FORECASTING MODE CHOICE IN PRESENCE OF INERTIA AND SHOCK EFFECT: THE CASE OF TRANSANTIAGO IMPLEMENTATION

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ABSTRACT

Demand forecasting is a fundamental element of medium to long term transport planning, and modelling the choice of mode is a key element of this process. Most modelling work has been based on cross-sectional data, but this data structure does not allow one to correctly ascertain how choices evolve over time. Models that fail to account for temporal effects (such as habit and inertia) might severely overestimate demand as well as user benefits due to new policies, leading the administration to take wrong decisions about their implementation. The use of panel data constitutes a good alternative but, up to now, most work reported in the literature has focused on model estimation; indeed, problems associated with applying panel models in prediction have been hardly tackled. Starting from a case study based on a the *Santiago Panel* (Yáñez *et al.*, 2010a), this paper discusses the theoretical and practical problems involved in forecasting demand using panel models and in particular analyses the role of the temporal effects. Our results provide empirical evidence that a model considering temporal effects dominates traditional models not only in terms of explaining the real phenomena (estimation), but also in predicting future demand. However, forecasting requires predicting all elements (attributes and temporal effects) that were found relevant during model estimation, and the presence of some temporal effects may be questionable in middle/long term applications as they depend on each particular case.

Keywords: temporal effects, panel data, prediction capability.

INTRODUCTION

Large cities depend heavily on the correct and efficient workings of their transport systems. Improving current transport services or introducing new transport systems, requires large amounts of money, so it is essential to count on consistent analysis tools to minimize planning errors and avoid unjustified expenditures. In this sense, demand forecasting is fundamental for medium to long term transport planning and modelling the choice of mode is a central element of this process.

The last decade was characterized by an intense and fruitful research effort on travel demand modelling. But most demand models to date have been based on cross-sectional data so temporal effects have been mostly ignored in practical studies. Panel data models have started recently spreading a little based on a few available data panels (Van Wissen and Meurs, 1989; Murakami and Watterson, 1990; Zumkeller *et al.*, 2004; 2006; *Yáñez et al.*, 2010a). Cherchi and Cirillo (2010) present a good review of panel data used in travel behaviour modelling.

It is well known that panel data allow considering temporal effects that are crucial to understand long term choices properly; however, it is not trivial how to correctly account for these effects in forecasting. Many factors remain uncovered and the issue deserves to be analysed in more depth. Swait *et al.* (2004) and Cantillo *et al.* (2007) developed temporal-effects models and reported the advantages of including previous decisions in choice models not only in terms of goodness-of-fit but also in terms of prediction capability using fictitious scenarios. Cantillo *et al.* (2007) did not question the inclusion of inertia in middle and long term predictions, and produced their forecasts using exactly the same model found during the estimation stage. Contrariwise, Swait *et al.* (2004) analysed whether the effect of previous choices should be included in forecasting. For the prediction stage they redefined a binary variable associated with state dependence during estimation (which was equal to one when the alternative was chosen in the previous period), to take into account the probabilities predicted by the model for the previous period. Thus, since the predicted probabilities were sensitive to policies (through the changes of the alternative attributes), the state dependence in their model became sensitive to the policies as well. Finally, Cherchi and Cirillo (2010) studied issues related to model validation and forecasting but used a continuous data set and did not consider inertia.

Based on this background, the aim of this paper which starts from a case study is to discuss the theoretical and practical problems involved in forecasting demand using temporal-effects models. Empirical evidence on how to use temporal effects in prediction are provided using the best models estimated with data corresponding to the first three waves of the Santiago Panel (Yáñez *et al.*, 2010a) and applying these models to the fourth wave of the same panel, which took the role of a validation sample. The remainder of the paper is organized as follows. In section 2, we summarise the main characteristics of our temporal-effects model formulation. In Section 3 we analyse our most important results and discuss the effect of accounting for temporal effects in prediction. Finally, in section 4 we summarises our main conclusions.

