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Dynamic responses of freight operators to government policies: a latent curve modelling approach

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Abstract

Using a unique dataset collected from Australian (urban) freight operators using an adaptive-dynamic simulation method, firms' dynamic responses are modelled using latent curve models to investigate firms' adaptation strategies in response to new government policies. Latent curve models are used to identify the magnitude and timing of the responses as well as what factors influence the changes. The results show that firms adapt gradually to the policies with some decisions changing quicker than others. Furthermore, the drivers of responses changes during the adaptation process and that not all incremental decisions are made solely on the basis of cost.

Keywords: Freight transport, Government policies, Dynamic decision making, Congestion charge, Low Emission Zone

1. Introduction

Many parts of freight transport carriers' operations are restricted or dictated by government regulations as well as practical considerations and shippers' and receivers' requirements. In doing so carriers must balance the effects on the company of making these changes, such as increased costs, whilst still meeting the constraints imposed by government regulations and customer requirements. Previous studies have demonstrated that both government regulations and the requirements imposed by shippers and receivers have a direct influence on how carriers operate and the decisions firms make (Danielis and Marcucci, 2007). However, as these requirements and regulations change frequently, carriers are required to continually adapt to the new regulations or requirements. This means that the decisions made by freight operators are not only made at a single point in time but are instead frequently, if not continually, re-evaluated and adjusted. These frequent or continual adjustments mean that these decisions cannot be considered static but are instead dynamic (i.e., changing over time). This is important for several reasons but arguably most importantly because of how externally imposed requirements, whether through regulation or shipper/receiver demands, are known to affect freight operations. The changing nature of these requirements means that decisions made by carriers must be analysed and interpreted in the context of when the decisions were made, as well as previous decisions and possible future changes. Broadly, it is understanding the effects of these dynamic (i.e. changing) requirements and decisions in the context of freight carriers operations in response to government policies and regulations that is the focus of this paper.

1.1. Background, approach and aims

Governments have long attempted to minimise the negative effects of freight transport by introducing policies that attempt to restrict or change how freight carriers operate. Despite this, freight transport still contributes disproportionately to emissions and congestion relative to its proportion of the vehicle fleet. A rapid expansion in the number of freight vehicles being used (in part due to a dramatic increase in internet shopping) in recent years has further necessitated policies that can reduce the negative effects whilst still allowing freight transport to provide its substantial benefit to the economy. Doing this effectively requires an understanding of how firms adapt to government policies as well as other measures not only at a particular point in time but over a longer period of time. Generally, behavioural models for freight have focused on

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parameterising attributes for a specific choice (e.g., mode) but have made the implicit assumption that these attributes do not change over time (Danielis and Marcucci, 2007; Fowkes et al., 2004). Although these models provide a reasonable basis for behavioural models for freight, the lack of a temporal component means they cannot be used to assess how the influence of each attribute on decisions changes over time. Furthermore, they are unable to be used to investigate how quickly freight carriers adapt to changes in government policies.

To address these limitations, this paper explores the dynamic (change over time) responses of freight carriers to two government policies, a Low Emission Zone (LEZ) and a cordon-based congestion charge. To do this, this paper uses a simulation method that incorporates both dynamic elements that change through (simulated) time in successive time periods each representing six months, and adaptive elements that change in response to respondents' decisions, to measure the responses of carriers to the policies. It is important to emphasise that the dynamic elements refers to those that change externally to the firm/respondent and the adaptive components are those that change due to the firm's previous decision (even if those decisions were prompted by external changes). These six-month time periods are designed to represent different points of the adaptation process and include one time period before any policy is introduced to respondents (i.e., the *status quo*), two following a policy announcement but before any changes come into effect, and two following the implementation of the policy. During each of these simulated time periods, respondents are provided with new information about the policy and the likely effects on their operations and given the choice to change their decisions (or not if they prefer). This being the case, it is important to note that although this simulation method has some similarities to similar methods used in freight carrier surveys (Puckett, 2009; Fowkes et al., 2004), it differs in that rather than measuring decisions for a single shipment, delivery or route, this simulation is intended to measure the overall responses for a sample of receivers and associated deliveries. As such, the responses are measured as a set of decisions relating to the choice of number of routes, the overall amount of toll road use across all routes, mix of vehicle classes and emissions standards in the vehicle fleet, and a set of departure times. This means that each of these decisions should be not be seen as a single choice (whether binary or categorical) as they would be for a single route but are instead multiple decisions that can be collapsed into a single 'aggregate' decision variable using several different forms as are appropriate for each model.

With these issues in mind, the primary aim of this paper is to identify the magnitude and speed of the adaptation process used by road freight carriers to a number of policy initiatives by investigating both how different attributes are important to each stage of the adaptation process but also how quickly the changes, if any, occur for each of the four decisions being measured (i.e., use of toll roads, number of routes, vehicle class and emissions standard, and departure time). These are identified using a set of latent curve models that estimate the influence of different attributes and firm characteristics (e.g., size and type of firm) during each stage. Crucially, these models (that are described in detail in Section 3.2) model the *relative changes* observed through a set of latent constructs rather than the absolute values directly, allowing for both the overall trajectory of the changes as well as the drivers of the incremental changes to be identified and estimated (Bollen and Curran, 2006). As a result, the dependent variables of the models (which in this case are the four decisions being measured) are influenced by the latent constructs (factors) that are in turn influenced by the independent variables (the attributes). The focus on the incremental changes means this approach is particularly well suited to modelling changes such as those made by freight carriers because small changes can be estimated without being overwhelmed by more structural decisions that are unable to be changed.

1.2. Paper overview

The following section provides a brief literature review on the behaviour of freight firms, with a focus on carriers and the use of policy as a mechanism to change behaviour as well as a review of how firm behaviour in response to policies has been incorporated into freight models. This is followed by an overview of the survey used for collecting the data underpinning the analysis in this paper, an introduction to and discussion of the appropriateness of the methodology used, and a comprehensive discussion of models for each decision being evaluated. Lastly, the conclusions summarise the key findings and contributions of this paper.

2. Literature review

Changes in government policies, either through a change to an existing policy such as tightening restrictions that already exist, or the addition of a completely new policy, are frequently used as (reasonably) blunt instruments that are applied to all freight carriers. However, the freight industry in Australia (and elsewhere) is fragmented with carriers often focusing on specific types of shipments, a handful of very large companies and many much smaller carriers. In addition, how a policy is likely to change freight carriers' behaviour is likely sensitive to specifics of the policy design with some types of policies or regulations' being more effective than others (Anderson et al., 2005). The effects of these issues means that accounting for this heterogeneity, both between firms and between policies, may be critical to accurately predicting the responses of carriers to changes in government policies. These effects may be further compounded when looking at the adaptation process undertaken by firms as they respond to policies. Given these possible effects, the following sections of this literature review discuss the evidence for the existence of behavioural heterogeneity between different types of freight carriers, the evidence for the effects of different types of policies on freight transport, and how these issues have been incorporated into freight modelling. This evidence is discussed both in terms of the overall changes, but more relevantly to this paper, primarily in terms of the adaptation process itself.

2.1. Behavioural heterogeneity between firms

Although a policy may be designed to elicit a specific response, there is some evidence to suggest that the factors firms take into account when making decisions differ depending on the characteristics of the firm. Furthermore, firms are likely to be limited by somewhat different constraints, even within the same industry, such that two firms may make different decisions than would be expected were they assumed to be behaviourally homogenous. Multiple studies looking at the interaction between shippers and carriers have shown that carriers' decisions are strongly constrained by shippers and receivers with their requirements setting limits on how the carrier operates. These constraints include constraints on which vehicle classes can be used as a result of the choice by the shipper of shipment size and limits in when deliveries can be made that are set by the receiver (Abdelwahab and Sargious, 1991; Holguín-Veras, 2008; Holguín-Veras et al., 2009; Roorda et al., 2010). Holguín-Veras et al. (2009) conducted experiments on shipper-carrier interactions and concluded that shippers and carriers co-operate to maximise the benefits to both. However, they also found that in the longer term shippers choose carriers that align with their preferences for shipment size and mode and so effectively select the mode. This is consistent with the observed fragmentation of the freight carrier industry where carriers tend to focus on specific shipment sizes in combination with the shippers who use them. Nonetheless, this does not suggest that carriers have no flexibility in the vehicles they use but instead that they are heavily constrained within the requirements set by the shipper. As such, a carrier may be constrained to using trucks but be free to choose between light and heavy rigid vehicles subject to their ability to handle the required shipment sizes. Similarly, Holguín-Veras (2008) found receivers to be the primary constraint on delivery hours, particularly in terms of using off-peak deliveries. Specifically, they found that receivers were not sensitive to financial incentives (or disincentives) imposed on carriers that made it more attractive to deliver during off-peak hours when carriers were unable to pass the additional costs onto receivers. Furthermore, even when shippers were able to do so, the costs to receivers of facilitating off-peak deliveries was higher than the costs of paying any additional costs passed on by carriers. A related study of shippers' freight choices showed that firm characteristics are particularly important in predicting how changes in the attributes of the freight transport service are likely to lead to a change in decisions from their current state (Bolis and Maggi, 2003). It is possible that this may also apply to carriers as well as shippers. However, even between firms with similar shipper and receiver requirements could have different behavioural responses depending on the characteristics of the firm itself. A study by Murphy et al. (1992) showed that firms of different sizes, even within the same sub-industry (Less than truckload carriers) placed different levels of usefulness on different sources of information, including from regulatory sources. The same study also found that a firm's financial performance has a significant effect on how important they see economic information when making decisions. In addition, the differences in how decision makers treat internal feedback when making decisions also appears to have an effect on how firms actually respond (Holguín-Veras et al., 2009). This suggests that two firms may have different responses to the same policy even if their requirements (i.e., constraints) are similar and is an additional indication that although the requirements of the shippers and receivers largely define the operating decisions of the carrier, different carriers may still be able to respond slightly different to changes in government policies.

This heterogeneity in firm behaviour is clear from an empirical study on the response of freight carriers to the introduction of environmental policies, by Anderson et al. (2005). This study looked at how freight operators would respond to four different policies, specifically low emission zones, congestion charging, vehicle weight restrictions and vehicle access time restrictions. The results of this study show that the responses of firms to these policies depended on a variety of firm-specific characteristics including the firm's operating area, the type of company and its existing vehicle fleet. A study on the possibility of switching deliveries to off-peak periods by Holguín-Veras et al. (2008) involving a larger number of firms also found that firm characteristics play a part in how the company responds. The size of the company (by number of employees), how often they operate in the affected area and the commodity transported were identified as some of the primary factors in how a firm responds. This was the case despite carriers being constrained in how they could respond by the requirements imposed on them by shippers and receivers (Holguín-Veras, 2008).

While both Anderson et al. (2005) and Holguín-Veras et al. (2008) look at how firms respond to policies, they assume responses to a policy are static once a decision has been made. This means that the response provided by the participant is assumed to be the only response a firm will have. Crucially for an assessment of how the heterogeneity of firms affects their responses to policies, this does not consider if some firm characteristics are particularly important (or constraining) in the short-term and less important in the long-term. A further limitation of these studies is that they do not assess how quickly changes are likely to be made in response to policies nor if firm characteristics influence how quickly firms adjust. Furthermore, although these studies show that certain factors make a difference to how the firm responds, they do not explain how they do.

