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ABSTRACT

This paper reports the results of an econometric analysis of the influences on on-road behaviour of long distance truck drivers in Australia. The approach is couched in terms of a utility maximisation framework in which a driver trades-off economic reward with occupational risk. The physical risks to the driver due to driving while fatigued are proxied by the use of stimulants. Drawing on a 1990 survey of a sample of 402 truck drivers selected from owner drivers and employee drivers, we evaluate a number of alternative hypotheses on the relationship between drug taking, compliance with schedules and the propensity to speed. A system of structural equations is specified to test alternative hypotheses on causality between the endogenous variables and a set of exogenous effects. The models are estimated using distribution-free methods for mixed dichotomous and continuous variables. The main findings within the set of endogenous variables is that increasing speed is positively influenced by the propensity to take stay-awake pills which is itself positively influenced by the propensity to self-impose schedules. After controlling for a number of contextual influences on the endogenous variables, rates of financial reward have a significant impacts on all three endogenous variables. This study has highlighted the complex relationships which exist between speeding, social behaviour and economic reward.

This research was partially funded by a grant from the Australian Federal Office of Road Safety, whose support is gratefully acknowledged. The contribution of Helen Battellino in the overall study has been extensive. Tom Golob is a Research Specialist in the Institute of Transportation Studies, University of California, Irvine. This paper was first drafted while Tom Golob was a visitor at ITS-Sydney and completed when David Hensher was a Visiting Professor at ITS-Irvine. The authors are placed alphabetically, but contributed equally to the paper.

1. Background

Safety on our roads, particularly the national highways, continues to be a major policy issue. It is often claimed that the on-road behaviour of long distance truck drivers in particular exposes all road users to high levels of risk. In most countries this view is reinforced whenever there is an increase in fatal crashes involving large trucks, and even more so when public passenger vehicles are involved. The media attention given to crashes involving long distance heavy vehicles has helped create a negative image of the long distance truck driver and the trucking industry as a whole. The negative image has evolved with very little questioning of the reasons behind truck driver behaviour. Is it valid to assume that all operators in the industry are irresponsible "cowboys", who spend long hours speeding along the highways without thought for their own or other road users' safety? For example, analysis of crash statistics in Australia shows that the incidence of heavy vehicle crashes relative to exposure on the road is very small and represents an impressive safety record (Hensher et al. 1991).

Theories and anecdotes about the causes of unsafe on-road behaviour of heavy vehicle drivers abound. But there is a dearth of *substantive* studies which have investigated the causes of particular on-road behaviour and hence levels of exposure to risk of a crash (Savage 1989, Sweatman et al. 1990). This paper is a contribution from a larger study (see Hensher et al. 1991, 1992, 1993) designed to evaluate the relationship between on-road performance and the structural characteristics of the long-distance trucking industry. Without better evidence, we run the risk of regulatory authorities proposing inappropriate strategies to modify the on-road behaviour of the long distance trucking industry in the hope of improving the safety of the road environment. Often "band-aid" policies are introduced in response to a particular incident receiving public attention. For example *immediately* following a major truck and coach crash in October 1989 on the Pacific Highway between Sydney and Brisbane (Australia), the speed limit for heavy vehicles was reduced from 100 km per hour to 90 km per hour.

This paper explores the possibility of links between the propensity of a driver to speed and given the economic conditions in the industry in general, the driver's own particular economic operating environment. We concentrate on speed and its variance as indicators of exposure to risk. These factors were found to be major contributors to crashes in a study of all heavy vehicle crashes in NSW in 1988 (Sweatman et al. 1990). Given that there are a number of complex inter-relationships which contribute to the ultimate on-road performance of truck drivers (Hensher and Battellino 1990), the separation of the major sources of influence can only satisfactorily be achieved by a formal quantitative investigation using econometric techniques. The interactions between the major elements of the study are summarised schematically in Figure 1. The critical dimensions of interest in the current paper, investigated in the context of a sampled trip, are the incidence of speeding, the speed profile of a trip, the incidence of pill taking and self-imposition of schedules and their linkage with on-road performance with respect to sources of exposure to risk. The physical risks to the driver due to driving while fatigued are proxied by the use of stimulants. Hensher et al. (1993) complements this paper; it investigates the overall economic status of truck drivers, especially productive and unproductive hours worked to secure an acceptable income.

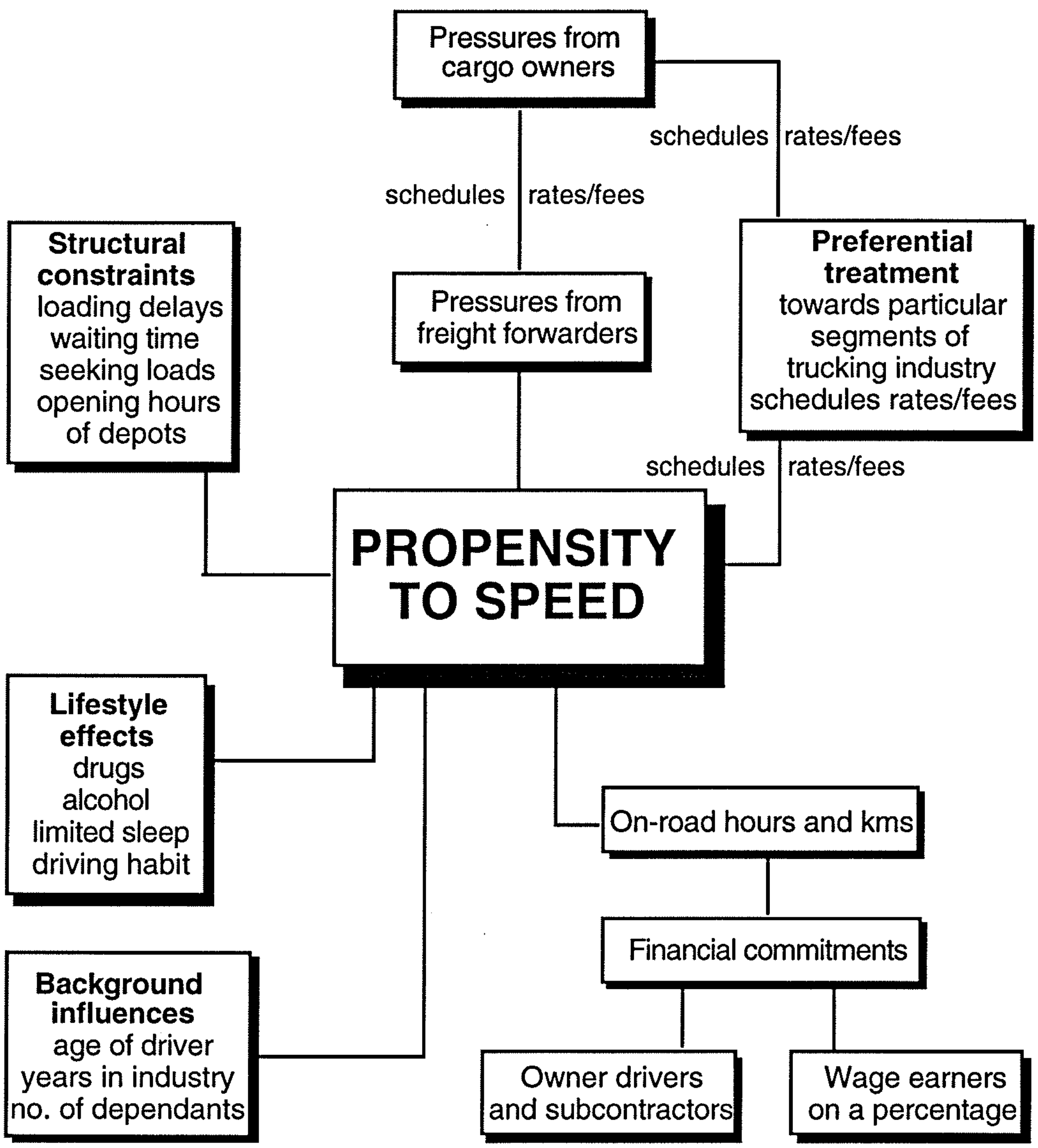

Figure 1 Major elements of the study

Data was collected in 1990 from an in-depth face to face interview of 800 long distance truck drivers throughout Australia. A key aspect of the survey was data on a recent trip undertaken by each driver. Descriptive analysis of the sample data is reported fully in Hensher et al. (1991) and summarised in Hensher et al. 1992 and the Appendix.

The paper is organised as follows. A theoretical model is specified in terms of utility maximising behaviour and an explicit relationship between economic reward and occupational risk. A number of testable causal structures associated with behavioural influences on trip-specific exposure to risk are then presented. The alternative structural equation models are formally specified and estimated. The empirical results and interpretation of alternative behavioural hypotheses are then presented. A summary of the major findings is given in the conclusion.

