Investigating Travel Behaviour Dynamics and Their Incorporation into Transport Models

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Background and context

When the transport system changes it can be expected that some individuals may react immediately and change their behaviour, others will take some time before changing their behaviour and others will not change at all. The overall change in travel patterns at any time point will depend on the aggregation of individual responses. A *dynamic model* will recognise time as a dimension and that travel choices at a point in time will be dependent on earlier conditions and events. Longitudinal data is required in order to estimate dynamic models. Longitudinal data is commonly used in other fields (e.g. health, employment) but has been used to a limited extent in transport where it is usual practice to collect cross-sectional data, compare different people's behaviour at a single point in time and infer how behaviour may change in the future from this. It is well known that longitudinal data offers advantages in terms of plausibility, insights provided on process of change, statistical efficiency and reliability and forecasting capabilities.

In 2001 a report for the UK Department for Transport *A New Look at Multi-Modal Modelling* concluded that future transport models should incorporate dynamic characteristics. In the 2000 *Handbook of Transport Modelling* (chapter 7) Kitamura suggested that advances in computing and methodological capabilities are such that there is potential that 'longitudinal methods can be developed and applied with the same ease as cross-sectional models, to make transportation analysis more coherent, accurate and richer'. Panel data is the most common form of longitudinal data and Bradley noted in the 1997 *Panels for Transportation Planning* book (chapter 11) that when studying the impacts of interventions 'multiple "after" periods are necessary (in panel surveys) to determine whether policies grow, diminish, or remain stable over time'. In the last few years there has been a lot of interest in transportation in understanding behavioural change but very little detailed empirical data to develop predictive models for travel demand. This is particularly the case for 'strategic' travel decisions such as mode choice and the effect on these from interventions designed to change the relative attractiveness of different modes. Given the importance of mode change to transport policy it is imperative to understand and predict the dynamics of travel mode responses to interventions in the travel environment.

This research project has used longitudinal travel data sets to obtain a better understanding of behavioural dynamics and to develop dynamic relationships of travel behaviour. The implications of behavioural dynamics for forecasting have been explored and have enabled conclusions to be drawn concerning the wider adoption of travel behaviour dynamics in transport models. In order to meet the project objectives the following two-year programme of work was pursued:

1. Identification of modelling requirements.
2. Review of dynamic methods of modelling travel behaviour.
3. Development of dynamic relationships of travel behaviour from longitudinal data.
4. Application of dynamic relationships of travel behaviour in the Dynamic Urban Model (DUM) system.
5. Preparation of guidelines on incorporating dynamics in travel demand models.

This work has been completed according to the programme without any significant changes. Working reports have been prepared for each of the five areas listed above plus a report on the panel survey data. A project seminar was held in the middle of the project, rather than at the end of the project as envisaged in the original proposal. Reasons are outlined later under **Research Impact and Benefits to Society**. The project was undertaken by the principal investigator with a post-doctoral researcher, Dr Kang-Rae Ma, employed throughout the two year period.

Achievements

Modelling Requirements

At the commencement of the project general requirements were identified for incorporating dynamics into travel demand modelling and these were set out in a working report. Specific requirements were identified with respect to forecasting using DUM. DUM is a systems dynamics model developed by Steer Davies Gleave (SDG) and designed to analyse the relationship between transport and the population and economy, using the concepts of 'stocks', 'flows', and causal links. Within DUM parameters such as *'average time to adapt to mode change'* and *'time to adapt to network changes'* can be used to represent lagged responses. At present arbitrary values are used for these lag parameters and the requirement was identified to gain empirical evidence from longitudinal data to use for these parameters.

Review of Dynamic Methods

Previous reviews undertaken by the principal investigator (*1,2*) had surveyed the literature on transport modelling theory and practice and shown that static modelling dominates the practice of transport modelling but the review conducted within the project widened the scope to include fields of study outside of transport and to consider: (i) *theoretical models* of behaviour change; (ii) *monitoring* of behavioural change; (iii) *estimation* of behavioural models; and (iv) *forecasting* of behaviour. Of particular usefulness was work in the following areas:

- Habit and behaviour stability – this included theoretical conceptualisations of behavioural change, monitoring of experimental investigations and estimation of models (using structural equation modelling and choice modelling in particular).
- Learning models – this included theoretical models of individual and social learning, including some applied to travel demand, for example to the day to day decisions of motorists and to activity scheduling.
- Life course approach to travel behaviour – this included theoretical conceptualisations of life course-mobility interactions and the design of retrospective methods for collecting data on this.
- Analyses of national panel surveys – there is a well established body of work in various fields of study using statistical/econometric models to analyse social outcomes at the individual level for issues such as employment and health. This offered important insights on modelling methodology.

