Sources of Errors and Biases in Traffic Forecasts for Toll Road Concessions

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Sources of Errors and Biases in Traffic Forecasts for Toll Road Concessions

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Mention Economie des Transports

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"I have been impressed with the urgency of doing.
Knowing is not enough; we must apply.
Being willing is not enough; we must do."
Leonardo da Vinci

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Summary

The objective of this thesis is to study the sources of discrepancy between the actual traffic in motorways under concession schemes and the traffic forecast ex-ante.

The demand forecast for a specific project is the main variable influencing its realization. From a public sector perspective, socio-economic evaluations are driven by demand forecasts, which gives the basis for choose and hierarchy public projects in order to maximise social welfare. From a private sector perspective, traffic forecasts are the base of financial evaluation and toll setting.

Despite its importance and the numerous and important developments in the field, the differences of forecast and ex-post traffic are usually very high. Some recent studies show that differences as big as 20% are much more the rule than the exception.

A huge amount of uncertainty is associated with the forecasting exercise. First because transport is a derived demand and depends on many exogenous variables, also uncertain; because modelling is and simplification exercise, implies many assumptions and rely on field data, many times incomplete or of low quality; moreover, modelling human (in this case users) behaviour is always a dangerous enterprise.

Although these arguments could explain at least the larger part of errors associated with forecasts, one can wonder whether the agents implicated in the forecast would or could use this uncertainty strategically in their favor. In a competition for the field scheme (bids), the bidder may overestimate the demand in order to reduce the toll included in the bid. This strategic behaviour can introduce a high bias in forecasts. Also, overoptimistic (or overpessimistic) forecasters may introduce a bias in the forecast.

We propose to focus in turn on the three main groups of agents involved in the demand forecast process. The forecasters, the project promoters and the users. Study all the issues related to them would be a too ambitious (or more concretely impossible) task. We then focus on some particular issues related to the modelling of the actors' behaviour in the context of the demand forecast for toll roads.

First, the forecaster behaviour. The forecaster can have some individual influence on the study, either by his own opinion about the project, by the external pressure he receives, or by his opinion about his own judgment capacity. Despite of the highly quantitative aspect of demand forecasting, the individual opinion about the chances of success (or failure) of a project can influence the modeling exercise in a way the results best fit the forecaster's expectation. Furthermore, if the forecaster overestimate his own capacity of decide whether a project is good or not, his individual evaluation will be biased.

Second, in particular when there is competition for the market, the project promoter behaviour has fundamental importance. Private promoters may have incentives to adjust the level of traffic in order to make the project more attractive or to have the best bid. This situation is exacerbated in regulatory frameworks in which renegotiations are easier. The opportunistic strategy consists in bidding a low price by increasing the forecast traffic level.

Then, we study the user's behaviour at two levels. First, at the aggregated level, we analyze the long term traffic growth and its relationship with the economic growth.

Second, at the disaggregated level, we study the value of travel time savings, the main variable guiding individual mode choice and probably the most important value in socio-economic evaluation as well as in demand and revenue forecast.

The thesis is organised as follows. Chapter 1 presents a general introduction to the topic of errors and biases in forecasting demand for transport infrastructures and services.

Chapter 2 focus on transport forecasters' behaviour. It presents the results of the first large sample survey on forecasters' perceptions and opinions about forecasting demand for transport projects, based on an on-line survey. We first describe the main characteristics of forecasters, as age, gender, education, working sectors and experience. We then describe the last forecast forecasters prepared in terms of oldness, project's advancement, mode, financing and operation. We then turn to the models forecasters apply, the errors they declare on past forecasts and the main sources of errors according to them. We then describe the forecast environment in terms of pressure forecasters receive. These unique results provide a picture of the world of forecasters and forecasts, allowing for a better understanding of them.

We turn then to the study of the optimism and overconfidence in transport forecasts. Optimism and overconfidence in general are recognized human traits; most of us are overconfident about our own abilities and overoptimists about the future. There is also a growing literature in behavioural economics and finance arguing that the role of optimism in economic decisions and economic forecasts is not negligible.

We analyze the overoptimistic bias by comparing the distribution of stated errors with actual errors found in literature; we also compare the own skillful of subjects in doing forecasts with studies showing self-evaluations of a common skill - driving. We finally propose a regression of the competence, quality and errors on the main forecasters' and projects' specific variables.

Results show that the distribution of errors transport forecasters state has a smaller average magnitude and a smaller variance than those found in literature. Comparing forecasters perception of their own competence with the results found in literature about drivers skill self-evaluation, however, we could not find a significant difference, meaning that the forecasters' overconfidence is in line with what could be viewed as a normal human overconfidence level.

The regression analysis finds that elder, more experienced forecasters working in the university tend to more valuate their competence. Also, the experience seems to be the only significant variable driving the self-appreciation regarding the quality of own results. There is also a relationship between the stated error in the last forecast and their self-evaluation about competence. Moreover, the forecast error tends to increase as the perception of the importance of strategic manipulation of results increases. This result corroborates recent studies pointing out that traffic forecasts are strategic variables subject to manipulation.

In chapter 3, we study the bidders' strategic behaviour in auctions for road concessions. We address three questions in turn. First, we investigate the overall effects of the winner's curse on bidding behaviour in such auctions. Second, we examine the effects of the winner's curse on contract auctions with differing levels of common-value components. Third, we investigate how the winner's curse affects bidding behaviour in such auctions when we account for the possibility for bidders to renegotiate.

Using a unique, self-constructed, dataset of 49 worldwide road concessions, we show that the winner's curse effect is particularly strong in toll road concession contract auctions. Thus, we show that bidders bid less aggressively in toll road concession auctions when they expect more competition. Besides, we observe that this winner's curse effect is even larger for projects where the common uncertainty is greater. Moreover, we show that the winner's curse effect is weaker when the likelihood of renegotiation is higher, *i.e.* bidders will bid more strategically in weaker institutional frameworks, in which renegotiations are easier. Besides, our conclusion contrasts with standard results. While the traditional implication would be that more competition is not always desirable when the winner's curse is particularly strong, we show that, in toll road concession contract auctions, more competition may be always desirable.

Chapter 4 focus on the aggregated users' behaviour, in particular in the long term traffic maturity. We argue that traffic maturity results from decreasing marginal utility of transport. The elasticity of individual mobility with respect to the revenue decreases after a certain level of mobility is reached. In order to find evidences of decreasing elasticity we analyse a cross-section time-series sample including 40 French motorways' sections. This analysis shows that decreasing elasticity can be observed in the long term.

We then propose a decreasing function for the traffic elasticity with respect to the economic growth, which depends on the traffic level on the road. Although "unconditional" decreasing elasticities were already proposed in the literature, this is the first work, as far as we know, putting this idea in evidence and giving it a functional form. This model provides better interpretation of the coupling between traffic and economic growth, and a better long-term forecast.

In chapter 5 we study the main individual modal choice variable, the value of time. The value of travel time savings is a fundamental concept in transport economics and its size strongly affects the socio-economic evaluation of transport schemes. Financial assessment of tolled roads rely upon the value of time as the main (or even the unique) willingness to pay measure. Values of time estimates, which primarily represent behavioural values, as then increasingly been used as measures of out-of-pocket money. In this setting, one of the main issues regarding the value of time is its distribution over the population.

We discuss the importance of the value of time and its particular role in the case of private motorways and present the econometric models currently used to estimate it, giving a special attention to the Bayesian procedures, since it is a relatively new method with only a few results in the literature. We also discuss the main challenges in estimating the value of travel time savings. We then describe the revealed preference survey we realized, including 1027 vehicles in order to study the trade-off between the free roads and the tolled motorway.

We apply the Logit, the Mixed Logit and the Bayesian Mixed Logit models to estimate the value of time in freight transport in France. Estimations with mixed logit faced many difficulties, as expected. These difficulties could be avoided using the Bayesian procedures, providing also the opportunity of properly integrating a priori beliefs.

Results show that 1) using a single constant value of time, representative of an average, can lead to demand overestimation, 2) the estimated average value of time of freight transport in France is about €45, depending on the load/empty and hire/own account variables, which implies that 3) the standard value recommended in France should be reviewed upwards.

Résumé

Cette thèse a pour objectif d'étudier les sources d'écart entre le trafic réel vérifié ex-post sur les autoroutes en concession et les prévisions ex-ante.

La demande prévue pour un projet est la principale variable déterminant sa réalisation. Du point de vue du secteur public, les gains socio-économiques sont déterminés par les prévisions de la demande, ce que sert de base de choix et hiérarchisation des projets publics en vue de maximiser le bien-être social. Du point de vue du secteur privé, les prévisions de trafic sont à la base de l'évaluation financière et de la fixation du montant du péage.

Malgré son importance et les nombreuses et importantes évolutions dans le domaine, les différences entre les prévisions et le trafic ex-post sont souvent très élevées. Des études récentes montrent que des différences de l'ordre que 20% constituent plutôt la règle que l'exception.

Une part d'incertitude très élevée est associée à l'exercice de prévision. D'abord parce que le transport est une demande dérivée et dépend de plusieurs variables exogènes, aussi incertaines; Parce que la modélisation est un exercice de simplification qui implique des nombreuses hypothèses et s'appuie sur des données de terrain, souvent incomplètes ou de mauvaise qualité; En outre, la modélisation du comportement humain (dans ce cas, les usagers) relève toujours du défis.

Bien que ces arguments puissent expliquer au moins la plus grande partie des erreurs associées aux prévisions, on peut se demander si les agents impliqués dans les prévisions pourraient utiliser cette incertitude stratégiquement en leur faveur. Les promoteurs privés peuvent êtres incites a ajuster le niveau du trafic, afin de rendre le projet plus attractif ou d'avoir la meilleure offre dans une enchère. Cette situation est exacerbée dans les cadres régle-

mentaires faibles, dans lesquels les renégociations de contrat ex-post sont plus faciles. La stratégie opportuniste dans une enchère consisterait donc à baisser le prix propose en augmentant le niveau des prévisions du trafic.

Aussi, un comportement suroptimiste (ou trop pessimiste) de la part des prévisionnistes peut introduire un biais dans la prévision. La confiance que l'on porte sur le projet ou bien sur nos propres capacités d'évaluer le projet peut donc s'avérer un facteur de biais en plus.

On propose ici d'étudier les trois principaux groupes d'agents impliqués dans le processus de prévision de demande en transport, dans le cadre particulier d'une autoroute concédée (à péage): les prévisionnistes, les enchérisseurs et les utilisateurs. L'étude de toutes les questions liées à leur comportement serait une tâche trop ambitieuse (ou plus concrètement impossible). Nous nous avons donc concentres sur certaines questions particulières liées à la modélisation du comportement des acteurs dans le contexte de la demande prévue pour les autoroutes à péage.

Tout d'abord, le comportement des prévisionnistes. Les prévisionnistes peuvent avoir une certaine influence sur l'étude, soit par leur propre opinion sur le projet, soit par la pression extérieure qu'il peut recevoir, ou bien par son opinion sur sa propre capacité de jugement. En dépit de l'aspect très quantitatif de la prévision de la demande, l'avis individuel sur les chances de succès (ou d'échec) d'un projet peut influer l'exercice de modélisation d'une certaine façon que les résultats correspondent le mieux aux attentes des prévisionnistes. En outre, si le prévisionniste surestime sa propre capacité de décider si un projet est bon ou pas, son évaluation individuelle sera biaisé. Nous proposons donc une enquête à fin de mieux connaître le comportement des prévisionnistes.

Deuxièmement, en particulier quand il y a concurrence pour le marché, le comportement de l'enchérisseur. Lors d'une enchère, l'enchérisseur peut surestimer la demande en vue de réduire le péage inclus dans l'offre. Ce comportement stratégique peut introduire un biais dans les prévisions.

Par ailleurs, nous étudions le comportement des usagers à deux niveaux. Premièrement, au niveau agrégé, nous analysons la croissance du trafic à long terme et de sa relation avec la croissance économique. Deuxièmement, au niveau désagrégé, nous étudions la valeur du temps de transport, la principale variable influençant le choix modal et probablement la valeur la plus importante dans les évaluations socio-économique, ainsi que pour la prévision de la demande et de la recette.

La thèse est organisée comme suit. Le chapitre 1 présente une introduction générale sur le thème des erreurs et biais en prévision de demande en transport.

Le chapitre 2 analyse le comportement des prévisionnistes de transports. Il présente les résultats de la première enquête par sondage avec un gros échantillon sur les prévisionnistes, leur perceptions et opinions au sujet des la prévision de la demande pour les projets de transport, en se fondant sur une enquête en ligne.

Nous décrivons d'abord les principales caractéristiques des prévisionnistes, comme l'âge, le genre, l'éducation, les secteurs de travail et l'expérience. Nous avons ensuite décrit les dernières prévisions préparés en termes d'ancien-neté, de l'avancement du projet, le mode de financement et d'exploitation. Nous nous sommes tournés vers les modèles appliques, les erreurs qu'ils déclarent avoir commit et les principales sources d'erreurs selon eux. Nous décrivons ensuite l'environnement des prévisions en termes de pression reçue pour des résultats. Ces résultats uniques fournissent une image du monde des prévisionnistes et des prévisions, ce qui permet de mieux les comprendre.

Un résultat important concerne la pression pour obtenir des résultats que les prévisionnistes affirment recevoir. Elles impliquent que le promoteur du projet peut influer sur les prévisions en pressant les prévisionnistes à produire des résultats qui correspondent mieux à leurs attentes.

Nous nous sommes tournés alors à l'étude de l'optimisme et de l'opportunisme dans les prévisions. Optimisme et opportunisme en général sont reconnues comme des traits humains très communs; La plupart d'entre nous somme sur-confiants à propos de nos propres capacités et suroptimistes quant à l'avenir. Il y a aussi une vaste littérature en économie et finance comportementale montrant que le rôle de l'optimisme dans les décisions économiques et les prévisions économiques ne sont pas négligeables.

Nous avons analysé le biais d'optimisme en comparant la distribution des erreurs déclarées et les erreurs réelles trouvées dans la littérature; Nous avons également compare le niveau de compétence propres déclarées par les prévisions avec des études montrant des auto-évaluations de l'habilité au volant. Les résultats montrent que la distribution des erreurs déclarées a une moyenne plus faible et un plus faible écart-type que celles trouvées dans la littérature, comme le montre la figure 1.

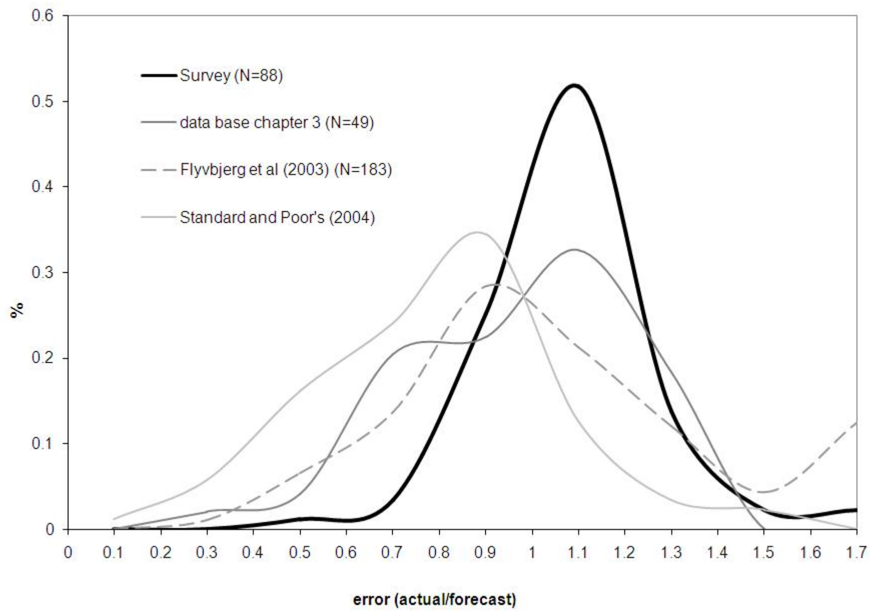

Figure 1: Ecarts (réel/prévu)

En comparant la perception de leur propre compétence avec les résultats trouvés dans la littérature sur les compétences des conducteurs, toutefois, nous n'avons pas trouvé une différence significative, ce que signifie que la surconfiance des prévisionnistes est comparable a ce que l'on pourrait considérer comme un niveau normal.

Nous proposons enfin une régression de la compétence, la qualité et les erreurs déclarées sur les principales variables spécifiques des prévisionnistes et des projets. L'analyse montre que les personnes plus âgées, plus expérimentés et travaillant a l'université ont tendance à meilleur évaluer leur compétence. Aussi, l'expérience semble être la seule variable significative quant à la qualité des propres résultats. Il existe également une relation entre l'erreur déclarée dans la dernière prévision et leur auto-évaluation sur la compétence.

