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AN ECONOMETRIC APPROACH TO DEMAND, SUPPLY AND SERVICE QUALITY IN THE TAXI INDUSTRY

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An Econometric Approach to Demand, Supply and Service Quality in the Taxi Industry.

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Abstract.

This paper uses data collected during various unmet demand studies to build econometric models of the taxi market. The aim is to use these models to derive the elasticities of demand for taxis with respect to price and service quality.

It is found that the cross-sectional approach adopted fails to pick up any significant service quality effects. The price elasticity was about -2 under a constant elasticity formulation, and ranged between -2.5 to -3.5 if allowed to vary with price.

AN ECONOMETRIC APPROACH TO DEMAND, SUPPLY AND SERVICE QUALITY IN THE TAXI INDUSTRY.

1 Introduction.

This section uses data collected during various unmet demand studies to build econometric models of the taxi market. The system it was hoped to model is depicted in figure 1.

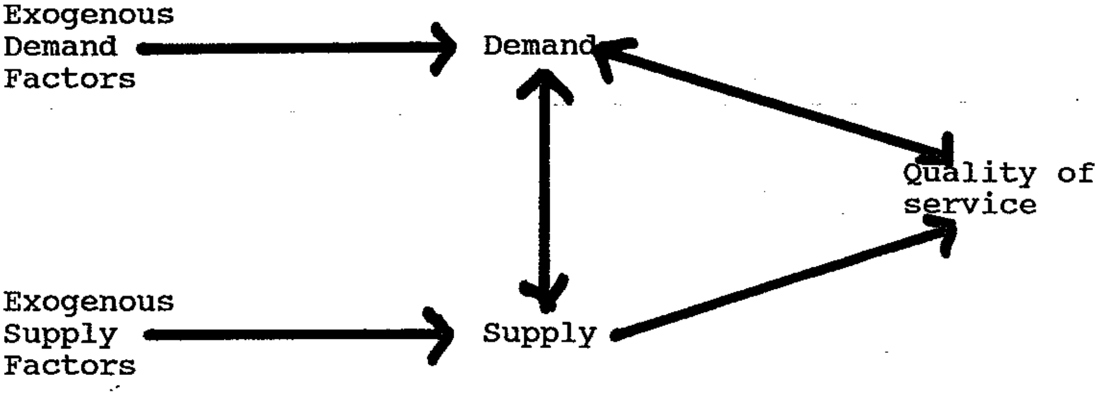

Figure 1: cross-sectional econometric model

It can be seen that three models are required for the system; a demand model, a supply model and a quality of service model. The first is clearly some measure of the use of taxis in the districts and the second some indicator of vehicle stock; the third is a representation of waiting time or the probability of waiting.

Although the model building procedure is quite simple in theory (demand is a function of price, service quality/supply, other relevant variables; supply is a function of demand, any other relevant variables; service quality is a funtion of demand and supply), there is considerable room for manoeuvre in deciding on the appropriate variables to include. The first consideration is whether to model actual trips taken (number of trips is a function of fare, population, etc) or a trip-rate model (number of trips per capita is a function of fare, etc); there is no <u>a priori</u> reason to favour one method over the other, and it is therefore a question of which approach gives the best models. The second consideration is which indicators of demand, supply and service quality to use. For demand, we can use data derived from rank observations (which cover only rank trips) or from interviews (which cover all trips); these can be adjusted by the known breakdown of trips between rank and phone booking to give estimates of total demand based on rank observations or rank demand based on interviews. Supply can be either the hackney carriage fleet or the combined hackney and hire car fleet. Service quality can be represented by average waiting times derived from rank observations, average waiting times derived from interviews or proportion of taxi users having to wait (again derived from interviews). Once more, it is not clear that any of these options is inherently superior to another. Table 1 below shows some of the different demand measures which can be used.