Very limited work directly applied to travel demand forecasting was found, although the examples that exist (some reviewed in *3*,*4*) were helpful in showing possibilties and methodological approaches. Given that panel data is the main potential data source for dynamic modelling of behaviour major emphasis was placed on reviewing literature, developing expertise and acquiring analysis tools for panel data modelling. A detailed review on panel data methods is included in the working paper for this work area. In Table 1 a summary is provided of different methods that can be used for panel data modelling and to what purposes they can be applied.

To apply dynamic models in forecasting involves a series of forecasts at appropriate intervals. Stochastic microsimulation is becoming an increasingly popular analysis tool for social and economic policy analysis, as it provides results that can be analysed at the level of individuals. In transport it has been most commonly applied to traffic networks with only a few exceptions in travel demand analysis (*5*). The main reason is the lack of panel data and models to develop relationships to utilise within a microsimulation framework. Within this project there was not scope to develop a forecasting model system to apply dynamic relationships but this is a valuable direction of future efforts.

Table 1. Modelling methods for panel data

<table>
<tr><th>Methods</th><th>Dependent variable</th><th>Dynamics considered</th></tr>
<tr>
<td>Aggregate time-series analysis
Markov chains
Switching models
Choice models
Multi-level analysis
Event history analysis (duration or survival models)
Structural equation modelling
Path analysis
Latent growth</td>
<td>Time elapsed
Change or not
Choice
Continuous
Discrete (qualitative, e.g. mode)
Discrete (ordered, e.g. none, once a week, more than once a week)</td>
<td>Non-stationarity
Socio-economics
Transport system
Life events
Time explicit effect
Lag (and lead) responses
State dependence
Markovian
Occurrence
Duration
Serial correlation
Unobserved fixed preferences</td>
</tr>
</table>

Panel Data

Suitable data needed to be obtained to develop dynamic relationships and, as expected in the proposal, this required new primary data to be collected as part of the project. Before collecting new data, analysis was conducted of a panel survey data set obtained for the London congestion charging scheme. The survey obtained information on travel perceptions and behaviour six months before and after the scheme's introduction. The analysis was constrained to developing simple binomial models for whether car drivers changed mode or not and it was found that the limited information collected on the specifics of behaviour and on attributes of modal alternatives, as well as the limitations inherent in two wave panel data, prevented development of models with more sophisticated dynamic characteristics (*6*).

The new data collection involved a four wave panel survey of the travel behaviour of residents of Crawley, West Sussex, before and after the introduction of a second guided bus service route (Fastway Route 20) in the town in September 2005. The Fastway bus system began operating in the area in September 2003 with the introduction of Route 10. The target population for the panel survey was residents living close to the route of the new Route 20 service. The electoral register was used to identify 2,500 residents for contact for the survey. Self-administered postal questionnaires were used as the survey instrument throughout the survey. Attempts were made to minimise attrition, although it was not the expressed aim of the panel study to obtain and maintain a representative sample of the population of interest. The first wave of the postal survey (in August 2005, one month before Route 20 introduced) achieved 554 responses. 361 respondents said they were willing to participate further in the study. These were sent the second questionnaire and 220 responses were received (in October 2005, one month after Route 20 introduced). To maximise subsequent participation a £20 incentive was offered to those participating in the final two waves. 254 responses were received for wave 3 (in December 2005) and 247 responses were received for wave 4 (in March 2006).

Descriptive analysis of the panel data revealed important insights into the impact of the new bus service. Figure 1 shows an increase in positive perceptions towards bus services through the survey period and that the number of residents who used the Route 20 service increased from 34 in wave 2 to 61 in wave 4 (these are with respect to the 187 residents who participated in all four waves of the questionnaire). The timing of responses is shown in Figure 2 in terms of new users of the Route 20 service in each week after its introduction (this is with respect to the sample of 247 respondents completing waves 3 and 4). The number of new users is largest in the first week after introduction of the new service and declines over time but there continue to be some additional new users until the end of the survey period. A key transport policy question is what impact has the Route 20 service had on general bus use of the residents of the areas served. The residents participating in the survey were asked at each wave to indicate how often they used different modes of transport including the bus. Overall, between waves 1 and 4 there was a statistically significant (McNemer-Bowker test, $p = 0.002$) change in general bus use with 35 residents increasing bus use and 13 decreasing bus use (N=187).