2. A Theoretical Framework for Linking Economic Reward and Occupational Risk

What is the influence of earnings opportunities and wage levels on the on-road performance of truck drivers, the latter measured by average speed? What role do intervening influences such as fatigue (linked to pill taking) and scheduling constraints (self-imposed or externally imposed) have on the utility maximising behaviour of truck drivers? To give some structure to an economic framework, we need to set out a standard utility maximising model with appropriate constraints.

Define a direct utility function in which a driver faces a choice between a divisible consumption good - work hours - and other consumption embodied in leisure. In addition the utility derived from truck driving hours varies across the population of drivers for many reasons, broadly defined as occupational risk due to speeding or fatigue, but conditioned by other job attributes such as certainty of income, regularity and desirability of work time.

$$V(x_h, x_l, b) \qquad (1)$$

where

x_h is hours worked x_l is other consumption embodied in leisure, and b is an index function of the quality of driver working environment, in part representing the physical risks due to driving while fatigued. We assume that V(.) is strictly quasi-concave and continuously differentiable, with no corners or kinks (Pudney 1990). Furthermore, the inclusion of b recognises that observed variation of preferences among drivers can be explained by reference to particular job attributes and observable personal characteristics of drivers. We can then specify:

$$V(x_h, x_l, b) = v\{x_h, x_l, \psi(b)\} \tag{2}$$

The driver's gross earnings is the sum of unearned income y^* and earned income $w(T-x_l)$, where w is the hourly wage and T is the driver's total time endowment. We assume w is exogenous for the driver which as a rate for a job is true. Driver labour supply is $T - x_l$ hours. It has two components - directly earning hours $\left(x_h^d\right)$ and non-earning investment hours worked to secure a load $\left(x_h^l\right)$. A driver pays income tax. Assume initially a single uniform rate of company taxation τ and this applies to the entire earnings (a valid assumption for company tax, but not so for an unincorporated partnership). The budget constraint becomes:

$$p_h x_h + r^c + \sum_{\substack{i=1 \\ i \neq h}}^{I} p_i x_i \leq (1-\tau)\left\{y^* + w\left(T - x_l\right)\right\} \tag{3}$$

where r^c is the annualised capital cost of a truck, $\sum_{\substack{i=1 \\ i \neq h}}^{I} p_i x_i$ is the other non-labour and non-capital input costs. Alternatively:

$$w(1-\tau)x_l + p_h x_h + r^c + \sum_{\substack{i=1 \\ i \neq h}}^{I} p_i x_i \leq (1-\tau)\left\{y^* + wT\right\} \tag{4}$$

where $w(1-\tau)$ is the price of leisure, and the measure y^* of total resources includes the post-tax value of both unearned income and the market value of the time endowment T. It is known as the post-tax full income (Becker 1962). Maximisation of equation (1) subject to the constraint equation (4) gives a number of optimal conditions. The key dimensions in this system relevant to a particular trip, the focus of this paper, are the hours worked, the earnings rate and the quality of the driver working environment. This latter construct is represented by three endogenous variables - speed, the propensity to self-impose schedules, and the propensity to take pills. Self-imposition of schedules is endogenous to both owner drivers and employee drivers; for employee drivers they often have a choice to pursue bonuses and other benefits associated with scheduling performance beyond the minimum requirement. Other variables such as the annualised capital cost of a truck are not considered important influences on the on-road behaviour of truck drivers for a particular trip.

3. Identifying Testable Hypotheses

It is hypothesised that a truck driver is motivated by economic reward and seeks to obtain a return for his efforts through participation either as an owner driver or employee driver. The decision on whether to be an employee or to be self-employed is in part influenced by the opportunities for reward, the flexibility of lifestyle and the extent of a real choice (i.e. the availability of employment in the employee driver sector). Given the highly competitive "cut-throat" nature of the long distance trucking industry, drivers exhibit substantial variations in strategic behaviour in order to survive. The pressures on drivers come from freight forwarders, cargo owners, and the large number of operators competing for loads.

The lifestyle element of trucking, especially for owner drivers and small company employees, has reinforced the acceptability of working practices which in other industries would be regarded as totally unacceptable. Typically, many drivers spend considerable time waiting for an opportunity to secure a load, they rarely sleep at their "permanent residence", spend considerable hours in the cabin of their truck, and live on a "junk-food" diet (AUSTROADS 1991). Reliance on "stay-awake" pills is quite widespread (46% of sampled drivers take pills on some trips or all the time) in order to maintain very long working hours, typically averaging 100 hours per week (Hensher et al. 1992). Self-imposed schedules which may encourage excess speed are often the outcome of the pressures on truckies, especially owner drivers.

The task in this paper is to establish some of the important links between good and bad practice, positive and negative incentives and on-road performance in the context of exposure to risk. The evidence can be used to establish some guidelines for changes to be encouraged in the industry which will improve the working environment in a way that enhances on-road performance. With this context in mind, a number of alternative causal structures are proposed. A sub-sample of 402 truck trips which gave complete information on trip financial rates are used to empirically investigate these hypotheses. The richness of the information from the survey available to draw on is summarised in Table 1.

Table 1 Data available to investigate potential sources of influence on the propensity to speed

1. On-Road Profile
- Total kilometres (TS)
- Total time (TS)
- Total number of legs (TS)
- Incidence of drive time per leg (TS)
- Variance of drive time incidence per leg (TS)
- Speed profile of trip (TS)
- Average speed per leg (TS)
- Speed variance across legs (TS)
- No. of stops involving particular activities (sleep, rest, eat, etc.) (TS)

2. Trip Timing
- Depart during the weekend (TS)
- Depart early morning (TS)
- Depart during the day (TS)
- Depart during the evening (TS)
- No. and % of hours driving in the dark (TS)

3. Pressures on Performance
- External schedule constraints (TS)
- Self-imposed schedules (TS)
- Loan repayments

4. The Road Environment
- Specific-roads (quality proxy) (TS)
- Direction of travel on a specific road (TS)
- Major origin-destination pairs (TS)
- Frequency of trips on major routes

5. Vehicle Characteristics
- Body type (rigid, articulated) (TS)
- Age (TS)
- Weight (TS)

6. Cargo Characteristics
- Weight (TS)
- General cargo (TS)
- Perishable cargo (TS)
- Express freight (TS)
- Specialised cargo (TS)

7. Safety and Security Control
- Speed limiter installed (TS)
- Tachograph on board (TS)
- Incidence of fines (speeding, log book, truck defaults, overloading)

8. Driver Background
- Age
- Number of dependants (children)
- Prior occupation
- Undertaken a training course
- Number of crashes in previous 2 years

9. Industry Experience
- Years driving
- Annual kilometres
- Annual working hours
- Annual driving hours
- Number of trucks possessed

10. Lifestyle Attributes
- Reliance on pills (always, some trips)
- Means of maintaining alertness en route
- Activities in 8 hours prior to departure (TS)

11. Preferential Treatment
- Regular contracts (for all, some, no loads)
- Access to load (TS)
- Backload provisions

12. Sub-Industry Status
- Employee driver (small, medium, large co.)
- Owner driver fleet owner
- Owner driver prime contractor
- Owner driver independent sub-contractor
- Independent owner driver

13. Economic Reward Determination
- Owner driver (c/km) (TS)
- Employee driver - fixed salary, % of truck earnings, per trip

14. Structural Constraints
- Backload available (TS)
- Unloading time (TS)
- Waiting to unload (TS)
- Time to usually secure loads

15. Financial Status
- Annual truck-related income
- Annual truck-related expenses (OD)
- Non-truck related income
- Truck financial commitments

16. Other Dimensions
- State location of base

TS = data specific to one trip

On-road performance as measured by average speed per trip leg is hypothesised to be influenced by a number of exogenous variables and three *endogenous* effects - the propensity to take pills, the propensity to adopt self-imposed schedules, and the number of speeding fines per annum. Schedules imposed by a company or freight forwarder are exogenously determined and hence are treated as given constraints on behaviour. This influence is hypothesised to operate in a number of possible pair-wise causal relationships:

Hypothesis H_1: self-imposed schedules promote the propensity to take pills.

Hypothesis H_2: drivers can increase their average speed over the trip legs by taking pills.

Hypothesis H_3: higher average speed over the trip legs promotes the propensity to take pills. (H_3 reverses the direction of the H_2 causality between the propensity to take pills and average trip speed.)

Hypothesis H_4: self-imposed schedules lead directly to higher average speeds over trip legs.

Hypothesis H_5: the propensity to take pills leads to greater numbers of speeding fines.