Table 1: demand indicators

DIST	RDEM	IDEM	RDEMPC	IDEMPC	FARE
A	10000	128064	0.0216	0.276	215
B	3200	42975	0.0168	0.225	230
C	5400	91098	0.0143	0.241	210
D	5900	117480	0.0083	0.165	235
E	3800	57846	0.0122	0.186	175
F	28500	142788	0.0651	0.326	220
G	8000	129584	0.0385	0.623	185
H	2500	62400	0.0240	0.600	200
I	2000	26334	0.0260	0.342	200
J	7500	86420	0.0259	0.298	200
K	12700	157634	0.0236	0.293	205
L	6500	19686	0.0637	0.193	260
M	3000	25661	0.0448	0.383	200
N	7500	179955	0.0269	0.645	210
O	3000	61500	0.0244	0.500	200
P	2300	13000	0.0115	0.065	240
Q	11500	157200	0.0383	0.524	190

Key
RDEM = Weekly rank hirings from rank observations
RDEMPC = RDEM per capita
IDEM = Total weekly hirings from interviews
IDEMPC = IDEM per capita
FARE = fare for one person making 2½ mile trip during the day

There was considerable scope for including different fare variables. Although there was generally no information about trip lengths, ruling out the possibility of using an average fare, there was some thought given to the mileage figure to use in calculating the fare and also whether to use night time rather than day time fares. To include two fare variables would have introduced a multicollinearity problem, and the choice of mileage could have ranged quite reasonably from about 2 miles to 4 miles. 2½ miles was chosen as a typical trip length. It is in fact the existence of the "drop" which creates a problem. If fares were calculated simply on a mileage basis, then the choice of trip length included in the analysis would not affect the elasticities; however, for certain model forms, the elasticities depend on the trip length used. However, since there are potentially appropriate functional forms in which allowances can be made for trip length assumption, notably linear and exponential models, the 2½ mile assumption need not be too restrictive.

2 Demand models.

When modelling total demand (using RDEM or IDEM) it is obviously not wise to expect variations in fare alone to pick up changes in demand; allowance needs to be made for the population (POP). Using rank observations to generate the dependent variable RDEM, very few acceptable models were obtained. The best (t-statistics in parentheses) was

$$LRDEM = \underset{(5.500)}{8.285} + \underset{(2.862)}{2.44E\text{-}06POP} - \underset{(0.229)}{0.16FARE}$$

$R^2=0.369$ $F=4.100$ $\epsilon_l=-0.29$ $\epsilon_h=-0.43$ $\epsilon_m=-0.35$

ϵ_l is the price elasticity of demand at the lowest observed fare
ϵ_h is the price elasticity of demand at the highest observed fare
ϵ_m is the price elasticity of demand at the mean of observed fares
FARE is in pounds

Clearly the coefficient on fare is insignificant, the model being swamped by the presence of POP. Use of interview data to generate demand levels proved more fruitful. Presented below are linear, exponential and double-log models. (L preceding a variable indicates $\log_e$.)

LINEAR

$$IDEM = \underset{(2.164)}{213599} + \underset{(3.7)}{0.207POP} - \underset{(1.86)}{87284FARE}$$

$R^2=0.531$ $F=7.927$ $\epsilon_l=-1.22$ $\epsilon_h=-29.27$ $\epsilon_m=-2.07$

EXPONENTIAL

$$LIDEM = \underset{(10.78)}{13.99} + \underset{(4.28)}{3.14E\text{-}06POP} - \underset{(2.88)}{1.78FARE}$$

$R^2=0.634$ $F=12.125$ $\epsilon_l=-3.11$ $\epsilon_h=-4.62$ $\epsilon_m=-3.73$

DOUBLE LOG

$$LIDEM = \underset{(2.60\ )}{18.29} + \underset{(4.66)}{0.834LPOP} - \underset{(2.59)}{3.275LFARE}$$

$R^2=0.6625$ $F=13.74$ $\epsilon=-3.275E$

In comparing these models, it is incorrect to use R^2 as a criterion since the dependent variable is not the same in all models. It is possible to calculate an adjusted R^2 which allows for this; but here we can compare the models on other grounds. The linear model clearly does not work well in extreme cases - note the very high price elasticity (-29.27) for the district with the highest fare. This arises because the elasticity in this case is -87284*FARE/DEM (predicted demand) and any elasticity formulation with demand in the denominator will give high values at low demand (whether the low demand is caused by the high fares or by a small population); the same problem appears with a semilog demand function.