MODEL FORMULATION AND ESTIMATION

Model Formulation

Our temporal-effects model can be described as a Mixed Logit (ML) formulation for panel data. It is based on the formulation proposed by Yáñez *et al.* (2010b) for a journey-to-work context, who extended the work of Cantillo *et al.* (2007). Our model assumes that in each choice situation (i.e. panel wave) the individual chooses among a finite group of alternatives, which can vary over time. We also assume that in the first period (wave $w = 1$) an individual q chooses her usual alternative A_r to travel[1], but between time $w = 1$ and $w = 2$ a new public policy is introduced, changing the transport system radically in terms of several attribute values. These changes are captured in the subsequent waves of the panel. Temporal effects are accommodated specifying a modal utility that accounts for three different forces: (1) differences in modal attributes, as in any choice model; (2) an inertia effect and (3) a shock effect caused by the radical new policy. Thus, the utility function for alternative j at wave w for individual q is given by:

$$\widetilde{U}_{jq}^{w} = U_{jq}^{w} - I_{jrq}^{w} + S_{jq}^{w} \qquad (1)$$

where:

- $U_{jq}^{w} = V_{jq}^{w} + \zeta_{jq}^{w}$, is a traditional utility function, with V_{jq}^{w} its observable component based on level-of-service (LOS) and socioeconomic (SE) characteristics, and ζ_{jq}^{w} the non-observable component, i.e. a random error term formulated as $\zeta_{jq}^{w} = \upsilon_q + \varepsilon_{jq}^{w}$, where υ_q is a random effect specific to the individual and ε_{jq}^{w} is the typical random error distributed independent and identically Gumbel;
- $I_{jrq}^{w} = (\beta_{Ij}^{w} + \delta_{Iq} \cdot \sigma_{Ij}^{w} + \beta_{I\_SE} \cdot SE_I) \cdot \left(V_{rq}^{w-1} - V_{jq}^{w-1}\right)$ is an inertia effect (see Cantillo *et al.*, 2007), which is a function of the previous valuation of the options; we assume that each individual q compares the current options A_j^w (i.e. the options available at wave w) with the option A_r^{w-1} that was chosen in the preceding wave (w-1). Thus, the inertia effect may vary for each wave and may also vary among individuals due to either systematic or purely random effects. Additionally, the effect of inertia might be positive or negative; the former representing the "typical" inertia effect in the absence of changes, while the latter indicates the preference for changing that might occur after a significant variation in the system;
- $S_{jq}^{w} = (\beta_{Sj}^{w} + \delta_{Sq} \cdot \sigma_{Sj}^{w} + \beta_{S\_SE} \cdot SE_S) \cdot \left(V_{jq}^{w} - V_{jq}^{w-1}\right)$ is the shock effect triggered by the new policy. This effect is a function of the difference between the utility of option A_j^w, evaluated at wave w and its utility evaluated at the preceding wave (w-1). Hence, the shock effect is expected to be negative when A_j worsens (making its utility lower), and positive when it improves (making its utility higher). The perception of the shock may be different for each

[1] Our models were estimated using data from the *Santiago Panel* that includes only trips to work.

wave and may vary among individuals due to systematic or purely random effects. The shock effect should have its highest value immediately after the introduction of the new policy, and then its magnitude should attenuate.

- β_{Ij}^{w} and β_{Sj}^{w} are the population means, and σ_{Ij}^{w} and σ_{Sj}^{w} the standard deviations, of the inertia and shock parameters respectively, for option A_j on wave w; SE_I and SE_S are socioeconomic variables that allow for systematic variations of the inertia and shock parameters and δ_{Iq}, δ_{Sq} are the standard factors to introduce panel correlation.

In the presence of inertia and shock the probability to change from the usual option A_r (i.e. the option chosen in the previous wave) to A_j for individual q on wave w, is given by:

$$P_q\left(A_j^w\right) = P\left(\tilde{U}_{jq}^w - \tilde{U}_{rq}^w \geq 0 \quad \wedge \quad \tilde{U}_{jq}^w - \tilde{U}_{iq}^w \geq 0, \quad \forall A_i^w \in A_{(q)}^w, \text{ except } r = j\right) \tag{2}$$

while the probability to remain with the option chosen in the previous wave (A_r) is given by:

$$P_q\left(A_r^w\right) = P\left(\tilde{U}_{rq}^w - \tilde{U}_{jq}^w \geq 0\right) \tag{3}$$

As individual responses present panel correlation, given a sequence of modal choices, A_j^w, one for each wave, the probability that a person follows this sequence is given by:

$$P_q\left(A_j^1 \wedge A_j^2 \wedge ... A_j^W\right) = \prod_{w=1}^{W} P_q\left(A_j^w\right) \tag{4}$$

As inertia, shock and panel correlation are actually unknown, the probability of this sequence of choices takes on a Mixed Logit form (Train, 2009). The identification issues associated with this temporal-effects model have been analysed in depth by Yáñez *et al.* (2010b).