2.2. Effectiveness of policy design in promoting behavioural responses

A series of experiments on measures to encourage off-peak deliveries including measures of road pricing and financial incentives for off-peak deliveries showed that road pricing alone is insufficient to encourage behavioural change of carriers (Holguín-Veras, 2008). Instead, Holguín-Veras (2008) suggests that either the pricing mechanism must be designed such that the charges are incorporated into the freight rates (which can then be used to influence receivers) or that incentives be provided to receivers to encourage receivers to relax their requirements preventing off-peak deliveries. These results suggest that for a policy to successfully change the behaviour of carriers, the policy must ensure both that the desired change is in the control of carriers and not shippers or receivers, and that any pricing measures are those that would be internalised by the carriers and as a result affect the freight rates offered. This is consistent with the framework proposed by Roorda et al. (2010) that incorporates policy scenarios that (potentially) affect all agents in the logistics chain, including carriers. As is stated by Roorda et al. (2010), the decisions that affect freight transport as a whole range from longer term decisions to more short-term operational decisions. Each of these decisions is affected in different ways by different types of policies and the time and frequency with which these decisions are made have a flow on effect on broader, more strategic decisions that are made less frequently and apply to multiple agents within the supply chain. This suggests that there remains a need to gain a better understanding of exactly how policies, both specific policies and more generally, influence changes in the decisions over the short to medium term which may in turn influence the longer-term decisions that are made by freight carriers as well as shippers, receivers and others involved in the freight industry.

Other studies that have looked at the differences in responses to different policies also provide evidence of the importance of ensuring that policy design is consistent with the behavioural decisions made by carriers to ensure the policies achieve the desired objectives. The study by Anderson et al. (2005) discussed previously also looked at the effects of several different policies with a focus on the environmental effects of the policies. The study looked at four policies, specifically low emission zones, congestion charging, weight restrictions and time of day restrictions. Of these, low emission zones, weight restrictions and time of day restrictions are regulatory policies while a congestion charge is a market-based mechanism. As could be expected, Anderson et al. (2005) found that the impact on emissions of each of the policies is very different. Although they found that the effects of each policy depends on firm characteristics, they also found that the regulatory policies had fewer options for avoiding the policy and as a result had somewhat more consistent behavioural responses.

However, since this study focused only on the changes that were likely to occur and it is not known how long it would take for the full effects of the policies to be realised.

Another study by Browne and Allen (1998) used London as a case study for five policies. These were a ban on heavy vehicles in urban areas, a generic policy that improves load consolidation, a combination of a ban on heavy vehicles and an improvement in load consolidation, a generic policy that reduces empty running and a policy to build and run urban transhipment centres. This study used a combination of the London Area Transport Surveys of 1981 and 1991 as well as data on fuel efficiency of freight vehicles to estimate fuel use and emissions of freight in London. This data was then adjusted based on estimates of the changes to freight flows and vehicle classes and used to estimate the changes to emissions under the different policy options. Similar to the results from Anderson et al. (2005), this study found that each of the policies would result in very different behavioural responses and as a consequence, changes to emissions. The generic policy for improving load consolidation resulted in the greatest reduction in emissions while the ban on heavy vehicles resulted in the largest increase in emissions. This significant heterogeneity between policies would suggest that some types of policies result in a greater overall change in emissions. However, the time required to see the full effects of the policies was not modelled in this study (likely because of the lack of data) and so it is not possible to determine if certain changes are made by carriers quicker than others. Similarly, Link (2008) conducted a stated preference survey on the acceptability and likely responses of freight carriers to the heavy goods vehicle charges on German motorways and found both that some aspects of the scheme were more widely accepted but also that there was a range of likely responses with only a handful of responses being seen as either "very likely" or "very unlikely". Interestingly given the context of the current study, they found that carriers were less likely to respond by changing the class of vehicles used than some other responses although it should be noted that this scheme primarily affects long-haul deliveries rather than intra-urban deliveries.

2.3. Incorporating behaviour into policy modelling

One of the primary difficulties in assessing how the introduction of a policy by governments will change freight transport operations is understanding the responses of carriers both initially and over time. The distinction between initial responses and ongoing or long-term responses is important for two reasons. First, as discussed earlier in this literature review, carriers are constrained in how they can change their operations by decisions made by shippers and receivers and this is particularly true initially. Second, carriers may make a number of decisions over time as they gain knowledge of the policy and how it affects their operations and as they cooperate with shippers and receivers to find mutually beneficial solutions. Freight transport models have become increasingly sophisticated as they have started to incorporate some of these considerations to improve the accuracy and reliability of the predictions.

Many behavioural models for freight have relied on the use of stated choice experiments, often with a focus on mode or route choice by shippers, carriers, or increasingly, both (Danielis and Rotaris, 1999; Roorda et al., 2010; Hensher et al., 2007; Holguín-Veras et al., 2009). A number of these have looked at the likely effects of different policies on freight decisions. One such study of 22 firms in Switzerland and Italy applied the Leeds Adaptive Stated Preference (LASP) approach (Fowkes and Shinghal, 2002) to shippers' decisions on their choice of freight transport services by mode. The study found that shippers were generally willing to change mode if either service was improved (through speed, reliability or flexibility) or the cost was reduced (Bolis and Maggi, 2003). A study of freight carriers in Indonesia that used a standard stated choice experiment found similar results for switching between rail and road (Norojono and Young, 2003) albeit with different magnitudes as would be expected given the different economic conditions. Puckett et al. (2006) used a stated choice experiment to develop a behavioural model of both carriers and shippers in Australia in a study on road user charges. This behavioural model was used to predict what the effects of road user charging would be on freight carriers in Sydney and found that carriers would largely benefit from an improvement in travel times and that these benefits would offset any additional costs from the charges. As already discussed, Holguín-Veras et al. (2009) looked at policies to encourage off-peak deliveries using a set of discrete choice models and was able to incorporate the interaction between carriers, shippers and receivers. Mesa-Arango and Ukkusuri (2014) looked at how shippers choose between different road freight carriers and the willingness to pay for various service attributes including freight rates, delivery time and shipment value.

Further advances in behavioural modelling for freight have recently been made with the use of microsimulation and agent-based models (Davidsson et al., 2005). In contrast to traditional freight models that are based on aggregate data, these models are used to simulate the decision making of individual 'actors' or 'agents' (firms in this case) based on behavioural models estimated from disaggregate data (Liedtke and Schepperle, 2004). Although the specific form of each of these models differs somewhat, a comprehensive framework for implementing behaviour into micro-simulation is proposed by Roorda et al. (2010). Key examples of these models include the model developed for Calgary by Hunt and Stefan (2007) that was used to predict the effects of various policies on commercial vehicles and Wang and Holguín-Veras (2008) who developed a microsimulation of freight tours. These agent-based models provide a powerful alternative to the more widely implemented discrete-choice models but are typically much more data-intensive. Micro-simulation models do have the potential to incorporate the full adaptation process taken by carriers in response to government policies but to the authors' knowledge these have not yet been fully implemented and modelled within a microsimulation framework.

2.4. Contributions

Although this literature review has discussed a variety of different approaches to studying the responses of freight carriers to government policies, much of the focus has been on the overall responses. This is undoubtedly important given the long-term effects of government policies. However, as shown by Holguín-Veras (2008), it is important to understand how carriers adapt to government policies, such as a congestion charge, to ensure that policies are well designed and are targeting decisions that carriers can make within the constraints imposed by shippers and receivers. To do this effectively requires a more thorough understanding of what is driving the incremental changes made by carriers in the short and medium terms as these decisions have consequences for how carriers (and shippers and receivers) ultimately adapt to the new *status quo*. This paper attempts to provide an initial understanding of how carriers, operating within the constraints set by government regulations and shipper and receiver requirements, adapt to the changes in policies by providing insights into the likely speed and magnitude of the incremental changes and overall response as well as the drivers of the changes at each point in the adaptation process.

3. Data and methodology

The data used in this paper were collected from logistics managers, operations managers and managing directors[1] of Australian freight carriers using an adaptive-dynamic simulation method that was designed to collect longitudinal data from freight carriers in situations in which it would be impractical (if not impossible) to collect detailed data on decision making. This adaptive-dynamic simulation method uses simulation techniques to generate a hypothetical scenario that involves changes across time that are dependent on the earlier decisions of respondents. This provides a learning mechanism through which the decisions made by respondents during earlier time periods affect the alternatives shown to respondents and the attribute values during each of the (simulated) time periods and incorporates consequences (in terms of the values of the attributes) for the decisions made by respondents. Although stated choice experiments are widely used to collect data on behavioural responses to policies (both for freight and passenger transport), they are less well suited to the collection of (hypothetical) longitudinal data (Puckett, 2009). Puckett (2009) argues that "whilst stated choice may be able to capture important behavioural information under a given scenario, there may be little to nothing relating the choices made by respondents with potential consequences of these choices. Other approaches may be able to be tailored to represent consequences of chosen strategies, which could serve the joint benefits of reinforcing the motivation to make informed choices in experimental settings and capturing information on the ways in which decision makers adjust to a range of outcomes as they relate to decision makers expectations." This simulation approach was used in an attempt to capture this information.

The survey instrument used for this paper needed to be able to collect data on the likely decisions of freight carriers in a way that was understandable to respondents and straightforward to complete. However,

[1]In larger firms the logistics or operators manager was typically responsible for the decisions under investigation while in smaller companies this was generally the managing director. Whoever was the main decision maker for these decisions in each company completed the survey.

this needed to be done while allowing for as large a variation in allowable decisions as possible without masking time-varying and complementary decisions. To achieve this, this survey used an approach with a web-based simulation 'game' written in the PHP[2] programming language, that is typically used for internet-based systems including surveys, and provides the ability to embed user-specific data into the survey. The simulation was focused around a hypothetical road freight carrier that needed to make deliveries to several customers subject to a variety of constraints that are typically encountered in reality, with a particular focus on time windows, delivery requirements and various government policies. The simulation in this study used five consecutive six-month time periods and simulated the changes to costs, emissions and reliability for each of the time periods given decisions made by respondents and the effects of a government policy. It must be emphasised that since the purpose of this survey was to look at the responses to changes in government policies, the requirements set by shippers and carriers were presented to respondents before the simulation began and remained constant for the duration of the survey. This ensured that any changes observed were in response to the effects of the government policy (or the policy itself) rather than any potential changes made by shippers or receivers. The survey was focused on two government policies, a Low Emission Zone (LEZ) aimed at accelerating the fleet replacement rate for cleaner vehicles, and a congestion charging zone aimed at reducing overall traffic levels. The survey was divided into three parts: the initial section asked respondents to answer some basic questions about their experience as well as some information about their firm. This includes a question on the primary type of deliveries made by the respondent's firm of either parcels and small packages, or pallets and other larger deliveries. These were drawn from the sample of firms that were recruited to participate. The answer to this question was used to condition the scenarios to ensure relevance to the respondent and was not one of the decisions made by respondents made during the simulation. The survey then continued to the main simulation 'game' where respondents were asked to complete the delivery task in a hypothetical scenario using their knowledge of the industry and some additional information provided on the screen. An example of the simulation screen shown to respondents is shown in Figure 1. Each row of the table shows a single alternative with the attributes shown across the columns. The information in the table is complemented by a diagram showing the requirements of the customers and a graph showing the current and forecasted total costs and emissions of each alternative.