Dans le chapitre 3, nous étudions les comportements stratégiques des enchérisseurs lors des enchères pour des contrats de concessions. Nous analysons trois questions. Tout d'abord, nous examinons l'effet global de la malédiction du vainqueur sur le comportement des enchérisseurs (variation de l'offre selon le niveau de concurrence). Deuxièmement, nous examinons les effets de la malédiction du vainqueur dans les enchères avec différents niveaux de valeur communes. Troisièmement, nous tenons compte de la possibilité de renégociation du contrat ex-post dans l'analyse de la malédiction du vainqueur.

En utilisant une base de données unique que nous avons bâtie, comprenant 49 concessions autoroutières dans différents pays du monde, nous montrons que la malédiction du vainqueur est particulièrement forte dans les enchères pour des contrats de concessions d'autoroutes à péage. Ainsi, nous montrons que le l'offre gagnante est moins agressive (moins d'écart entre le trafic prévu et le réel) quand la concurrence est accrue (plus d'enchérisseurs).

Par ailleurs, nous constatons que cet effet est encore plus grand pour les projets dont l'incertitude commune est plus grande. En outre, nous montrons que la malédiction du vainqueur est plus faible lorsque la probabilité d'une renégociation est plus élevée, c'est-à-dire, les enchérisseurs enchérissent plus stratégiquement dans les cadres institutionnels plus faibles, dans lesquels les renégociations sont plus faciles. Nous montrons donc que, dans les enchères pour des contrats de concession d'autoroutes à péage une plus forte concurrence est toujours souhaitable.

Dans le chapitre 4 on étudie le comportement agrégé des usagers, en particulier la croissance du trafic à long terme (maturité). Nous soutenons que la maturité du trafic est un résultat de l'utilité marginale décroissante du transport. L'élasticité de la mobilité individuelle par rapport au revenu diminue après qu'un certain niveau de la mobilité est atteint. Dans le but de mettre en évidence la décroissance de l'élasticité nous analysons les séries chronologiques d'un échantillon de 40 sections autoroutières françaises. Cette analyse montre que la diminution de l'élasticité peut être observée dans le long terme.

Nous proposons ensuite une fonction décroissante de l'élasticité du trafic par rapport à la croissance économique, qui dépend du niveau de trafic sur la route, sous la forme suivante:

$$\varepsilon_{T/GDP}(T) = \frac{\frac{\delta T}{T}}{\frac{\delta GDP}{GDP}} = kT^{\gamma}$$

La relation explicative devient donc:

$$lnT_{it} = \beta_{0i} - \frac{1}{\gamma_i} ln(1 - \gamma_i k_i lnGDP_t) + \alpha_{2i} lnPF_t + \alpha_{3i} lnToll_{it}^M + \varepsilon_{it}$$

Bien que des formulations de décroissance "inconditionnelle" des élasticités ont déjà été proposées dans la littérature, ceci est le premier travail, a notre connaissance, la mettent en évidence et lui donnant une forme fonctionnelle. Ce modèle fournit une meilleure interprétation du couplage entre le trafic et la croissance économique et produit une meilleure prévision à long terme.

Cette approche a été appliquée à grande échelle pour des prévisions de trafic à l'horizon 2030 pour les principales autoroutes concédées françaises. Les résultats montrent que le modèle a élasticité de la variable produit des prévisions plus conservatrices. En outre, en estimant avec le nouveau modèle et le modèle classique linéaire en utilisant les données jusqu'en 1999 et comparant les prévisions entre 2000 et 2005 avec le trafic réel, nous avons trouve que le modèle à élasticité variable a été deux fois plus précis.

Dans le chapitre 5, nous étudions le principal déterminant du choix modal individuel, la valeur du temps. La valeur du temps de transport est un concept fondamental en économie des transports et sa magnitude a une forte incidence sur l'évaluation socio-économique des projets de transport. L'évaluation financière des autoroutes à péage dépend de la valeur du temps comme mesure de la disponibilité à payer. Les estimations des valeurs de temps, qui représentent à la base des valeurs comportementales, sont de plus en plus utilisées en tant que mesures de la réelle disponibilité à payer. Dans ce contexte, l'une des principales questions concernant la valeur du temps est sa distribution dans la population.

Nous discutons donc l'importance de la valeur du temps et son rôle particulier dans le cas des autoroutes concédées et présentons les modèles économétriques utilisés actuellement pour l'estimer, en accordant une attention spéciale aux procédures bayesiennes, puisqu'elle est une méthode relativement nouvelle avec seulement quelques résultats dans la littérature. Nous discutons également les principaux défis dans l'estimation de la valeur du temps de transport. Nous décrivons ensuite l'enquête de préférence révélée que nous avons réalisée, comprenant 1027 véhicules de transport de marchandises, afin d'étudier le choix entre les routes nationales et les autoroutes à péage.

Nous appliquons modèles Logit, Logit Mixte et Logit Mixte Bayesien pour estimer la valeur du temps dans le transport de marchandises en France. Les estimations du type Logit Mixte se heurtent à de nombreuses difficultés, comme prévu. Ces difficultés ont pu être évitées en utilisant les procédures de Bayes, offrant aussi la possibilité d'intégrer proprement des informations à priori.

Les résultats montrent que: 1) en utilisant une valeur de temps unique, représentative de la moyenne, peut conduire à la surestimation de la demande, 2) la valeur moyenne du temps de transport de marchandises en France est d'environ €45, comme le montre la figure 2, variant en fonction des variables chargé/vide et compte propre/compte d'autrui, ce que implique que 3) la valeur préconisée en France devrait être revue à la hausse.

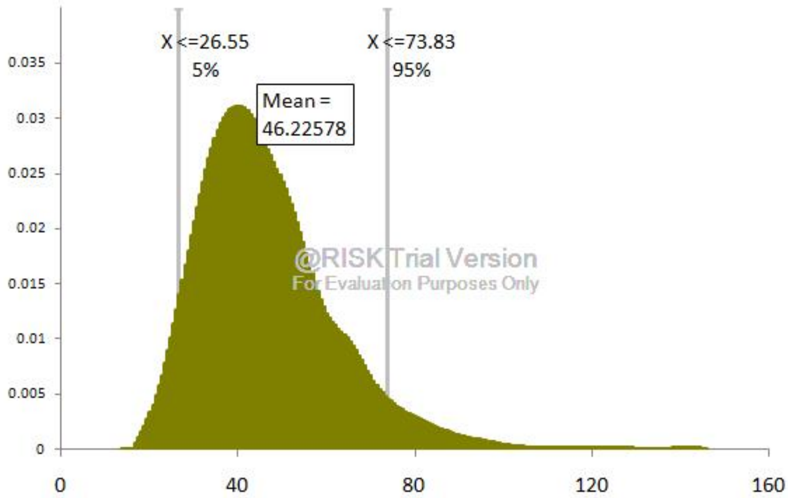

Figure 2: Distribution de la valeur du temps PL.

Introduction

The demand forecast for a specific project is the main variable influencing its realization. From a public sector perspective, socio-economic evaluations are driven by demand forecasts, which gives the basis for choose and hierarchy public projects in order to maximise social welfare. From a private sector perspective, traffic forecasts are the base of financial evaluation and toll setting. Furthermore, demand forecasts are used for several other key purposes in transport policy, planning, and engineering: to calculate the capacity of infrastructure, e.g., how many lanes a bridge should have and to calculate environmental impacts, e.g., air pollution and noise.

Despite of its importance and the numerous and important developments in the field, the differences of forecast and ex-post traffic in usually very high. Some recent studies show that differences as big as 20% are much more the rule than the exception. Moreover, and despite the improved knowledge in transport demand models, it does not seem to reduce the errors in estimations over time.

A huge amount of uncertainty is associated with the forecasting exercise. First because transport is a derived demand and depends on many exogenous variables, also uncertain; because modelling is and simplification exercise, implies many assumptions and rely on field data, many times incomplete or of low quality; moreover, modelling human (in this case users) behaviour is always a dangerous enterprise.

Although these arguments could explain at least the larger part of errors associated with forecasts, one can wonder whether the agents implicated in the forecast would or could use this uncertainty strategically in their favor. In a competition for the field scheme (bids), the bidder may overestimate the demand in order to be reduce the toll included in the bid. This strategic behaviour can introduce a high bias in forecasts. Also, overoptimistic (or overpessimistic) forecasters may introduce a bias in the forecast.

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Then, we study the user's behaviour at two levels. First, at the aggregated level, we analyze the long term traffic growth and its relationship with the economic growth. We argue that traffic maturity results from decreasing marginal utility of transport, so that the elasticity of individual mobility with respect to the revenue decreases after a certain level of mobility is reached, implying that instead of a constant elasticity between the traffic and the GDP most models assume, we should consider a decreasing relationship between these two variables.

Second, at the disaggregated level, we study the value of travel time savings, the main variable guiding individual mode choice and probably the most important value in socio-economic evaluation as well as in demand and revenue forecast. We apply the Logit, the Mixed Logit and the Bayesian Mixed Logit models to estimate the value of time in freight transport in France.

Plan of the Manuscript

Chapter 1 presents a general introduction to the topic of errors and biases in forecasting demand for transport infrastructures and services.

Chapter 2 focus on transport forecasters' behaviour. It presents the results of the first large sample survey on forecasters' perceptions and opinions about forecasting demand for transport projects, based on an on-line survey. We first describe the main characteristics of forecasters, as age, gender, education, working sectors and experience. We then describe the last forecast forecasters prepared in terms of oldness, project's advancement, mode, financing and operation. We then turn to the models forecasters apply, the errors they declare on past forecasts and the main sources of errors according to them. We then describe the forecast environment in terms of pressure forecasters receive. These unique results provide a picture of the world of forecasters and forecasts, allowing for a better understanding of them.

We turn then to the study of the optimism and overconfidence in transport forecasts. Optimism and overconfidence in general are recognized human traits; most of us are overconfident about our own abilities and overoptimists about the future. There is also a growing literature in behavioural economics and finance arguing that the role of optimism in economic decisions and economic forecasts is not negligible.

We analyze the overoptimistic bias by comparing the distribution of stated errors with actual errors found in literature; we also compare the own skillful of subjects in doing forecasts with studies showing self-evaluations of a common skill - driving. We finally propose a regression of the competence, quality and errors on the main forecasters' and projects' specific variables.

Results show that the distribution of errors transport forecasters state has a smaller average magnitude and a smaller variance than those found in literature. Comparing forecasters perception of their own competence with the results found in literature about drivers skill self-evaluation, however, we could not find a significant difference, meaning that the forecasters' overconfidence is in line with what could be viewed as a normal human overconfidence level.

The regression analysis finds that elder, more experienced forecasters working in the university tend to more valuate their competence. Also, the experience seems to be the only significant variable driving the self-appreciation regarding the quality of own results. There is also a relationship between the stated error in the last forecast and their self-evaluation about competence. Moreover, the forecast error tends to increase as the perception of the importance of strategic manipulation of results increases. This result corroborates recent studies pointing out that traffic forecasts are strategic variables subject to manipulation.

In chapter 3, we study the bidders' strategic behaviour in auctions for road concessions. We address three questions in turn. First, we investigate the overall effects of the winner's curse on bidding behaviour in such auctions. Second, we examine the effects of the winner's curse on contract auctions with differing levels of common-value components. Third, we investigate how the winner's curse affects bidding behaviour in such auctions when we account for the possibility for bidders to renegotiate.

Using a unique, self-constructed, dataset of 49 worldwide road concessions, we show that the winner's curse effect is particularly strong in toll road concession contract auctions. Thus, we show that bidders bid less aggressively in toll road concession auctions when they expect more competition. Besides, we observe that this winner's curse effect is even larger for projects where the common uncertainty is greater. Moreover, we show that the winner's curse effect is weaker when the likelihood of renegotiation is higher, i.e. bidders will bid more strategically in weaker institutional frameworks, in which renegotiations are easier. Besides, our conclusion contrasts with standard results. While the traditional implication would be that more competition is not always desirable when the winner's curse is particularly strong, we show that, in toll road concession contract auctions, more competition may be always desirable.

Chapter 4 focus on the aggregated users' behaviour, in particular in the long term traffic maturity. We argue that traffic maturity results from decreasing marginal utility of transport. The elasticity of individual mobility with respect to the revenue decreases after a certain level of mobility is reached. In order to find evidences of decreasing elasticity we analyse a cross-section time-series sample including 40 French motorways' sections. This analysis shows that decreasing elasticity can be observed in the long term.

We then propose a decreasing function for the traffic elasticity with respect to the economic growth, which depends on the traffic level on the road.

Although "unconditional" decreasing elasticities were already proposed in the literature, this is the first work, as far as we know, putting this idea in evidence and giving it a functional form. This model provides better interpretation of the coupling between traffic and economic growth, and a better long-term forecast.

In chapter 5 we study the main individual modal choice variable, the value of time. The value of travel time savings is a fundamental concept in transport economics and its size strongly affects the socio-economic evaluation of transport schemes. Financial assessment of tolled roads rely upon the value of time as the main (or even the unique) willingness to pay measure. Values of time estimates, which primarily represent behavioural values, as then increasingly been used as measures of out-of-pocket money. In this setting, one of the main issues regarding the value of time is its distribution over the population.

We discuss the importance of the value of time and its particular role in the case of private motorways and present the econometric models currently used to estimate it, giving a special attention to the Bayesian procedures, since it is a relatively new method with only a few results in the literature. We also discuss the main challenges in estimating the value of travel time savings. We then describe the revealed preference survey we realized, including 1027 vehicles in order to study the trade-off between the free roads and the tolled motorway.

We apply the Logit, the Mixed Logit and the Bayesian Mixed Logit models to estimate the value of time in freight transport in France. Estimations with mixed logit faced many difficulties, as expected. These difficulties could be avoided using the Bayesian procedures, providing also the opportunity of properly integrating a priori beliefs.

Results show that 1) using a single constant value of time, representative of an average, can lead to demand overestimation, 2) the estimated average value of time of freight transport in France is about €45, depending on the load/empty and hire/own account variables, which implies that 3) the standard value recommended in France should be reviewed upwards.

Chapter 1

Errors and Biases in Transport Demand Forecasts

> "The field [of transport demand forecasts] still suffers from bad reputation as many analytically advanced studies continue to disappoint, leaving significant wedges between realized and forecast traffic"
>
> Trujillo, Estache and Quinet (2002)

Forecasting stands at the heart of the transport planning process. Decision makers, in transport, use forecasts to select projects and to decide whether invest or not. From a public sector perspective, socio-economic evaluations are driven by demand forecasts, which gives the basis for choose and hierarchy public projects in order to maximise social welfare. From a private sector perspective, traffic forecasts are the base of financial evaluation and toll setting.

The planner's problem consists in maximise the social welfare subject to certain private revenue. The demand forecast is then the key variable in both equations. From both public and private perspectives, poor forecasts can lead to disastrous decisions. Despite its importance, many recent ex-post analysis have been showing that forecasts are sometimes very inaccurate and, especially in the case of toll roads, overestimated. As note Trujillo et al. (2002), while public-private partnerships in the delivery of transport infrastructures and services is expanding, there is also growing evidence of the lack of appreciation of the importance of demand forecasting in preparing and monitoring these partnerships.

This increasing evidence of discrepancy between actual and forecast demand may have numerous reasons in the context of growing participation of private sector. First, for the first time, ex-post demand really matters, traffic counts are systematic and before-after studies become a good practice in many countries.

Second, transport demand forecasting faces many methodological difficulties. Moreover, forecasting transport for toll roads faces much more difficulties than for a public/free road. The hypothetical willingness to pay used to monetize time savings is now used to estimate the actual out of pocket money; failing to identify the right value of time distribution in the population can lead to erroneous market shares. Also, competition matters. Improvements in concurrent roads or other modes may have strong effects on the demand market share.

Furthermore, the diversity of objectives across actors increases. Trujillo et al. (2000) argue that in practice, at least four groups of actors are involved: consumers, operators (in a large sense, that is including sponsors and financiers), the government (which represents the taxpayers and the voters) and the regulator and it is important to understand how their concerns differ. Users will worry about prices, service quality and reliability. All influence demand. The operators typically worry about profits, risks and market power. All are influenced by demand. Governments, who are often the dominating players in the context of the reform of the sectors covered here, are generally interested in reducing the fiscal burden imposed by the public enterprises of the sector and often also try to generate a flow of resources through the reform process. They generally want to please tax payers by cutting taxes and respond to some environmental and distributional concerns. These concerns can both influence demand and be influenced by demand. In this context, many of the players have a strong incentive to play strategically.

In this context, minimizing errors by understanding their sources and improving methods and procedures accordingly is important in the delivery of robust appraisals.