Hypothesis H_6: self-imposed schedules lead directly to greater numbers of speeding fines.

Hypothesis H_7: higher average speed over the trip legs leads to greater numbers of speeding fines.

Hypothesis H_8: greater numbers of speeding fines lead to lower average speed over the trip legs. (H_8 reverses the direction and sign of the H_7 causality between average speed over trip legs and the number of speeding fines per annum.)

It was found that sixteen exogenous variables were effective explanators of at least one of the three endogenous variables. The total set of nineteen endogenous and exogenous variables are defined in Table 2. The descriptive statistics in Table 2 are divided into mean and standard deviation for the continuos variables and category frequencies for the dichotomous variables.

Table 2. Descriptive Statistics of the endogenous and exogenous variables

Variable	Acronym	Continuous Vars. Mean	Continuous Vars. Std.Dev.	Dichotomous Vars. n = 0	Dichotomous Vars. n = 1
Self-imposed arrival time	ARRB			159	243
Pill taking on some or every trip	PILLS			199	203
Log (total ave. speed on sampled trip)	LTOTASP	4.39	0.167		
Total ave. speed on sampled trip	*TOTASP*	*82.1*	*12.1*		
No. of speeding fines per annum	FINES	5.62	8.93		
Time working but not driving	OFFRDTIM	12.62	12.11		
Age of driver	AGE	37.38	9.42		
Co. or forwarder imposed schedule	SCHARR			229	173
No. of stops: sleep + rest activities	SLPREST	0.36	0.68		
Driver has always been a truck driver	NOPRVOCC			313	89
Hours slept in 8 hours prior to trip	SLEEP8	2.25	3.00		
Gross weight of truck in tonnes	TRKWT	16.89	3.06		
Load is perishable cargo	GDPER			309	93
All trips with regular contract	RCALL			307	95
No. of no-sleep stops	NOSLEEP	2.00	5.62		
Weekend start to trip	DAYSTRT			301	101
Trip rate for owner driver ($/km)	DKMOD	0.70	0.68		
Owner-drivers only (DKMOD > 0)	*(n=241)*	*1.16*	*0.48*		
Trip rate for employee driver ($/km)	DKMED	0.49	0.79		
Employee-drs. only (DKMED > 0)	*(n=161)*	*1.23*	*0.80*		
Trip started before 8AM	TSTL8			366	36
Standard deviation of proportion of total time actually driving	RATIOSD	0.29	0.08		

4. Structural Equations Methodology

Each of our hypothesis can be expressed in terms of a link in a structural equation system and an arrow between two variables in a corresponding flow (path) diagram. The general structural equation system model (without latent variables) is given by

$$\mathbf{y} = \mathbf{B}\mathbf{y} + \mathbf{\Gamma}\mathbf{x} + \boldsymbol{\zeta}$$

where the structural parameters are the elements of the matrices:

$\underset{(m \times m)}{\mathbf{B}}$ = causal links between the endogenous variables,

and

$\underset{(m \times n)}{\mathbf{\Gamma}}$ = direct causal (regression) effects from the exogenous variables to the endogenous variables,

and the error term parameters are the elements of the covariance matrices:

$\underset{(mxm)}{\mathbf{\Psi}} = E(\zeta\zeta') =$ variance-covariances of errors-in-equations

and

$\underset{(pxp)}{\mathbf{\Theta}_{\varepsilon}} = E(\varepsilon\varepsilon') =$ variance-covariances of y-variable measurement errors (errors-in-variables).

Each structural equation model specified in terms of its parameter matrices corresponds to a flow (path diagram. The usual convention, followed here, is to depict causal parameters (the elements of the beta and gamma matrices) as unidirectional arrows connecting the explanatory variable to the dependent variable. The error-term covariance parameters are depicted in the flow diagrams as two-headed errors connecting the two endogenous variables whose unexplained portions (unique portions, or error terms) are specified as being correlated.

The parameters of the matrix representing hypotheses H_1 through H_8 are depicted in the flow diagram in Figure 2. In addition to the direct effects linking the endogenous variables, a free error-term covariance is also specified between the two dichotomous variables AARB and PILLS (matrix parameter $_{2,1}$). This allows correlation between the unique or unexplained portions of these variables, which will be treated as discrete choice variables in the estimation.

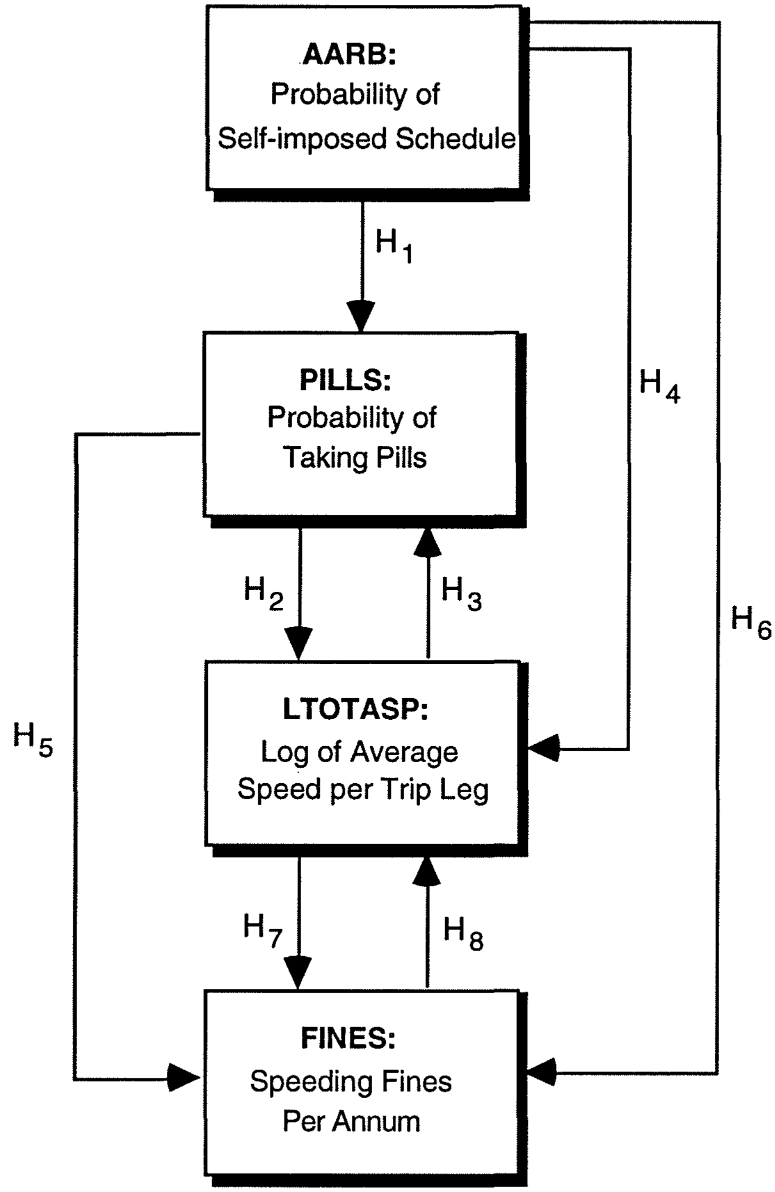

Figure 2 Hypotheses of Direct Effects Among Endogenous Variables

Structural equations models containing all or some of these causal links among the endogenous variables can be estimated after specifying an exogenous variable causal structure (matrix parameters). Estimation of structural equation models is typically performed using normal-theory maximum likelihood. However, two of the four endogenous variables in our model are dichotomous, as are many of the exogenous variables. The assumptions underlying maximum likelihood estimation will be violated, leading to biases in model goodness-of-fit statistics and parameter standard errors (Bentler and Bonett, 1980; Bollen, 1989). We use an alternative estimation method.

5. Estimation with Mixed Continuous and Dichotomous Variables

An estimation method variously known as “arbitrary distribution function”, or “asymptotically distribution-free” (ADF) weighted least squares (WLS), or “generally weighted least squares” (GWLS) has been developed to estimate structural equation models with non-normal endogenous variables. The method proceeds in three distinct steps.

Step 1: Estimation of Probit Models

First, ordered categorical (ordinal) endogenous (y) variables are "normalized" by estimating thresholds on normal functions that can generate the non-normal variables. Ordinal variables include dichotomous (binomial discrete choice) variables as a special case (of two categories).