The values of the attributes in the alternatives are a combination of variables that describe the decisions (i.e., class of vehicle, emissions standard of vehicles, toll road use, departure times and number of routes) and cost, time, emissions and reliability attributes calculated using an embedded vehicle routing and scheduling problem with time windows algorithm. The vehicle routing and scheduling algorithm ensures that the values of the attributes are consistent with the actual values in reality given the scenario and the decisions embedded in each alternative. These values were updated as the respondent completed each of the simulation six-month time periods to account for changes as a result of the policies. Alternatives shown to respondents were selected automatically based on a weighting algorithm that selected two alternatives with similar levels of costs, emissions and fleet mix to the respondent's previous decisions as well as two alternatives with lower levels and two with higher levels and then randomly ordered. For the 'base case' the alternatives (and associated attributes) were chosen based on the respondent's firm, favouring alternatives with similar fleet mixes in particular.

Lastly, respondents completed some additional questions on their perceptions and attitudes to the importance of various factors to freight carrier operations. This survey provided data that could then be used for developing a model that is able to assess the (potentially) varying importance of different factors on freight carriers' operational decisions as they adapt to government policies and that can account for both time-invariant and time-varying factors and how the influence of these changes over time.

3.1. Dataset

The dataset contains four types of variables, each of which measure the decisions made by each respondent during each (simulated six-month) time period and the context in which they were made. Specifically, these four types are: 1) Variables measuring respondents decisions including what alternative was chosen and the

[2] PHP is a recursive acronym standing for: PHP: Hypertext Preprocessor

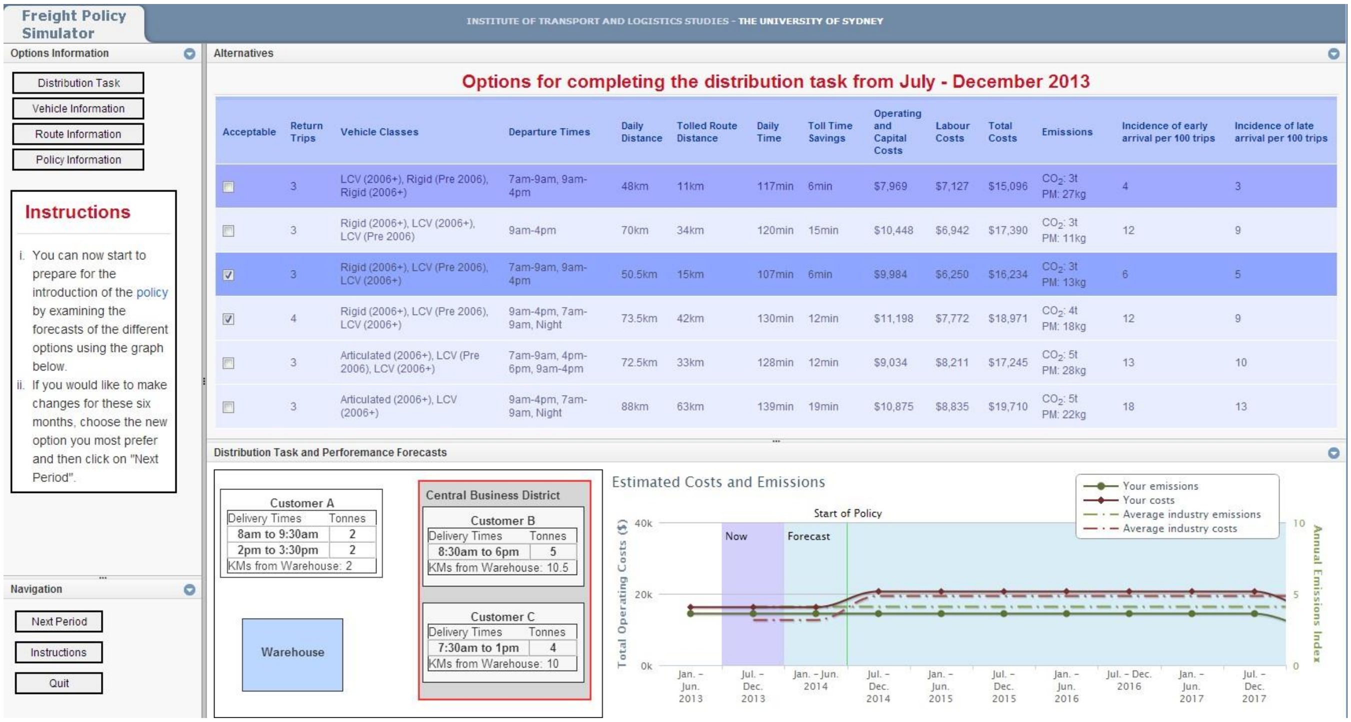

Figure 1: Example simulation game screen shown to respondents

attributes that made up that alternative for each six-month time period; 2) Variables describing the non-chosen alternatives presented during each of the six-month time periods; 3) Variables describing the scenario (i.e., one of either the 'couriers/packages' or 'pallets' scenarios) and policy (i.e., one of the LEZ or Congestion Charge) shown to respondents; 4) Variables related to the respondent themselves (e.g., years of experience, position) and those of the firm they are representing (e.g., size, fleet mix, type of deliveries made). A full list of variables in the dataset including general statistics are shown in Appendix A.

3.2. Methodology

A variety of different methods have been used for developing freight models based on both stated preference and revealed preference data. Amongst the most frequently used of these are various forms of discrete choice models, some of which incorporate methods for auto-correlation and interdependence between observations common to time-series data. Discrete choice models are a well established method for parameterising attributes in discrete choices such as those under investigation in this paper and have been applied to many aspects of freight transport (Li and Hensher, 2012; Masiero and Hensher, 2012). These models estimate the effect of a change in the value of an attribute on the probability of a specific discrete choice (i.e., decision) being made. These can then be used to estimate the likely decisions that are made when the values of the attributes (or independent variables) change. However, the focus of this paper is not on the influence of the attributes on the overall decisions but instead on the incremental and relative changes that occur during the adaptation process used by firms in response to changes in government policies. This slightly different focus means that it is of interest to identify what influence each of the attributes have on driving the changes made at each point in time. This makes it difficult to apply discrete choice models as the influence of the attributes on the changes themselves can not be estimated while retaining the context of the overall (or absolute) decisions[3].

[3] Latent curve models have been used extensively in other disciplines for analysing responses to policy interventions in behavioural science, social science, psychology and public health disciplines. It adds a useful feature not well incorporated in discrete choice methods,

In addition to discrete choice models, analysis of time-series panel data (behavioural or otherwise) has traditionally made use of methods like autoregressive integrated moving average (ARIMA), repeated measures regression, and repeated measures analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA) (Chan, 2003). All three of these methods provide mechanisms through which various aspects of longitudinal data can be investigated yet some of the limitations of these models mean they are not always appropriate for assessing behavioural changes of firms across time, particularly in response to a policy intervention.

ARIMA suffers from several limitations that prevent it from being used effectively with some longitudinal datasets. ARIMA models require a relatively large number of repeated observations of the same individual (or firm), preferably with only a short, and equal, period of time between observations (Schinka and Velicer, 2003). Collecting data from freight firms repeatedly over a length of time when firms could reasonably respond to an intervention is likely to be time consuming regardless of the method employed. Although some extensions to ARIMA models have been developed that improve its ability to handle longitudinal data from intervention studies, these methods generally require more observations than would otherwise be required (Schinka and Velicer, 2003). Furthermore, ARIMA can be used to analyse either inter-individual changes or intra-individual changes across time, but not both in the same model (Chan, 2003). This is a crucial limitation because it means that it is not possible to identify what are the common (group or industry-level) effects of an intervention and what are the individual effects.

Repeated measures regression and repeated measures ANOVA and MANOVA are based on linear regression techniques and have often been used to model growth curves (Duncan and Duncan, 2004). These methods rely on comparing the change from one observation to the next in the case of ANOVA, or over several observations for MANOVA. Repeated measures MANOVA can be used to model the changes in the sample including the influence of some covariates (Curran and Muthén, 1999). In contrast to ARIMA, these methods can be used for datasets with only a small number of repeated observations spaced further apart. However, although these methods can and have been used to model growth curves, they require that variances are assumed to be constant across time and as a result, individual changes are also effectively assumed to be the same across the sample (Chan, 2003). This assumption means that the differences between individual changes and the mean changes can not be investigated since these are not estimated (Chan, 2003).

Latent curve models use structural equations to model the changes over time as a function of several latent variables representing the different components of the initial observations and any subsequent changes (Chan, 2003). This separation of the initial (or *status quo*) decisions and subsequent changes mean that it becomes possible to estimate the influence of different attributes specifically on the changes that are observed. As a result, a specific attribute may be found to be significant during some stages of the adaptation process but not in others while still being significant in the estimation of the initial decision. It is important to emphasise that this does not mean that the attribute is not important to the decisions made during these time periods, but rather that the attribute is only not significant in the change in the decisions relative to the status quo. This is a key benefit to latent curve models over discrete choice models for the purpose of this analysis because of the focus on investigating the responses to the policies specifically since it is the changes that are of specific interest in these models.

Latent curve models can also overcome some of the limitations of the traditional time-series techniques. By using structural equation modelling techniques where the intercept and slope of the changes are measured by latent factors, the assumption of repeated measures MANOVA of equal variances (errors) over time can be relaxed and the variances can be estimated and investigated (Duncan and Duncan, 2004). This allows not only for a potentially less biased estimate of the mean change but also a more thorough investigation of how individual patterns of change have (or have not) diverged from the mean (Muthén and Curran, 1997). Latent curve models also provide additional flexibility in the specification of the causal relationships between variables and time allowing for covariates to be treated as constant over time, varying for each observation, or a combination of both (Stoel et al., 2004). Similarly, this approach incorporates the time structure of the dataset in the estimation of the model meaning that the intervals between observations need not be short

namely the ability to investigate systematic and incremental changes and the relationship between the change trajectory and both time-invariant and time-varying predictors (Bollen and Curran, 2006).

nor equal. However, it is important to note that unlike time-series methods, latent curve models are less well suited to very long datasets where the observed variables have a cyclical pattern (although these can be accommodated). This flexibility makes it ideal for use in studies where it is hypothesised that certain covariates have a constant influence over time and others vary for each observation. However, this flexibility means that interpretation of model results can be challenging, particularly for more complex models, since the estimates must be interpreted in terms of the factor means, the variances and the specific time structure used in the model (Bollen and Curran, 2006). Nonetheless, latent curve models were found to be the most appropriate method for investigating the adaptation strategies of freight operators in response to mitigation policies.

3.2.1. Overview of latent curve models

Latent curve models are based on the same underlying principles as growth curve models[4] but apply a structural equation modelling (SEM) approach by treating the intercepts and slopes of the growth curves as latent variables. This approach has several advantages over a standard growth curve model. First, heteroscedasticity and autocorrelation can be incorporated into the models since the assumptions of errors being independent and homoscedastic (Kaplan, 2009) are no longer required with the errors now fully estimated from the data. Second, models can be estimated using a variety of different estimators including Maximum Likelihood (ML) (Bollen and Curran, 2006). Third, the SEM framework facilitates the use of lagged predictors (Duncan and Duncan, 2004). These advantages allow for more flexible model specifications that can better handle longitudinal travel behaviour data that can have both high variability and correlation.