1.1 What is Forecasting?

A forecast can be defined as a prediction or estimate of an actual value in a future time period or for another situation. It is related to estimating in unknown situations and then with the notion of risk. Forecasting is important in many aspects of our lives. As individuals, we try to predict success in our marriages, occupations, and investments. Organizations invest enormous amounts based on forecasts for new products, factories, retail outlets, and contract with executives. Government agencies need forecasts of the economy, environmental impacts, new sports stadiums, and effects of proposed social programs (Armstrong, 2001).

The ability to define what may happen in the future and to choose among alternatives lies at the heart of contemporary societies. The modern conception of risk is rooted in the Hindu-Arabic numbering system that reached the West seven to eight hundred years ago. But Arabic numbers were not enough to introduce Europeans to explore the radical concept of replacing randomness with systematic probability and its implicit suggestion that the future might be predictable and even controllable to some degree. That advance had to wait the realization that human beings are not totally helpless in the hands of fate, nor is their worldly destiny always determined by God (Bernstein, 1996).

Most cultures have been concerned with forecasting. Sometimes the forecaster was held in high regard, as was the oracle at Delphi. Often, however, forecasting is regarded as a necessary evil and is frowned upon. According to a current sage (Drucker, 1973, p.124), "...forecasting is not a respectable human activity and not worthwhile beyond the shortest of periods." Sometimes it has been illegal. For example, in Rome in 357 A.D. Emperor Constantius issued an edict forbidden anyone "to consult a soothsayer, a mathematician, or a forecaster... May curiosity to foretell the future be silenced forever" (Armstrong, 2001).

In recent years, however, forecasting seems to have become a respectable activity and there is a growing need for more reliable methods (Figure 1.1 lampoons this idea). Nowadays, a formal forecast is needed for all decision-making. Demand forecasts precede almost every new product or service launching. Public projects like transport, energy and sanitation are preceded by forecasts including demand, socio-economic impacts as well as environmental effects.

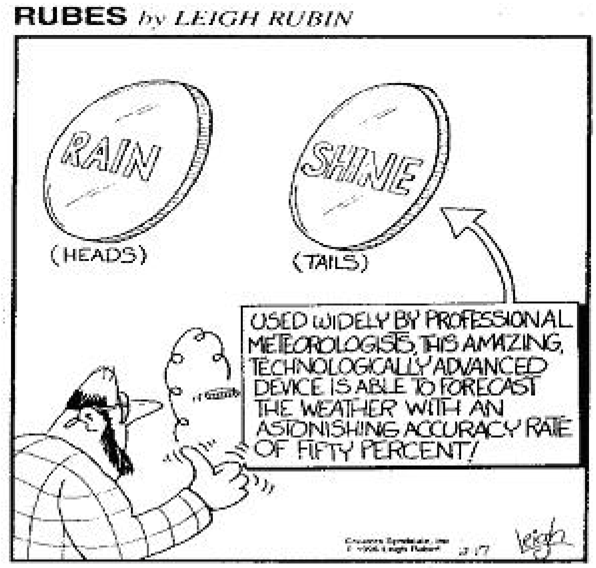

Figure 1.1: Caricature of weather forecasts

1.2 Forecasting in Transport

Transport forecasting is the process of estimating the number of vehicles or travelers that will use a specific transportation facility in the future. A forecast estimates, for instance, the number of vehicles on a planned motorway or bridge, the ridership on a railway line, the number of passengers patronizing an airport, or the number of ships calling on a seaport.

Demand forecasts are used for several key purposes in transport policy, planning, and engineering: to calculate the capacity of infrastructure, e.g., how many lanes a bridge should have; to estimate the financial and social viability of projects, e.g., using cost-benefit analysis and social impact analysis; and to calculate environmental impacts, e.g., air pollution and noise.

Transport forecasts have three main characteristics; they are unconditional, circular, and influential. Unconditional (or ex-ante) forecasts are estimates of what will happen in a situation when no actual data from that situation are used to produce the forecast; they use only information that would have been available at the forecast origin.

The circularity is an inherent characteristic of public projects and policies forecasts. Circularity arrives when choosing an action affects the future in a way that makes difficult or impossible the assessment of the action's impact. The demand which is later observed might have been "correctly" forecast, or might have been instigated by the forecast and the action which it spurred (Wachs, 1982). Consider a toll motorway for which a high traffic level is forecast. Later, having huge capacity they advertise, create frequency cards and lower the tariffs. Do the earlier forecasters of great demand now have the right to claim that their forecasts were accurate?

Forecasts in transport are influential. Influential forecasts occur when the forecast itself determines whether the forecast is tested. Forecasts for new products and new projects are often influential because a low forecast may cause the project is not launched and then the actual demand will not be observed. Although market (and transport) forecasts are often influential, many forecasts are not. Economic forecasts, for example, seldom influence evaluation. In forecasts for GDP or employment, we observe the outcomes, whatever the forecast. Not validating all forecasts causes two effects: Survivor's Curse and Prophet's Fear (Ehrman and Shugan, 1995). Statistically unbiased forecasts should appear optimistic because some forecasts remain untested. This effect is called the Survivor's Curse and reviewed in section 1.4.3. Prophet's Fear encourages pessimistic forecasts because these forecasts cause hidden opportunity losses while optimistic forecasts cause observable actual losses.

The development of traffic demand models began in the fifties in the United States, in the context of the pioneering Detroit and Chicago Transportation Studies. In the sixties, traffic models began to be used in England. From England it spread to the rest of Europe. There is an extensive literature on traffic modelling and forecast. The main reference is Ortuzar and Willumsen (2001); good reviews of the classic models as well as recent innovations are provided by Hensher and Button (2000). Bonnel (2004) provides a review of the main transport forecast techniques and the history of the transport planning in France.

Traffic forecasting begins with the collection of data on current traffic. Together with data on population, employment, trip rates, travel costs, etc., traffic data are used to develop a traffic demand model. Feeding data on future population, employment, etc. into the model results in output for future traffic, typically estimated for each segment of the transportation infrastructure in question, e.g., each roadway segment or each railway station. The basic idea behind this procedure is that transport is a derived demand, so what is to be forecast is not the transport itself, but what drives people to travel or not, where, when and how.

1.2.1 The Classic 4-step Model

The history of transport demand modelling has been dominated by the modelling approach which has come to be referred to as the four step (or four stage) model. The steps are: trip generation, trip distribution, modal split and network assignment.

Trip generation determines the frequency of origins or destinations of trips in each zone by trip purpose, as a function of land uses and household demographics, and other socio-economic factors.

Trip distribution matches origins with destinations, to develop a "trip table"; a matrix that displays the number of trips going from each origin to each destination, often using a gravity model or an entropy maximizing model.

Mode choice computes the proportion of trips between each origin and destination that use a particular transportation mode. They are estimated by either aggregated of disaggregated choice models, the later have recently been brought into widespread use.

Network assignment allocates trips between an origin and destination by a particular mode to a route. Often (for highway route assignment) Wardrop's principle of user equilibrium is applied (equivalent to a Nash equilibrium), wherein each traveler chooses the shortest (travel time) path, subject to every other driver doing the same.

One of the main criticisms regarding the four step model is the assumed stability over time. Once a travel model has been validated to base year conditions, forecasts for future years are generally made by replacing base year input data with forecast of those same model inputs. However, base year forecasts parameters (e.g. trip generation and mode choice coefficients) are generally assumed to hold over time because analysts have difficulty predicting the magnitude and the extent of parameter change. This builds an implicit assumption of system stability into the forecasts that may not be correct.

The science and art of travel forecasting is immersed in a period of transition, equally for the dissatisfaction with models performance as for the inherent interest in building a better mouse trap. However, the conventional modelling process is so firmly institutionalized that only a full replacement for the system, or modular and integrable component parts, could be accepted in practice and satisfy institutional constraints. This institutional inertia placed much of onus for model improvement in academia, where well-defined contributors to the state of the art often provide only marginal value to the state of the practice or to any comprehensive innovation (McNally, 2007).

1.3 Errors in Traffic Forecasts

> "Forecasters generally do a poor job of estimating the demand for transportation infrastructure projects" (Flyvbjerg et al., 2006)

Very little ex-post analysis has been done on the accuracy of forecasts; First because data that allow the calculation of inaccuracies in traffic forecasts unfortunately are relatively rare. For public sector projects, often the data are simply not produced. And even where the intention is to produce the data, projects may develop in ways that it is difficult or impossible to compare forecast with actual traffic (Flyvbjerg et al., 2006). Quinet (1998) argues that when the topic is traffic, it is difficult to compare comparable things; the situation in which the project is implemented is often different from that defined for the forecast.

Flyvbjerg et al. (2003) performed the largest study on forecast accuracy for roads, including 183 road projects worldwide (and also 27 rail projects). Figure 1.2 show the distribution of the forecasting error (for the first year of operation) in their sample.

Moreover, and despite the improved knowledge in transport demand models, it does not seem to reduce the errors in estimations over time. Flyvbjerg

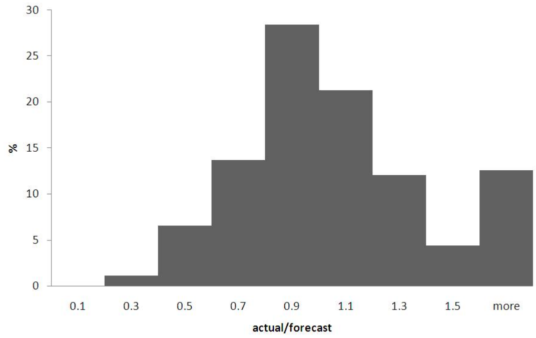

Figure 1.2: Errors on Flyvbjerg et al (2003) sample

et al. (2005, 2006) also show that there is no indication that traffic forecasts have become more accurate over time (figure 1.3).

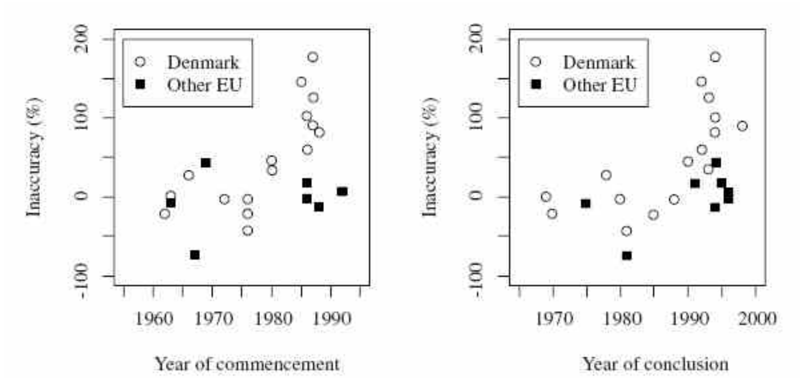

Figure 1.3: Errors variation over time on Flyvbjerg et al. (2005) sample

Standard and Poor's (2002, 2003, 2004, 2005) review a sample which increases from 38 in 2002 to 87 in 2005.

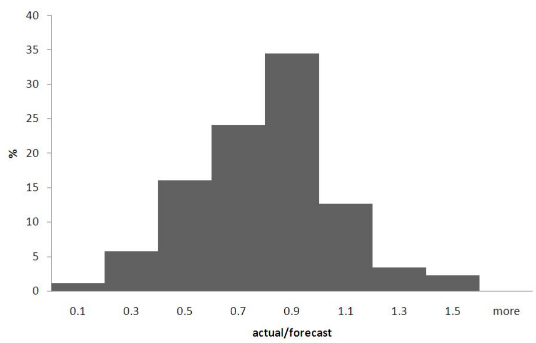

Figure 1.4: Errors on Standards and Poor's (2005) sample

In chapter 3 of this thesis we analyse a sample of 49 road concessions worldwide and show also significant traffic forecast errors.

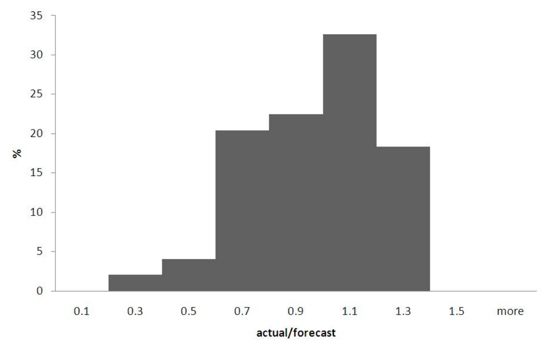

Figure 1.5: Forecasting error in 49 road concessions (chapter 3 sample)

These studies show that errors in forecasts are much more the rule than the exception and lead to the question about the possible sources of these errors.

1.4 Sources of Errors

Transport forecasts result from the combination of different models, for different purposes and of different nature, in which each one has number of parameters, data sources, estimation procedures and hypothesis.

Quinet (1998) distinguishes three sources of inaccuracy: the inadequacy of the model structure; the inaccuracy of the current data; and the uncertainty of prediction of the future value of exogenous variables.

Flyvbjerg et al. (2003), in a different way, classify the sources of inaccuracy in seven groups: methodology applied; poor database; discontinuous behaviour and the influence of complementary factors; unexpected changes of exogenous factors; unexpected political activities or missing realisation of complementary policies; implicit appraisal bias of the consultant; and appraisal bias of the project prompter.

In this work, we distinguish three main groups of sources of inaccuracy in traffic forecasts: the pure uncertainty, related to the fact that the future is uncertain by its nature; data and methodological sources, associated with the availability and quality of data and the models and assumptions used; and the behavioural sources, namely optimism and opportunism.

1.4.1 Uncertainty About the Future

One of the problems with the forecast assessment of models is that it is very difficult to predict the future values of the explanatory variables. Growth factors are used to estimate future year trip matrix. The development of appropriate growth factors depends on forecasts of demographic and economic variables such as population, employment, household income and gross domestic product for the study area. Errors in such assumptions can have a significant impact on growth forecast.

Morrison and Winston (1995), for example, indicate that poor predictions of income are the main reason why U.S. airline companies often overinvest during periods of macroeconomic expansion.

The work of the U.K. Ministry of Transport's Mathematical Advisory Unit in the 1960's offers a rather quirky example of what this can lead to. At the time, trend-based car ownership forecasts were proving more accurate than those of National Income. Since the link between income and car ownership had been established, efforts were made to generate GDP forecasts derived from the trend-based car ownership model. Causality was seen as less relevant than forecasting performance.

Sudden changes of exogenous factors can hardly be controlled by demand modelling and scenario techniques. For instance abrupt social and political changes such as the breakdown of the communism regimes in the east-west relationship in Europe are not predictable. Another example is the development of energy prices, which underlies influences that are hard to predict, as for instance in the cases of the two oil crises in 1973 and 1979 (Flyvbjerg et al., 2003).

The 21st century has been characterised as a period in which new forms of mobility both produce and change societies (Thrift, 1996; Urry, 2000). Low-cost airlines, widespread car ownership, and new mobile communications allow people to travel further, more quickly, and more frequently, and enable transactions that previously required face-to-face contact to be undertaken at a distance or even on the move. It is argued that these processes of time-space compression and time-space convergence (Gregory, 2000; Harvey, 2000, 1990, 1973; Thrift, 1990) are producing new challenges both at societal and at individual levels as people, organisations, and governments adjust to the consequences of new mobilities (Adams, 1999; Cairncross, 1997; Urry, 2000).

In this sense, forecasting the future of technology is a dangerous enterprise. Schnaars (1989) examined hundreds of technology forecasts. He found that there is a myopia, even among experts, that causes them to focus upon the future in terms of present conditions. Cerf and Navasky (1998) give interesting examples of errors in expert judgments about the future of technology. Perhaps the most famous is the 1899 call by the US Commissioner of Patents to abolish the Patent Office on the grounds that there was nothing left to invent.

1.4.2 Methodology, Assumptions and Data

Model Weaknesses and Inadequacies

Models are simplifications by definition. The level and way of simplifying the reality can strongly affect the results a model is able to produce. Different models are used in transport demand modelling, which one with its own limits and weaknesses. Each parameter, each functional form specification will impact the results in a certain way. Moreover, models rely on numerous hypotheses about human behaviour that are seldom validated.

The treatment of models as black-boxes can also be a danger. Many users settle for the direct application of commercial models without a correct understanding of its models and assumptions.

Furthermore, the sequential and aggregate nature of transportation forecasting has come under much criticism. While improvements have been made, in particular giving an activity-base to travel demand, much remains to be done.

Errors in Assumptions

Ascher (1978) has pointed out that forecasting is critically dependent on the use of assumptions. He wrote that:

> The core assumptions underlying a forecast, which represent the forecaster's basic outlook on the context within the specific forecast trend develops, are the major determinants of forecast accuracy. Methodologies are basically the vehicles for determining the consequences or implications of core assumptions that have been chosen more or less independently of the specific methodologies. When the core assumptions are valid, the choice of the methodology is either secondary or obvious. When the core assumptions fail to capture the reality of the future context, other factors such as methodology generally make little difference; they cannot "save" the forecast.