Model Estimation: Application to the Santiago Panel

The data set used in this research belongs to the *Santiago Panel* (Yañez *et al.,* 2010a), which is fairly unique in being a five-day pseudo diary with four waves, one before and three after the implementation of Transantiago, a radically different public transport system for the city of Santiago de Chile (Muñoz *et al.,* 2009). The original sample consisted of 303[2] individuals who lived and worked in Santiago. Using the first three waves of the panel and the temporal-effects model formulation summarized above, models of increasing complexity were estimated (see details in Yáñez *et al.*, 2010b). In particular, the specifications used to test the prediction capabilities of the model are shown below; Table 1 presents the estimated

[2] Because of attrition (i.e. loosing respondents), panel sample sizes reduce wave by wave. However, the *Santiago Panel* managed to control attrition effectively and attrition was just 5, 3 and 7% in waves 2, 3 and 4 respectively.

parameters belonging to the traditional observable utility term (V_{jq}^{w}), while Table 2 reports the results for the inertia and shock effects.

Table 1 – Model Results: Non Temporal Parameters

Attributes	Non-Temporal-Effects		Inertia		Inertia-and-Shock	
	Mean	t-test	Mean	t-test	Mean	t-test
Number of cars	2.32	8.71	2.13	9.64	1.96	8.87
Cost/Wage (mean)	-0.154	-20.12	-0.16	-21.2	-0.106	-19.95
Cost/Wage (st.dev.)	0.256	21.95	-		-	
Travel Time	-0.0316	-8.49	-0.09803	-7.23	-0.0404	-10.4
Waiting Time	-0.102	-11.98	-0.218	-13.12	-0.1677	-11.09
Walking Time	-0.0739	-12.92	-0.1297	-14.13	-0.0977	-16.85
Transfers	-0.721	-8.92	-0.628	-8.4	-0.496	-4.83
Comfort	1.3	6.28	1.17	8.45	0.869	8.33
Car Driver	0.154	1.02	0.237	1.55	0.143	1.16
Car Passenger	-1.83	-10.69	-1.7	-10.37	-1.45	-8.46
Shared Taxi	-0.896	-5.11	-0.465	-3.02	-0.767	-4.64
Metro	0.363	3.64	0.324	3.47	0.414	4.07
Walk	0.49	2.24	0.272	1.53	0.59	4.54
Bicycle	-2.69	-10.95	-2.9	-14.76	-3.24	-13.08
Park'n'Ride	-0.898	-4.6	-0.862	-4.47	-1.46	-6.43
Kiss'n'Ride	-0.806	-4.96	-0.739	-4.68	-0.497	-2.61
Shared Taxi-Metro	0.758	5.07	1.12	8.04	0.514	3.46
Bus-Metro	0.476	5.82	0.631	8.35	0.328	3.16
Bus-Shared Taxi	-0.111	-0.46	0.162	0.71	-0.476	-2.08
Log-likelihood(max)	-2848.53		-2659.61		-2541.92	
ρ^2 corrected	0.441		0.475		0.497	

The *Non-Temporal-Effects* model is the simplest one (it assumes generic parameters over waves and no temporal effects); the cost/wage parameter is considered randomly distributed but specified generic among options and took account of panel correlation. The *Inertia* model accommodates the inertia effect, the parameters of which were assumed specific across options and Normal distributed across individuals to account also for panel correlation. The *Inertia-and-Shock* model had the same specification of the *Inertia* model, but the shock effect was also estimated. The parameter of the shock effect was considered generic among options, but still randomly distributed and accounting for panel correlation. As expected, the model performance improved when representation of both the inertia and shock effects were introduced in the model. Indeed, according to the LR-test (Ortúzar and Willumsen, 2001), the *Inertia-and-Shock* model (with the shock effect being variable among waves) was the preferred specification, while the *Non-Temporal-Effects* model presented the poorest fit.