For each ordered categorical (ordinal) variable y with k categories it is assumed that there is a latent continuous variable y^* which is normally distributed with mean zero and unit variance. The latent variable itself is not observed, but the ordinal indicator is related to it in the following way

$$
\begin{aligned}
y &= 1 \quad \text{iff} \quad \alpha_0 < y^* \le \alpha_1 \\
y &= 2 \quad \text{iff} \quad \alpha_1 < y^* \le \alpha_2 \\
y &= c \quad \text{iff} \quad \alpha_{c-1} < y^* \le \alpha_c
\end{aligned}
$$

where $\alpha_0 = -\infty$; $\alpha_1 < \alpha_2 <\ldots< \alpha_{c-1}$; and $\alpha_1 = \infty$ are the threshold values of the cumulative normal distribution corresponding to the marginal distribution of the population over the categories. An ordinal variable with c categories has $c - 1$ thresholds to be estimated.

These thresholds are estimated using the ordered-response probit regression model, developed by Aitchison and Silvey (1957) and Ashford (1959) as an extension of the binomial probit model. This model describes the probability of observing category j for observed variable y, conditional on the q exogenous ($\mathbf{x}$) variables:

$$P(y = 1|\mathbf{x}) = P(\alpha_{j-1} < y \le \alpha_j) \\ = \Phi(\alpha_j - \boldsymbol{\omega}'\mathbf{x}) - \Phi(\alpha_{j-1} - \boldsymbol{\omega}'\mathbf{x})$$

where Φ denotes the standard comulative normal distribution function and $\boldsymbol{\omega}$ is a vector of reduced-form regression coefficients defining the conditional mean $E(y^*|x)$. For $c = 2$ categories, this reduces to the binomial probit model:

$$P(y = 1|\mathbf{x}) = 1 - \Phi(\alpha - \boldsymbol{\omega}'\mathbf{x})$$

The α_j ($i = 1$ to $k - 1$) thresholds and ω_j ($j = 1$ to q) conditional means are estimated using the maximum likelihood method (Maddala, 1983). We define, for individual i in the sample ($i = 1$ to N),

$$z_{ij} = 1 \text{ if } y_i \text{ falls in category } j \\ z_{ij} = 0 \text{ otherwise}$$

Then

$$P(z_{ij} = 1) = \Phi(\alpha_j - \boldsymbol{\omega}'\mathbf{x}_i) - \Phi(\alpha_{j-1} - \boldsymbol{\omega}'\mathbf{x}_i)$$

where x_i is the vector of exogenous variable values for observation i. The likelihood function, defining the set of thresholds and regression coefficients for which the normal distribution of the population is least surprising is given by

$$L = \prod_{i=1}^{N} \prod_{j=1}^{c} \left[\Phi(\alpha_i - \boldsymbol{\omega}'\mathbf{x}_i) - \Phi(\alpha_{j-1} - \boldsymbol{\omega}'\mathbf{x}_i)\right]^{z_{ij}}$$

$$\log L = \sum_{i=1}^{N} \sum_{j=1}^{c} z_{ij} \log \left|\Phi(\alpha_i - \boldsymbol{\omega}'\mathbf{x}_i) - \Phi(\alpha_{j-1} - \boldsymbol{\omega}'\mathbf{x}_i)\right|$$

Adopting the simplifying notation $\Phi_{i,j} = \Phi(\alpha_j - \boldsymbol{\omega}'\mathbf{x}_i)$, and noting that

$$\frac{\partial \Phi(\mathbf{x})}{\partial \mathbf{x}} = \phi(\mathbf{x})$$

$$\frac{\partial \phi(\mathbf{x})}{\partial \mathbf{x}} = -\mathbf{x}\phi(\mathbf{x})$$

where is the normal probability density function, the conditions for *maximum* likelihood are

$$\frac{\partial(\log L)}{\partial\omega} = \sum_{i=1}^{N}\sum_{j=1}^{c} z_{ij}\,\frac{\phi_{i,j-1}-\phi_{i,j}}{\Phi_{i,j}-\Phi_{i,j-1}}\mathbf{x}_i = 0$$

and

$$\frac{\partial(\log L)}{\partial\alpha_k} = \sum_{i=1}^{N}\sum_{j=1}^{c} z_{ij}\,\frac{\delta_{j,k}\phi_{i,j}-\delta_{j-1,k}\phi_{i,j-1}}{\Phi_{i,j}-\Phi_{i,j-1}} = 0$$

where $\delta_{j,k}$ denotes the Kronecker delta

$$\delta_{j,k} = 1 \text{ if } j = k; \quad \delta_{j,k} = 0 \text{ otherwise}$$

The maximum likelihood equations are solved iteratively.

Step 2: Estimation of the Correlation Matrix

The y^* latent variables corresponding to the ordered categorical variables are multivariate normally distributed. The second step in the ADF WLS estimation method is to obtain estimates of the covariances or correlations among them, and between each of them and any multinormal continuous observed variables in the system.

When both y_i and y_j are continuous, their correlation is estimated using the conventional Pearson product-moment correlation. When both y_i and y_j are dichotomous (ordinal with two categories), a correlation coefficient known as tetrachoric correlation is used (Kirk, 1973). When both y_i and y_j are ordered categorical with at least one variable with three or more categories, the polychoric correlation is used (Olsson, 1979). When one variable is ordered categorical and the other is continuous, the polyserial correlation coefficient is used (Olsson, et al., 1982).

The basic concept underlying these correlation coefficients can be demonstrated by considering the polychoric correlation coefficient. Suppose we have an ordinal variable y_1 with c categories and an ordinal variable y_2 with d categories. The cross-tabulation of these two variables produces cell frequencies N_{ij}, i = 1,2,c and j = 1, 2,,d. We postulate that y_1^* is an ordered-response probit latent variable responsible for y_1:

$$\begin{aligned}
y_1 = 1 \text{ iff } &\quad a_0 < y_1^* \le a_1 \\
y_1 = 2 \text{ iff } &\quad a_1 < y_1^* \le a_2 \\
&\vdots \\
y_1 = c \text{ iff } &\quad a_{c-1} < y_1^* \le a_c
\end{aligned}$$

and y_2^* is responsible for y_2:

$$\begin{aligned}
y_2 = 1 \text{ iff } &\quad b_0 < y_2^* \le b_1 \\
y_2 = 2 \text{ iff } &\quad b_1 < y_2^* \le b_2 \\
&\vdots \\
y_2 = d \text{ iff } &\quad b_{d-1} < y_2^* \le b_d
\end{aligned}$$

The log-likelihood resulting from the cross-tabulation (contingency table) frequencies is then

$$\log L = \text{constant} + \sum_{i=1}^{c} \sum_{j=1}^{d} N_{ij} \log (\pi_{ij})$$

where

$$\pi_{ij} = \Phi_2(a_i, b_j) - \Phi_2(a_{i-1}, b_j) - \Phi_2(a_i, b_{j-1}) + \Phi_2(a_{i-1}, b_{j-1})$$

and Φ_2 denotes the bivariate normal distribution function with correlation ρ. The problem is to determine ρ given the a_i (i = 1 to c) and b_j (j = 1 to d) thresholds found in the first step of the estimation method by finding the ρ value that maximizes the likelihood of observing the cross-tabulation frequencies. This is known as limited-information maximum likelihood, because the thresholds are taken as given at this second step.

The correlation matrix of our four endogenous variables, estimated according to these first two steps of the estimation method, is shown in Table 3. The two endogenous variables that are treated as discrete choice variables, AARB and PILLS, are now interpreted as "the propensity to self-impose schedules" and "the propensity to take pills," respectively. The correlations between each of these variables and one of the continuos variables is similar to the standardized coefficient in a single-variable probit model. The tetrachoric correlation between AARB and PILLS is the estimated correlation of their bivariate normal distribution.

The strongest relationships are measured by the positive tetrachoric correlation between the propensity for self-imposed schedules and the propensity to take pills, and the positive polyserial correlation between the propensity to take pills and the number of speeding fines per annum. All endogenous variable correlations except the polyserial correlation between the propensity for self-imposed schedules and log of average speed over trip legs are significantly different from zero at the $p = .05$ level.

Table 3. Endogenous Variable Correlations

	AARB	PILLS	LTOTASP	FINES
AARB	1			
PILLS	0.198^{TC}	1		
LTOTASP	0.035^{PS}	0.112^{PS}	1	
FINES	0.060^{PS}	0.195^{PS}	0.059^{PE}	1

TC = tetrachoric correlation
PS = polyserial correlation
PE = Pearson product-moment correlation

The similarly-estimated correlations between the exogenous and endogenous variables are listed in Table 4. An important aspect of this modeling is that it treats both the endogenous and exogenous dichotomous variables in a consistent manner; all dichotomous variables are modelled as discrete-choice probit variables.