Mackie and Preston (1998) report that the M65 was built on the assumption that Central Lancashire New Town would be fully developed and the Concorde was developed under the assumption that supersonic flights would be granted access to inland air space throughout the world.

Some kind of mix between exogenous source and error in assumptions are the impacts of political activity. Unexpected political activities or unfulfilled promises for political actions have become a problem since the scenario-technique of forecasting became popular. Usually scenario forecasts are prepared in a way where the political side describes that part of the future world that is influenced direct by political actions. Examples are taxation policy, regulations and complementary activities for the project under investigation (for example access roads, urban/spatial development or international agreements).

But stated political preferences and actual political activities are often very different. We find a central example of such differences in the European Union. While the Green and White papers on the common transport policy promote sustainable development in words, actions that would match the words still lag behind and actual developments proceeds in the opposite direction from the established policies. The state of discussion for CO2 taxation or driving regulations for lorries are cases in point. Consequently, ecological oriented forecasting scenarios may very well fail for the transport sector, as happened in both Germany and Denmark (Flyvbjerg et al., 2003).

Ieda (2003) proposes a distinction between “be” and “do” forecast, where “be” forecast represents that would be naturally realized, or the estimated value and the “do” forecast which could be realized only through policy efforts, or the target value. This forcibly clarifies the type of “policy effort” which is necessary in order to achieve the target, and monitors whether enough “policy efforts” are put in or not, based on the commitment. Figure 1.6 illustrates this idea.

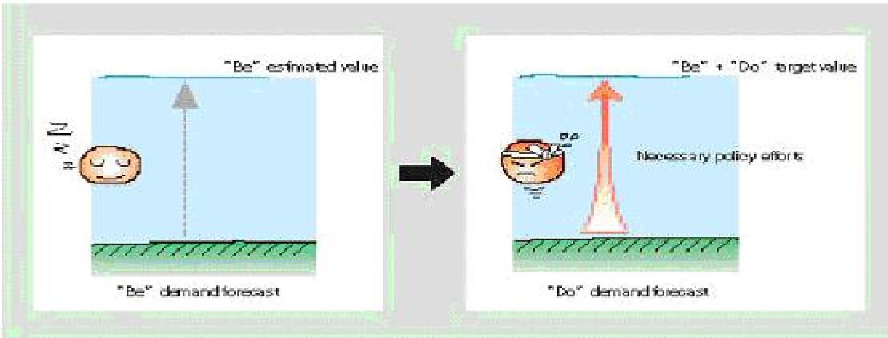

Figure 1.6: From “be” forecast to “do” forecast

Data Availability and Quality

In the field of transportation research, nothing is more valuable yet simultaneously more limiting to the valuation of theory and models than are data (McNally, 2007). Data are seldom or never of the quality we would like them to be. The quality of data as traffic forecast model input represents one of the major sources of potential forecasting error. These data include traffic counts, transportation networks characteristics, travel costs, the location and size of households and car ownership to list a few.

Flyvbjerg et al. (2003) claim that poor data is a more important reason for prediction failures than methodology. They argue that in many countries there is no continuous generation of field data. This means that traffic demand models can not be calibrated on the basis of observed traffic behaviour (the revealed preference approach). This gap can partly, but not completely, be close by stated preference analysis. The problem is that actual behaviour of people may, and often does, deviate substantially from the stated preferences.

1.4.3 Behavioural Sources

Although the forecasting exercise is about understanding and modelling human (users) behaviour, some biases and errors are directly related to the agents involved in the forecast processes. In this sense, transport forecasts can include or reflect some forecasters' or decision makers' biases. Whenever this occurs, the forecast produced will not represent the forecaster's true expectations as assumed.

Before discussing the behavioural sources of errors and biases we want to clarify an important aspect of demand overestimation. Many authors argue that in absence of strategic or optimism biases, traffic forecast errors should be equally distributed above and bellow zero error:

- "Significant errors, and furthermore biased in the sens of overestimation, show strategic biases from analysts." (Quinet, 1998).
- "Although scientific uncertainty should be, a priori, evenly distributed between under and over-estimation[...]"(Trujillo et al., 2002).
- "Instead of being random errors, however (with the possibility of canceling each other out), these are systematic errors reflecting optimism bias" (Standard and Poor's, 2002).

Although at first sight unbiased estimations should be symmetric distributed around the zero error, the influential characteristic of transport forecasts makes this assumption wrong. Statistically unbiased forecasts should appear optimistic because some forecasts remain untested. This effect is called the Survivor's Curse (Ehrman and Shugan, 1995). Suppose (1) we supply unbiased forecast (zero reporting bias) for a series for projects each having the same expected sales, (2) the client launches some but not all of those projects and (3) launched projects average higher forecast than unlaunched. Then, the unbiased forecast, for launched projects, appear optimist and biased. Mathematically, let f_A be the average forecast for all projects, fL be the average forecast for launched projects and f_N be the average forecast for projects not launched.

Since f_N is the average of independent normal variables, f_N is normal with mean μ and variance σ^2. According to David (1957), $E[f_N|f_L > f_N] = \mu-(\sigma/\sqrt{2})$. But $E[f_N+f_L|f_L > f_N] = \mu$, so $E[f_L|f_L > f_N] = \mu+(\sigma/\sqrt{2}) > \mu$. Finally, f_A is a convex combination of f_L and f_N, so $f_L > f_N$ requires $f_L > f_A$.

This implies that even when forecasters make unbiased forecasts, the forecast traffic for launched projects will tend to overstate their actual traffic. Survivor's Curse works as follows. Most forecast contain some error. Positive errors enhance the probability of launching projects and the forecast survives to be tested. Negative errors enhance the probability of not launching and the forecast remains untested. Those projects surviving the screening process, by exceeding the critical value, are more likely to have positive errors because projects with negative errors may not survive to be tested. Here, the bias (expected error) across all forecasts is zero, but the bias for tested forecasts is positive. So survivors tend to disappoint.

Opportunism

Forecasts rely upon so many assumptions that it is usually possible to adjust forecasts to the extent that they meet such demands. The question here is to know in which measure the field of traffic forecast is a world of honest numbers.For example, Wachs (1982) affirms that most of the forecasts used in the planning of America's rail transit systems are statements of advocacy, rather than unbiased estimates.

This problem takes a particular importance in the case of road concessions. Private promoters may have incentives to adjust the level of traffic in order to make the project more attractive or to have the best bid. This situation is exacerbated in regulatory frameworks in which renegotiations are easier. The opportunistic strategy consists in bidding a low price[1] by increasing the forecast traffic level.

Once an enterprise has been granted a concession in an infrastructure sector - and the eventual bidding competitors are gone - that enterprise may correspondingly be able to take actions that "hold up" the government, for example

[1] as reviewed in chapter 3, lowest toll is the most wide used criteria in auctions for transport infrastructures.

through insisting on renegotiating the contract ex post. The extensive informational advantages that the enterprise possesses over the government and its perceived leverage vis à vis the government in a bilateral negotiation is a powerful potential factor to seek renegotiation of the contract and secure a better deal than the initial one.

When bidders expect a high likelihood of renegotiation that renders it possible to avoid any losses, they have strong incentives to submit bids containing promises difficult to satisfy, with the sole purpose of being awarded the tender (Spulber, 1990). Uncertainty in forecasts is then used in a strategic way by the bidders. This is exacerbated by the information asymmetries in concession projects. Moreover, traffic overestimation may represent an equilibrium in the short-term. In fact, while candidates submit opportunistic bids to increase their probability of success, the more aggressive the bids, the better it would be for the public procuring authority, since it is more efficient in the short-term. Besides, financial agencies and lenders, suspecting that traffic forecasts are strategically increased, find a risk-sharing agreement that cushions them against any losses.

Optimism and Overconfidence

> "There are two kinds of forecasters: those who don't know, and those who don't know they don't know." *J. K. Galbraith.*

The tendency to be overoptimistic is perhaps the best documented of all psychological errors (Montier, 2002). Psychological studies demonstrate that most individuals are overconfident about their own abilities, compared with others, as well as unreasonably optimistic about their futures (e.g., Taylor and Brown (1988); Weinstein (1980). When assessing their position in a distribution of peers on almost any positive trait such as driving ability or income prospects, most of people say they are in the top half (Svenson, 1981).

Russo and Shoemaker (1992) find that professional managers perceive their judgment to be too exact. CEOs who have chosen an investment project are likely to feel illusion of control and to strongly underestimate the likelihood of project failure. (Langer, 1975; Weinstein, 1980; March and Shapira, 1987). Cooper et al. (1988) look at entrepreneurs who overestimate their chances of success with their business. In their sample of 2994 entrepreneurs 81% believe their chances to survive are better than 70% and 33% believe they will survive for sure. In reality 75% of new ventures did not survive the first 5 years.

Schultz (2001) addresses the point that despite dramatic progress in consumer research product failure rates have remained on a high level. He argues that overconfidence might account for the fact that managers constantly overestimate the success chances of their projects which leads to constantly high product failure rates despite better marketing research techniques.

1.4.4 The Particular Case of Road Concessions

Since the seminal paper by Demsetz (1968),competition for the field has been considered as a tool of government to allow private sector participation and benefit from efficiency advantages of competition while retaining some degree of control and guaranteeing the respect of community service obligations (Baldwin and Cave, 1999; Engel et al., 2002). The fact is that in the last couple of decades, many countries have promulgated directives on public procurement so as to bring in competitive tender mechanisms, e.g. the Federal Acquisition Regulations' mandate to use auctions in the U.S. public sector, the 1989 European directive on the obligation of competitive tendering, the 1988 Local Government Act in the United Kingdom or the 1993 "Sapin Act" in France.

Although traffic forecasts are fundamental in public (socio-economic) evaluation, in order to choose the most valuable projects for the hold society, avoiding waste public funds and improve social welfare; the growing participation of the private sector in infrastructure provision brings a financial perspective since in private applications, forecasting errors can easily have multi-million dollar impacts.

Trujillo et al. (2002) argue that the introduction of private finance and operation of motorways brings two main changes; the amplification of information asymmetries and the payment of a toll.

Politicians will want to look good during their tenure and support policies that maximize short run fiscal payoffs and/or minimizes tariffs. They can do so quite consciously and knowing perfectly well that requiring high payments and expenses from the operators while imposing low tariffs are generally not consistent and sustainable policies. Willingness or ability to pay and hence the real potential value of a business are seldom analyzed very analytically in this context.

The political gain for them to announce a new infrastructure is much higher than the political loss of having to increase taxes; furthermore these concerns and the eventual renegotiation of the deal is left to their successors since they generally imply political costs. But it is clear that private operators happily play in this game. For many of the best deals, their main concern is to get the contract signed by the government, knowing quite well that there is generally significant room for renegotiation. Patience in this field is often rewarded once the contract is won.

In sum, there are enough reasons and there is enough evidence to argue that in the context of privatization, it is not easy to achieve convergence on the views of what a good demand forecast should be because both firms and government have some interest in playing strategically with the demand forecast.

This should make a convincing case to ensure that regulators do their best to come up quite early on in their tenure with independent assessments of demand. This assessment will be useful at almost every stage of a regulator's activity. Demand is important in most types of conflicts that have to be resolved through tariffs or quality adjustments. Demand is important when assessing financial support requirements for projects requiring subsidies. Demand is also important in understanding the distributional consequences of any regulatory decision. Demand is finally important every time there is a renegotiation and this means it will often matter because most contracts end up being subject to some degree of renegotiation.

Table 1.1 shows the policy and regulation issues related to the demand forecast in the context of private participation.

1.5 Objectives of this Research

One can think of transportation as a technological behemoth bedeviled by human behaviour. Transportation research contributes technological and management innovations that drive this beast forward, and can also offer insights into the limits that human actors and institutions can impose on implementation of an efficient transportation system. Transportation is affected by human behaviour through its consumers (drivers, riders, vehicle buyers, and shippers); through its managers and workers; and through the policy-makers and voters who determine transportation infrastructure and policy (McFadden, 2007).

Demand forecasting is all about behaviour. The success of any product or service will be determined by its potential to meet customers' expectations. In this sense, a good forecast shall understand the individual choice criteria and model it properly. The behavioural side of transport has been focusing in disaggregated users' choice (particularly modal choice, but also departure time, location, among many others). Also, drivers behaviour has been extensively studied in psychology and accident analysis.

However, in transport demand forecasts, in addition to user's behaviour, the behaviour of at least two more actors should be taken in account. First, the forecaster behaviour. Forecasters can have some individual influence on the study, either by his own opinion about the project, by the external pressure he receives, or by his opinion about his own judgment capacity. Despite of the highly quantitative aspect of demand forecasting, the individual opinion about the chances of success (or failure) of a project can influence the modeling exercise in a way the results best fit the forecaster's expectation. Furthermore, if the forecaster overestimate his own capacity of decide whether a project is good or not, his individual evaluation will be biased.

Second, in particular when there is competition for the market, the project promoter behaviour. Project promoters want to maximise they chances to get the project. In a competition for the field scheme (bids), the bidder may overestimate the demand in order to be reduce the toll included in the bid. This strategic behaviour can introduce a high bias in forecasts

Then we study the user's behaviour at two levels. First, at the aggregated level, we analyze the long term traffic growth and its relationship with the economic growth.

Second, at the disaggregated level, we study the value of travel time savings, the main variable guiding individual mode choice and probably the most important value in socio-economic evaluation as well as in demand and revenue forecast.

In this sense, this thesis intends to represent a small contribution to the understanding and reduction of errors and biases, sources of traffic forecast overestimation in toll motorways. The infinity of sources of errors and biases that can affect traffic forecasts constraints our research to the study of some particular points; the objective of this research is to examine some key points in forecasting. Although many points merit special attention and need developments, our choice in this thesis was guided by the practical needs we have faced in the studies for Cofiroute S.A. (Vinci Concessions) and by the author's insights, focusing in academic innovative topics but which present a high interest for practitioners and decision makers.

Table 1.1: Transport Modelling

Stage	Transport decisions	Policy and regulatory issues in the context of privatization	Modelling
Trip generation	How many trips does the user in some specified location wants to take in day/week/month?	Is there an obvious unmet willingness to pay for and zoning improvements in services which could be met by a new project or a concession to improve existing services?	Land planning and zoning
Trip distribution	Where is the user going with each trip among all possible destinations of interest to the transport service provider?	What would be the optimal size of the project to be packaged for private sector participation?	Origin-Destination matrix
Modal distribution	Which transport mode does the user adopt for each trip? What are the factors influencing that decision and to what extent?	What price-quality combination should the privatization commission aim at and how much margin should the regulator give to the private operator to adjust price and quality given the overall objectives of the "privatization". Also, how much coordination is needed between different modal regulators (if these are at different government levels for instance)?	Demand models (aggregated or disaggregated)
Route allocation	Which route between the origin and the destination does the users pick under various types of service packages?	How do pricing (including access pricing) and quality rules influence the efficient use of the transport infrastructure?	Network simulation models

Chapter 2

Transport Forecasters' Behaviour and overconfidence[1]

Abstract

This chapter presents the results of the first large sample survey on forecasters' perceptions and opinions about forecasting demand for transport projects, based on an on-line survey. We first describe the main characteristics of forecasters, as age, gender, education, working sectors and experience. We then describe the last forecast forecasters prepared in terms of oldness, project's advancement, mode, financing and operation. We turn to the models forecasters apply, the errors they declare on past forecasts and the main sources of errors according to them. We describe the forecast environment in terms of pressure forecasters receive. We then analyse the overoptimistic bias by comparing the distribution of stated errors with actual errors found in literature; we also compare the own skillful of subjects in doing forecasts with studies showing self-evaluations of a common skill - driving. We finally propose a regression of the competence, quality and errors on the main forecasters' and projects' specific variables.

[1]We thank Louis Alligier, whom kindly managed the on-line survey form on his self-developed platform; Michel Bierlaire and Concepción Ramón for their help in diffusing this survey and Sthe'phane Saussier for his helpful comments in a earlier version of this chapter. We gratefully acknowledge all responses received.

2.1 Introduction

As argued before, recent ex-post studies have been showing that demand forecasts for new transport infrastructures present significant differences when compared to ex-post realizations and also that they tend to overestimate the future demand (Flyvbjerg et al., 2003; Standard and Poor's, 2004) and chapter 3 of this thesis.

Moreover, the reliability of transport demand forecasts has been questioned. Trujillo et al. (2002) points that "the field [of transport demand forecasts] still suffers from bad reputation as many analytically advanced studies continue to disappoint, leaving significant wedges between realized and forecast traffic". Flyvbjerg et al. (2006) affirm that " . . . forecasters generally do a poor job of estimating the demand for transportation infrastructure projects".