Using the notation described by Bollen and Curran (2006), the general form of the latent curve model can be defined using equations 1 to 3. In equation 1 y_{it} represents the value of the response variable for each firm i at time t, α_i represents the intercept for firm i, β_i represents the slope for firm i and ϵ_{it} is the conditional variance for firm i at time t. λ_t is a variable with a constant value for the current time period for all responses of $t-1$. One of the main benefits of the latent curve model is the ability for the influence of a time-varying covariate to change across time. This (potentially) changing influence is included in the model by using the product of the coefficient γ, specific to each time period and time-varying covariate k and the value w of the covariate k for firm i at time t.

$$y_{it} = \alpha_i + \lambda_t\beta_i + \sum_{k=1}^{K} \gamma_{tk} w_{itk} + \epsilon_{it} \tag{1}$$

Equations 2 and 3 define the equation for the intercept (α) and slope (β) respectively for each firm i. Both equations follow a similar general form where μ_α and μ_β are the mean intercept and slope of all firms and ζ_{α_i} and ζ_{β_i} are the conditional variances for each firm for α and β. As in Equation 1, γ is the mean influence of each of the time-invariant covariates q on the slope and intercept with the value of x for each firm and time-invariant covariate.

$$\alpha_i = \mu_\alpha + \sum_{q=1}^{Q} \gamma_{\alpha q} x_{iq} + \zeta_{\alpha_i} \tag{2}$$

$$\beta_i = \mu_\beta + \sum_{q=1}^{Q} \gamma_{\beta q} x_{iq} + \zeta_{\beta_i} \tag{3}$$

These equations are often shown in matrix form as in Equation 4 where $\boldsymbol{y}$ is the observed variable represented by the combination of the latent factors, $\boldsymbol{\Lambda}$ is a vector containing the latent factors, $\boldsymbol{\mu}$ is the

[4]Growth curve models are a set of statistical methods used to estimate the variability between individual patterns of change (the "growth curve") across time (Curran et al., 2010).

means of the latent factors, η represents each of the latent factors, $\boldsymbol{\zeta}$ is the vector of disturbances (individual deviations from the mean) and $\boldsymbol{\epsilon}$ is the vector of error terms. Throughout the rest of this paper, the matrix form is used to describe the different components of the models when appropriate. Most commonly this is used to describe the factor scores with Λ_α being the factor scores for the latent variable, α (intercept), and Λ_β being the factor scores for the latent variable, β (slope). When Λ_α and Λ_β are subscripted by a number (1 to 5), this specifies the factor score (for either α or β) at the time period indicated by the number.

$$\boldsymbol{y} = \boldsymbol{\Lambda}(\boldsymbol{\mu}_\eta + \boldsymbol{\zeta}) + \boldsymbol{\epsilon} \tag{4}$$

It must be emphasised that this is the general model structure for a latent curve model with both time-varying and time-invariant covariates but with a single continuous response variable and a linear slope. In all cases, the coefficients of the time-varying components of the model as well as the latent slope factor (Λ_β) must be interpreted with reference to those of the intercept (the status quo) as these are the changes (or responses) relative to the status quo. Put another way, the overall decisions in each time period are a result of the sum of the latent intercept factor (and associated time-invariant predictors) and the latent slope factor at that point in time (and associated time-varying predictors). These equations form the basis from which further models can be developed incorporating the interaction between multiple response variables, some of which may be categorical, and models where the shape of the curve is predetermined to be nonlinear (quadratic or logistic for instance) or is freely estimated. In interpreting the models throughout this paper it is important to understand that the use of an adaptive design[5] in the survey tool, coupled with the limited set of alternatives available to choose from, may somewhat influence the results of the models. Although the effect is thought to be small due to the ability of respondents to choose not to change their previous decisions, it is possible that this effect may be included in the disturbance parameters of the models.

Latent curve models can also be used with ordinal and categorical dependent variables by modifying the model form to incorporate a continuous variable, generally referred to as y^*, with estimated thresholds and scale parameters that match the ordinal (or categorical) categories to values on the continuous scale. Crucially, y^*, threshold values and scale parameters are all estimated from the data within the model and as a result are not sensitive to any *a priori* definitions of the appropriate threshold values. Furthermore, it must be emphasised that y^* is not simply a linear transformation of the ordinal variables. However, this does make interpretation of model results somewhat more difficult as estimates of coefficients are relative to y^* and not the original variables (whether ordinal or categorical).

The fit of the latent curve models can be evaluated using a set of measures of model fit. Although there is some debate regarding what is considered "good" model fit and which measures should be used some general rules of thumb have been developed (Barrett, 2007; Goffin, 2007). The most frequently used measures of model fit are the χ^2 p-value statistic, the Comparative Fit Index (CGI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and the Standardised Root Mean Square Residiual (SRMR). The interpretation of these measures of model fit differ somewhat from their typical use in standard regression models. In particular, models with a significant χ^2 value (less than 0.05) are rejected and "good" models are expected to have insignificant χ^2 values. It must be emphasised that this relates to the χ^2 as a measure of model fit specifically and the interpretation of the p-value statistic in the model results are consistent with those in regression (Bentler, 2007). The CFI and TLI are measures of model fit where values range from zero (worst) to one for CFI and approximately one for TLI. Generally, values greater than 0.9 are considered good. In contrast, the scales of the RMSEA and SRMR indices have zero as the ideal model and "good models" having values of 0.08 and 0.06 respectively. However, the values of RMSEA and SRMR are often inflated for models with small sample sizes and so these are generally interpreted in context of the other measures of model fit.

Latent curve models, and the SEM framework more generally, have significant flexibility in how models can be defined. This flexibility provides the opportunity to analyse the data in different ways using the same underlying methodology. This is particularly powerful in the analysis of decision making where there is some uncertainty as to the relationship between different decisions and between decisions and a variety of different (potential) predictors.

[5] Where each question or screen is based on previous responses.

4. Analysis and Discussion

In completing the survey respondents chose a single alternative during each time period with each alternative describing several related decisions (e.g., number of routes, vehicle classes and use of toll roads). For the purposes of this paper, each of these underlying decisions, as described by the alternative, are modelled separately. In effect, this makes the implicit assumption that the decisions are made independently of each other with the choice of an alternative being a collection of the underlying decisions rather than a decision in and of itself. In this sense, the interaction between the decisions is assumed to be limited to both the influence each has on the attributes that are calculated jointly (Figure 2) and the use of the other decisions as covariates in each of the models. Furthermore, the value of the remaining (non-decision) attributes that are used as covariates in the models, are common between the decisions although different decisions contribute to each of the attributes to varying degrees. Because each of these models make an independent prediction of the choice in the relevant decision, this structure mimics that of models with only a single dependent variable. However, it should be noted that although the decisions are modelled independently, the resulting attributes can not be considered to be independent since they are a result of the combination of the decisions and as a result making a different choice for one decision will also change the attributes of all the other decisions.

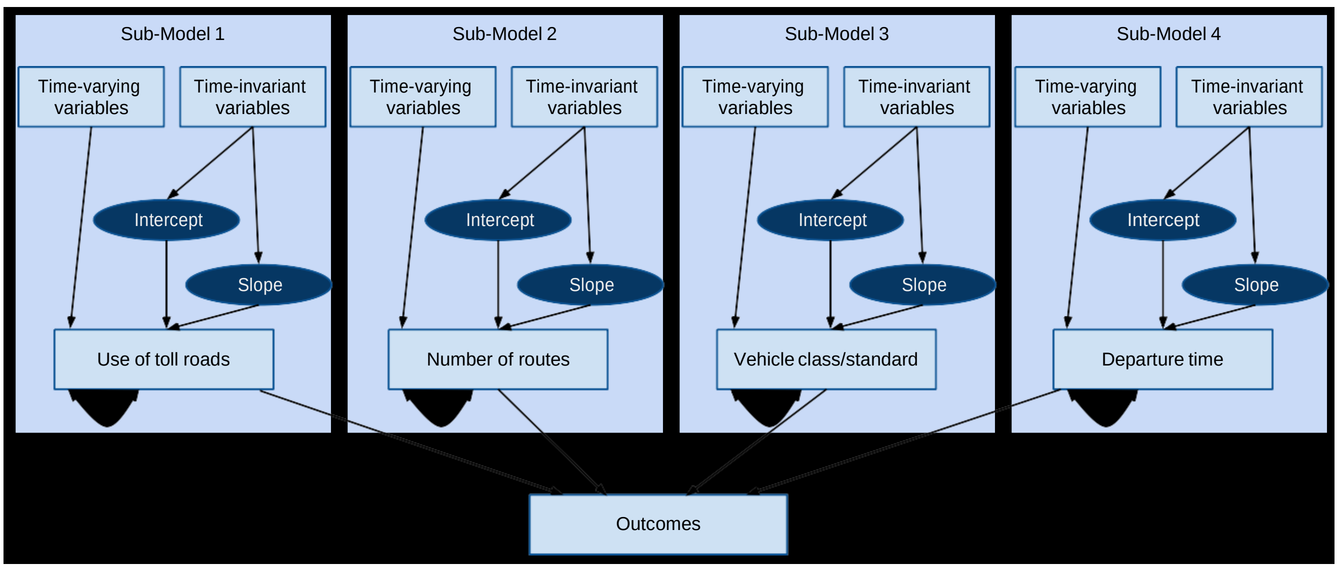

Figure 2: Independent models structure

Since response variables are recorded for four decisions, this structure uses four sub-models with a single, different, response variable in each. As shown in Figure 2, in the first sub-model the response variable is the use of toll roads, in the second it is the number of routes used to complete the delivery task in the scenario, the third is the choice in vehicle class and emissions standard and the fourth is the choice of departure time. The results of each of these sub-models (e.g., toll road use) must then be interpreted assuming that the other response variables (e.g., number of routes, vehicle class and standard and departure time) are unobserved. The following sections develop and analyse each of the decisions using these sub-models.

4.1. Use of toll roads

This first model looks at the decision regarding the use or avoidance of toll roads when choosing what routes to take. Tolls were calculated at a rate of $0.40/km for the portion of each route that used toll roads. Respondents were made aware that the toll cost was added to the operating costs as well as the proportion of the tolled distance as a separate attribute. Although several specifications can be used to measure the use of toll roads, the unit presented to respondents is thought to be the most appropriate. Given the survey design where respondents were presented with both the total distance and the tolled distance, either the tolled distance or the proportion of the total distance where a toll road was used for each alternative solution may be appropriate. Although this measure could be collapsed into a simple binary choice of using or not using toll roads, since respondents were provided with a range of alternatives for which the use of toll roads was predetermined and that in practice the specific use of toll roads may well be determined on a day-to-day basis, the magnitude of toll road use appears to be more relevant to the decision-making process.