FORECASTING

The models presented in Tables 1 and 2 were applied to the fourth wave of the Santiago Panel which took the role of a validation sample.

Table 2 – Model Results: Temporal Parameters

Model	***Inertia***				***Inertia-and-Shock***			
	INERTIA							
	Inertia effect (mean)	*t-test*	Inertia effect (st.dev)	*t-test*	Inertia effect (mean)	*t-test*	Inertia effect (st.dev)	*t-test*
Car Driver	-0.14	*-1.40*	0.408	*4.35*	0.21	*1.86*	1.25	*6.75*
Car Pass	-1.32	*-3.39*	1.70	*4.32*	-0.06	*-1.3*	0.39	*2.90*
Metro	0.91	*5.06*	2.24	*4.50*	0.33	*4.34*	0.98	*2.45*
Bus	1.03	*6.73*	1.15	*8.49*	1.43	*7.42*	1.19	*8.16*
Walk	-3.53	*-1.97*	15.3	*1.52*				
Shared Taxi-Metro	-0.086	*-1.90*	0.14	*3.32*				
Bus-Metro	0.896	*5.05*	0.56	*5.61*	1.08	*6.87*	1.26	*6.5*
	SHOCK							
	Shock effect (mean)	*t-test*	Shock effect (st.dev)	*t-test*	Shock effect (mean)	*t-test*	Shock effect (st.dev)	*t-test*
$w_1 - w_2$	-	-	-	-	0.24	*2.01*	0.198	*5.82*
$w_2 - w_3$	-	-	-	-	0.07	*1.95*	0.13	*3.23*

As the forecasting version of a model needs to examine the role of each force in explaining future demand, it seems clear that the traditional force, related to the modal attribute values, must always be present. However, the presence of temporal effects should be at least questionable in middle/long term evaluations as it depends on the case study under examination. In this particular case, after applying the *Inertia-and-Shock* model to the whole panel (i.e. four waves), we found that the choice environment stabilized after the third wave (i.e. the shock effect became not significant after the third wave). Thus, the fourth wave provided almost unbeatable characteristics to allow testing the quality of predictions for a stable choice environment (desirable for long term assessments). As a consequence, even though the shock effect was significant in the estimated models, this effect was a clear candidate to leave the models in forecasting.

Our validation test consisted of applying the models estimated with the first three waves to the data for the fourth wave. As shown below, the real market shares are better recovered when we remove the shock effect from the *Inertia-and-Shock* model previously estimated. Thus, the validation test confirmed that the predictive version of the *Inertia-and-Shock* model should only consider its inertia component ($\widetilde{U}_{jq}^{w} = U_{jq}^{w} - I_{jrq}^{w}$).

However, this model does not ignore *a priori* the shock effect as the parameters associated with the alternative attributes (and the inertia parameters) were estimated in the presence of the shock effect in the first three waves. Contrariwise, the originally estimated *Inertia* model, which has apparently the same forecasting formulation, omitted the presence of the shock at the initial estimation stage. In fact, the results in Table 2 show us that the *Inertia* model presents different signs for the inertia parameters associated with Car Driver, Walk and

Shared taxi - Metro. This may be because these parameters are masking part of shock effects.

To examine the general fit to the fourth wave data we used the following test:

$$\chi^2 = \sum_i \frac{\left(\hat{N}_j - N_j\right)^2}{N_j} \tag{5}$$

where $\hat{N}_j$ is the number of individuals who choose alternative A_j according to the model, while N_j is the observed number (i.e. in this case given by the fourth wave data). In addition, to evaluate the forecasting capability by alternative, we calculated the variation (percent change) in aggregate market shares as follows:

$$\Delta P_j = \frac{P_j - P_j^0}{P_j^0} \tag{6}$$

where P_j and P_j^0 are, respectively, the aggregate probabilities of choosing mode A_j observed (i.e. given by the fourth wave) and predicted by the model using sample enumeration (Ortúzar and Willumsen, 2001).

Table 3 shows that the best model in terms of fit (*Inertia-and-Shock* model) was also the best model in terms of general forecasting capability. However, this model satisfied the critical value $\chi^2_{95\%,\, J-1=11} = 19.68$ if and only if the shock effect is removed from its forecasting version. Also in line with the results from the estimation stage, the *Non-Temporal-Effects* model presented the worst forecasting capability. Table 3 also shows that the combined Park'n'Ride mode seems to be the most difficult to predict. In fact, its market share was overestimated by all models with the exception of the *Inertia-and-Shock* model. On the other hand, the Metro market share was reasonably well estimated by all models. Indeed, only the *Inertia* model presents a larger difference.