While many efforts have been done in order to understand and reduce forecast errors by improving methods and by understanding the motivations and rules of strategically playing, not any study has focused on the forecasters' point of view.

In order to better understand forecaster's behaviour, we designed an online questionnaire with the objectives of identify (1) the main characteristics in terms of age, gender, education and experience of forecasters, (2) the characteristics of their last forecast, (3) the models they apply and (4) how they evaluate their results and their performance.

Email invitations were sent to about five thousand transport researchers and practitioners, whatever their field of specialization. We received a total of 307 responses, from which 178 presented a considerable amount of responses and constitute the sample analyzed in this study. As each question was optional, in many cases the total number of responses is inferior to the sample size, so that we specify the sample size for each question.

Section 2 presents the main characteristics of subjects. Section 3 describes the latest transport demand forecast they prepared. Section 4 presents the results about the models they apply. Section 5 discusses the errors in forecast and the sources of these errors according to forecasters. Section 6 presents results regarding the environment in which forecasts are prepared. Section 7 discusses the existence and magnitude of overconfidence in transport forecasts. Section 8 presents the econometric regression of forecasters self evaluation. In section 9 we list the more interesting comments made about the survey. Section 10 briefly concludes the chapter.

2.2 Who Forecasts Transport Demand?

Our sample is composed manly of forecasters working in the USA; they represent 26,4% of subjects. About 13% work in France, 10.6% in the UK, 10% in Brazil and 9% in Spain. Other countries represent less than 5% each. The questionnaire was available only in English and French, what could represent a bias in the origin of subjects. Figure 2.1 shows the distribution of the country where subjects work in.

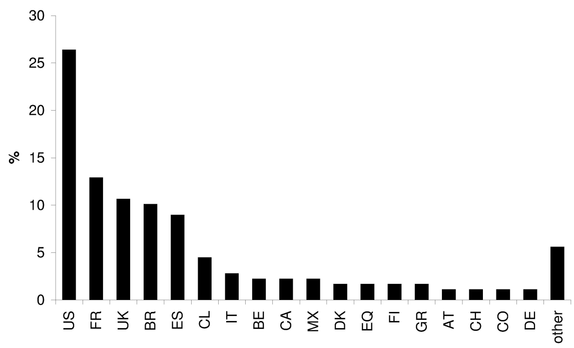

Figure 2.1: In which country do you work?(N=178)

Figure 2.2 shows that the large majority of subjects forecast demand mainly for projects in the country in which they work, emphasizing the local aspect of transport forecasts.

Perhaps the main characteristic of a profession is the diploma giving access to it. A priori, any graduated (or even not graduated) with a quantitative basis can study and develop transport demand forecasts. But in reality, in which discipline are the forecasts graduated?

Figure 2.3 shows that transport demand forecasting industry is dominated

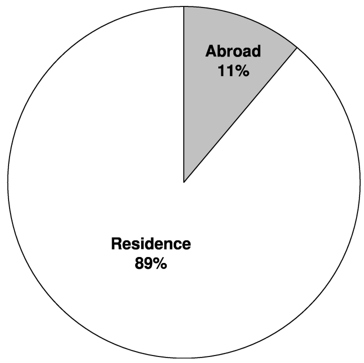

Figure 2.2: Location of the projects.(N=178)

by engineers; they represent 60% of the sample. Economists represent 20%, and other filds sum up 20%. Despite the multidisciplinary characteristic of transport, transport studies are mainly taught as a specialization in engineering schools, especially the forecast techniques, which is highly quantitative, rich in mathematical and statistical models.

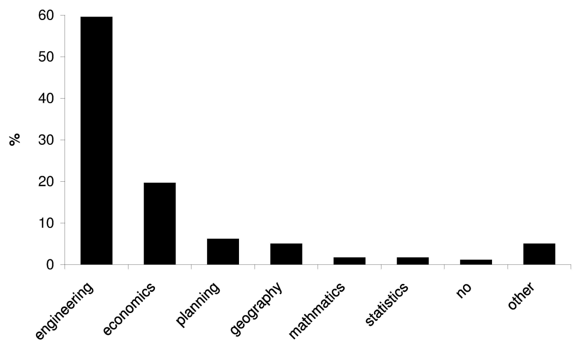

Figure 2.3: Universitary Degree.(N=178)

Furthermore, most forecasts hold a post-graduate degree. 47% hold a master degree and 40% a PhD as we can see bellow in figure 2.4. This result is very correlated with the fact that transport studies are specializations and that most forecasters are academicians.

The academic sector concentrates the largest share of our sample; they are

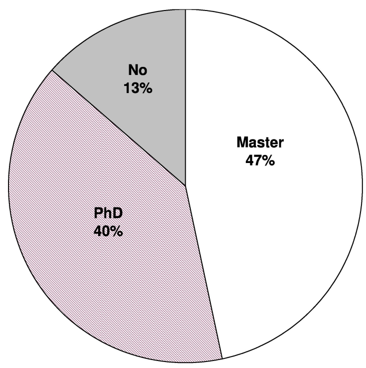

Figure 2.4: Post-grad degree. (N=178)

almost 30% working in a university or research centre (figure 2.5). Moreover, subjects working simultaneously in the academic and in another sector represent 13% of the sample. Consultancy firms employ about 25% of forecasters and the government 21%. Public and private companies represent less than 5% each.

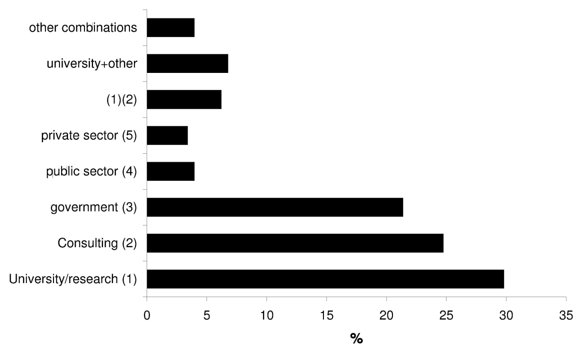

Figure 2.5: Sectors forecasters work in.(N=178)

Gender distribution is far from equilibrated among forecasters. Women represent only 16% of the sample (figure 2.6); this share is however comparable with the concentration of women in most engineering schools.

Regarding the age, a quite uniform distribution is found between 25 and 55 years, decreasing after (figure 2.7). The average age is 45 years.

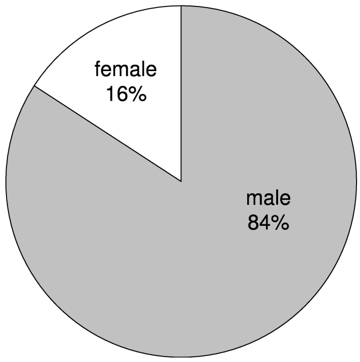

Figure 2.6: Gerder distribution.(N=178)

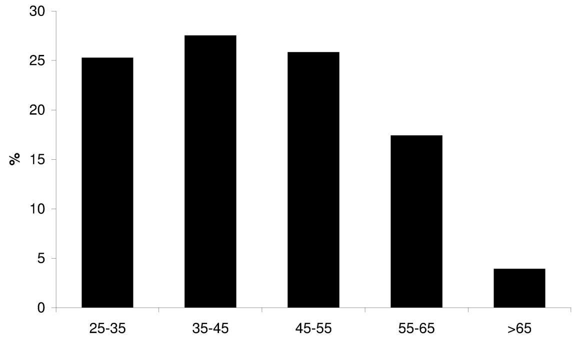

Figure 2.7: Distributions of respondents' age. (N=178)

If we could caricature an "average" forecaster, he would be a 45 years old male engineer and hold a post-grad diploma.

2.3 The Latest Forecast

This group of questions regard the latest study the forecaster prepared. We can see (figure 2.8) that 36% of them were prepared less than one year ago; another 36% between one and three years ago.

Figure 2.9 shows that 40% of subjects declare the latest project for which they forecast demand has already been launched. Almost 27% of them affirm

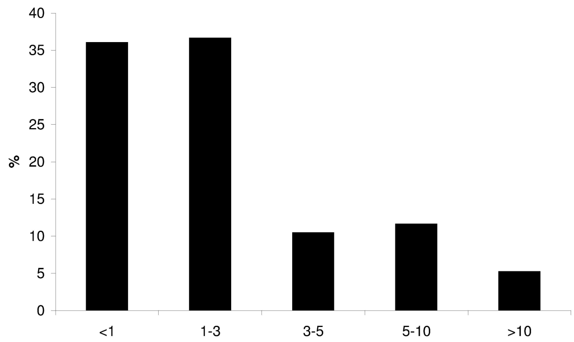

Figure 2.8: When did you prepare your latest forecast? (N=172).

that it has not yet been launched, but it is planned to be. 26% are not sure about the future of the project and only 7% declare that the project will certainly not be launched.

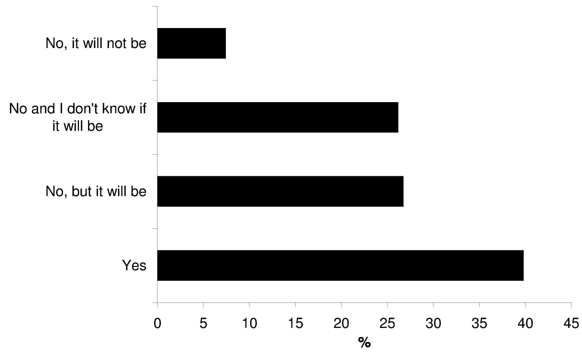

Figure 2.9: Has the project been launched?(N=176)

The road transport responds to the higher number of traffic forecast studies (figure 2.10). This number (about 45%) corroborates the idea that despite the effort to develop alternative modes, the road transport still captures the largest share of investments in most countries.

Despite the increasing participation of the private sector in financing new transport infrastructures the pure private financing represented only a small share of the latest project forecasters in our sample were involved in (figure

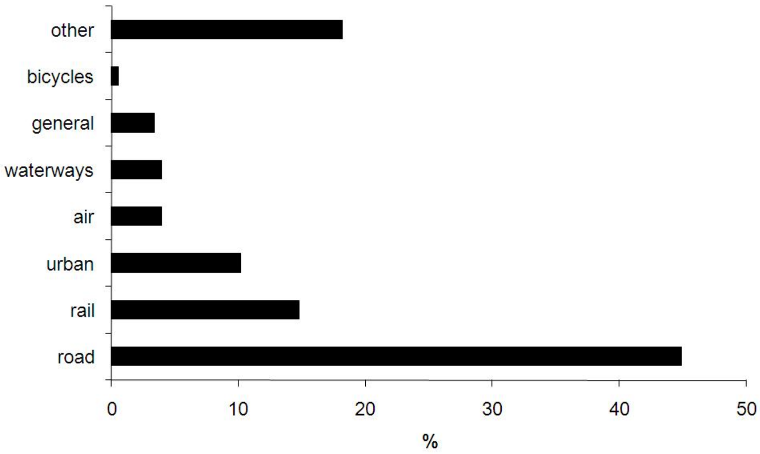

Figure 2.10: Modes in the last forecast.(N=176)

2.11). Mixed financing represented about 25% and pure public forecast represents the largest share with about 65%.

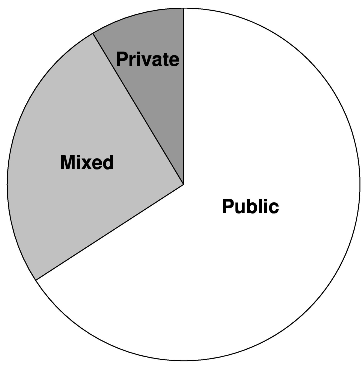

Figure 2.11: Financing.(172)

In terms of operation (figure 2.12), the scenario is quite similar; public operation represents 70% of the sample. We can deduce that most mixed financed projects are private operated.

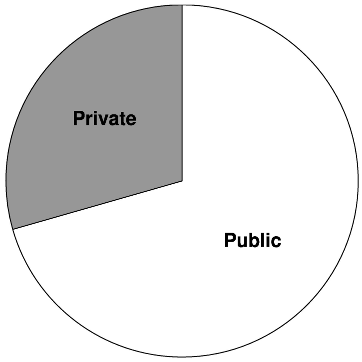

Figure 2.12: Operation. (N=167)

2.4 Models

Among the number of questions about the methods transport forecasters apply, we focus here on those related to the value of time and the traffic growth since they have been pointed as major sources of demand overestimation (Flyvbjerg (2005); Hensher and Goodwin (2004); Hensher and Greene (2003); Standard and Poor's (2005), chapters 4 and 5 of this thesis).

45% of respondents affirm they use distributed values of time in their studies (figure 2.13). We failed in this survey, however, to identify whether what is said as "distributed value" corresponds to random or systematic variations.

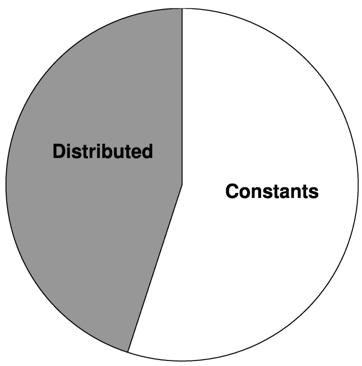

Figure 2.13: Constant x Distributed VTTS. (N=153)

More than a half (58%) claim that the traffic growth is more difficult to forecast than the initial traffic (figure 2.14). This result can appear contradictory with the standard practice in forecasts since forecasters usually spend much more effort to estimate the initial traffic (base year) and apply growth rates on the socio-economic variables, usually produced by other institutes or government agencies.

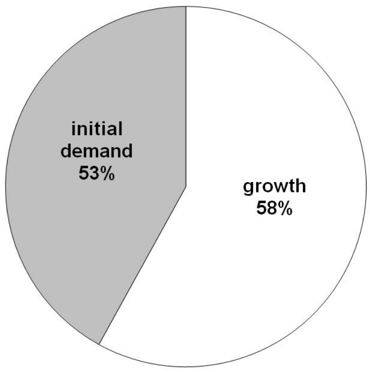

Figure 2.14: initial *versus* growth in demand forecasts. (N=162)

Despite the recent advances in discrete choice modeling, including mixed logit and Bayesian estimations, almost 50% of subjects apply aggregated modal share models (figure 2.15).

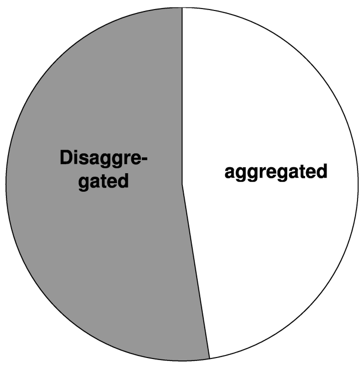

Figure 2.15: Aggregated or disaggregated modal share.(N=156)

The use of sequential models (4-step like) is predominant since 41% of forecasters declare they apply mainly sequential methods (figure 2.16). 31% use mainly tendencies such as time-series extrapolation and estimation of elasticities. 12% affirm they use mainly activity-based models. This result show the increasing role of this kind of model.

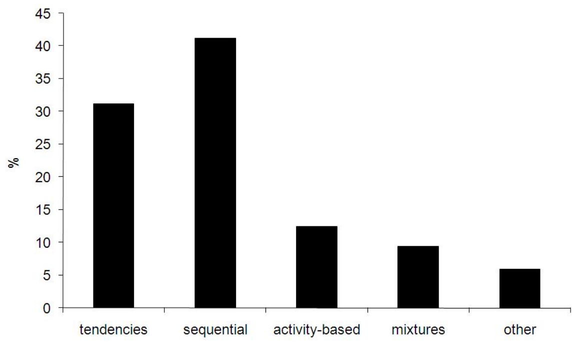

Figure 2.16: Models forecasters apply. (N=170)

2.5 Forecast Errors

Figure 2.17 shows the distributions of stated latest forecast error. This error is measured as $((Actual - Forecast)/Actual)$. About 42% of forecasters declare that they overestimated traffic in their last forecast; 8% that they precisely forecast (less than 5% of error) and 50% that they underestimated the traffic. Moreover, 88% declare they error was within the ± 20% interval. These results are quite divergent from the results of the ex-post analysis presented in the introduction of the paper.

Another interesting question about the last forecast would be its horizon, as noted by one respondent, since the difficulty associated to a forecast depends on its time horizon.

Most of respondents (52%) consider their average results are "good". 19.7% declare they judge their results "very good" and another 19.7% consider their average results as "fair". Less than 5% consider their results either excellent or poor. While the scale was originally designed to be symmetric around "fair" we can see that results are almost perfectly symmetric around "good"(figure 2.18).