Table 4. Correlations Between the Exogenous and Endogenous Variables

	AARB	PILLS	LTOTASP	FINES
OFFRDTIM	-0.158^{PS}	-0.126^{PS}	-0.135^{PE}	-0.044^{PE}
AGE	-0.129^{PS}	-0.262^{PS}	-0.176^{PE}	-0.149^{PE}
SCHARR	0.089^{TC}	0.121^{TC}	0.149^{PS}	0.147^{PS}
SLPREST	-0.214^{PS}	-0.154^{PS}	0.000^{PE}	-0.089^{PE}
NOPRVOCC	-0.017^{TC}	0.190^{TC}	-0.021^{PS}	-0.015^{PS}
SLEEP8	-0.078^{PS}	-0.168^{PS}	0.035^{PE}	-0.050^{PE}
TRKWT	0.097^{PS}	0.116^{PS}	0.069^{PE}	0.059^{PE}
GDPER	0.367^{TC}	0.205^{TC}	0.132^{PS}	0.033^{PS}
RCALL	-0.051^{TC}	-0.080^{TC}	-0.013^{PS}	0.086^{PS}
NOSLEEP	-0.183^{PS}	-0.040^{PS}	0.041^{PE}	-0.045^{PE}
DAYSTRT	-0.041^{TC}	-0.098^{TC}	0.201^{PS}	0.124^{PS}
DKMOD	0.089^{PS}	-0.164^{PS}	-0.237^{PE}	-0.116^{PE}
DKMED	0.045^{PS}	0.150^{PS}	0.029^{PE}	0.069^{PE}
TSTL8	-0.108^{TC}	-0.123^{TC}	-0.082^{PS}	-0.118^{PS}
RATIOSD	0.151^{PS}	0.141^{PS}	-0.053^{PE}	0.135^{PE}

TC = tetrachoric correlation
PS = polyserial correlation
PE = Pearson product-moment correlation

Step 3: Estimation of the structural Equation Model Parameters

The final step in the ADF WLS method is to estimate the parameters, $\hat{\theta}$, of the structural equation model by making the model-implied covariance matrix, $\Sigma(\hat{\theta})$ as close as possible to the sample covariance matrix, **S**, where **S** is composed of product-moment, tetrachoric, polychoric, polyserial and censored correlation coefficients, depending upon variable type. It is not appropriate to use normal-theory maximum likelihood estimation, because the assumptions underlying this method do not hold for these types of variables. Maximum likelihood estimation in this case will yield consistent estimates but incorrect standard errors (z-statistics) and ^{2} statistics.

The estimation method of choice is generally weight least squares (WLS). The fitting function for WLS is

$$F_{WLS} = [s - \sigma(\theta)]' \mathbf{W}^{-1}[s - \sigma(\theta)]$$

where s is a $\left[\frac{1}{2}(p+q)(p+q+1)\right]\times 1$ vector of product-moment, polychoric, polyserial, and censored correlation coefficients for all pairs of endogenous and exogenous variables, $\sigma(\theta)$ is a vector of model-implicated correlations for the same variable pairs, and **W** is a $\left[\frac{1}{2}(p+q)(p+q+1)\right]\times\left[\frac{1}{2}(p+q)(p+q+1)\right]$ positive-definite weight matrix. Minimizing F_{WLS} implied that the parameter estimates are those that minimize the weighted sum of squared deviations of s from $\sigma(\theta)$. This is analogous to weighted least squares regression, but here the observed and predicted values are variances and covariances rather than raw observations.

The best choice of the weight matrix is a consistent estimator of the asymptotic covariance matrix of **s**:

$$\mathbf{W} = ACOV(s_{ij}, s_{gh})$$

Under very general conditions

$$\mathbf{W} = \frac{1}{N}(\sigma_{ijgh} - \sigma_{ij}\sigma_{gh})$$

is a consistent estimator, where σ_{ijgh} denotes the fourth-order moments of the variables around their means, and σ_{ij} and σ_{gh} denote covariances. Brown (1982, 1984) demonstrated that F_{WLS} with such a weight matrix will yield consistent estimates $\hat{\theta}$ which are asymptotically efficient with correct $ACOV(\hat{\theta})$ (leading to correct parameter z-statistics) and correct X^2 test values. These properties hold for very general conditions, and consequently such F_{WLS} estimators are known as arbitrary distribution function, or asymptotically distribution free (ADF) estimators.

ADF WLS structural equation model estimators are available in the LISCOMP program developed by Muthén (1983, 1984), in the EQS program developed by Bentler (1985) and in LISREL with PRE-LIS (Jöreskog and Sörbom, 1993). We used the LISREL/PRE-LIS (Versions 8/2 for Windows) programs.

4. An Assessment of the Trip Specific Activity Profile

The structural equation model represented by Figure 2 and an exogenous structure involving a matrix with 45 free elements was estimated using the ADF WLS method. This model, designated Model I, can be shown to be identified, and the goodness-of-fit X^2 = -2nF_{WLS} = 8.47 with 12 degrees of freedom. This corresponds to p = .747, indicating that the model *cannot* be rejected.

The estimated endogenous variable direct effects (matrix) and error-term correlations (Ψ matrix parameters) for Model I are shown in Table 5.

Table 5. Estimates of Direct Effects and Error Correlations Among Endogenous Variables for Model I

Structural Element	Hypothesis	Direct Effect From	To	Coefficient	*t*-statistic
$\beta_{2,1}$	H_1	AARB	PILLS	0.433	12.3
$\beta_{3,2}$	H_2	PILLS	LTOTASP	0.052	0.97
$\beta_{2,3}$	H_3	LTOTASP	PILLS	0.000	0.004
$\beta_{3,1}$	H_4	AARB	LTOTASP	-0.034	-1.21
$\beta_{4,2}$	H_5	PILLS	FINES	0.170	6.16
$\beta_{4,1}$	H_6	AARB	FINES	-0.006	-0.24
$\beta_{4,3}$	H_7	LTOTASP	FINES	0.125	0.839
$\beta_{3,4}$	H_8	FINES	LTOTASP	-0.173	-1.69
$\Psi_{2,1}$		Error-term correlation: AARB / PILLS		-0.256	-6.13

It is apparent that Model I is over-structured in terms of direct causal relationships among the four exogenous variables. Simplification is required. The strongest hypotheses are clearly H_1 (self-imposed schedules promote the propensity to take pills) and H_5 (pill taking leads to more speeding fines). Hypothesis H_8 (fines reduce speeds) is also represented by a coefficient that is significant at the p = .05 confidence level for one-tailed tests.

A series of nested models were estimated in search of a simplified causal structure. These nested models represent a systematic elimination of the weakest hypotheses. Hypothesis H_2 (drivers can increase their average speed over the trip legs by taking pills) was found to be strong once the weakest of the original eight hypotheses, H_3 was eliminated at the first simplification step. Consequently, the hypotheses eliminated were, in order: H_3, H_6, H_4, H_7, and H_8. The estimation results are shown in Table 6. All of the models had the same exogenous variable (Γ matrix) and error-term correlation (Ψ matrix) structure. Each of Models II through VI is nested with Model I, and the difference in model ^{2} values is distributed as a chi-square statistic with degree-of-freedom equal to the difference in degrees of freedom between the two models being compared. None of the models can be rejected at the p = .05 level, but the reduction in model goodness-of-fit, measured by changes in ^{2} statistic, is insignificant until the simplification from Model V to Model VI. The simplification represented by Model VI can be rejected at the p = .05 level (critical value = 11.07). This indicates that the four hypotheses -- H_1, H_2, H_5, H_8 -- taken together are an effective representation of the causal structure among the endogenous variables.

Table 6. Nested Models Involving Between Eight and Three Common Hypotheses

Model	Hypotheses: Included	Hypotheses: Excluded	X^2	Deg.-of-freedom	p	Comparison with Model I: X^2	Comparison with Model I: D-o-f
I	H_1 *through* H_8	*none*	8.47	12	.747	-	-
II	*all but* H_3	H_3	8.48	13	.811	.01	1
III	*all but* H_3, H_6	H_3, H_6	9.09	14	.825	0.62	2
IV	H_1, H_2, H_5, H_7, H_8	H_3, H_4, H_6	10.65	15	.777	2.18	3
V	H_1, H_2, H_5, H_8	H_3, H_4, H_6, H_7	10.81	16	.821	2.34	4
VI	H_1, H_2, H_5	H_3, H_4, H_6, H_7, H_8	20.59	17	.245	12.12	5

Model V involves four direct causal links between pairs of endogenous variables. It is possible that another four-link (four free **B** matrix elements) structure, not derived through the same stepwise elimination, would perform as well or better than Model V. In order to test for this, many other four-link were estimated and compared against Model V. No other model fitted as well as Model V. Results for the best alternative four-link models are summarised in Table 7. No other model fit with equal complexity fit as well as Model V.