The double-log model achieves a better R^2 than the exponential, but the t-statistic on FARE is not as good. Furthermore, the double-log formulation is sensitive to the 2½ mile trip length assumption; the given figure of -3.275 is an upper limit as the drop tends to zero or the mileage rate to infinity. For all our districts, the elasticity with resoect to the mileage rate is smaller than -3.275, although that is the elasticity with respect to the price of a 2½ mile trip. It is not possible to say what the elasticity with respect to the price of (say) a four mile trip would be, since the coefficient would change.

In the exponential model, the elasticity with respect to the price of a 2½ mile trip varies between -3.11 and -4.72 . Again, the elasticities with respect to the mileage rate are smaller than these by an amount (1.78*DROP). However, the mileage elasticities thus calculated would be the same for a four mile trip or a twenty mile trip. We can also calculate the price elasticity of demand for four mile trips; this is given by

$$\epsilon_4 = \epsilon_{2\frac{1}{2}} \cdot \frac{F_4 / 4}{F_{2\frac{1}{2}}/2\frac{1}{2}}$$ where F_n is the fare for an 'n' mile trip.

Clearly a drop of zero which means a strictly mileage related fare would give the elasticity of demand for trips constant in each district irrespective of the trip length assumption.

Overall, the indication from these models is that the price elasticity of demand is of the order of -3 in our districts. However, with only two independent variables in the above models, it is possible that other relevant factors were omitted. The best models calibrated including other variables were:

EXPONENTIAL

$$\text{LIDEM} = \underset{(11.3)}{12.77} - \underset{(2.32)}{1.24}\text{FARE} - \underset{(2.20)}{0.5}\text{RV} + \underset{(2.93)}{6.4\text{E-06}}\text{POP} + \underset{(3.35)}{1.86\text{E-07}}\text{DENSQ}$$

R^2=0.818 $\bar{R}^2$=0.757 F=13.46 ϵ_1=-2.18 ϵ_h=-3.23 ϵ_m=-2.61

DOUBLE LOG

$$\text{LIDEM} = \underset{(1.78)}{-14.78} - \underset{(1.64)}{1.95}\text{LFARE} - \underset{(1.90)}{1.24}\text{LRV} + \underset{(2.63)}{1.27}\text{LPOP} + \underset{(3.26)}{0.86}\text{LDENSQ}$$

R^2=0.8235 $\bar{R}^2$=0.765 F=14.0 ϵ=-1.954

The $\bar{R}^2$ are both better than for the two independent variable models (0.617 and 0.582 for double-log and exponential respectively) and the t-statistics are still significant even with the reduced number of degrees of freedom. The elasticities turn out lower than before, broadly in the range -2 to -3. Looking at the other variables included, we found significant effects for the total rateable value of the district and the population-weighted population density. Total rateable value is included as a proxy for the wealth or prosperity of the district. The negative coefficients, suggesting less taxi trips in a more prosperous district, imply that taxi travel is an inferior good. It may reflect higher car ownership levels in more affluent districts; this would be expected to suppress the demand for taxi travel. The DENSQ term is population times population density; the positive coefficients mean that for a given population, more densely populated areas generate more trips; for a given population density, a greater population generates more trips; and there is an interaction between the two which generates even more trips.

Another factor which influences demand is the quality of service. We attempted to calibrate models based on the observed average waiting time, the reported average waiting time and the proportion of people waiting at least a minute. Many models generated wrong-sign coefficients, suggesting a simultaneity problem; more people travelling causes higher waiting times, although higher waiting times would be expected to reduce demand. The former effect was the one usually picked up by the models, although some achieved plausible results. In all cases, demand measured by rank observation was easier to predict than any measure based on interview data.

$$\underset{}{LRDEM} = \underset{(23.8)}{7.99} + \underset{(2.86)}{2.45E\text{-}06POP} - \underset{(0.262)}{0.00586RWAIT}$$

R^2=0.370 F=4.133 τ_l=-0.01 τ_h=-0.165 τ_m=-0.086

$$\underset{}{RDEM} = \underset{(2.15)}{-51416} + \underset{(2.80)}{5716.8LPOP} - \underset{(1.46)}{3343.9LWAIT1}$$