Also, 45% of them declare in average their forecasts are equally distributed

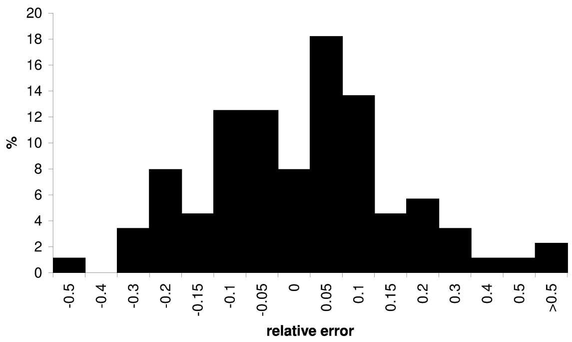

Figure 2.17: Stated error in the latest forecast.(N=88)

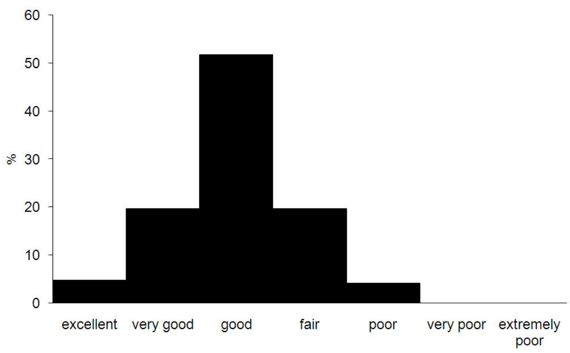

Figure 2.18: Perception of own's quality of results. (N=147)

between over and underestimation. 37% declare in they more underestimated traffic and 18% that their forecasts were in average higher than actual traffic (figure 2.19). This result also contradics the current ex-post results.

2.5.1 Sources of Errors

Although many theoretical and applied research are devoted to the improvement of transport (and marketing in general) forecasting, it's very difficult to evaluate which topics, models or issues merit more attention. In this survey, we identify the sources subjects in the sample judge the most important. The question took form of a opened question so that subjects were free to declare what they wanted. This procedure prevents the risk of too limited possibilities. The responses were then regrouped in "groups of sources". Results are

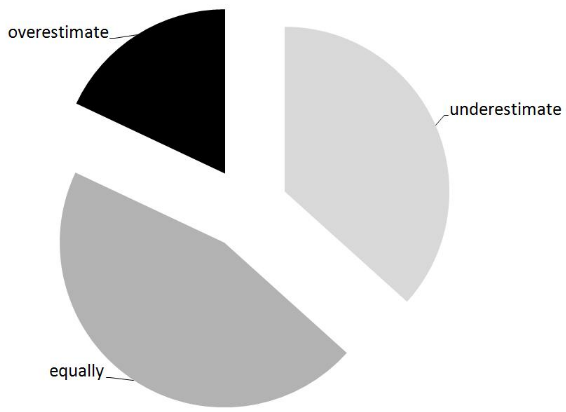

Figure 2.19: Average distribution of under/overestimation.(N=150)

presented in table 2.1.

Issues related to models and modeling are pointed as the main sources of uncertainty in traffic forecasts. Within this category, modelling errors and land use changes or spatial interactions are pointed as the most important. Great attention is given also to value of time issues and to the lack of behavioralism of models.

Data is viewed as a very important issue. This result regarding the lack and the low quality of data shows that in transportation analysis, not only the future is uncertain but also is the present.

Exogenous and behavioral sources are substantially less evocated, despite the responses regarding the difficulty to forecast traffic growth they declare and the importance of strategic manipulation pointed out by ?????.

2.6 Forecast's Environment

Pressure for a given result seems to be common in transport forecast. Actually, project promoters have "a prioris" about what traffic will be and that they would like it to be. Groups of pressure, for or against the project can also rely in the expected (according to their own interest) traffic level to advocate in favor or against the project. High traffic level roads for example means higher socio-economic benefits but also more external costs (noise, pollution,. . .). These expectations may influence, directly or indirectly, the forecaster.

Moreover, it's been recently argued that private projects promoters tend to overestimate traffic in terms to be sure they will get the project, as discussed in the precedent chapter. In order to identify the role of pressure in forecasts we asked with which frequency forecasters fell under pressure. We can see in the figure 2.20 that few forecasters (25,6%) declare they are rarely or never under pressure.

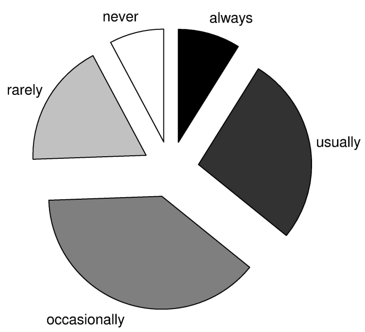

Figure 2.20: Forecasters under pressure. (N=168)

However, when asked whether they could produce better forecasts in absence of pressure, the result is ambiguous. We can see in figure 2.21 that 33% are sure that yes, they could produce better forecasts if they wouldn't fell under pressure. 40% say no, so they view pressure as positive, and 27% do not know if they prefer work under pressure or not.

Between the technical study and the final forecast adopted for decision, the client can modify the results (directly or by influencing the forecaster) in order to suit his own interests. This is called strategic manipulation. We asked how important (in terms of impact on the final result) is the role of strategic manipulation according to forecasters (figure 2.22).

We can see that about 45% of subjects judge the strategic manipluation important or very important and other 42% that it is somewhat important. Only 12.3% believe that the strategic manipulation is insignificant. In the next chapter, the bidding behavior and its relationship to the strategic manipulation will be analysed.

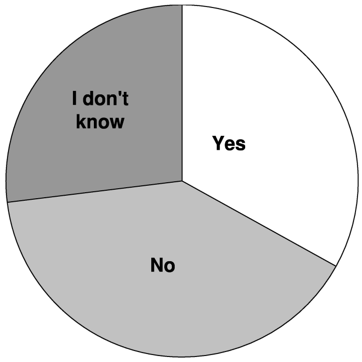

Figure 2.21: Would they produce better forecasts without pressure? (N=167)

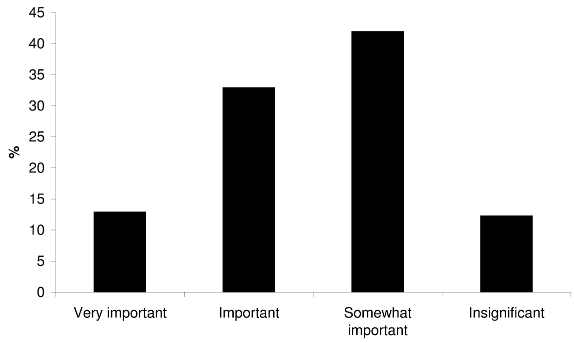

Figure 2.22: Role of strategic manipulation.(N=155)

Also, we asked for an appreciation of the sense in which this strategic manipulation plays (if it tends to increase the level of traffic (overshooting) or decrease (undershooting)). We can see in figure 2.23 that in the large majority of cases, forecasters affirm that strategic manipulation plays in the sense of overestimate demand. This result corroborates the empirical evidence of strategic manipulation in order the make projects look more attractive or increase the probability of winning an auction.

The demand forecast is supposed to be the main variable influencing the decision to go ahead with a project or not. But in many cases the influence of the technical study on the final decision is not always clear. Decisions are

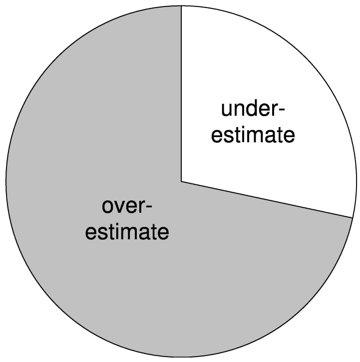

Figure 2.23: Sense of strategic manipulation.(N=134)

in many cases a matter of politics and driven by a multitude of interests. The question here is to identify, according to forecasters, the role of the technical study on the final decision making. A strong influence means that most of projects with high traffic levels are launched and most of projects with low traffic levels are not, more precisely, "absolute" means that decision takers always follow forecasts and "weak" that decision takers rarely follow forecasts (figure 2.24).

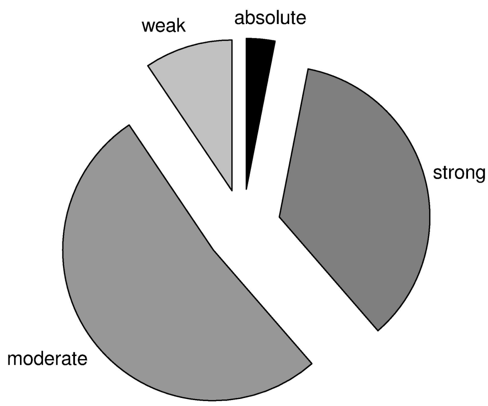

Figure 2.24: Influence of the technical study on the decision. (N=158)

We can see that most forecasters judge the role of their studies as "moderate", so that the traffic forecast is viewed as a piece among others of the decision process. A big share of forecasters considers the importance of forecast as "strong"; they believe forecasts play a major role in decision making.

Figure 2.25 report the responses on whether forecasts knew, with a good precision, the minimum traffic level necessary to attain the requested level of return. Results indicate that most of times forecasters know the profitability level of the projects they study. This result is very intuitive since except for particular projects, forecasters have a good idea of the economic costs of the projects and some times the same person makes the forecast study and the economic/financial evaluation.

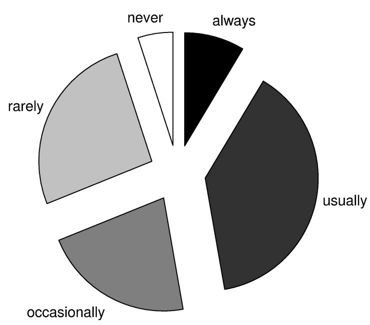

Figure 2.25: Knowledge of the minimun demand level. (N=161)

2.7 Overconfidence in Transport Forecasts

Individual's expectations play an important role in most decision environments. As such, the presence of any bias in subjective expectations can affect many economic outcomes.

The results about the forecast errors and quality of results suggest that forecast may be falling in an overoptimistic bias. The tendency to be overoptimistic is perhaps the best documented of all psychological errors (Montier, 2002). Psychological studies demonstrate that most individuals are overconfident about their own abilities, compared with others, as well as unreasonably optimistic about their futures (e.g., Taylor and Brown (1988); Weinstein (1980). When assessing their position in a distribution of peers on almost any positive trait such as driving ability or income prospects, most of people say they are in the top half (Svenson, 1981).

There are interesting exceptions. For many traits, women are not optimistic (and even pessimistic; e.g., Maccoby and Jackli (1974), and clinically depressed patients are not optimistic (e.g., Alloy and Ahrens (1987). The latter finding calls into question the common psychiatric presumption that "realistic" people are well-adjusted and happy and also raises the question of whether optimism might be evolutionarily adaptative (Tiger, 1979).

Overconfidence is, in behavioral economics, used as a common label to: too narrow confidence intervals, self serving bias, illusion of control and optimism. Some of the main studies in overconfidence are related below.

- People are overly optimists about their own ability as compared to others. 80% of drivers in Texas believe their driving ability is above the average (Svenson, 1981);

- People are aware that half of US marriages fail but are convicted theirs won't fail (Lehman and Nisbett, 1985).

- People name dramatically too narrow confidence intervals for their estimates (Alpert and Raiffa, 2007)

- Professional managers perceive their judgment to be too exact. (Russo and Shoemaker, 1992)

- Illusion of control: people strongly prefer lottery tickets that they picked themselves as compared to randomly assigned ones.

- People believe favorable events are more likely then they actually are;

- Dubra (2004) looks at the role of overconfidence in a labour market search problem and finds that overconfident agents tend to search longer as they overestimate the chances to find a better offer.

- CEOs who have chosen an investment project are likely to feel illusion of control and to strongly underestimate the likelihood of project failure. (Langer, 1975; Weinstein, 1980; March and Shapira, 1987). Cooper et al. (1988) look at entrepreneurs who overestimate their chances of success with their business. In their sample of 2994 entrepreneurs 81% believe their chances to survive are better than 70% and 33% believe they will survive for sure. In reality 75% of new ventures did not survive the first 5 years.

- Schultz (2001) addresses the point that despite dramatic progress in consumer research product failure rates have remained on a high level. He argues that overconfidence might account for the fact that managers constantly overestimate the success chances of their projects which leads to constantly high product failure rates despite better marketing research techniques.

- Frank (1935) and Weinstein (1980) provide evidence that people are especially overconfident about projects to which they are highly committed. This would be a rationale for a forecaster regarding his own projects.

When evaluating past events, past errors or difficulties tend to be minimized while past success, maximized. This phenomenon is usually referred to as "Memoria Praeteritorum Bonorum", or Rosy retrospection (Mitchell and Thompson, 1994). The effect refers to the finding that subjects later rate past events more positively than they had actually rated them when the event occurred. In this study we can not estimate this effect, but we should have in mind that it affects the judgment forecasters make of a past forecast.

We first compare the error subjects declare about their last forecast with the results in literature[2]. We can see in figure 2.26 and table 2.2 that forecasters tend to underestimate the magnitude of the errors (low standard deviation) and that they judge they symmetrically under- and over-estimate traffic while in practice overestimate prevails. While ex-post studies show that the share of forecasts within the interval of 10% error is inferior to 50%, forecasters evaluate

[2]The three studies used as reference include only roads and motorways. However, if we consider only the results for roads and motorways in our sample, the distribution of errors do not change significantly.

it at 65%. The *t-test* on the difference of the means shows that the mean of the survey results is different of each other (at less than 1% significance level when compared to samples in S&P and in chapter 3 and at 6% when compared to Flyvbjerg's sample).

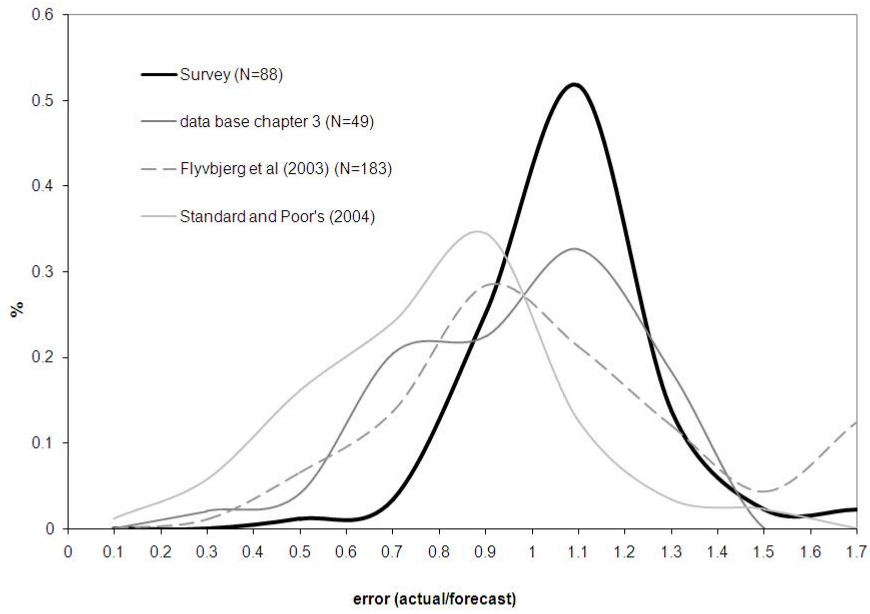

Figure 2.26: Distributions of forecast errors.

When asked to class themselves, compared with forecasters in transport known to them, according their level of competence (in a percentile scale, where higher percentiles represent better forecasters), we can see a skewed distributions in the sense of overestimating the own abilities, or a self-serving bias. The results presented in figure 2.27 show that transport forecasters tend to be overconfident about their skills.

However, as argued before, overconfidence is a normal psychological trait, so the results regarding overconfidence should be viewed with caution. In order to have a relative measure, we compare the self-evaluation of forecasters with that of car drivers. The most common and best known example of overconfidence is that of drivers skillfulness; most drivers tend to believe that they are better than the average driver, so in order to give a basis of comparison for our results about the level of competence of forecasters, we compare our results with those of (Svenson, 1981) for American (Texan) and Swedish drivers. The

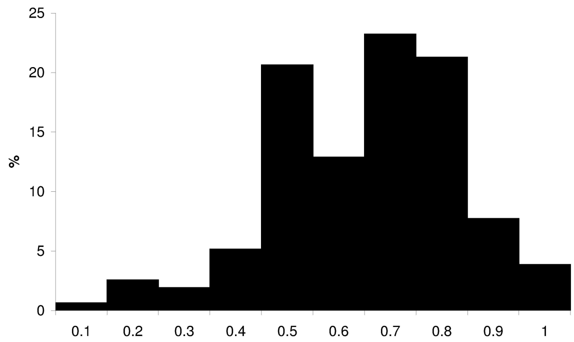

Figure 2.27: Self-evaluation of competence level.(N=155)

distributions are shown in figure 2.28. Table 2.3 compares the median, mean and standard deviations of these distributions.