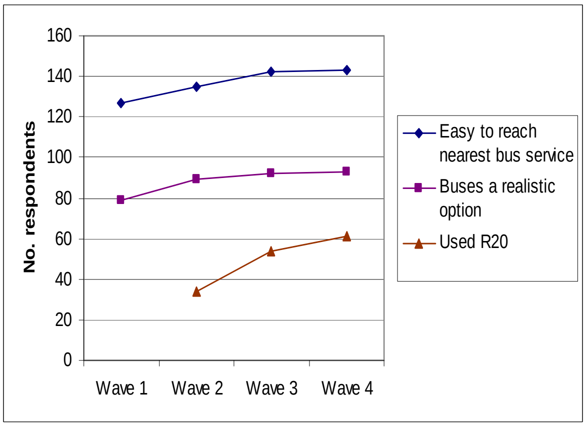

Figure 1. Perceptions and Use of Route 20

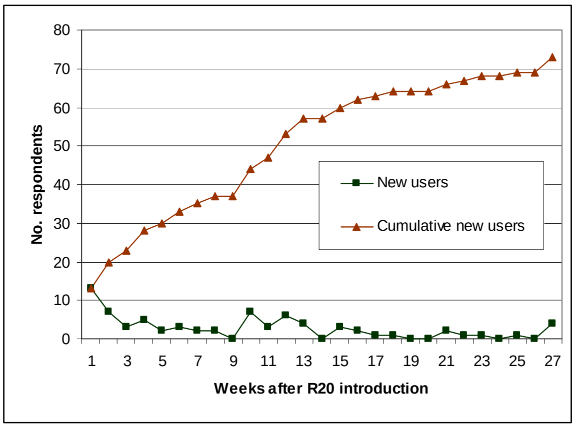

Figure 2. Number of New Users after Route 20 Introduction

Development of Dynamic Relationships

The analysis of the panel data has used two main methods: (i) duration analysis to analyse timing of behaviour change; and (ii) discrete choice modelling to analyse the transition in bus usage over course of survey period. Duration data is available in the form of a date when a resident started to use the Route 20 service (estimated by participant to the nearest week) if they did so in the period of the survey. There have been surprising few applications of duration modelling in the transport field and none found with respect to time to 'adoption' or first use of a new public transport system. The standard duration model assumes that all subjects will eventually experience the event of interest (or 'fail'). In our case, the event of interest is the use of Fastway Route 20 bus. A split population duration (SPD) model that relaxes such a strong assumption identifies the probability of eventual failure and the survival function simultaneously (*7*). Taking into account the probability of eventual failure is considered to be particularly important in the case of mode choice behaviour where some travellers are unlikely to ever use the new travel mode option.

Both standard duration models and SPD modes were estimated. The standard duration model showed, amongst other (study area-specific) findings, that those with access to a car have been slower in trying the new bus service. Younger individuals and those with a bus pass have been faster in using the service. Individuals gaining a reduction in distance from their home to bus services have been faster in using the service. In the SPD model, an estimate of the average value of the probability of eventual failure is 0.63, which means that 37% of travellers are not expected to ever use the Route 20 bus service. A value significantly less than one, as in this case, implies that the SPD model is favoured specification to use. With the SPD model, it is found that those gaining a reduction in distance from their home to bus services are more likely to (eventually) use the new service, but not faster to use the service. The effect of other variables on time to use the new service is also different in the SPD model compared to the standard model. Figure 3 shows a comparison of the standard duration model and SPD model demonstrating the improved predictive performance of the SPD model at least for the initial part of the survey period.

