that, from (5) and (7):

$$F/P = 9x10^{4}(P/A)^{-1} \qquad \text{(approx)} \qquad (8)$$

This is an equation for a line of best fit through the points in Fig. 1, in the form of a power model (c.f. eq. (3)). Note that the curve in Fig. 1 appears to have been "fitted" by eye by its originators.

Attempts to validate Fig. 1 by "improving" the data, or to enlarge the data set, are futile. As long as you obtain both the fuel use and density data by operations on population, you will only ever get a tendency towards a hyperbola (even if, as we have seen, F, P and A were random numbers). Furthermore, the production of more data which seems to strengthen the hyperbolic relationship (which the authors of Fig. 1 have announced they are doing) would only serve to confirm the evidence that fuel use and area were linearly related.

Note that these phenomena result because the values used to plot Fig. 1 were derived from three primary variables, one of which is common to both axes. This does not necessarily occur in all cases where there are common units on both axes (e.g. litres/100 km vs. km/hour) if these are direct measurements and not variables compounded from primary data.

A final caution should be sounded about data of this sort The risks of spurious correlations are present in any case where the variables are not independent (as in the case of storks and babies, where season played a role in both). In urban studies, another example would be "correlations" between road length per capita and population density (such a relationship being physically inevitable, as well as statistically spurious)

4. INTERPRETATION

With this statistics tutorial behind us, let us now consider what this means for interpretation of the data, and its implications for policy

Many statistical implications flow from the rich data set behind Table 2 and Fig. 1, even acknowledging some flaws in specification and consistency and despite the fact that the familiar hyperbola turns out to be not particularly useful or insightful. This is not to say that there is no relationship between vehicular travel and density, only that the data in Fig. 1 are not useful in proving such a relationship. The basic data in Table 2 in fact offers a simpler and more direct observation through eq (4): the bigger a city gets, the more automotive fuel it uses, *regardless of its density*. This is a non-trivial finding, which is not as obvious as may at first appear. Not only is the establishment of a relationship between total fuel use and city size a statistically valid use of the 32 cities data (in contrast to relationships involving "per capita" transformations of the data) - these two variables also prove to be highly correlated

There is thus stronger evidence from this data for a policy of urban containment than there is for density increases per se.

Constraints on city growth would imply constraints in fuel use. Thus, by implication, more people in the same area (i.e. at higher density) would mean less fuel use per person. While this seems to provide encouragement for urban consolidation, it seems also to refute the present enthusiasm for higher-density new residential development in green fields sites. It also seems to suggest that population policy deserves higher attention than it has been getting in the urban debate. Note that these observations are subject to the caveat that fuel consumption is notoriously difficult to specify, especially by region and sub-region within nations. Schipper (1993) has indicated concern about uncritical acceptance of, and comparisons between officially reported fuel consumption data. In essence, lack of consistency in definitions of "automobile fuel" as distinct from other fuels, the mixture of automobile fuel types in different countries, variations in fuel taxation policies, and other significant variations between countries all make the collection of valid comparative data a far from simple task. In personal correspondence, Schipper has indicated even more reservations about fuel consumption data for individual urban areas.

Note also that others have observed that the data set offers other apparently plausible relationships not considered here, e.g. between fuel consumption and fuel price (Kirwan

1992). This is supported by the long-term studies of the International Energy Studies Group at Berkeley, California (e.g. Schipper and Meyers 1992).

We are still left with the problem of causation. Even if all else were true, it has not been proved from the data being examined here that an increase in density is a necessary (never mind a sufficient) condition for travel changes, any more than reducing the number of fire engines will reduce the number of fires even though they are correlated

Then we must consider the significance of the 30-40 p/ha threshold at which the curve in Fig. 1 appears to turn rapidly upwards. Unfortunately for those who share the convictions quoted on the first page of this paper, this transition point on the graph appears to be merely an artefact of the statistical process and the scale used to plot it. That this is so is supported by common observation, e.g.:

(a) As noted elsewhere (Brindle 1992), the 3 million residents of Los Angeles County live at nearly 30 p/ha overall.

(b) Suburban densities in places like Copenhagen appear to be decreasing to below this threshold, yet are still characterised by higher levels of public transport use.