In aggregate, the proportion of the total distance for which toll roads were used during the simulation were fairly stable across the different time periods although there is a notable increase in the range of responses in the first time period in which the policy is in effect (i.e., period 4). Figure 3 shows the use of toll roads by firms primarily involved with pallet deliveries compared to firms primarily involved with delivery of packagers and parcels for the two policies shown to respondents, namely, the congestion charge and the LEZ. As is described in section 3, policies were first presented to participants after the first time period and then implemented (with the attributes updated) after the third time period. The time of the announcement and implementation of the policies are indicated in the graph by the black vertical solid and dashed lines respectively. Each point on the graph represents individual observations (i.e., the alternatives chosen), the lines represent the mean use within that delivery type and policy combination, and the shaded areas indicate the standard deviation of each combination. The two colours represent the two different policies with the red being the congestion charge and blue the LEZ. However, although the mean is fairly stable over time it is not clear if one of the attributes, such as travel time or reliability, is driving a decision on the use of toll roads nor if there is a difference between the two types of deliveries (i.e., pallets/large deliveries and packages) in how and why they change their use of toll roads. The differences in the means and standard deviations of toll road use shown in Figure 3 suggests that there is a difference in how firms chose to repond to the policies depending on the type of deliveries made by the firm despite having similar levels of toll road use before the announcement of the policies. However, it is unclear what is driving these differences.

The development of latent curve models that incorporate time-invariant and time-varying predictors will enable these influences to be estimated and provide a measure of how important each of the attributes are to the choice of toll road use as well as how this changes over time. Several specifications of the time-invariant model were tested including models that estimated different values of Λ_β for the two different policies (allowing for different adaptation rates). The results of all of these models showed that the number of rigid vehicles, and newer rigid vehicles in particular, were a significant predictor of both a lower initial rate of toll road use but also small increases in toll-road use in the later time periods for firms presented with the LEZ. Of interest was that the type of delivery made by the firm was a significant predictor of changes in subsequent time periods only for firms shown the congestion charge suggesting that it is the design of the policies and how they affect the time-varying attributes (e.g., cost and travel time) of the different types of firms differently that drives some of the changes observed.

The individual parameter estimates for the time-varying models are almost all significant across all time periods although their estimates vary slightly when they are significant. There appears to be three distinct phases in the estimates corresponding to the time period in which no policy was in place (i.e., the *status quo*), the periods in which the policies had been announced but not yet implemented, and the periods after they had been implemented. In the first (base) time period, three time-varying predictors are significant, the operating costs, time savings from toll roads and the emissions index. In the second and third time periods (the two periods between the announcement and implementation of the policy), operating costs become insignificant but the forecasted total costs under the policy become significant. Similarly, emissions became insignificant but the log of travel time becomes significant. In part this can be explained by the high correlation between travel time and labour costs since labour costs may have become more important to respondents' choices due to the expected increase in future costs as shown by the forecast of total costs.

The full model including both time-invariant and time-varying predictors has broadly similar results to those of the time-invariant and time-varying models (see Table 1 on page 15). The results show that the number of rigid vehicles that meet or exceed the Euro III emissions standard[6] and the policy shown to

[6]The European emissions standards for light and heavy vehicles are used as the minimum standards for Australian vehicles. The Euro III standard was the minimum emissions standard required for newly registered heavy vehicles in Australia at the time the survey was conducted. The equivalent standard for light vehicles is Euro-3.

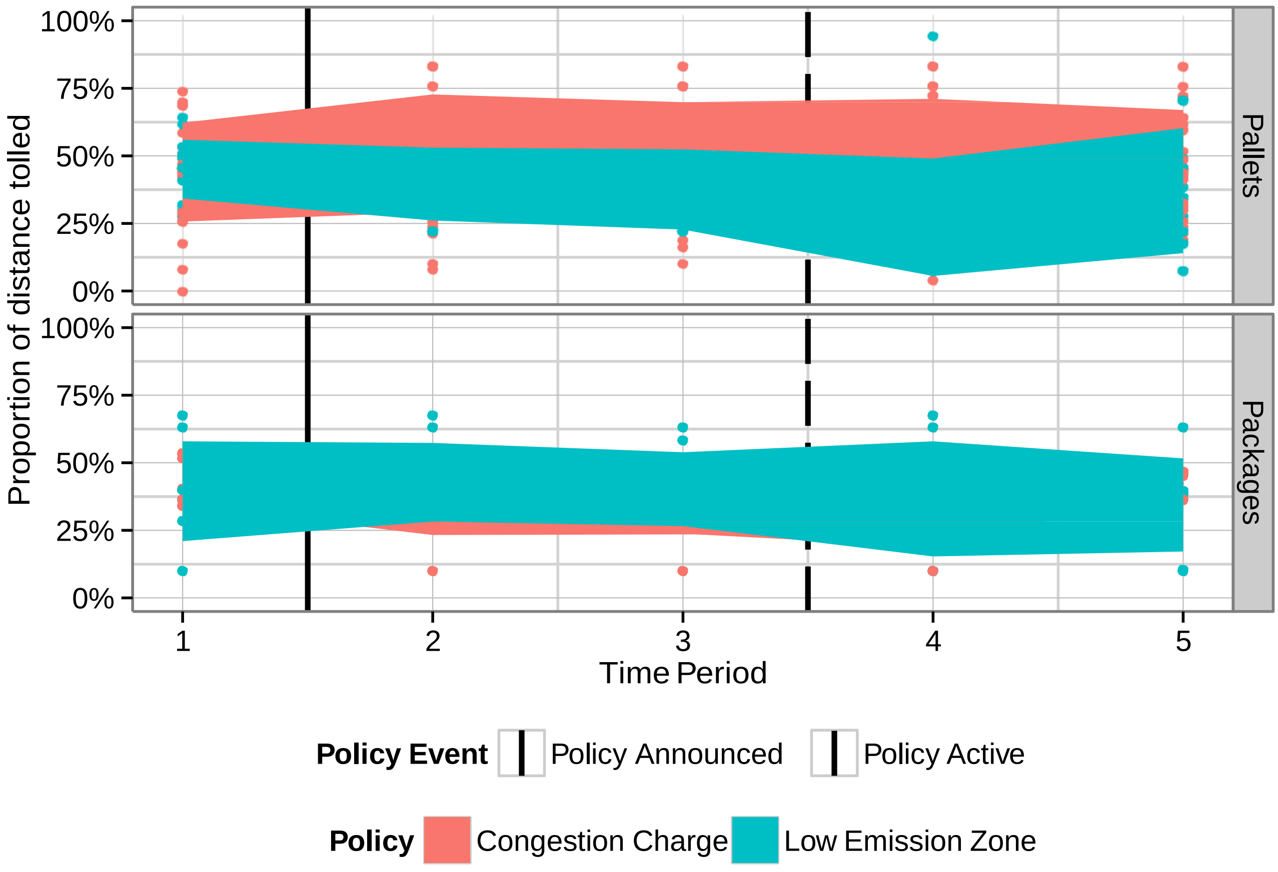

Figure 3: Mean and standard deviation of proportion of distance tolled by policy

respondents are the two significant time-invariant predictors once the time-varying predictors have been included in the model. The significant time-varying predictors are largely similar to those in the model with only time-varying predictors with the exception that operating costs does not appear to be a significant factor in the first time period. Of interest is that (as in the time-varying model), the forecast total costs for when the policy is introduced is a significant predictor of the decisions in the second and third time periods despite relatively small changes in the choice of the proportion of toll roads used.

Table 1: Parameter estimates of time-invariant and time-varying model of toll road use

Parameter	Estimate	Z-Value	Standardised Estimate	P-Value
Time scores (Λ_β)				
Λ_{β_1}	0.000		0.000	
Λ_{β_2}	6.063	4.608	0.297	0.000
Λ_{β_3}	9.124	7.629	0.468	0.000
Λ_{β_4}	4.709	2.714	0.194	0.007
Λ_{β_5}	4.000		0.181	
Intercepts				
μ_α	22.553	5.155	3.036	0.000
μ_β	4.105	2.013	4.380	0.044
Time-invariant predictors				
Intercept predictors				
Policy	0.000		0.000	
Euro III Rigid vehicles	-0.014	-1.967	-0.170	0.049
Slope predictors				
Policy	0.798	3.433	0.420	0.001
Euro III Rigid vehicles	0.004	2.712	0.362	0.007
Time-varying predictors				
Period 1				
Toll road time Savings	2.924	11.556	0.795	0.000
Emissions	-2.194	-3.226	-0.158	0.001
ln(Forecast Total Costs)	0.000		0.000	
Period 2				
Operating Costs	0.754	1.787	0.079	0.074
ln(Total Time)	-23.487	-5.984	-0.149	0.000
Toll road time Savings	3.171	14.578	0.864	0.000
ln(Forecast Total Costs)	-11.580	-2.949	-0.099	0.003
Period 3				
ln(Total Time)	-24.542	-8.821	-0.166	0.000
Toll road time Savings	3.317	3.924	0.900	0.000
ln(Forecast Total Costs)	-14.697	-2.535	-0.130	0.011
Period 4				
Operating Costs	-1.320	-3.031	-0.180	0.002
ln(Total Time)	-32.982	-5.392	-0.255	0.000
Toll road time Savings	3.415	3.954	0.844	0.000
ln(Forecast Total Costs)	0.000		0.000	
Period 5				
Operating Costs	-1.280	-3.011	-0.174	0.003
ln(Total Time)	-24.588	-6.324	-0.258	0.000
Toll road time Savings	3.152	3.956	0.826	0.000
ln(Forecast Total Costs)	0.000		0.000	

Continued on next page...

Table 1: Parameter estimates of time-invariant and time-varying model of toll road use

Parameter	Estimate	Z-Value	Standardised Estimate	P-Value
Variances				
$\psi_{\alpha\alpha}$	53.585	4.096	0.971	0.000
$\psi_{\beta\beta}$	0.597	3.137	0.680	0.002
$\psi_{\alpha\beta}$	-1.806	-1.863	-0.319	0.062
ψ_{y1}	31.176	11.316	0.118	0.000
ψ_{y2}	24.653	3.222	0.067	0.001
ψ_{y3}	0.000	0.508	0.000	0.611
ψ_{y4}	53.976	4.119	0.105	0.000
ψ_{y5}	36.285	4.508	0.084	0.000
Measures of Model Fit				
χ^2 p-value	0.294			
SRMR	0.056			
RMSEA	0.043			
CFI	0.965			
TLI	0.954			

4.2. Number of routes

In practice, decisions on the number of routes to use is largely constrained by shipment size (determined by shippers) and the related decisions of the classes of vehicles to use. This also applies to the context of the scenarios presented to respondents in that the delivery requirements constrain the ability of respondents to choose the number of routes. Furthermore, the routing and scheduling algorithm used for the generation of the alternatives ensures that there is a strong relationship between the vehicle classes in an alternative and the number of routes in the same alternative, mirroring what would be expected in practice. However, the algorithm is designed to ensure that some of the alternatives are sub-optimal in terms of the number of routes for the given set of vehicles, resulting in alternatives that (for instance) contain four routes when it would have been more efficient to use three. This means that respondents are able to make a decision on the number of routes that is not entirely constrained by the choice of vehicles and as a result it is possible to determine if there are other factors that, given some flexibility, carriers consider when determining the number of routes to use as they adapt to policies. Employing the same general procedure used for the models on toll road use, choice of the number of routes used were modelled.