R^2=0.37 F=4.09 τ_l=-0.14 τ_h=-0.155 τ_m=-0.143

The first model was the best using RWAIT, the observed average waiting time. As can be seen from the insignificant t-statistic, RWAIT does not have a significant effect on demand levels, and thus yields very small elasticities. The second model, using WAIT1, might best be interpreted as the effect on the level of demand of the probability of having to wait. The coefficient is significant at the 10% level (one tailed test with 14 df) and provides elasticities in a close range around -0.15 . No model using IDEM as the dependent variable produced any meaningful results. Considering that IDEM was better than RDEM when using the fares data, it is clear that we have a problem in modelling demand as a function of both fare and quality of service; it was not possible to produce significant and sensible coefficients on each independent variable and, given the relative insignificance of waiting time on demand, the favoured approach for an overall demand model was to use IDEM as the dependent variable and disregard quality of service.

Turning to per capita demand models, the same sort of results were produced, but with less good fits. Using RDEMPC, only one model produced the correct sign on fare; and that had all parameters insignificant and R^2= 0.0004 . Clearly not worth pursuing. Using IDEMPC, the linear and semilog models had the same problem at high fares as the direct demand models - very high elasticities. The double-log and exponential models gave more plausible results;

$$\text{LIDEMPC} = \underset{(2.46)}{16.55} - \underset{(2.64)}{3.332}\text{LFARE}$$

R^2=0.318 F=6.98 ϵ=-3.332

$$\text{LIDEMPC} = \underset{(1.76)}{2.145} - \underset{(2.76)}{1.6}\text{FARE}$$

R^2=0.336 F=7.6 ϵ_l=-2.8 ϵ_h=-4.16 ϵ_m=-3.36

Once again, we get price elasticities of the order of -3 and subject to the same caveats and interpretations as previously. The influence of waiting time on demand was even more negligible in the per capita models. The only right sign model with even borderline significance (coefficient not quite significant at 10%) was

$$\text{RDEMPC} = \underset{(2.54)}{0.059} - \underset{(1.34)}{0.0087}\text{LWAIT1}$$

R^2=0.106 F=1.783 τ_l=-0.11 τ_h=-0.165 τ_m=-0.157

Again, low elasticities and an inability to incorporate fare and service quality in the same demand model.

Generally, the per capita approach provided better models when looking at the influence of supply on demand. The total vehicle fleet had little effect on demand, whether the latter was measured by RDEMPC or IDEMPC; it was the supply of hackney carriages per head of population which had the anticipated effect; a more generous provision was related with a greater use of cabs.

$$\text{RDEMPC} = \underset{(3.30)}{0.156} + \underset{(2.70)}{0.017}\text{LTAXPC}$$

SEMILOG

R^2=0.328 F=7.30 π_l=1.03 π_h=0.33 π_m=0.51

$$LRDEMPC = 0.83 + 0.615 LTAXPC$$
$$(0.51) \quad (2.82)$$

DOUBLE-LOG

$R^2=0.346$ $F=7.94$ $\pi=0.615$

$$IDEMPC = 1.309 + 0.13 LTAXPC$$
$$(2.39) \quad (1.76)$$

SEMILOG

$R^2=0.172$ $F=3.106$ $\pi_l=0.54$ $\pi_h=0.25$ $\pi_m=0.35$

The elasticities require careful interpretation; as elasticities of demand with respecty to level of supply, they are not directly analagous to waiting time elasticities. However, it can be seen that an increase in supply would be expected to have a positive effect on demand.

The conclusion from the demand analysis is that demand is elastic with respect to price (probably with elasticity in excess of two in most cases) and inelastic with respect to waiting time (of the order of -0.15). However, this cross-sectional approach is clearly not able to pick up waiting time effects and to do so will require a different technique.