(c) Many Australian suburbs have overall densities at or above this level. Meanwhile, Perth's new Northern Suburbs railway apparently thrives in a region having about half the claimed "threshold" density.

(d) Travel choice changes over time in suburbs where gross densities may in fact have risen are not explained by the "model"

Commentators - not all of them antagonistic to the cause of urban change - have expressed disappointment and puzzlement about the use of simple paired linear correlations rather than multi-variate analysis of the "32 cities" data (e.g. Gomez-Ibañez 1991; Kirwan 1992). In their response to Gomez-Ibañez in the Summer 1992 APA Journal, the analysts disarmingly stated:

> "Our statistical analysis is undoubtedly not very sophisticated and could have used more of Gomez-Ibañez's skill although we still remain to be convinced that more sophisticated analysis would fundamentally change the results".

By now, the reader will have decided whether or not the statistical basis of Fig. 1 is fundamentally flawed - be it sophisticated or otherwise. For his part, one reviewer, exasperated at the "conceptual, methodological and analytical flaws" in the analysis of the "32 cities" data, confessed that "it is hard to be patient with all that follows" (Warnes 1991).

The reader would be excused for wondering, if there is such a serious flaw in the way Fig. 1 is derived, why has no-one mentioned it in the 5 years since it was first published. The answer is that it has, but quantitative urbanists such as Warnes, who are familiar with the techniques and hazards of correlation analysis, seem to assume that practitioners would not need to have it spelt out. The rest, the vast majority of people accepting and repeating the popular message of Fig. 1, are regrettably under-informed about basic statistics and the proper use of data. (Here I share some of the blame, having taught statistics to planning students for several years.)

"Automobile dependence"

Finally, a comment about the term "automobile dependence". All that we can hope to glean from mass data analyses is the extent of a behaviour or *usage*. The word "dependence" implies the absence of will or choice. Canberra, for example, is described as having "developed in a pattern of automobile dependence" (Newman and Kenworthy 1991). Yet Manning (1991) would not be alone in thinking that:

> "Though Canberra has been much criticised as a motorist's city, its planners may some day have the last laugh, for in the event of fuel shortages it may turn out to be the most liveable city in the country - albeit one blessed with hectare upon hectare of useless freeway."

The reality is that, just as the 1950's suburbs are still with us but with higher car usage, the present inefficient patterns and linkages adopted by Canberra's residents are not necessarily a measure of the efficiency of the urban structure in that city, nor are they necessarily an absolute indicator of locational and travel behaviour in the future. What people do and what they have to do are two different things. As in Canberra's model neighbourhoods, people in "traditional neighbourhoods" (old and new) all over Australia drive to local shops and schools which are within walking and cycling distance, and indulge in remote employment and other activities rather than accept the nearest opportunities.

5. CONCLUSIONS

The definition of "automobile dependence", and attempts to prove its link with gross indicators of urban structure such as population density, turn out to be far more elusive than the recent "evidence" has suggested. Clearly, this is a complex subject that deserves close attention and better analysis. We ultimately do a disservice to the cause of urban improvement and human sustainability on Earth if, in our haste to promote visions, no matter how well-meant, we are careless about the cause-and-effect interconnections between various parameters. There are good reasons for improving the range of choice in cities, including appropriate increases in density. The problem is, Fig. 1 is not one of them.

This paper has hinted at the well-established problems encountered when trying to obtain reliable city-by-city data on automobile fuel use of sufficient consistency to permit cross-sectional comparisons. But even accepting the data commonly referred to in Australian urban policy discussions, it is clear that the conclusions drawn from it about the importance of density are statistically (and that means logically) invalid because of the unavoidable consequences of the way the variables are derived. Consequently,

- It is not valid to read off the graph in Fig. 1 to predict the effect on vehicle use of changes in population density. (The converse is even less valid.)

- The graph does not in reality demonstrate a "30-40 persons/ha threshold"

Re-analysis of the data suggests that total fuel consumption is more obviously and significantly related to city area (eq 4), and that fuel use per person is strongly affected by price differences between cities and countries. These parameters may in turn interact with urban density, but the selection of density as the primary "explanatory" variable and policy tool out of these cannot be sustained by recourse to statistical analysis, as the proponents of that belief have attempted to do.