The variable recording the number of routes selected in each alternative is an integer with the lower-bound constrained to always be at least two (the minimum number of routes used in any of the alternatives). Although the number of routes is truncated at the lower-end to two routes, the overall distribution for the number of routes in the alternatives approaches a normal distribution. Furthermore, the estimation of the latent intercept and slope factors in the model accounts for the range of values in the variances and disturbances (i.e., the factor-specific error terms). As such, when interpreting these models it is important to note that the models estimate the number of routes as chosen within the scenarios and that it is the relative influence of each of the predictors that is of interest. A basic descriptive analysis of the scenario data shows that the number of routes chosen remains relatively stable with an average of three routes for firms focusing on pallet deliveries and four for those delivering packages. Although some firms do change how many routes they use over time, the overall trend is fairly constant.

Three of the models tested for choice of number of routes are shown in Table 2. All three models have reasonably good measures of model fit with insignificant χ^2 p-values, high CFI and TLI values (close to 1), and RMSEA values of close to 0, but the model with both time-varying and time-invariant predictors has the best overall fit.

These results show the general stability in the number of routes is driven primarily by the fleet mix of the chosen alternatives but with small changes (in both directions) to the number of routes in small parts of

Table 2: Parameter estimates of conditional models of number of routes

	Time-Invariant		**Time-Varying**		**Both**	
	Est.	**Z-val.**	**Est.**	**Z-val.**	**Est.**	**Z-val.**
Time scores (Λ_β)						
Λ_{β_1}	0.000		0.000		0.000	
Λ_{β_2}	0.000		0.000		0.000	
Λ_{β_3}	0.000		0.000		0.000	
Λ_{β_4}	4.089	1.954	4.392	3.244	7.151	6.150
Λ_{β_5}	4.000		4.000		4.000	
Intercepts						
μ_α	3.678	4.058	3.290	3.998	3.460	4.003
μ_β	0.011	0.580	-0.533	-2.730	-0.235	-1.925
Time-invariant predictors						
Intercept predictors						
Delivery Type	0.375	4.598			0.284	3.985
Policy	0.000				0.000	
Slope predictors						
Policy	-0.015	-0.517			-0.000	-0.000
Time-varying predictors						
Period 1						
Proportion LCV			0.749	2.700	0.670	2.493
Period 2						
Proportion LCV			0.512	2.323	0.423	2.060
Period 3						
Proportion LCV			0.546	2.565	0.463	2.335
Period 4						
Number of routes (at t=3)			0.736	2.428	0.760	3.190
Operating Costs					-0.057	-2.985
Period 5						
Number of routes (at t=3)			0.671	2.960	0.321	2.200
Variances						
$\psi_{\alpha\alpha}$	0.312	4.972	0.402	5.074	0.322	4.989
$\psi_{\beta\beta}$	0.008	1.584	0.030	1.963	0.014	2.008
$\psi_{\alpha\beta}$	-0.021	-1.790	-0.096	-2.807	-0.054	-2.660
ψ_{y_1}	0.543	5.228	0.505	5.203	0.506	5.224
ψ_{y_2}	0.079	3.240	0.060	2.381	0.063	2.726
ψ_{y_3}	0.068	2.961	0.081	3.049	0.077	3.148
ψ_{y_4}	0.137	1.961	0.135	2.082	0.000	4.275
ψ_{y_5}	0.153	2.247	0.153	2.756	0.191	5.354
Measures of Model Fit						
χ^2 p-value	0.519		0.578		0.500	
SRMR	0.100		0.090		0.078	
RMSEA	0.000		0.000		0.000	
CFI	1.000		1.000		1.000	
TLI	1.005		1.012		1.004	

the sample. Further, despite changes to many of the attributes (including costs) after the introduction of the policy, respondents' previous choices heavily influence their choice after the policy was introduced. This is of interest because it suggests that in making a decision on the number of routes (i.e., tours) to use, respondents place more emphasis on their previous choices than in the changes to many of the attributes and those choices are driven primarily by their chosen fleet mix. Furthermore, although this suggests that respondents may have made decisions on the proportion of Light Commercial Vehicles (LCV) in the fleet based on the forecasts of costs and other attributes, the forecast attributes were not found to be significant predictors of the number of routes. However, it should be noted that the model on vehicle class and standards may reveal that the forecasted attributes do have an effect on their choice of fleet mix. This would mean that the effect of the forecasted attributes in decisions made during the second and third time periods have an indirect effect on their choice of number of routes. It should be noted that although autocorrelation between the number of routes in the initial three periods was also tested, these were not significant. This suggests that although the number of routes is relatively stable in the first three periods, a not insignificant proportion of the sample made some changes that were more closely related to a change in the choice of fleet mix than to previous decisions on the number of routes. In addition, these changes appear to have been made in anticipation of the policy being introduced and that this does not continue once it has been introduced. The development of the third sub-model, related to vehicle class and standards, provides further insight into how the fleet mix changes over time.

4.3. Vehicle class and emissions standard

This model is intended to explore what influences the choice of vehicle class and standard over time, particularly in response to the policies of which one (the LEZ) is designed to reduce the number and use of vehicles not meeting the European emissions standard for heavy vehicles of Euro III. Although it is possible (and even desirable) to model both the choice of vehicle class and choice of emissions standard in a single model, in this paper these are modelled separately to ease interpretation.[7] Given the likelihood of some interdependence between these decisions, the separate models mean the estimates of one decision need to be interpreted as the changes over time given constant levels for the other decision.

4.3.1. Vehicle emissions standard

In the scenarios used for this study, each vehicle used in the alternative is either compliant or not compliant with the Euro III standard for emissions of heavy vehicles (or Euro-3 for the equivalent standard for LCVs). It should be noted that although the choice of emissions standard for this scenario is a binary choice for each vehicle, the fleet as a whole may include varying mixes of vehicles meeting each emissions standard. The dependent variable in this model can be defined as either the absolute number of vehicles of each type or a proportion of the vehicles chosen with an emissions standard before Euro-3 (for LCVs) and Euro-III (other classes). Using the proportion means that the emissions standard can be compared more easily across alternatives with different numbers of vehicles of each class. This facilitates the comparison both between firms and over time and for this reason is the preferred choice as the measure of the dependent variable. However, this does mean that the estimation procedure should use a robust estimator.

Similar to the previous models, several different specifications of the model were tested using both time-invariant and time-varying predictors. The full time-invariant model (Table 3 on the next page) shows that the only significant time-invariant predictor appears to be the policy shown to respondents with the LEZ reducing the proportion of pre Euro III vehicles by an average of approximately 3.5 percentage points per six-month period. The estimate of μ_β being insignificant suggests that the congestion charge had no effect on the emissions standard of vehicles chosen by respondents.

The results of the time-varying models suggest that the primary predictors of the choice of emissions standard are the labour costs and time savings from the congestion charge as well as emissions. These results are surprising because neither labour costs nor time savings (from any source) should have been affected by the introduction of the LEZ. Furthermore, although these attributes would have been affected by the congestion charge, the time-invariant models indicate that the congestion charge had no effect on the choice of emissions

[7]The simultaneously estimated model will be presented in a future paper.

Table 3: Parameter estimates of full time-invariant model of emissions standards

	Full model		Reduced model	
	Est.	**Z-val.**	**Est.**	**Z-val.**
Time scores (Λ_β)				
Λ_{β_1}	0.000		0.000	
Λ_{β_2}	-0.102	-4.154	0.000	
Λ_{β_3}	-0.497	-4.513	0.000	
Λ_{β_4}	2.026	5.053	2.537	2.312
Λ_{β_5}	4.000		4.000	
Intercepts				
μ_α	0.391	5.119	0.510	3.936
μ_β	-0.006	-0.283	-0.003	-0.313
Time-invariant predictors				
Intercept predictors				
Policy	0.000		0.000	
Delivery Type	-0.047	-1.450		
Number of Euro III+ Rigid vehicles	-0.001	-0.870		
NSW dummy	-0.060	-1.098		
Self Administered dummy	0.048	0.841		
Number of Drivers	0.000	1.131		
Industry Experience (yrs)	0.004	1.745		
Slope predictors				
Policy	-0.034	-2.542	-0.030	-2.000
Delivery Type	0.010	1.243		
Number of Euro III+ Rigid vehicles	0.000	0.133		
NSW dummy	0.001	0.056		
Self Administered dummy	-0.008	-0.556		
Number of Drivers	0.000	0.068		
Industry Experience (yrs)	0.001	1.034		
Variances				
$\psi_{\alpha\alpha}$	0.036	4.665	0.042	4.641
$\psi_{\beta\beta}$	0.002	3.238	0.002	2.018
$\psi_{\alpha\beta}$	-0.002	-1.384	-0.003	-1.400
ψ_{y_1}	0.029	4.642	0.029	4.449
ψ_{y_2}	0.021	4.248	0.021	4.086
ψ_{y_3}	0.014	3.060	0.016	3.514
ψ_{y_4}	0.031	4.785	0.028	3.382
ψ_{y_5}	0.000	0.000	0.008	0.465
Measures of Model Fit				
χ^2 p-value	0.090		0.160	
SRMR	0.078		0.119	
RMSEA	0.077		0.078	
CFI	0.937		0.970	
TLI	0.903		0.965	

standard. One possible explanation is that the switch to newer vehicles was made in conjunction with one of the other decisions that together resulted in efficiency gains and a reduction in travel time. However, these results should be treated with caution since the goodness of fit of both time-varying models is substantially worse than for the time-invariant models with both time-varying models having a significant χ^2 p-value and very low CFI and TLI values.

Taken together, the results of these models suggest that the LEZ did have a reasonably large effect on the choice of emissions standards for the vehicles compared to the congestion charge but that this switch occurred primarily after the LEZ came into effect after the third time period. Furthermore, they suggest that firms that did switch to newer vehicles also made other decisions that resulted in reduced travel times.

4.3.2. Vehicle class

The vehicle class model is somewhat more complex than the emissions standards model since rather than having only two possible options, there is a choice of three different vehicle classes, LCVs, rigid vehicles, and articulated vehicles. As such, the dependent variable can be defined as a set of three variables with each variable being either the number of vehicles of that class or, alternatively, their proportion in the vehicle fleet. Alternatively, they can be defined as a set of binary variables indicating if the vehicle class was used in the selected alternative, or as a single categorical variable with potential values for each of the eight possible combinations of binary indicators. Since using the number of vehicles of each class in the fleet, or more specifically, the number of routes using vehicles of each class, is consistent with the dependent variable in the number of routes model and allows for analysis of the switching between vehicle classes, the number of vehicles in each class as a set of three variables will be used as the dependent variables for vehicle class in this model.

The results of the time-invariant model showed that the type of deliveries made by the firm had a significant effect on number of LCVs chosen although, interestingly, not on the choice of rigid vehicles. Furthermore, it showed that there will little difference in the effects of the two policies on the choice of vehicle class suggesting that the majority of switching was for newer vehicles of the same class. The time-varying model (see Table 4 on the following page) provides further insight into what drives the changes to vehicle class. The model shows that time savings from toll roads are a significant predictor of the number of LCVs and rigid vehicles but operating costs emerge as the primary predictor of both LCVs and rigid vehicles with the exception of the final time period for LCVs in which the significant time-varying predictor is labour costs rather than operating costs. It should be noted that the dependent variables in this model are ordinal variables where the highest values are grouped into a single ordinal value. The thresholds and scale estimates describe how the ordinal variables are mapped to a continuous variable used within the model estimation (y^*).