3 Waiting time models.

Waiting time was modelled as a function of demand, supply and other indicators such as the licence premium. Using RWAIT as the dependent variable, both IDEM and IDEMPC were able to achieve significant coefficients, albeit with poor R^2.

$$RWAIT = 0.586 + 4.73E\text{-}06 IDEM$$
$$(1.88) \quad (1.56)$$

$R^2=0.14$ $F=2.43$

$$RWAIT = 0.517 + 1.406 IDEMPC$$
$$(1.40) \quad (1.47)$$

$R^2=0.13$ $F=2.152$

These models reflect the simultaneity problem; they are right sign and hence wrong sign if the dependent and independent variables were transposed. Using WAIT1 as the dependent variable, we obtained

$$LWAIT1 = -1.6 - 0.696 LTAXPC$$
$$(0.94) \quad (3.02)$$

$R^2=0.374$ $F=9.09$

$$LWAIT1 = 4.17 - 861.5 TAXPC$$

(19.2) (3.42)

R^2=0.438 F=11.86

LWAIT1 = 2.12 + 0.167PREM
(4.45) (3.09)

R^2=0.389 F=9.53

The first two demonstrate a negative relationship between supply and the probability of waiting; the last shows that the probability of waiting is higher where the premium is higher, an unsurprising result given that the premium arises because of limitations on supply. Overall, the waiting time models were of little use on their own, and were subsequently used in an attempt to model demand and waiting time simultaneously to see if the correct signs could be achieved on waiting time in the demand equation.

4 Supply models

Here, we attempted to predict taxi numbers (or taxis per head) using the other data. Stepwise regression techniques were used with an entry level of 15%. All the "successful" models had taxis only and not total fleet size as the dependent variable. The level of demand as derived from the rank observations entered all the models and other frequently occurring variables were the licence premium and the district's total rateable value.

TAXI = 22.46 + 0.013RDEM + 2.0E-08RV
(4.27) (2.0)

$\bar{R}^2$=0.76 F=26.39

TAXI = -416.9 + 83.6LRDEM + 58.3LRV - 22.2LPREM - 192.9LPHONE
(2.45) (1.73) (3.2) (2.31)

$\bar{R}^2$=0.76 F=13.56

LTAXI = -9.407 + 0.45LRDEM + 0.53LRV - 0.124LPREM
(2.63) (2.94) (3.37)

$\bar{R}^2$=0.77 F=18.82

The first model predicts the number of taxis rising with demand and the wealth of the district. The second also models the impact of the premium (it reduces the number of cabs) and the proportion of all trips (taxi and hire car) undertaken by phone. As more trips are booked by phone, the number of taxis decline;

while the result is to be expected, the direction of causality is unclear since it is not known whether the large amount of phone booking obviates the need for taxis or whether the lack of taxis increases the demand for phone bookings.

Using TAXIPC as a measure of supply, we see fare and population density entering the model:

$$LTAXIPC = -12.87 + 0.342 LRDEMPC + 1.302 LFARE + 0.341 LPOPDENS - 0.137 LPREM$$
$$\qquad (2.12) \qquad (1.80) \qquad (2.00) \qquad (4.44)$$

$\bar{R}^2=0.731$ $F=11.87$

Thus districts with a higher per capita supply of taxis have higher fares; this is the argument of anti-deregulationists, that extra capacity has to be paid for through higher fares. More densely populated districts have more taxis per head. Because demand entered into the supply models and supply entered demand models, it was decided to attempt simultaneous estimation. The results are reported in section 5 below.

5 Simultaneous estimation

A number of different ways were tried to model the simultaneity apparent in the system from figure 1 . Three different techniques were used; two-stage least squares (2SLS) for exactly-identified systems; three-stage least squares (3SLS) for over-identified systems; and joint generalised least squares (JGLS) where dependent variables did not appear in other equations burt it was still felt that because of the inter-relationship an overall "best" set of models would be preferable to individual "best" models.

We looked first at demand and waiting time. An exactly-identified system (below) was calibrated using 2SLS. As we have

$$IDEMPC = f(RWAIT, FARE)$$
$$RWAIT = g(IDEMPC, IDEM)$$

already seen, there is a conflict in choosing the variables to enter; IDEMPC rather than RDEMPC works with FARE, but RDEMPC is better with RWAIT. Not surprisingly, therefore, the results were poor, especially for the waiting time model, and the simultaneity problem (RWAIT having the wrong sign in the demand equation) was not resolved.

$$IDEMPC = 0.974 + 0.21 RWAIT - 0.399 FARE$$
$$\qquad (2.00) \qquad (1.25) \qquad (1.95)$$