Comparing the two forecasting versions of the *Inertia-and-Shock* model (i.e. keeping and taking out the shock effect, as shown in the right columns of Table 3), it can be seen that the *with-shock* version performs worse than the proposed version *without-shock* for combined modes (Park'n'Ride and Kiss'n'Ride), while it performs better for the Shared Taxi mode. Finally, although the *without-shock* version of the *Inertia-and-Shock* model had, as expected, a good general predictive capability, its worst predictions were for the Shared Taxi and Bus–Shared Taxi modes, but these are relatively marginal modes in our data set.

CONCLUSIONS

In this paper we have discussed some practical problems involved in forecasting demand using panel data models. In particular, we analysed the incorporation of temporal effects in forecasting middle to long term decisions.

Table 3 – General Fit to Validation Data

	Non-Temporal-Effects	***Inertia***	***Inertia-and-Shock***	
			Version with Shock	***Version without Shock***
χ^2	***107.96***	***58.28***	***32.36***	***14.55***
	ΔP_i			
Car Driver	-0.29	-0.13	0.06	-0.07
Car Passenger	0.37	0.24	0.10	0.02
Shared Taxi	-0.32	-0.3	-0.09	-0.34
Metro	0.03	0.2	-0.10	-0.02
Bus	0.32	-0.02	-0.23	0.17
Walk	0.41	0.05	0.11	0.01
Bicycle	-0.03	0.06	0.21	-0.12
Park'n'Ride	-0.6	-0.57	0.26	0.08
Kiss'n'Ride	0.24	0.44	0.21	0.04
Shared Taxi-Metro	-0.58	-0.34	-0.19	0.07
Bus-Metro	-0.01	0.1	0.09	-0.04
Bus-Shared Taxi	-0.42	-0.78	0.39	-0.31

The analysis was based on an empirical application with data from the *Santiago Panel*. Contrary to what Cherchi and Cirillo (2010) found using a short data panel (i.e. observations for six consecutive weeks), our empirical results show that the statistical fit of the models and their capability to reproduce the real phenomenon are directly correlated.

We have shown that the forecasting version of a panel model demands studying the participation of each force involved in the decision process (and previously accommodated in the estimated version of the model) in explaining future demand. We found that the traditional force, related to the modal attribute values, must be always present, while the presence of temporal effects may be questionable in longer term evaluations as it depends on each particular case. In our case study, the existence of a shock effect – caused by the introduction of a radical policy – is important in estimation (as it affects the estimated parameters of the other two forces, traditional attributes and inertia effect) but is best taken out in forecasting, as its importance vanished with time.

From our findings based on the *Santiago Panel*, we would recommend:

- Future applications should start by assuming that the forecasting and estimation version of the models might be different.
- The *Santiago Panel* gave us the uncommon chance to know *a priori* the evolution of the temporal effects wave by wave. Thus, we can say that the shock effect should not be significant in long term assessment if the choice environment stabilizes some time after the policy is introduced.
- Now, the definition of long term demands certain assumptions from the analyst. For example, we saw that the Santiago transport system stabilized after two years, but this will probably vary case by case; it may depend on the dimension of the policy and the cultural behaviour of the users, among other factors. However, as most long-term

transport policies are part of plans with stable and consistent aims, we could expect that shock effects vanish and need not be considered in long-term forecasts.

- Regarding the inertia effect, our case study suggests that inertia should be included in both estimation and forecasting stages. Indeed, Table 3 shows that even the *Inertia Model* (which omits *a priori* the presence of the shock effect) is better than the *Non-Temporal-Effect Model*. Thus, even for changing environments, if the temporal effects are correctly accommodated at the estimation stage, the inertia parameter should be considered without any alteration in the forecasting version of the models.

Although the use of temporal-effect models in forecasting will depend on each particular case, we believe that our results and the considerations that can be drawn from them are generally valid and useful. Inertia effects are present in almost any panel data and analogously shock effects are likely to be present any time new transport policies imply major changes in individual life.

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