This model has several important results. First, the effects of operating costs on $y*$ is positive for LCVs but negative for rigid vehicles. Furthermore, for the only time period in which labour costs were found to be a significant predictor of the number of LCVs, the estimate was also negative. This suggests that operating costs, that includes not only the fuel, maintenance and capital costs of the vehicles but also toll charges and additional charges (if any) for the policies, heavily influences the choice of vehicle classes. Specifically, it is an indication that firms that are particularly concerned about operating costs are more likely to use LCVs than those focused on other service attributes. In contrast, firms for which higher costs may not be considered an impediment to making a specific choice of vehicle class in the presence of other desirable attributes appear more likely to choose more rigid vehicles. This may be related to the likelihood of higher costs being able to be passed onto customers as well as other differences between firms focused on larger deliveries and those focused on package deliveries. It must be emphasised that the scenarios and alternatives developed for the survey were designed such that no vehicle class was always the cheaper (or more expensive) choice with the cheapest vehicle class being determined by a combination of the other decisions and the specific routes used for each alternative.

The second result of interest is that the estimates of operating costs on the choice of vehicle class remains reasonably consistent for the first three periods before becoming insignificant for LCVs but increases gradually (approaching zero) over time, including as the policies come into effect, for rigid vehicles. Despite the (potential) increase in costs from the policies only applying to the fourth and fifth time periods, the difference in the estimates between the third and fourth time periods are no larger than for between the first and second, and second and third time periods. This suggests that there is a gradual adaptation process

Table 4: Reduced time-varying vehicle class factor scores, thresholds and scales

	LCV		Rigid	
	Est.	**Z-val.**	**Est.**	**Z-val.**
Time Scores				
Λ_{β_1}	0.000		0.000	
Λ_{β_2}	2.707	1.235	1.836	1.099
Λ_{β_3}	1.300	1.097	2.655	2.411
Λ_{β_4}	0.712	0.583	3.995	3.019
Λ_{β_5}	4.000		4.000	
Intercepts				
μ_α	-0.620	-0.565	-1.579	-0.827
μ_β	-0.470	-1.139	1.082	0.350
Time-varying predictors				
Period 1				
Operating Costs ($,000s)	0.413	2.933	-0.353	-2.657
Time savings from tolls	-0.122	-2.951	0.135	2.693
Period 2				
Operating Costs ($,000s)	0.355	1.677	-0.294	-2.373
Period 3				
Operating Costs ($,000s)	0.400	1.913	-0.221	-1.974
Period 4				
Operating Costs ($,000s)			-0.160	-2.008
Period 5				
Labour Costs ($,000s)	-0.704	-3.749		
Operating Costs ($,000s)			-0.151	-1.788
Covariances				
Intercepts on Intercepts				
LCV			-0.157	-2.905
Rigid	-0.157	-2.905		
Intercepts on Slopes				
LCV	0.106	2.897		
Rigid			-0.067	-1.059
Slopes on Slopes				
LCV			-0.008	-0.940
Rigid	-0.008	-0.940		
Thresholds				
Threshold 1	-0.821	-1.551	-0.589	-0.955
Threshold 2	0.383	1.043	-0.041	-0.064
Threshold 3	1.647	3.414	0.835	1.250
Scales				
Period 1	1.000		1.000	
Period 2	0.990	2.218	1.480	12.790
Period 3	1.537	3.041	1.809	
Period 4	1.638	2.913	1.654	6.585
Period 5	0.673	28.350	1.210	7.064
Measures of Model Fit				
χ^2 p-value	0.089			
RMSEA	0.058			
CFI	0.988			
TLI	0.985			

taking place in terms of the choice of rigid vehicles but that this adaptation process takes the costs in the current time period as a reference rather than the (provided) forecast costs.

4.4. Departure time

The departure time model is intended to determine if the use of the congestion charge or low emission zone has an effect on when firms choose to make deliveries as well as how this decision is influenced by the costs and other attributes of the alternatives. The primary interest is in how (and if) peak-hour deliveries shift to off-peak times and how this changes over time. In the context of this study, the respondents were limited in when they could make deliveries by the time windows imposed by the scenario. These time windows are briefly summarised here.

For the scenario shown to respondents whose primary business is the delivery of pallets and other large deliveries, there were three customers of which two were located in the central business district (the area in which the two policies apply). The time windows for these two customers was 08:30 to 18:00 and 07:30 to 13:00 respectively. The remaining customer had two time windows in which deliveries had to be made, one from 8:00 to 9:30 and the other from 14:00 to 15:30. In the scenario shown to respondents whose primary business is package and courier deliveries, there were a group of nine customers located in the CBD for which the time window was 08:30 to 18:00 with the remaining customers having time windows of either 8:00 to 16:00 or 7:30 to 16:00. The LEZ was applied at all times while the congestion charge was in effect from 07:00 to 18:00 but applied based on the time the vehicle enters the congestion charge zone. This means the LEZ could not be avoided simply by changing trip times but there is some flexibility in how firms can respond to the congestion charge by changing delivery times.

Given the time windows for the customers in the CBD, firms had to make at least one trip into the CBD within the time when the congestion charge was in effect but could avoid the congestion charge if the vehicle arrived in the zone before 07:00. Furthermore, since the scenarios assumed a reduction in congestion because of the policy, travel times were reduced compared to the pre-policy time periods and this could reduce both labour and operating costs (excluding the congestion charge itself) as well as improve reliability if respondents made decisions that maximised the benefit of reduced travel time. However, it should be noted that since the earliest time window starts at 07:30, respondents choosing to avoid the congestion charge by entering the zone before 07:00 would need to wait until the first delivery can be made (an option allowed for in the generation of alternatives). As such, respondents were able to avoid paying the congestion charge by switching vehicles to leave the depot before 7:00 or they could minimise its effect on their costs by limiting the number of different vehicles used in the congestion charge zone and by selecting an alternative that maximised the benefit of reduced congestion within the zone.

The model of departure time (Table 5) has a reasonable goodness of fit with an insignificant χ^2 p-value, reasonably high CFI and TLI values as well as an RMSEA value within the acceptable range.[8] The estimates of Λ_β show that there are three distinct trajectories in how the changes to each time of day are made. The largest initial effect is on morning peak departures with night time departures being somewhat similar. In contrast, the changes to the interpeak departures appear to be small until the final time period. Although the estimates of μ_β seem to suggest that the general trajectory is of an increase in departures during the morning peak and a decrease in departures during the interpeak period, care must be taken when interpreting the results. The small values for Λ_β for the interpeak period in the first to fourth time periods of the interpeak period coupled with the significance of the decisions made during the fourth time period on the decisions of the morning peak and interpeak departures means that the predictor of interest is the effect of total costs on the morning and interpeak departures during the fourth time period (immediately after the introduction of the policy). The estimate of this predictor shows that for firms with higher costs, the number of morning-peak departures decreases and of interpeak departures increases. Nonetheless, the differences in the estimates of Λ_β suggest that respondents made gradual changes to the departure times focusing first on departures potentially most affected by the policies before making further changes to the remaining time periods.

The results show that significant predictors include travel time remaining a key predictor of night time departures, costs for the morning peak, and the number of rigid vehicles in the afternoon peak. Respondents'

[8] SRMR values are not produced for this model form.

Table 5: Reduced time of day model factor scores, thresholds and scales

	Night		A.M. Peak		Interpeak	
	Est.	Z-val.	Est.	Z-val.	Est.	Z-val.
Time Scores						
Λ_{β_1}	0.000		0.000		0.000	
Λ_{β_2}	1.076	1.197	2.710	12.965	0.011	1.071
Λ_{β_3}	0.514	1.518	1.043	4.392	0.058	2.772
Λ_{β_4}	2.876	2.910	4.004	4.495	-0.115	-2.287
Λ_{β_5}	4.000		4.000		4.000	
Intercepts						
μ_α	-6.395	-7.423	-0.829	-0.766	3.384	4.643
μ_β	3.677	3.627	33.542	4.400	-25.625	-4.660
Time-invariant predictors						
Intercept predictors						
Policy	0.000		0.000		0.000	
Delivery Type					-0.974	-2.649
Slope predictors						
μ_α (A.M. Peak)	0.153	4.314				
μ_α (P.M. Peak)	-0.599	-4.440	-0.515	-2.042		
μ_α (Night)			4.777	7.577		
Time-varying predictors						
Period 1						
ln(Total Time)	5.395	44.758				
Total Costs			0.017	0.270		
Rigid vehicles as proportion					1.104	1.443
Period 2						
7:00-9:00 Departures ($t=1$)			-0.321	-3.769		
9:00-16:00 Departures ($t=1$)					-0.195	-0.732
Period 3						
ln(Total Time)	3.859	4.019				
7:00-9:00 Departures ($t=1$)			-0.737	-4.457		
9:00-16:00 Departures ($t=1$)					0.044	0.175
Period 4						
ln(Total Time)	-11.498	-4.120			20.914	4.299
Total Costs			-0.649	-2.184	0.669	2.488
9:00-16:00 Departures ($t=3$)					1.516	2.348
Period 5						
ln(Total Time)	1295.702	6.964			-590.463	-6.320
Night Departures ($t=4$)	118.251	5.311				
7:00-9:00 Departures ($t=4$)			0.723	2.443		
Toll time savings					-14.555	-4.289
9:00-16:00 Departures ($t=4$)					39.085	4.546
Thresholds						
Threshold 1	-1.560	-1.948	-1.050	-1.407	-3.946	-8.170
Threshold 2			0.510	0.770	-1.995	-8.049
Threshold 3					-0.695	-1.984
Scales						
Period 1	1.000		1.000		1.000	
Period 2	0.657	3.125	0.488	6.194	1.251	3.042
Period 3	1.547	5.637	1.570	12.445	1.081	3.197
Period 4	0.478	4.029	0.377	4.761	0.305	5.015
Period 5	0.003	4.189	0.200	4.709	0.006	4.281
Measures of Model Fit						
χ^2 p-value	0.101					
RMSEA	0.046					
CFI	0.964					
TLI	0.953					

decisions on the number of morning peak departures from the warehouse during the initial period are significant predictors of the number of departures during the second and third periods. Of interest is that total costs is a significant predictor for the number of departures in the morning peak and interpeak periods during the fourth time period and that their estimates have opposite signs. This is an indication that higher costs as a result of the policy results in a switch from departures during the morning peak to the interpeak period. Since both the congestion charge and the LEZ applied equally to both these time periods, this suggests that the additional costs imposed by both policies appear to have resulted in respondents making decisions that reduced their costs elsewhere (for instance by switching vehicle class) and this in turn resulted in a switch to primarily off-peak departures. The absence of the policy being a significant predictor of the latent slope factor (Λ_β) suggests that the additional costs imposed by the policies had similar effects on the choice of time of day despite the differences in the charges and exemptions associated with the two policies. One final result of interest is the significance of the (logged) time taken to complete the delivery task in the number of night time and interpeak departures from the warehouse. Since the primary benefit of early morning departures from the warehouse is (under the scenarios presented) substantially reduced travel times and improved reliability before the start of the morning peak period at 7:00, it is reasonable to expect that this would be a primary driver of the choice to make more early morning trips. This benefit also applies (albeit to a lesser degree) to routes scheduled for the interpeak period. Furthermore, since early morning departures would by necessity involve some travel within the morning peak, reducing the amount of time taken would limit the effects of the additional congestion and lower reliability on the firm's deliveries.