Table 7. Alternative Models Involving Four Hypotheses

Model	Hypotheses	X^2	D-of-f	p
V	H_1, H_2, H_5, H_8	10.81	16	.821
VII	H_1, H_2, H_5, H_7	12.21	16	.730
VIII	H_1, H_4, H_5, H_7	16.14	16	.443
IX	H_1, H_2, H_7, H_8	92.55	16	.000

Finally, Model V was compared to all logical three-link models to determine whether or not the endogenous variable structure could be simplified any further. The results of these comparisons are in shown in Table 8. Models VI, X, XI, and XII are formed by eliminating one hypothesis (direct effect between a pair of endogenous variables) from Model V. Each of these models is nested with Model V, and the difference in model X^2 values is distributed as a chi-square statistic with one degree-of-freedom. All four of these simplifications of Model V can be rejected at the $p = .05$ level (critical value = 3.84). The remaining models are not nested with Model V, but it is apparent that each model fits substantially less well when compared to Model V.

Table 8. Comparison of Chosen Model V with Alternative Three-Hypothesis Models

Model	Hypotheses	X^2	D-o-f	p	Comparison with V X^2	Comparison with V D-o-f
V	H_1, H_2, H_5, H_8	10.81	16	.821	-	-
VI	H_1, H_2, H_5	20.59	17	.245	9.78	1
X	H_1, H_2, H_8	128.47	17	.000	117.66	1
XI	H_1, H_5, H_8	16.90	17	.461	6.09	1
XII	H_2, H_5, H_8	205.27	17	.000	194.46	1
XIV	H_1, H_5, H_6	15.77	17	.540	4.96	1
XV	H_1, H_4, H_5	21.01	17	.226	10.20	1
XVI	H_1, H_2, H_7	131.40	17	.000	120.59	1
XVII	H_1, H_4, H_6	34.27	17	.008	23.46	1

Chosen Model V was re-estimated with insignificant exogenous direct effects eliminated. The coefficient estimates for the elements of endogenous variables structure are listed in Table 9, and the flow diagram for this portion of the model is shown in Figure 3. As the estimation is performed on a correlation matrix, these coefficient estimates are fully standardized and can be directly compared in magnitude. It is apparent from the estimates and from the preceding model comparisons that the most important component of the this structure is the causal link from self-imposed schedules to the propensity to take pills (Hypothesis H_1). Conditional upon this direct effect, the next most important link is from pill-taking to speeding fines (Hypothesis H_5).

Completing the causal structure, speeding fines reduce average speeds (Hypothesis H_8), and pill-taking also allows increased average speeds (Hypothesis H_2). Conditional upon these four relationships, the data do not support any of the remaining hypotheses.

Table 9. Direct Effects and Error Correlations Among Endogenous Variables for Chosen Model V

Structural Element	Hypothesis	Direct Effect From	To	Coefficient	*t*-statistic
$\beta_{2,1}$	H_1	AARB	PILLS	0.436	13.2
$\beta_{3,2}$	H_2	PILLS	LTOTASP	0.051	2.33
$\beta_{4,2}$	H_5	PILLS	FINES	0.178	7.58
$\beta_{3,4}$	H_8	FINES	LTOTASP	-0.083	-3.12
$\Psi_{2,1}$		Error-term correlation: AARB / PILLS		-0.257	-6.24

All Model V direct effects are listed in Table 10, in order of the endogenous variables.

The total effects of the exogenous variables on the endogenous variables in a structural equations model of this type are given by:

$$T_{yx} = (\mathbf{I} - \mathbf{B})^{-1}\, \Gamma.$$

These are the so-called reduced-form equations. The total effects of the endogenous variable on themselves is given by

$$T_{yy} = (\mathbf{I} - \mathbf{B})^{-1} - \mathbf{I}\,.$$

The total effects for Model V are given in Table 11.

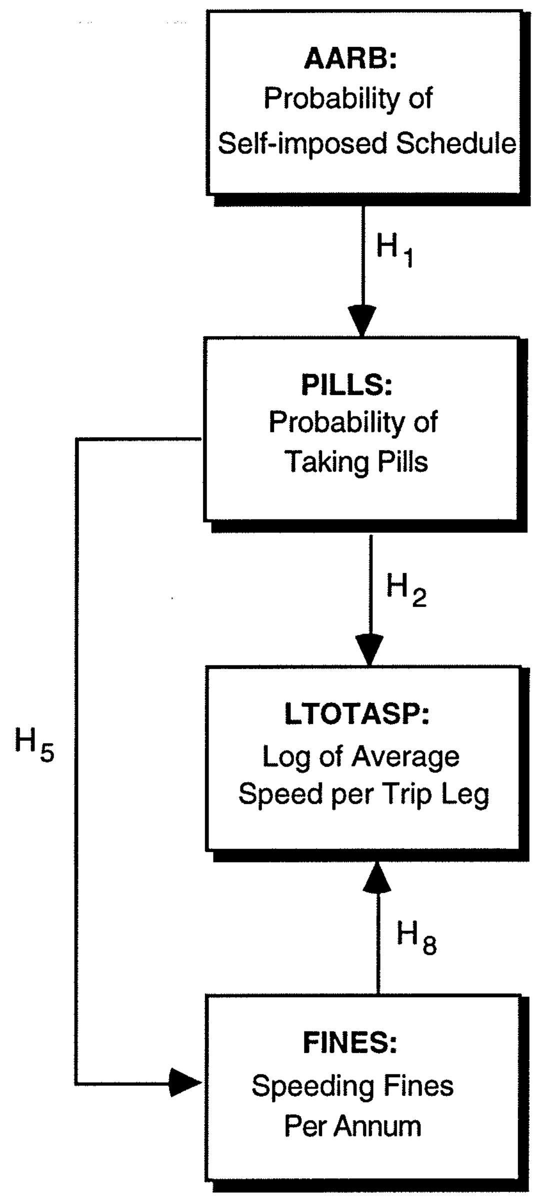

Figure 3 Chosen Model V: Direct Effects Among Endogenous Variables

Table 10. Complete set of Direct Effects for Chosen Model V

Structural Element	Direct Effect From	To	Coefficient	t-statistic
$\gamma_{1,1}$	OFFRDTIM	AARB	0.091	3.96
$\gamma_{1,2}$	AGE	AARB	-0.124	-5.71
$\gamma_{1,4}$	SLPREST	AARB	-0.243	-10.0
$\gamma_{1,5}$	NOPRVOCC	AARB	0.0610	4.87
$\gamma_{1,7}$	TRKWT	AARB	0.0300	1.98
$\gamma_{1,8}$	GDPER	AARB	0.410	43.7
$\gamma_{1,10}$	NOSLEEP	AARB	-0.147	-6.70
$\gamma_{1,11}$	DAYSTRT	AARB	0.0790	6.38
$\gamma_{1,12}$	DKMOD	AARB	0.208	9.22
$\gamma_{1,13}$	DKMED	AARB	0.0926	5.08
$\gamma_{1,14}$	TSTL8	AARB	-0.108	-12.5
$\gamma_{1,15}$	RATIOSD	AARB	0.127	6.55
$\beta_{2,1}$	AARB	PILLS	0.436	13.2
$\gamma_{2,1}$	OFFRDTIM	PILLS	-0.0377	-1.86
$\gamma_{2,2}$	AGE	PILLS	-0.206	-8.79
$\gamma_{2,3}$	SCHARR	PILLS	0.0423	3.86
$\gamma_{2,5}$	NOPRVOCC	PILLS	0.183	13.5
$\gamma_{2,6}$	SLEEP8	PILLS	-0.131	-6.71
$\gamma_{2,7}$	TRKWT	PILLS	0.0785	4.78
$\gamma_{2,9}$	RCALL	PILLS	-0.076	-5.32
$\gamma_{2,10}$	NOSLEEP	PILLS	0.089	4.22
$\gamma_{2,11}$	DAYSTRT	PILLS	-0.0504	-3.13
$\gamma_{2,12}$	DKMOD	PILLS	-0.119	-5.25
$\gamma_{2,15}$	RATIOSD	PILLS	0.0685	3.45
$\beta_{3,2}$	PILLS	LTOTASP	0.0509	2.33
$\beta_{3,4}$	FINES	LTOTASP	-0.0834	-3.12
$\gamma_{3,1}$	OFFRDTIM	LTOTASP	-0.120	-3.01
$\gamma_{3,2}$	AGE	LTOTASP	-0.0934	-2.86
$\gamma_{3,6}$	SLEEP8	LTOTASP	0.106	2.68
$\gamma_{3,8}$	GDPER	LTOTASP	0.0756	5.53
$\gamma_{3,11}$	DAYSTRT	LTOTASP	0.206	13.1
$\gamma_{3,12}$	DKMOD	LTOTASP	-0.380	-7.42
$\gamma_{3,13}$	DKMED	LTOTASP	-0.246	-7.60
$\gamma_{3,14}$	TSTL8	LTOTASP	-0.158	-9.85
$\beta_{4,2}$	PILLS	FINES	0.178	7.58
$\gamma_{4,1}$	OFFRDTIM	FINES	0.128	6.21
$\gamma_{4,2}$	AGE	FINES	-0.0755	-3.01
$\gamma_{4,3}$	SCHARR	FINES	0.133	13.6
$\gamma_{4,4}$	SLPREST	FINES	-0.139	-8.33
$\gamma_{4,5}$	NOPRVOCC	FINES	0.0902	7.35
$\gamma_{4,6}$	SLEEP8	FINES	-0.0963	-6.21
$\gamma_{4,9}$	RCALL	FINES	0.239	26.0
$\gamma_{4,10}$	NOSLEEP	FINES	-0.0594	-3.44
$\gamma_{4,11}$	DAYSTRT	FINES	0.253	17.1
$\gamma_{4,12}$	DKMOD	FINES	-0.116	-6.60
$\gamma_{4,13}$	DKMED	FINES	-0.118	-6.86
$\gamma_{4,15}$	RATIOSD	FINES	0.141	7.08