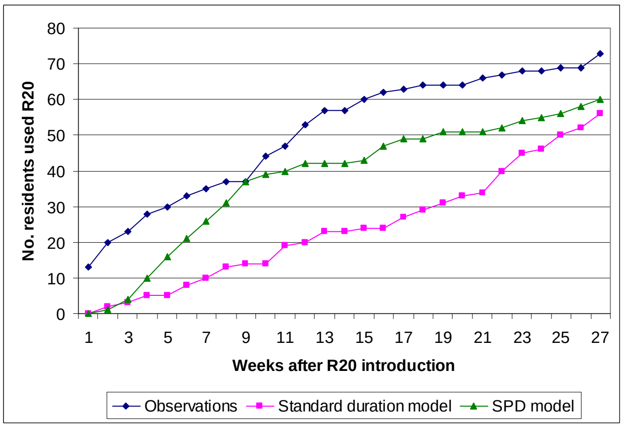

Figure 3. Comparisons of Observed Data and Predictions

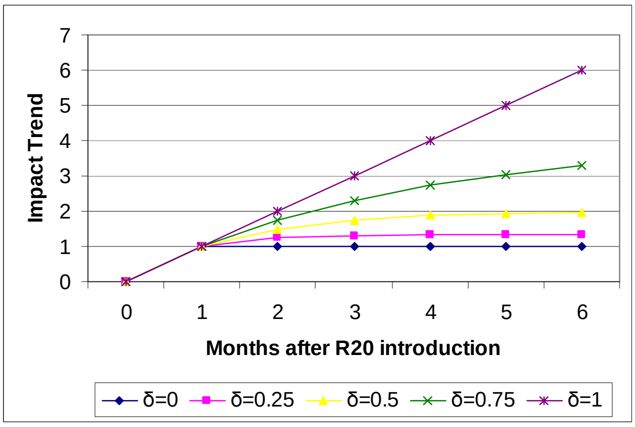

Figure 4. Impacts over Time of First-Order Impulse Models

After examining the timing of first usage of the Route 20 service, analyses were conducted of the changing frequency of usage of the (i) new Route 20 service and of (ii) buses in general over the course of the study period. Frequency of usage had been obtained from the survey in terms of a five-level ordinal variable (‘1 = not at all’, ‘2 = less than once per week’, ‘3 = 1-2 days’, ‘4 = 3-4 days’ and ‘5 = 5 or more days’). Ordered probit models was used to analyse this.

Methodological issues that present challenges to the analyst in panel data modelling (*8*) include distinguishing unobserved heterogeneity (unmeasured and sustained differences between individuals), state dependence (past behaviour affecting current behaviour) and serial correlation (persistent tendency towards behaviour). With state dependence models a particular problem is initial conditions which results from surveys not collecting data at the start of the process and assumptions having to be made regarding pre-survey behaviour. A strong appreciation of these issues was gained through the review of literature on panel data analysis mentioned earlier. Use was made of advanced econometric analysis software (LIMDEP, STATA) to enable suitable model specifications to be applied. It is suggested that the analyses provide a more advanced attempt at panel data modelling for travel demand analysis than has otherwise been reported in the transport literature. As shown in Table 2 a series of different models have been estimated using different specifications and involving different ways of exploring the impact of the intervention.

Table 2. Models estimated

Dependent variable	Model specification	Intervention impact
• General bus use frequency (waves 1-4) • Route 20 use frequency (waves 2-4)	• Cross-section pooled • Random effects (individual intercepts) • Random parameter (individual coefficients) • Multi-level model (coefficients modelled) • State dependence (various specifications of initial conditions)	• Change in level of service variable • Intervention analysis (explicit time variables) o Step function o First-order (gradual impact) • Distributed lag (for level of service variable) • State dependence o Lagged dependence

Key findings from the panel data modelling for general bus usage were:

- The estimated coefficient for level of service variable (travel time difference between bus and car) is larger when unobserved heterogeneity is taken into account (indicating the importance of doing so). A one minute increase in the travel time difference increases the probability of using the bus ‘not at all’ by 0.5%.
- One period lag specification for level of service variable provided better fitting model than non-lag version and suggests the typical response to the Route 20 intervention involved a three month delay.
- First-order impulse model with best fit was for δ=0.75, indicating a bus growth response to Route 20 as shown graphically in Figure 4 and that during survey period three-quarters of total eventual bus use growth had occurred.
- Lagged dependent variables improve model fit and show there is true state dependence effect as well as unobserved heterogeneity (for example, Orme specification of initial conditions showed using the bus ‘5 days a week or more’ in previous wave increased the probability of using the bus ‘5 days a week or more’ by 36.9% and decreased the probability of using the bus ‘not at all’ by 55.1%). Different methods of handling initial conditions have been tested including the Orme and Wooldridge methods currently put forward in the literature. The method used significantly affects parameter values for lagged dependent variables and other explanatory variables and must be carefully considered.
- Comparison of run pattern predictions (transition in individual bus usage over survey periods) shows random effects models better capture variety in patterns than pooled or state dependence models which overestimate behavioural stability (e.g. ‘0-0-0’ patterns in bus usage over waves 2-4).
- Forecasts for a future scenario of 10 minute reductions in bus travel times for all residents showed that similar numbers of bus users were predicted for a random effects model (using four waves) as a cross-sectional model (wave 1), implying that the cross-sectional model may be able to represent a reasonable equilibrium forecast. However, the first order impulse model with δ=0.75 predicted a larger number of bus users in the long run.

Key findings from the panel data modelling for Route 20 usage were:

- Coefficient estimates for Route 20 usage were quite different to general bus use usage with, for example, lesser importance of driving licence and car ownership. Implication is that new service was used by a broader selection of residents (which was intention of the higher specification service). Those changing jobs during the survey period were more likely to use Route 20, highlighting the importance of life events in travel behaviour.
- Multi-level model showed that lower walking time to bus service, resulting from Route 20, increased average usage of the new service (the model intercept) and the increase in usage over time (through time coefficient), demonstrating how this model specification is very useful in representing the dynamic impact of level of service variable.

- State dependence model performed less well relatively for Route 20 than general bus use, as would be expected since initial observation (at wave 1) took place before service operated (lagged variable at wave 2 therefore equals zero). For Route 20 it was possible to study the behavioural process from its start and (without problem of initial conditions) to distinguish true significance of socio-economic, life event and level of service variables.

Within the project extensive and rigorous analysis of the data has been possible but, given the wide range of panel data analysis methods, there exist potentially fruitful opportunities for further analysis. Of particular interest will be to use structural equation modelling methods (e.g. latent growth models as an alternative to multi-level models, which are potentially equivalent but with added capabilities such as incorporating measurement error).

Application of Dynamic Relationships in Dynamic Urban Model

The findings on lags obtained from the panel data analysis were used to run sensitivity tests, exploring the impact of different lag value assumptions on transport and economic forecasts for a case study model area representing the city of Hull and for the scenario of a new rail service. A simple example of the results that were obtained is shown in Figure 5 which shows varying growth curves of rail patronage according to specified lag values. This shows how the evolution of travel demand is affected over a longer period than the specific value of the lag period assumed. In general, the recommended approach to obtaining lag values is to obtain median survival times from duration models of the kind estimated in this project. Different values can be obtained for different person types.

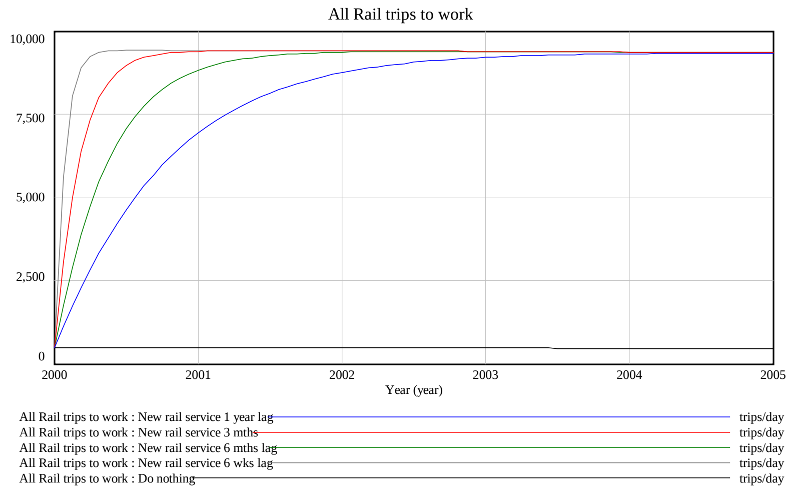

Figure 5. Impact on rail trips of different lag values

Guidelines for Incorporating Dynamics into Transport Modelling

Drawing on the findings of the research project and synthesising these across the different elements of the project, a set of guidelines has been produced which addresses motivations for dynamic modelling, conduct of panel surveys, methods of model estimation and forecasting using dynamic relationships. For example, it highlights how the problem of initial conditions in state dependent models can be best addressed by including retrospective questions in the first wave of a panel to attempt to obtain pre-survey measurements and how in examining the impact of an intervention through panel data more than one pre-intervention measurement can better enable stability of behaviour to be modelled.