There are obvious implications for urban policy if these observations are accepted; for a start, we shall have to find other proofs of a causal relationship between overall density and gross travel choice. It is less easy to know how to respond to the fact that "data" is frequently carelessly used in discussions on urban futures, and it does not seem to be a matter of concern to those involved. Even if the statistical reservations expressed in this paper were to be widely acknowledged, such is the nature of the present discussion on cities that one could not expect much change in direction among the wielders of influence in urban development and transport policy.

What should independent commentators on urban issues then do? The dilemma for those aware of the data and statistical problems, but who also want to support urban change (particularly appropriate increases in density) is this: Is it productive to focus on the quality and interpretation of urban data? Undoubtedly many "post modern" urbanists regard quantitative niceties as being irrelevant, stressing the need for vision more than knowledge. I make no judgement on that matter here (other than to suggest that honest visions are better than bad science), hoping that it will receive attention at the Conference and elsewhere. What we have here is a popular belief which is promoted *on the basis of an analysis of empirical data*. It must at least stand up to scrutiny on that score.

The thought that cities might be already or are becoming truly "automobile dependent" - that is, they *cannot* function effectively without widespread access to and use of private automobiles - is alarming and deserves our most intense attention. However, if we hope eventually to make real and effective change in cities rather than lurch from one fad to another the people responsible for implementing and supporting change will need realistic tools. While a preoccupation with getting the statistics right may not influence policy discussions in the present political climate, it may provide a better chance of affecting what actually happens by shedding light on processes of urban change rather than focussing solely on desired end states.

Edward de Bono calls for ideas in addition to knowledge in the search for progress, and urges us to be mindful of essential action. Urban policy contributions in Australia - and, indeed, around the world - currently seem more dominated by ideas than knowledge. Real and effective action in this field seems to require better quantitative tools than are being currently offered to us.

6. ACKNOWLEDGEMENTS

The author is grateful to Ben Ward who assisted with the analyses, and Dr David Andreassen who was a valuable sounding board on the subject of correlation. As usual, the author accepts all responsibility for the way in which these contributions have been used in the paper. I wish I could claim the statistical theory as my own, but I cannot; it it all very standard.

7. REFERENCES

ANDREASSEN, D.C. (1991) Population and registered vehicle data vs. road deaths *Accident Analysis and Prevention* 23(5), pp.343-351.

BRINDLE, R.E. (1992) Toronto - Paradigm lost? *Australian Planner* 30(3), pp.123-130.

BULL, P.S. (1991) *A critique of reurbanisation.* Master of Urban Planning Minor Thesis. University of Melbourne

GLAZEBROOK, G. (1992) Finance for urban development. *Australian Planner* 30(3), p. 159.

GOMEZ-IBAÑEZ, J.A. (1991) Book Reviews *Journal of the American Planning Association* 57 (Summer) pp.376-379.

HUFF, D. (1973) *How to lie with statistics* (London: Penguin)

KIRWAN, R. (1992) Urban form, energy and transport: A note on the Newman-Kenworthy thesis. *Urban Policy and Research* 10(1), pp. 6-22.

MANNING, I. (1991) *The open street.* (Sydney: Transit Australia Publishing)

NEWMAN, P. and KENWORTHY, J. (1989) *Cities and automobile dependence An international sourcebook* (Aldershot UK: Gower)

NEWMAN, P. and KENWORTHY, J. (1991) *Towards a more sustainable Canberra.* Institute for Science and Technology Policy, Murdoch University, WA

SCHIPPER, L., and MEYERS, S (1992) *Energy efficiency and human activity: Past trends, future prospects.* (Cambridge, UK: Cambridge Univ. Press.)

SCHIPPER, L., FIGUEROA, M.J., PRICE, L. and ESPEY, M. (1993) Mind the gap. The vicious circle of measuring automobile fuel use *Energy Policy* Dec 1993, pp.1173-1190.

WARNES, T. (1991) Book Review. *Urban Studies* (28)2, pp. 289-90.