Table 11. Total Effects for Chosen Model V

Total Effects

From	To	Effect	*t*-statistic
OFFRDTIM	AARB	0.091	3.96
AGE	AARB	-0.124	-5.71
SCHARR	AARB	(0)	(-)
SLPREST	AARB	-0.243	-10.0
NOPRVOCC	AARB	0.0610	4.88
SLEEP8	AARB	(0)	(-)
TRKWT	AARB	0.0301	1.98
GDPER	AARB	0.411	43.7
RCALL	AARB	(0)	(-)
NOSLEEP	AARB	-0.147	-6.70
DAYSTRT	AARB	0.0790	6.38
DKMOD	AARB	0.208	9.22
DKMED	AARB	0.0926	5.08
TSTL8	AARB	-0.108	-12.5
RATIOSD	AARB	0.127	6.55

Total Effects

From	To	Effect	*t*-statistic
AARB	PILLS	0.436	13.2
OFFRDTIM	PILLS	(0.0019)	(0.091)
AGE	PILLS	-0.260	-11.9
SCHARR	PILLS	0.0423	3.86
SLPREST	PILLS	-0.106	-8.27
NOPRVOCC	PILLS	0.210	14.1
SLEEP8	PILLS	-0.131	-6.71
TRKWT	PILLS	0.0916	6.01
GDPER	PILLS	0.179	13.4
RCALL	PILLS	-0.0760	-5.32
NOSLEEP	PILLS	0.024	(1.19)
DAYSTRT	PILLS	-0.016	(-0.91)
DKMOD	PILLS	-0.0279	(-1.22)
DKMED	PILLS	0.0404	5.19
TSTL8	PILLS	-0.0473	-10.1
RATIOSD	PILLS	0.124	6.14

Total Effects

From	To	Effect	*t*-statistic
AARB	LTOTASP	0.0157	1.72
PILLS	LTOTASP	0.0360	1.73
FINES	LTOTASP	-0.0834	-3.12
OFFRDTIM	LTOTASP	-13.1	-3.32
AGE	LTOTASP	-0.0965	-3.07
SCHARR	LTOTASP	-0.00964	-2.73
SLPREST	LTOTASP	(0.0077)	(1.60)
NOPRVOCC	LTOTASP	(0.0000)	(0.01)
SLEEP8	LTOTASP	0.110	2.81
TRKWT	LTOTASP	(0.0033)	(1.64)
GDPER	LTOTASP	0.082	5.94
RCALL	LTOTASP	-0.0227	-3.34
NOSLEEP	LTOTASP	0.00583	2.53
DAYSTRT	LTOTASP	0.185	12.4
DKMOD	LTOTASP	-0.371	-7.33
DKMED	LTOTASP	-0.234	-7.32
TSTL8	LTOTASP	-0.160	-9.95
RATIOSD	LTOTASP	(-0.00727)	(-1.47)

Total Effects

From	To	Effect	*t*-statistic
AARB	FINES	0.0778	7.00
PILLS	FINES	0.178	7.58
OFFRDTIM	FINES	0.128	6.13
AGE	FINES	-0.122	-5.00
SCHARR	FINES	0.141	14.3
SLPREST	FINES	-0.157	-9.38
NOPROCC	FINES	0.128	9.21
SLEEP8	FINES	-0.120	-8.13
TRKWT	FINES	0.0163	4.45
GDPER	FINES	0.0319	7.07
RCALL	FINES	0.226	26.2
NOSLEEP	FINES	-0.055	-3.28
DAYSTRT	FINES	0.250	17.3
DKMOD	FINES	-0.120	-6.65
DKMED	FINES	-0.111	-6.42
TSTL8	FINES	-.00843	-6.28
RATIOSD	FINES	0.163	8.20

Twelve exogenous variables had a statistically significant influence on the probability of a driver imposing a schedule (AARB). It is reinforced by (or may arise from) the imposition of a schedule from an employer or freight forwarder. Thirty-seven percent of the sample had such a constraint. Schedule self-imposition is most strongly related to perishable loads (GDPER), a low number of sleep and rest stops (SLPREST) and a higher earning rate for owner-drivers (DKMOD). Drivers who have a higher absolute amount of non-driving time prior to departure, post-arrival at the destination and en route (OFFRDTIM), tend to have a higher propensity to self-impose a schedule; however, where the number of en route stops (NOSLEEP) is higher, the propensity to self-impose schedules is reduced. The negative association arises most plausibly because of the lesser amount of pressure on the driver's earning opportunity. The relatively strong positive impact of OFFRDTIM suggests that the time securing a load and its final delivery are important influences on the propensity to self-impose a schedule, but where the non-driving time has a high incidence of en-route stopping that the self-imposed pressures are lessened.

The most important total effect on the propensity to take PILLS is that of the endogenous variable self-imposed schedules (AARB). Also relatively important are the AGE of the driver (negative) and whether or not the driver had a previous occupation, or was always a truckie (NOPRVOCC); no previous occupation is positively associated with pill-taking. Other important indications of pill-taking are perishable loads (GDPER) and a wide variation in the proportion of time actually driving over the trips segments (RATIOSD).

The greatest total effects on average speed (LTOTASP) comes from the earning rates of both owner drivers (DKMOD) and employee drivers (DKMED). Drivers with higher earnings rates exhibit lower speeds, and this is particularly true for owner drivers. Average speeds are also lower for trips with early starts (TSTL8) and trips with more time working but not driving. Average speeds are higher for trips that start on weekends (DAYSTRT) and for trips where the driver was able to sleep longer during the eight hours prior to the trip (SLEEP8).

Many of the variables have strong total effects on the number of speeding FINES per annum. Drivers starting trips on a weekend (DAYSTRT) and those with regular contracts (RCALL) are inclined to acquire more fines, as are drivers taking PILLS. Also, trips with high variation in the proportion of time spent actually driving (RATIOSD) and trips with company or forwarder-imposed schedules (SCHARR) are associated with drivers with more speeding fines. Younger drivers (AGE), those with no previous occupation (NOPRVOCC), and drivers that are less well-paid (DKMOD and DKMED) tend to acquire more speeding fines.

The overall effects of each endogenous and exogenous variable can be summarized as follows:

The propensity to self-impose schedules (AARB) strongly influences the propensity to take pills. Through this strong direct causality, self-imposed schedules also lead to speeding and speeding fines.

The propensity to take pills (PILLS) is directly related to both speeding and speeding fines, but the negative feedback from fines to reduced speeding results in a relatively weak overall effect of pills on speeding. The strongest effect of pills is an increase in the number of speeding fines.

The negative effect of FINES on speeding documents the effectiveness of the enforcement of traffic laws.

The total effect of off-road trip time (OFFRDTIM) is a positive impact on the propensity to self-impose a schedules, and a negative impact on overall speed, due to the presumably dominating incidence of en-route time compared to pre-and post-trip time. Off-road time has insignificant total effects on both the propensity to take pills and speeding fines per annum.

Regarding driver AGE, older drivers are less inclined to have self-imposed schedules, to take pills, or to receive speeding fines. Presumably, they tend to have a more established position in the market and greater certainty of jobs, less delays in securing a load, and acceptable rates.

Drivers with forwarder-imposed schedules (SCHARR) are more inclined to take pills and acquire speeding fines. However, while there is no direct effect between forwarder-imposed schedules and speed, the total effect of SCHARR on average speed is negative, due to the moderating effect of fines on speed.

The number of sleep and rest stops (SLPREST) is an important deterrent to self-imposed schedules, pills, and speeding fines.