Research Impact and Benefits to Society

It cannot be expected that there will be an immediate shift towards the use of dynamic models in travel demand analysis but it is hoped that this project will foster interest in their use. Papers presented on the work of this project at the 11th International Conference on Travel Behaviour Research (IATBR) in Kyoto in 2006 and at the 86th Annual Meeting of the Transportation Research Board, Washington, D.C., were part of sessions on the theme of dynamics of travel behaviour. Past work by the principal investigator on the 'asymmetric churn' of travel behaviour has directly influenced researchers (*9,10*) and it is hoped that this project will provide similar inspiration to researchers and practitioners.

The potential impact of the work on wider transport research and practice is illustrated by the willingness of the Department for Transport to host and support the project seminar that was organised by the principal investigator and held midway through the project. The event titled 'Longitudinal Methods for Understanding and Modelling Travel Behaviour' was attended by 40 people from government, consultancies and academia and brought together both those predominantly interested in behaviour and those predominantly interested in modelling. It provided a forum for presentation and discussion of topics associated with longitudinal data and analysis in transport planning and provided opportunity to present and receive feedback regarding the emerging work from the project. Timing at this stage of the project was considered to better enable useful external input to be provided to the work. Seminar presentations and materials are placed on the project website. Mutual interest in future research on longitudinal data collection and analysis has been discussed with one of the invited speakers at the event, Martin Lanzendorf, Centre for Environmental

Research, UFZ, Leipzig, and currently opportunities for funding of research visits and joint initiatives are being investigated.

The collaboration with SDG has led to SDG considering how the Dynamic Urban Model might be adapted to better represent lags and other aspects of behavioural dynamics. The collaborative relationship on this project has contributed to a joint bid being submitted to the Department for Transport (led by SDG) in response to an invitation to tender on 'The Role of "Softer" Factors in Influencing Patronage Growth and Modal Shift'. The principal investigator will provide specialist input on measurement of behavioural responses.

Finally, the panel data generated from this project offers a data set with significant further research potential. There have been few transport-specific multi-period panel data sets collected and the collection of this one represents a unique addition in that it coincided with a major transport intervention, thus incorporating dynamic response phenomena of key interest.

Expenditure

Expenditure was slightly lower than anticipated. Staffing costs were £5,800 lower than authorised, as a result of the pay scale level of the researcher and less use of technical staffing support than anticipated. Costs of £7,200 were associated with administration of the panel survey (£10,000 had been budgeted). The budget on computing was utilised to acquire a laptop and analysis software (Vensim, STATA and LIMDEP), which will serve as valuable resources for future work. Travel and subsistence expenditure was slightly greater than authorised (by about £500) and enabled attendance at a two-day Panel Data Analysis course at the University of Southampton and five conferences (two international) at which project presentations were made (*6,11,12,13,14,15*). These conferences enabled dissemination to a variety of audiences (UK university transport researchers, transport planning professionals, social statisticians, international travel behaviour researchers). The travel and subsistence budget also enabled six project meetings to be held with SDG through the project and ensure close collaboration took place regarding the application of dynamic relationships in DUM.

Further Research and Dissemination Activities

An immediate priority is to further disseminate the findings of the project through peer-reviewed journals. One paper on duration modelling has been accepted for the Transportation Research Record and another paper presenting descriptive results of the panel data analysis is currently being peer reviewed for inclusion in the book of proceedings of the 11th International Conference on Travel Behaviour Research. Papers will be submitted in the near future to transport journals on SPD modelling and dynamic choice modelling. There is also scope for journals papers to be submitted on panel survey methodology (particularly since respondents were asked for feedback on their survey experience at the last wave) and on bus policy implications of the panel survey results.

The principal investigator is considering how best to take forward this area of research and this may involve some further analysis of the collected panel data as well as work to apply dynamic relationships into practical model forecasting systems (using stochastic microsimulation) and to consider how panel data sets can be obtained more widely.

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