From a visual inspection of the histograms, it is hard to conclude something. We can see that whatever the curve, few subjects class their ability inferior to 0.4. Results from table 2.3 show that we cannot affirm that transport forecasters are more overconfident than drivers (we could say, in turn, that they are substantially less that the Texan one). A test on the difference of the means confirm this result. The mean in our sample is statistically different from the Texan drivers but not from the Swedish sample.

2.8 Econometric Analysis of Biases

Many personal characteristics may affect the self-evaluation. In order to test for gender effect, experience, education and professional biases we regress the competence and the quality of results on the characteristics of the forecaster.

We can see that the age, the experience and the variable accounting for the academic sector are the only significant variables. Elder and more experienced forecasters tend to more valuate their competence. Forecasters working in the academic sector are more humble than the average. The experience seems to be the only significant variable driving the self-appreciation regarding the quality of own results.

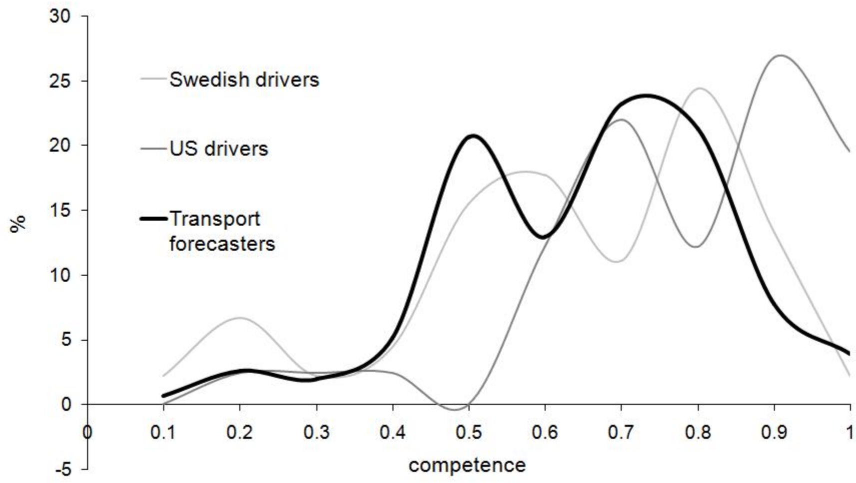

Figure 2.28: Distributions of self-evaluations.

To estimate the factors affecting the error in the last forecast, we add the project's specific characteristics and compute the squared error. We also added the competence, pressure and importance of strategic manipulation. Analyzing the significant variables (starred) we can see that forecasters using Activity-Based models declare a higher error. The error tends to reduce with the level of competence forecasters self-evaluate.

More interesting, the error tends to increase as the perception of the importance of strategic manipulation of results increases. This result corroborates recent studies pointing out that traffic forecasts are strategic variables subject to manipulation.

As one could expect, there is a correlation between the level of competence and the quality of results subjects declare (-0.44). Moreover, we can identify a relationship between the competence (or the quality of results) and the error in the last forecast. The direction of the relationship is not evident; do forecasters base their self evaluation in their last result or do they bias their error according to their self-evaluation?

2.9 Comments Uncommented

We received many comments, on the survey and on problems related to forecasting and forecasters. We reproduce some of these anonymously below.

> "Manipulation by politics is massive. If you are not willing to fit to the order to the expectations you will in future not receive new contracts. Most of people are not willing to see developments which are not favorable..."

> "About what? The fact that Parsons Brinckerhoff is paid $30 million to develop a demand model that is so fucked up it takes $3 million to apply it to a single project? And they continue to get paid for this shabby work? There are dozens of examples just in the NY metro area. It is disgrace."

> "Of course forecasters do not like their work being evaluated. Who does? And if there were no good forecasts, how could governments justify spending other people's money? Are not forecasts better when private investment is involved? (I know the Channel Tunnel is an exception to the last statement)."

> "Clients may try to influence the results but practitioners can successfully resist this if they have sufficient experience. Experience is of paramount importance. Excessive belief in models, in particular disaggregate ones, is a most dangerous trait and a risk to good forecasting."

> "I think this questionnaire is slightly biased against forecasting the changes due to road projects. The impact on public transport forecasts are complete opposite to highway forecasts especially in muti-modal models. Also there is bias towards more application oriented practically used models, there are modeling exercises carried out in the academia which would have a very different view of the forecasting mechanism."

> "Incorrect assumptions regarding the value of time or the value of predictability of travel time. There is too much faith in analytical forecasting models, and not enough attention to researching and collecting existing travel behavior data. This seems to be true especially in France, where analysts who get trained at the Grandes Ecoles get very excited about complicated theoretical models, but neglect collecting simple data on existing behavior..."

2.10 Conclusions

We presented here the results of the first large sample survey on forecasters' characteristics and their opinions about forecasting demand for transport projects, based on an on-line survey. Results describe which are their main characteristics, details about their latest forecast, the models they apply, the forecast errors they declare and the main sources of errors according to them and the environment these forecasts take place in terms of pressure forecasters receive. These unique results provide a picture of the world of forecasters and forecasts, allowing for a better understanding of them.

We turned then to the study of the optimism and overconfidence in transport forecasts. Optimism and overconfidence in general are recognized human traits; most of us are overconfident about our own abilities and overoptimists about the future. There is also a growing literature in behavioral economics and finance arguing that the role of optimism in economic decisions and economic forecasts is not negligible.

We analyzed the overoptimistic bias by comparing the distribution of stated errors with actual errors found in literature; we also compare the own skillful of subjects in doing forecasts with studies showing self-evaluations of a common skill - driving. We finally propose a regression of the competence, quality and errors on the main forecasters' and projects' specific variables.

Results show that the distribution of errors transport forecasters state has a smaller average magnitude and a smaller variance than those found in literature. Comparing forecasters perception of their own competence with the results found in literature about drivers skill self-evaluation, however, we could not find a significant difference, meaning that the forecasters' overconfidence is in line with what could be viewed as a normal human overconfidence level.

The regression analysis finds that elder, more experienced forecasters working in the university tend to more valuate their competence. Also, the experience seems to be the only significant variable driving the self-appreciation regarding the quality of own results. There is also a relationship between the stated error in the last forecast and their self-evaluation about competence. Moreover, the forecast error tends to increase as the perception of the importance of strategic manipulation of results increases. This result corroborates recent studies pointing out that traffic forecasts are strategic variables subject to manipulation.

The pressure for results forecasters receive and the strategical manipulation they affirm exist merit a special attention. They imply that while forecasters' behavioural biases may exist and should be take in account when evaluation forecasts, the project promoter may influence forecasts by pressuring the forecasters to produce results which better fit his expectancies. The bidders strategic behaviour in the context of an auction for a road concession contract will be studied in the next chapter.

Table 2.1: Sources of errors.

Group	Type of error	Representative responses
Exogenous sources (21)	Socio-economic growth (16)	"uncertainty about the future of the economy"
	Uncertainty/ exogenous factors (3)	"future and exogenous factors affecting the traffic"
	Political uncertainty (2)	
Data (47)	Availability and accuracy (32)	"the accuracy of the data used"
	Errors in collecting data, designing surveys and sampling (9)	"not enough time to collect data"
		"The input data. Rubbish in, rubbish out."
	Insufficient time or budget to collect (6)	
Models (104)	Modeling errors (17)	"modeling assumptions"
	Land use changes; spatial interactions (17)	"poor land use forecasts"
	Choice models and Value of Time (13)	"modal split assumptions"
	Lack of behaviouralism (12)	
	Induced traffic (9)	
	Extrapolations of trends (7)	
	Errors in the initial scenario (6)	
	Transfer models/parameters (5)	
	Elasticities (4)	
	Matrices estimation and evolution (4)	
	Other (10)	
Behavior (17)	Pressure of clients (4)	"pressure of the client for good results"
	Strategic manipulation (6)	"personal perception"
	Personal optimism (4)	
	competitor' strategies (3)	

Table 2.2: Comparing ex-post and revealed errors

	Survey	Chapter 3 sample	Flyvbjerg et al (2003)	Standard and Poor's (2004)
0.9-1.1	0.65	0.33	0.5	0.47
overestimated	0.5	0.67	0.5	0.88
mean	1.02	0.87	1.09	0.77
median	1.02	0.91	0.9	0.7
std dev	0.18	0.22	0.44	0.26
N	88	49	183	87

Table 2.3: Comparing drivers and forecasters skilful

	Mean	Median	std	>0.5 (%)	N
US drivers	0.78	0.7-0.8	0.19	92.7	81
Swedish drivers	0.64	0.5-0.6	0.22	68.7	80
Transport forecasters	0.65	0.7-0.8	0.18	69	88

Table 2.4: Impact of the main characteristics on self-evaluation.

	Competence	Quality	squared Error
Gender (male=1)	0.032	-0.150	0.031
	(0.92)	(-0.68)	(1.16)
Age1 (35-55 =1)	0.033	0.031	0.008
	(1.09)	(0.18)	(0.41)
Age2 (>55=1)	0.092**	-0.117	0.009
	(2.15)	(-0.51)	(0.35)
Experience (low=1)	-0.146***	0.386**	0.005
	(-5.2)	(2.47)	(0.32)
Engineer	0.006	0.058	0.001
	(0.23)	(0.4)	(0.06)
Master	-0.008	-0.004	-0.015
	(-0.2)	(-0.02)	(-0.59)
PhD	0.041	-0.165	0.005
	(0.85)	(-0.60)	(0.21)
Univ/research	-0.097***	0.050	-0.001
	(-2.64)	(0.23)	(-0.06)
Consulting	-0.001	-0.026	0.011
	(-0.04)	(-0.13)	(0.49)
Government	-0.045	0.167	-0.007
	(-1.09)	(0.70)	(-0.27)
HIC	-	-	0.01
			(0.55)
Road	-	-	-0.011
			(-0.74)
Private Operated	-	-	-0.008
			(-0.48)
Tendencies	-	-	0.018
			(0.75)
Sequential	-	-	0.021
			(0.87)
Activity-based	-	-	0.049*
			(1.86)
Choice (disag=1)	-	-	-0.002
			(-0.16)
Value of time (distr=1)	-	-	-0.005
			(-0.31)
Competence	-	-	-0.1**
			(-2.00)
Pressure	-	-	-0.006
			(-0.90)
Manipulation	-	-	0.016*
			(1.75)
Intercept	0.70	2.89	0.033
	(11.17)	(7.74)	(0.54)
R2	0.31	0.07	0.29
Adjusted R2	0.26	0.01	0.005
N	155	147	74

Chapter 3

Number of Bidders, Information Dispertion, Renegotiation and Winner's Curse in Toll Road Concessions [1] [2]

[1]We gratefully acknowledge comments and suggestions from Claude Abraham, David Azema, Steven Berry, Luis Cabral, Eduardo Engel, Antonio Estache, Elisabetta Iossa, Philip Haile, Gabriel Jacondino, Rui Manteigas, Rui Montero, Homero Neves, Charles Paradis, Vincent Piron, Maher Said, Stéphane Saussier, Karl Schlag, François Tcheng, Jose Vassallo, Anne Yvrande, and participants at the European Group of Public Administration (EGPA) Conference, Milan, September 6-9 2006, 24th Pan-American conference on Traffic and Transportation Engineering, Spain, September 20-23 2006, 5th conference WIP, Berlin, October 06-07 2006, the ATOM and ADIS Research seminars, the CEPR-EBRD conference, "Partnerships between Government and Private Sectors", London, 22-23 February 2007, the Prospectus Workshop in Industrial Organization, Yale University, February 27 2007, the 5th IIOC annual conference, Savannah, USA, April 14-15 2007, the 62nd annual congress of the ESEM (European Meeting of the Econometric Society), Budapest, August 27-31 2007, and the 56th annual congress of the AFSE, Paris, September 19-21 2007.

[2]A short version of this chapter was accepted to the Economics Letters

Abstract

We empirically assess the effects of the winner's curse in auctions for toll road concession contracts. Such auctions are common-value auctions for incomplete contracts prone to pervasive renegotiations. We address three questions in turn. First, we investigate the overall effects of the winner's curse on bidding behaviour in such auctions. Second, we examine the effects of the winner's curse on contract auctions with differing levels of common-value components. Third, we investigate how the winner's curse affects bidding behaviour in such auctions when we account for the possibility of renegotiation. Using a unique, self-constructed, dataset of 49 worldwide road concessions, we show that the winner's curse effect is particularly strong in toll road concession contract auctions. Thus, we show that bidders bid less aggressively in toll road concession auctions when they expect more competition. In addition, we observe that this winner's curse effect is even larger for projects where the common uncertainty is greater. Furthermore, we show that the winner's curse effect is weaker when the likelihood of renegotiation is higher, *i.e.* bidders will bid more strategically in weaker institutional frameworks, in which renegotiations are easier.

3.1 Introduction

Competition for the field, or franchise bidding, has become increasingly popular to expand private participation in the provision of infrastructure services. Under such auctions, the State or a representative (local public authorities) awards an exclusive contract to the bidder offering the lowest price after an ex ante competition. Since the seminal paper by Demsetz (1968), this policy option has been considered as a tool of government to allow private sector participation and benefit from efficiency advantages of competition while retaining some degree of control and guaranteeing the respect of community service obligations (Baldwin and Cave, 1999; Engel et al., 2002). The fact is that in the last couple of decades, many countries have promulgated directives on public procurement so as to bring in competitive tender mechanisms, e.g. the Federal Acquisition Regulations' mandate to use auctions in the U.S. public sector, the 1989 European directive on the obligation of competitive tendering, the 1988 Local Government Act in the United Kingdom or the 1993 "Sapin Act" in France.

The main economic literature emphasizes that the efficiency of this awarding procedure depends on the number of bidders. Nevertheless, the optimal number of bidders will depend on the exact structure of demand and information (Athey and Haile, 2007).

According to the Walrasian analogy of markets as auctions, an increase in the number of bidders should encourage more aggressive bidding, so that in the limit, as the number of bidders becomes arbitrarily large, the auction approaches the efficient outcome. But, while this may be true in private value auctions[3] ,*i.e.* for auctions in which a bidder's estimate is affected only by his own perceptions and not by the perceptions of others, it has been shown that it may not be true in common-value auctions in which the competing bidders are differentially (but incompletely) informed about the value of the auctioned item. If bidders shared the same information, they would equally value the item of the auction. [4]

[3] Even though Pinkse and Tan (2000) and Compte (2002) challenged this traditional view respectively in affiliated private-values models and in private-values models with prediction errors.

[4] Consider a bidder i of an auction who has a cost c_i associated with completing the project being auctioned. This bidder receives a private signal x_i about c_i . In the pure

A distinctive feature of common-value auctions is the winner's curse, an adverse-selection problem which arises because the winner tends to be the bidder with the most overly-optimistic information concerning the value (the first formal claim of the winner's curse was made by (Cappen et al., 1971), three petroleum engineers, who argue that oil companies had fallen into such trap and thus suffered unexpected low profit rates in the 1960's and 1970's on OCS lease sales "year after year"). Thus, bidding naively based on one's information would lead to negative expected profits, so that in equilibrium, a rational bidder internalizes the winner's curse by bidding less aggressively. In other words, bidders must bid more conservatively the more bidders there are, because winning implies a greater winner's curse. The greater the level of competition, the worse the news associated with winning (Milgrom, 1989; Bulow and Klemperer, 1999; Hong and Shum, 2002; Haile et al., 2003; Hendricks K. and Porter, 2003).

Thus, in common-value auctions, an increase in the number of bidders has two counteracting effects on equilibrium bidding behaviour. First, the increased competition leads to more aggressive bidding, as each potential bidder tries to miximise her chances of winning against more rivals: this is the *competitive effect*. Second, the winner's curse becomes more severe as the number of potential bidders increases, and rational bidders will bid less aggressively in response: this is the *winner's curse effect.* [5] If the winner's curse effect is large enough, i.e. more than compensates for the increase in competition caused by more bidders, prices could actually rise - in the context of procurement auctions - as the number of competitors increases. As a result, governments should restrict entry, or favour negotiations over auctions (Bulow, J. and Klemperer, P., 1996; Hong and Shum, 2002) when the winner's curse is particularly strong.

In this chapter, we empirically assess the impact of the number of bidders on bidding behaviour in the particular case of toll road concession contract auctions (highways, roads, bridges, tunnels). In these contracts, concessionaires undertake the design, building, financing and operation of the relevant

private-value paradigm, $x_i = c_i \forall i$ (*i.e.* each bidder knows his true valuation for the object) while in the pure common-value paradigm, $x_i = c \forall i$ (*i.e.* the value of the object is the same to all bidders, but none of the bidders knows the true value of the object).