5. Implications and conclusions

This paper has described an analysis of the adaptation process adopted by freight carriers in response to government policies. This paper has used latent curve models to investigate how several decisions made by freight carriers in the course of their operations are affected by two different policies and how various firm charactersitics influence their adaptation strategies. The models show that, overall, emissions themselves have little effect on how firms choose to operate even in response to government policies aimed at reducing emissions. Instead, it is the influence of the policies on the other attributes such as time, costs and reliability that most substantially affects firms' decisions. The constraints on firms business as a result of the firms' characteristics and the type of deliveries they make are also significant predictors of how firms will adapt policies over and above the constraints imposed by shippers and receiers. Crucially, the results show that firms adapt to changes gradually with some changes being made early in anticipation of the introduction of the policy and others being left as late as possible. Furthermore, the results show that the drivers of the incremental changes are not constant throughout the adaptation process providing evidence that it is important to consider the intermediate effects when considering policies targeting freight carriers. In addition, the results indicate that although carriers are largely constrained by the requirements of shippers and receivers, carriers do have the ability to make gradual changes to their operations. Arguably, these small incremental effects can have quite a large (positive) effect on carriers as a whole when replicated by other parts of the industry.

More broadly for policy design generally, arguably the most important implication of the results presented in this paper is that despite the undoubted importance of costs to the decisions made by firms, not all decisions are made primarily on the basis of costs, a finding that mirrors those of other road freight studies (Mesa-Arango and Ukkusuri, 2014). Furthermore, given the constraints on how carriers operate imposed by shippers and receivers, and the ability for firms to pass costs to some degree onto their customers, cost is not always a sufficient mechanism through which firms can be encouraged to change their operations. This is crucial for the design of policies based primarily on the introduction of a charge (including both a Congestion Charge and a Low Emission Zone) because it means that there is a limit to how much firms can change their operations and how quickly they can do so regardless of the additional costs imposed. For this reason, although imposing an extremely high cost on a specific action is likely to reduce the prevalence of that action, it will not eradicate it entirely and will at the same time likely increase prices to customers (both businesses and individuals). At the same time, the results make clear that an increase in costs imposed on one action (such as choosing a vehicle with a certain emissions standard) is very likely to also have an effect on the firms' other decisions, potentially to the detriment of overall efficiency and possibly negating any benefits of the targeted decision. This means that incorporating specific benefits (as opposed to costs) for related decisions into mitigation policies are likely to increase the compliance rate and effectiveness of policies. Studies that have applied prospect theory to freight transport support the principle that including clearly defined benefits to complying with a policy, in addition to imposing fines or charges for not complying, may improve compliance rates (Li and Hensher, 2011; Masiero and Hensher, 2010). This area is worth further study to assess if providing specific benefits can be as (or more) effective than using additional costs to influence behaviour. The results presented here would suggest that they would have some effect since non-cost attributes form an important part of the decision making process as modelled here.

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Appendix A: Dataset

Table 6: Dataset description and summary statistics

Variable	Time varying	Data type	Min.	Max.	Median	Mean	Std. Dev.
Delivery Type	No	Binary					
Policy	No	Binary					
Industry Experience (yrs)	No	Continuous	0.5	55	20	20.9	12.49
Years at company	No	Continuous	0.5	51	9	14.2	12.51
Number of drivers	No	Integer	1	2000	12	101	317.79
Number of pre Euro 3 LCVs	No	Integer	0	180	0	9.19	27.7
Number of Euro 3+ LCVs	No	Integer	0	220	1	13.1	35.84
Number of pre Euro III Rigids	No	Integer	0	660	1	23.6	100.9
Number of Euro III+ Rigids	No	Integer	0	660	1	23.6	100.9
Number of pre Euro III Articulateds	No	Integer	0	90	0	5.98	15.75
Number of Euro III+ Articulateds	No	Integer	0	160	1	11.5	25.32
Number of pre Euro 3 LCVs for urban use	No	Integer	0	180	0	9.19	27.7
Number of Euro 3+ LCVs for urban use	No	Integer	0	220	1	13.1	35.84
Number of pre Euro III Rigids for urban use	No	Integer	0	660	1	23.6	100.9
Number of Euro III+ Rigids for urban use	No	Integer	0	642	2	27.2	98.19
Number of pre Euro III Articulateds for urban use	No	Integer	0	90	0	5.98	15.75
Number of Euro III+ Articulateds for urban use	No	Integer	0	160	1	11.5	25.32
Importance rank of return trips	No	Integer	1	999	5	417	495.15
Importance rank of vehicle class	No	Integer	1	999	999	623	487.14
Importance rank of time of day	No	Integer	1	999	9	473	501.76
Importance rank of distance	No	Integer	1	999	999	548	500.23
Importance rank of total time	No	Integer	1	999	8	473	501.6
Importance rank of time savings from toll roads	No	Integer	2	999	999	736	442.4
Importance rank of time savings from congestion charge	No	Integer	1	999	999	642	481.58
Importance rank of operating costs	No	Integer	1	999	4	322	469.35
Importance rank of total costs	No	Integer	1	999	1	152	360.44
Importance rank of early arrival	No	Integer	1	999	999	755	431.57
Importance rank of late arrival	No	Integer	1	999	999	661	475.7
Would pass costs on	No	Categorical					

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Table 6: Dataset description and summary statistics

Variable	Time varying	Data type	Min.	Max.	Median	Mean	Std. Dev.
State (location)	No	Categorical					
Number of routes	Yes	Integer	2	7	3	3.51	0.75
Unique vehicles	Yes	Categorical					
Unique times of day	Yes	Categorical					
Total distance	Yes	Continuous	29.5	111	54.2	60.5	16.14
Toll distance	Yes	Continuous	0	62	26	25.5	11.77
Total Time	Yes	Continuous	58	155	101	102	16.34
Time savings from toll roads	Yes	Continuous	0	22	11	10.4	5.22
Time savings from congestion charge	Yes	Continuous	-22	7	-11	-7.18	8.24
Operating costs	Yes	Continuous	5120	21500	9830	10600	3236
Labour costs	Yes	Continuous	3080	9390	6030	6170	1071
Total costs	Yes	Continuous	9970	26900	16100	16800	3289
Total GHG emissions	Yes	Continuous	2	6	3	2.93	0.83
Total air pollutants	Yes	Continuous	5	49	22	23.8	9.35
Probability of early arrival	Yes	Continuous	2	12	6	5.57	2.38
Probability of late arrival	Yes	Continuous	2	9	4	4.25	1.67
Number of LCVs	Yes	Integer	0	7	1	1.43	0.98
Number of Rigids	Yes	Integer	0	4	2	1.95	1.02
Number of Articulateds	Yes	Integer	0	3	0	0.135	0.46
Number of pre Euro III vehicles	Yes	Integer	0	4	2	1.69	0.91
Number of Euro III+ vehicles	Yes	Integer	0	6	2	1.83	1.06
Number of pre Euro 3 LCVs	Yes	Integer	0	4	0	0.626	0.82
Number of Euro 3+ LCVs	Yes	Integer	0	3	1	0.8	0.84
Number of pre Euro III Rigids	Yes	Integer	0	3	1	0.971	0.83
Number of Euro III+ Rigids	Yes	Integer	0	3	1	0.981	0.78
Number of pre Euro III Articulateds	Yes	Integer	0	3	0	0.0903	0.39
Number of Euro III+ Articulateds	Yes	Integer	0	1	0	0.0452	0.21
Number of vehicle classes	Yes	Integer	1	4	3	2.55	0.6
Number of times of day	Yes	Integer	1	4	2	2.31	0.83
Number of peak periods used	Yes	Integer	0	2	1	0.968	0.62
Offpeak periods used	Yes	Integer	0	1	0	0.426	0.5
Proportion of distance tolled	Yes	Continuous	0	0.969	0.426	0.427	0.19
Proportion pre Euro III	Yes	Continuous	0	1	0.5	0.488	0.26
Proportion pre Euro 3 LCVs	Yes	Continuous	0	1	0.333	0.434	0.44
Proportion pre Euro III Rigids	Yes	Continuous	0	1	0.5	0.49	0.34
Proportion pre Euro III Articulateds	Yes	Continuous	0	1	1	0.597	0.47
Departures before 7:00	Yes	Integer	0	2	0	0.31	0.49
Departures 7:00 to 9:00	Yes	Integer	0	4	1	1.09	0.88

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Table 6: Dataset description and summary statistics

Variable	Time varying	Data type	Min.	Max.	Median	Mean	Std. Dev.
Departures 9:00-16:00	Yes	Integer	0	5	2	1.65	0.98
Departures 16:00 to 18:00	Yes	Integer	0	3	0	0.232	0.47
Departures after 18:00	Yes	Integer	0	2	0	0.226	0.43
Mean total costs of alternatives	Yes	Continuous	12400	24000	18000	18100	2953
Mean operating costs of alternatives	Yes	Continuous	6890	17400	11700	11600	2704
Mean labour costs of alternatives	Yes	Continuous	4600	8560	6290	6450	865.4
Mean GHG Emissions of alternatives	Yes	Continuous	2.17	5	3.17	3.19	0.64
Mean air pollutants of alternatives	Yes	Continuous	13.7	36.3	22.5	23	4.07
Mean probability of early arrival	Yes	Continuous	3.17	11.5	6.75	6.51	2
Mean probability of late arrival	Yes	Continuous	2.5	8.67	5	4.95	1.43
Mean total distance	Yes	Continuous	44.8	99.3	61.2	66.5	14.05
Mean distance tolled	Yes	Continuous	8.5	54.3	27.1	28.3	7.24
Mean proportion of distance tolled	Yes	Continuous	0.215	0.693	0.429	0.442	0.09
Mean total time	Yes	Continuous	80.7	137	105	107	12.52
Mean toll time savings	Yes	Continuous	3.83	17	10.7	10.7	2.41
Mean number of routes	Yes	Continuous	2.83	5	3.5	3.61	0.41
Driver categories	Yes	Categorical					
Difference from industry benchmark cost	Yes	Continuous	-43.7	82.1	16.5	18	21.05
Index of emissions (both GHG and air pollutants)	Yes	Continuous	2.34	8.38	4.84	4.55	1.2
Difference from industry benchmark emissions	Yes	Continuous	-48.4	158	34.2	32	38.77
Forecast operating costs	Yes	Continuous	7320	22100	13100	14000	3090
Forecast labour costs	Yes	Continuous	3080	9390	6030	6170	1071
Forecast total costs	Yes	Continuous	12200	29200	18800	20200	3288
Forecast GHG emissions	Yes	Continuous	2	6	3	2.93	0.83
Forecast air pollution	Yes	Continuous	5	49	22	23.8	9.35
Forecast both emissions	Yes	Continuous	2.34	8.38	4.84	4.55	1.2

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