$R^2=0.309$ $F=3.14$

$$RWAIT = 0.674 - 0.395 IDEMPC + 5.3E\text{-}06 IDEM$$
$$\qquad (1.10) \qquad (0.17) \qquad (1.15)$$

$R^2=0.135$ $F=1.09$

Clearly the waiting time model in particular is very poor; the insignificant coefficient on IDEMPC means that a simultaneous approach is not called for in this instance, and it would therefore appear that the problem of incorporating waiting time into the demand equation in a meaningful way is intractable given these data. This was confirmed by the inability of 3SLS operating on a three equation system (demand, waiting time, supply) to produce consistent, realistic results with acceptable t-ratios and goodness of fit statistics. In the demand equations, the right sign on TAXI (positive) gave the wrong sign on WAIT; when the model achieved the right sign on WAIT (negative), it had the wrong sign on TAXI. All in all, it was not possible to produce sensible results including a waiting time term or equation, so attention was turned to modelling demand and supply equations. Poor parameter estimates were obtained for truly simultaneous systems, and so reported below are the results from JGLS estimation. In both cases, the supply models are essentially linear (but with the log of the premium value). There are two demand models; one is exponential, the other constant elasticity. Linear and semilog models are not reported because of the problems with the elasticities in districts with small populations and hence low demand. The dummy variables used in the supply model require some explanation and justification. It was thought that metropolitan districts might be expected to have more taxis than shire districts, <u>cet. par.</u>. Two dummies cater for this; SAMET for five districts in the same county (which are thus under the same PTA and face the same competition from buses) and OMET for other metropolitan districts. TST is a dummy representing the existence of a tourist-type trade; two historic towns, a seaside resort and a city with a major international airport were awarded this dummy. SMPOP has been allocated to towns with a population under 100,000. Given the predominance of large metropolitan districts in the rest of the sample, it was felt that to ignore towns which were so different would distort the model.

The exponential model:

```
LIDEM = 13.11 - 1.40FARE - 0.48RV + 6.1E-06POP + 1.9E-07DENSQ
       (11.93) (2.68)     (2.16)   (2.84)       (3.44)

TAXI =208-34.9LPREM+182SAMET+97OMET+105SMPOP+148TST-2.6E-05DENSQ
     (6.07)(6.75)   (3.69)   (2.84) (5.41)   (5.20) (10.28)
```

Weighted system R^2=0.9185

The double-log model

```
LIDEM =-14.75 - 2.29LFARE - 1.27LRV + 1.26LPOP + 0.88LDENSQ
       (1.88 ) (2.04)      (2.08)    (2.73)     (3.47)

TAXI =205-33.9LPREM+178SAMET+98OMET+98SMPOP+147TST-2.5E-05DENSQ
     (6.13)(6.78)   (3.79)   (2.74) (5.54)  (5.17) (10.23)
```

Weighted system R^2=0.9201

Both models manage to predict both demand and the number of taxis quite well. The exponential model produces a correlation between actual and predicted demand of 0.82 and actual and predicted number of taxis of 0.97 . The corresponding figures for the double-log model are 0.89 and 0.97 . The price elasticities from the exponential model range from -2.45 to -3.63; the figure from the double-log model is -2.29 . In spite of the attractions of a variable price-elasticity model, the better predictive ability of the double-log model, in particular for districts which both models find difficult, means that is probably to be favoured.

6 Conclusion

We have demonstrated in this paper that a cross-sectional approach fails to pick up significant service quality effects on the demand for taxis. Whether this is because they do not exist or because of problems with the data is a moot point; whatever the cause, we cannot be satisfied that waiting time is completely insignificant, although it is clearly a minor influence compared with price. For simple per capita models, price elasticity of demand was found to be about -3.3 . More complex direct demand models suggested a figure of about -2 if we impose a constant elasticity form or between -2.5 and -3.5 if elasticity varies with price. The few insignificant waiting time elasticities were of the order of -0.15 . We found demand negatively related with the total rateable value of a district, but positively related with the population-weighted population density. While we consider that these models provide an indication of the sort of magnitude we may find for the demand elasticities, the problems involved in selecting the variables and the somewhat crude aggregation techniques employed mean that we cannot be as certain as we would wish that these are the true figures, and we have therefore attempted in other papers to establish these values by other means.