If a driver has no previous occupation (NOPRVOCC), there is a tendency to self-impose schedules, take pills, and acquire speeding fines. This could indicate a normal way of life for truckies.

The hours slept in the eight hours prior to the trip (SLEEP8) substantially reduce the need to take pills and the rate of occurrence of speeding fines. The total effect of SLEEP8 on FINES is less than the direct effect due to the moderating effect of SLEEP8 on PILLS and the direct link from PILLS to FINES. There is no total effect of SLEEP8 on self-imposed schedules, and the total effect on speeding is insignificant due to compensating influences.

Heavier truck gross weights (TRKWT) are associated with higher rates of all of the endogenous variables: self-imposed schedules, pill-taking, speeding, and speeding fines. The total effect of TRKWT on speeding is the weakest of the total effects four.

Carrying perishable goods (GDPER) tends to encourage the self-imposition of schedules, pill-taking, higher speeds and speeding fines. These effects are considerably stronger than those of truck weight.

Truckies with regular contracts (RCALL) are less likely to take pills and exhibit lower speeds, a result which may have important policy implications. However, those with regular contracts have higher numbers of speeding fines.

The number on en route stops without sleep (NOSLEEP) is an important indicator of a trip with high average speed, but a schedule that is *not* self-imposed, and lower numbers of speeding fines. The direct effects of NOSLEEP on pill-taking and speeding fines are insignificant.

Weekend trips (DAYSTRT) tend to incur higher propensity to self-impose schedules and higher speeds ("want to get home" or back to base). The total effect of weekend trips on the propensity to take pills is insignificant.

Earning rates for both owner drivers (DKMOD) and employee drivers (DKMED) are significant positive influences on the propensity to self-impose schedules, and significant negative influences on average speed and speeding fines. The rate for employee drivers is positively associated with the propensity to take pills, but the total effect of rate for owner drivers on pill-taking is insignificant. The behavioural implications are important. We see that higher rates tend to increase the propensity to self-impose a schedule, suggesting the view that the freight forwarders see such drivers with higher rates, ceteris paribus, as having the ability to deliver on time, the self-imposition of schedules being some sort of desirable discipline. However for employee drivers, the price of this schedule reliability is a higher incidence of pill taking (confirmed by exploratory analysis of the data which suggests that owner drivers are not necessarily the greater users of pills). Encouragingly, when rates are higher the average speed is lower, suggesting that drivers with a higher propensity to self-impose schedules are not necessarily the drivers who speed. The use of pills in the employee driver set appears to assist in the conformation of schedules.

Early trip starters (TSTL8) tend to not self-impose schedules, tend not to take pills, tend to travel at relatively lower speeds, and tend to acquire fewer speeding fines. This suggests that the security of early loads enables a truckie to complete a task and line up for the next load in reasonable time.

Finally, the variation in the proportion of time spent actually driving (RATIOSD) is highly related to self-imposed schedules, pill-taking, and speeding fines. Its relationship to overall average speed is insignificant.

These positive and negative influences when taken together are expressing a "lifestyle" phenomenon which in part is the historical product of pressures in the market to secure loads in order to earn an acceptable wage. Any assistance to this industry which can reduce the pressures in the market to a level which will reduce the reliance on pills must be desirable (even after allowing for the possibility of somewhat higher rates for moving goods). The current rates have not internalised the negative externalities rampant in this industry, which have spawned a lifestyle encouraging pill taking in order to stay awake long enough to improve the financial situation. The use of stimulants is as widespread in the employee driver sector as it is in the owner driver sector, and is regarded by many drivers as an acceptable practice (Hensher et al. 1992, 1993).

5. Conclusion

The influences on the performance of long distance truck drivers in Australia are related in a complex way. Although the centrepiece of a causal system is the linkage between potential earnings, lifestyle and pressures imposed on a driver by employers and the marketplace, there are some very explicit influences impinging on safe practices on the road where safety and exposure to risk are adequately represented by variations in average trip speed across the population of truck drivers.

The data obtained from 402 truck drivers are used herein to establish a first round understanding of some of the major endogenous linkages and exogenous determinants on travel practices in respect of a particular trip. This has enabled us to scientifically investigate a large number of the anecdotes and qualitative "evidence" previously used to develop positions in respect of strategies to "rid the industry and the road environment of cowboys".

The anecdotal evidence which tends to lay the blame for bad on-road behaviour on owner drivers is fallacious. Small company employee drivers have some of the worst industry practices in respect of speeding, use of stimulants and incidence of fines. Indeed many of the influences on variations in on-road performance, pill taking and self-imposition of schedules which often lead to speeding are not correlated with whether a driver is an owner driver or an employee driver. The distinction between owner driver and employee driver is somewhat arbitrary and misleading in the current context. A much more useful classification is in terms of the nature of contracts, work practices and opportunities to secure loads.

Lifestyle factors appear to have evolved as a result of the ease of entry to the industry coupled with its highly competitive nature which demands non-routine and unpredictable work practices for a significant number of drivers in the industry. There appears to be a case for much more stringent safety regulations centred on the health of the driver as distinct from the "health of the rig". There is a great temptation for commentators to argue that if someone wants to enter this industry, get burdened with high debts and work excessive hours to "make a quid" then they should be allowed to. This may be acceptable wisdom if safety of human resources at large were not at risk. It is precisely because of the negative externalities aligned to safety that changes are required in the competitive practices in the industry.

Appendix

Descriptive Background of Survey Sample

Some of the main findings from the descriptive analysis are summarised below.

Driver characteristics

¥ the majority of truck drivers (70%) had over 10 years experience driving large trucks on a regular basis
¥ the average number of annual vehicle kilometres driven by drivers in the sample was around 200,000 kms
¥ the majority of drivers (75%) were in the age group 25 to 44 years
¥ 25% of drivers had no previous occupation other than truck driving. For the others a range of occupations was represented, primarily the trades, farmers and general labourers, but also a significant number of managerial and professional positions

Income / payment

¥ the survey highlighted the low level of income earned by drivers, particularly owner drivers (36% earned less than $15,000 in 1989-90)
¥ the majority of employee drivers (79%) were paid directly in relation to the earnings of the truck

Work environment

¥ drivers believed that they worked an average of 105 hours per week. This included all work activities both on and off the road. Of this, about 65% on average was estimated to be driving time
¥ a considerable amount of time is spent by drivers in off-road work activities before embarking on the trip. Approximately 3.5 hours were spent on work related activities, such as unloading from a previous trip, loading for the next trip and maintenance of the truck, before beginning to drive
¥ approximately 35% of all drivers were travelling to a set schedule for the sampled trip
¥ but 60% of drivers maintained that even if they were not set a schedule by the freight forwarder they were aiming for their own self-imposed time of arrival. This was dictated primarily by concerns to be first in the queue to be unloaded and then to obtain the next load

Behaviour / on-road performance

¥ drivers from small companies recorded the highest average trip speed for the sampled trip (82.01 kph compared with the average for the sample of 81.06 kph)
¥ a higher average trip speed for the sampled trip was found on the longer trips
¥ the younger, less experienced drivers recorded the highest average trip speed on the sampled trip (those driving for less than 5 years had an average speed of 82.14 kph and those aged 17-24 years of age had an average speed of 84.72 kph compared with a sample average of 81.06 kph)
¥ 46% of drivers admitted to taking stimulant drugs at least on some trips
¥ 17% of drivers had been involved in a crash in the 2 years preceding the survey. Owner drivers and small company drivers were more likely to have been involved in more crashes than the other types of driver

Truck

¥ 40% of trucks were less than 3 years old. Owner drivers were more likely to have older trucks than any of the other types of driver
¥ the high cost of the commitment of financing the truck was highlighted by the low level of deposit of most owner drivers and the short period of the loan. The average loan period was 4.25 years and average monthly repayments were around $2,500
¥ repayments on the truck were the second highest component (after fuel) of total expenses for owner drivers
¥ at the time of the survey (September - October 1990) 13% of drivers were driving trucks which were fitted with a speed limiter. This varied greatly by type of driver with 42% of large company trucks being speed limited
¥ 19% of drivers were driving trucks which had a tachograph fitted

Driver comments

¥ the main issues confronting the industry mentioned by drivers were the low level of freight rates relative to their operating costs and the high cost of fuel and taxes
¥ the most important factors which drivers considered contributed to crashes involving heavy vehicles were the condition of the roads, the behaviour of other vehicle drivers, fatigue on the part of the truck driver and lack of driving skills by the truck driver

¥ drivers were very supportive of the need for specialised driver training courses to upgrade the skills of truck drivers and to improve their image with the general public. 80% of drivers were in favour of introducing driver training courses

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