[5]Thus, what is called winner's curse effect in the rest of the paper is actually the internalization of the winner's curse.

facility and their main source of revenue are the tolls that they can charge to users for the whole length of the concession. While there have been some empirical studies on the impact of the number of bidders on prices (Bulow and Klemperer, 1999; Gomez-Lobo and Szymanski, 2001; Hong and Shum, 2002) or on the impact of public information on bidding (De Silva et al., 2005) in procurement contract auctions, there has been, to our knowledge, no such analysis on concession contract auctions whereas these auctions are special in numerous ways and should deserve a special attention.

First, the stakes involved in such auctions are large since it has been recognised that infrastructure levels and quality significantly matter for economic growth and poverty alleviation. There are many of empirical studies illustrating the impact of infrastructure on economic growth, among the more recent are Canning (1998), Calderon et al. (2003) and Calderon and Serven (2003). These studies show that a 1 percent increase in the stock of infrastructure can increase GDP by up to 0.20 percent. In response to this and given the scarcity of public funds, most countries have been turning to the private sector for financing and operation of infrastructure services. Most often, as explained above, they award these services contracts via low-bid auctions, so there appears to be important efficiency and revenue lessons to be learned from the results.

Second, they are common-value auctions. In fact, uncertainty about future traffic - forecasting errors and associated risks are characteristics of infrastructure projects, the differing access to information about future states of the world across bidders, and their differing models, lead to common values.

Third, within the set of such auctions, projects appear to differ significantly in the level of common uncertainty associated with traffic forecasts. There are two main factors that can reduce the level of contract valuation common uncertainty: the public release of information about future traffic, and the length of the facility. As the theory suggests that the effects of the winner's curse should be more apparent in auctions with a greater degree of common uncertainty (Milgrom and Weber, 1982, theorem 16), these auctions permit the estimation of the importance of information dispersion relative to traffic uncertainty in these settings.

Finally, but perhaps more interestingly, a particular characteristic of such auctions is that they are for public private contracts, which potential for renegotiation becomes to be highlighted for less developed countries (Guasch et al., 2003, 2005; Estache, 2006; Guasch, 2004; Laffont, 2005), but also for developed countries (Gomez-Ibanez and Meyer, 1993; Engel et al., 2003, 2005, 2006; Athias, 2006), and clearly contributes to the inefficiency of PPPs. Imperfect enforcement leading to renegotiations is therefore a major characteristic of these contracts, which can strongly question the theoretical effects pointed out above. In fact, these effects stand under the classical assumption that bidders are able to commit with bidding promises. One obstacle to the theoretical conclusions may be the realization by the intelligent bidder that the contract price may later be subject to profitable renegotiation. This fact affects bidding behaviour in subtle ways, and may strongly question the two theoretical effects highlighted above (Milgrom and Weber, 1982).

In order to consider the empirical importance of these considerations, we collected original data, although very difficult to obtain, on the difference between the actual traffic and the traffic forecast included in the winning bids, for 49 worldwide toll road concession contracts. Thus, we use the availability of data on ex post realizations of common traffic value to determine whether firms are cognizant of the winner's curse, assuming that traffic forecast is a good proxy for the value of bids, and hence the ratio between traffic forecast and actual traffic a good proxy for bidding behaviour.

We show that bidders bid less aggressively in toll road concession auctions when they expect more competition, i.e. the winner's curse effect is particularly strong in toll road concession contract auctions. In addition, we find, in agreement with the theory, that the winner's curse effect is stronger for shorter facilities or for projects for which the procuring public authority did not release her own traffic forecasts, *i.e.* in auctions with a greater degree of common uncertainty. Finally, we show that, in concession contracts, the public authority is exposed to the risk that the private operator behaves opportunistically during the execution phase of the contract. In fact, we observe that bidders bid more strategically when they expect a higher likelihood of renegotiation. In other words, the perspective of later profitable renegotiation does question the theoretical framework.

The policy implication of our results is not straightforward. In fact, while the traditional implication would be that more competition is not always desirable when the winner's curse effect is particularly strong, in toll road concession contract auctions, more competition may be however desirable. In fact, even if the winner's curse effect in such auctions is particularly strong, it reduces the systematic traffic overestimation due to methodological and behavioural sources. Thus, governments, whose objective function is to maximise the long-term social welfare, and then minimize strategic renegotiations, may wish to maintain the procedure as open as possible.

We believe the contribution of this study is twofold. At the empirical level, using a unique dataset - the most exhaustive one on toll road concessions auctions -, we propose a test of auction theory. This kind of test has been quite limited by the lack of suitable data on bidding behaviour, as pointed out by Laffont (1997) in a survey of the empirical auctions literature. We also highlight the importance of the public release of contract information and the bid effects of uncertainty over the value of a contract, which has been largely ignored. At the theoretical level, we show that the perspective of later profitable renegotiation does affect bidding behaviour (we observe that the effect of the winner's curse depends on the likelihood of renegotiation), and thus we stress the necessity to improve the theoretical framework by considering the transaction as a whole, *i.e.* considering the impact of not only the ex ante but also the ex post conditions on bidding behaviour.

The chapter is organized as follows. Section 2 presents the particular features of toll road concession auctions. To formalize the effects of an increase in competition on bidding behaviour in such auctions, we present in Section 3 a simple model of competitive bidding with common value components, and state our three theoretical propositions. Section 4 provides a description of the data while section 5 reports the econometric results. In Section 6, we provide a robustness analysis of our results and Section 7 discusses the policy implications of our work and offers some concluding comments.

3.2 Auctions for Toll Road Concessions

3.2.1 First-Price, Sealed-Bid Auctions

We study here the bidding behaviour in first-price, sealed bid auctions, using data on road concessions. In a first-price, sealed-bid auction, each bidder independently and privately picks a price and offers to buy the contract at that price. The one who bids the lowest price wins (most of toll road concession contracts are awarded via low-bid auctions with adjudication criteria going from the lowest toll, to the lowest public subvention required, or to the shortest length of the concession).

Concession contracts are most often awarded in two stages; in the first stage, private consortiums submit their technical qualifications, following the rules defined by the public authority. In the second stage, qualified consortiums - the consortiums selected after the first step - are allowed to bid. The concession is then awarded to the consortium with the best bid (sometimes there is an additional stage between the second stage and the selection of the best bid, which consists in selecting the two best bidders and asking them to submit in a third stage their best and final offer). Except in exceptional cases, the number of bidders qualified to bid is published by the public authority as a matter of transparency. It is therefore a known variable to the participants.

3.2.2 Common Value Auctions

Toll road concession auction environments fall in the common values category. As a matter of fact, the concession contract being bid for will not be fulfilled immediately and bidders have different information about future states of the world - e.g. market conditions or the supply and demand of substitute objects.

The degree of complexity and uncertainty comes directly to bear in the design of infrastructure concession contracts. Forecasting errors and associated risks are characteristics of infrastructure projects. Studies of such errors (as discussed in the precedent chapters) show that future traffic is usually overestimated. In fact, the uncertainty in forecasts induces the possibility of manipulation that is exacerbated by the information asymmetries in concession projects.

In addition, bidders have access in such an environment to different information. A bidder might conduct her own traffic forecast survey of a toll road concession or might learn about market conditions from her own customers and suppliers. Furthermore, even if bidders have access to the same market data, they may have different methods or rules-of-thumb for using this information to form beliefs about the contract's value. The output of one bidder's model (her signal) might then be useful to another bidder in assessing her own valuation even after seeing the output of her own model (Athey and Haile, 2007). In such cases it may be appropriate to model bidders as having different private information of a common values nature.

Thus, each bidder's traffic appraisal represents just an estimate, subject to error. No bidder knows what future traffic will be and each realizes that the other bidders may possess information or analyzes that the bidder would find useful for her own traffic forecast.

As a result, in toll road concession auctions, the winning bidder may be the one who most overestimate future traffic. This is all the more true that under first-price, sealed-bid auctions, bidders have less information on other bidders' estimates of project value.[6]

Thus, there is a greater likelihood under sealed bidding that the winner's curse will occur - that the winning bidder is the unfortunate one who, out of ignorance, overestimates the value of what is being auctioned (Milgrom and Weber, 1982; Klein, 1998). Bidders who would fail to take this selection bias into account at the bidding stage would be subject to the winner's curse. How then should reasonably sophisticated bidders behave? A frequent piece of advice is: *bid cautiously*. Milgrom (1989) for example suggests that to make money in competitive bidding, you will need to mark up your bids twice: once to correct for the underestimation of costs - traffic overestimation in our case - on the projects you win, and a second time to include a margin for profits. Besides, since it is reasonable to expect the selection bias to increase when

[6]As first demonstrated by Milgrom and Weber (1982) for symmetric common values environments, the information revealed publicly by losing bidders' exits in an ascending auction reduces both the severity of the winner's cruse and the informational rents obtained by the winner, leading to higher expected revenues than with a first-price sealed-bid auction.

competition gets fiercer, he adds that the mark-up to adjust for underestimation - traffic overestimation - will have to be larger the larger is the number of your competitors.

3.2.3 Auctions with Differing Levels of Common Uncertainty

The theory suggests that the effects of the winner's curse (the internalization of the winner's curse by bidders) should be more apparent in auctions with a greater degree of common uncertainty. To the extent that the magnitude of the winner's curse decreases as the common uncertainty concerning the value of the auction decreases, bidders will less internalize the winner's curse as the common uncertainty concerning the value of the auction decreases. In other words, the larger the relative size of the common-value component, the more cognizant of the winner's curse bidders are expected to be when competition increases (Milgrom and Weber, 1982; Goeree and Offerman, 2003).

There are two main factors that can reduce the level of contract valuation common uncertainty in the first-price, sealed bid toll road concession auctions: the public release of information about future traffic and the characteristics of the facility. The impact of the public release of information on bidding behaviour in auctions with common value uncertainty begins to be studied in the experimental or empirical literature (Kagel and Levin, 1986; De Silva et al., 2005). Such studies show that, in first-price, sealed bid auctions, public information reducing item valuation uncertainty can lead to more aggressive bidding behaviour [7] and that this effect can be more pronounced in auctions with larger common uncertainty.

While the auction format for toll road concessions is quite similar across auctions, a feature that varies across auctions is the information provided to

[7] This effect has been mitigated by Kagel and Levin (1986). They show that in presence of a winner's curse (*i.e.* bidders do not internalise the winner's curse), providing public information generates lower average winning bids and reduced seller's revenues. To the extent that the magnitude of the winner's curse decreases as the common uncertainty concerning the value of the auction decreases, public information will result in a downward revision in the most optimistic bidder's valuation of the auction. They point out the fact that the differential response to public information conditional on the presence or absence of a winner's curse has practical implications which have largely gone unrecognized in the literature.

bidders regarding the procuring authority's internal forecast of the future traffic. Some procuring authorities release this information prior to bidding and others do not, so the level of information dispersion varies across auctions in the sample. This effect is all the more important that governments negotiators juggle with multiple concerns and more general expertise than private partners with focused specialized negotiators and advised by deal specialists with insufficient sectoral and macro vision. This variation helps identify the effect of changes in information dispersion on bids.

In addition, in a study of computer auctions on ebay, Yin (2005) examines the effect of value dispersion and seller reputation on prices. She finds that the seller's reputation complements information provided in the auction descriptions by lending more credibility to that information. Thus, we can also expect that the level of common uncertainty also varies with the procuring authority's reputation when the latter chooses to release her own traffic forecast.

Another way to distinguish toll road projects regarding their common traffic uncertainty is to account for their differing uncertainty-leading characteristics, in particular the physical length[8]. In fact, based on the preceding literature on this sector and on discussions with some private concessionaires, we believe that there is less uncertainty associated with traffic forecasts of longer facilities. Although no any study (as long as we know) has focused on the relationship between the physical length and the methodological problems associated with the forecasting exercise, we can give at least three arguments supporting this hypothesis; first, the large numbers law: since the number and size of zones involved (possible Origin-Destination pairs) is much higher in long interurban facilities than in short ones, misspecification or error prediction on some OD's has less impact in equilibrium; second, if the value of travel time savings increases with the travel length, misspecification should occur for small savings because studies on stated and revealed value of travel time savings usually evaluate large time savings; third, short distance travels do not follow the traditional relationship between GDP and mobility and are determined

[8]This is also a way for us to check the robustness of the results obtained with the public release of information criterion, since the public release of information may affect the number of bidders (if bidders base their decision to submit a bid on this type of information), implying that the coefficient of the PUBLICINFO variable crossed with the number of bidders may be biased.

by life patterns. In particular, in urban transport, demand growth is strongly impacted by urban, land-use and transport policy (Schafer, 2000).

Moreover, using an external sample (22 motorway sections in France, with forecast errors ranging from 5% to 50%, none of them included in our analysis) we can corroborate this hypothesis, as we can see in figure 3.1, where the tendency line represents a R^2 of 0.2. This relatively low R^2 is of course due to the fact that only a portion of the error is correlated with the lenght.

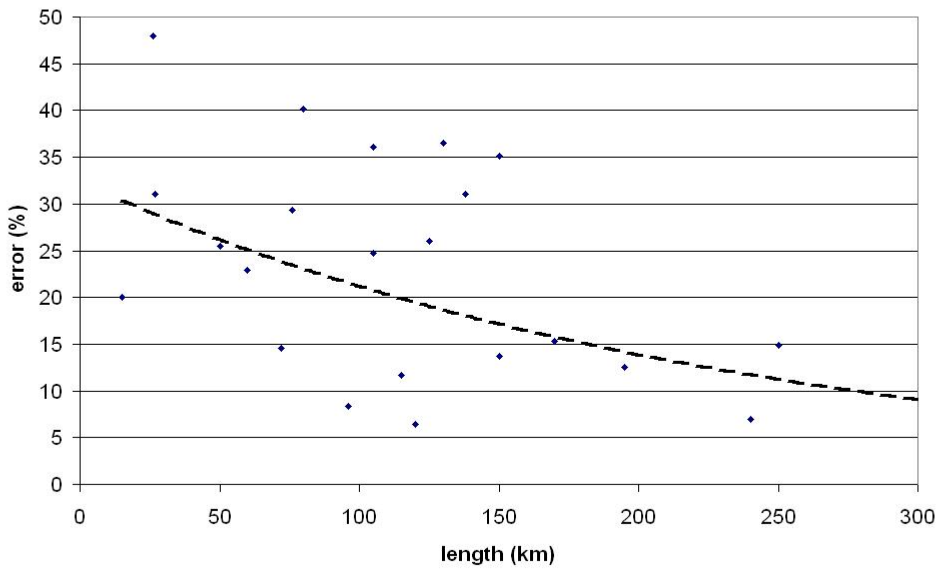

Figure 3.1: Length and Forecast Error.

3.2.4 Renegotiation in Toll Road Concessions

A particular characteristic of toll road concession auctions is that they are public-private contracts, which potential for renegotiation becomes to be highlighted for less developed countries (Guasch et al., 2003, 2005; Estache, 2006; Guasch, 2004; Laffont, 2005), but also for developed countries (Gomez-Ibanez and Meyer, 1993; Engel et al., 2003, 2005, 2006; Athias, 2006), and clearly contributes to the inefficiency of PPPs. For instance, in a study on more than 1,000 concession contracts awarded during the 1990s in Latin America, Guasch (2004) found that 53% of the concessions in the transport sector were renegotiated, and this took place on average only 3.1 years after the signing of the contract.

Some renegotiation is desirable and is to be expected as contracts are in practice necessarily incomplete. Exogenous events that are not induced by either the government or the operator (like currency devaluation) can significantly affect the financial equilibrium of firms, and can be used as an opportunity to redistribute rents. However, the high incidence of renegotiations, particularly in early stages, appears to be beyond the expected or reasonable levels, and raises concerns about the validity of the concession model in which renegotiations would not be taken into account (Guasch et al., 2003). It might induce excessive opportunistic behavior by the operators, or by the government, in detriment to the efficiency of the process and overall welfare.

Once an enterprise has been granted a concession in an infrastructure sector - and the eventual bidding competitors are gone - that enterprise may correspondingly be able to take actions that “hold up” the government, for example through insisting on renegotiating the contract ex post. The inherent contractual incompleteness, the potential incentives for political incumbents to use renegotiation to anticipate infrastructure spending and thereby increase the probability of winning an upcoming election (Engel et al., 2006), and the perceived leverage of the enterprise vis à vis the government in a bilateral negotiation constitute powerful potential factors to seek renegotiation of the contract and secure a better deal than the initial one.

Thus, when bidders expect a high likelihood of renegotiation that renders it possible to avoid any losses, they have strong incentives to submit bids containing promises difficult to satisfy, with the sole purpose of being awarded the tender (Spulber, 1990). Uncertainty in forecasts is then used in a strategic way by bidders, which is exacerbated by information asymmetries in concession projects. Moreover, traffic overestimation (up to the constraint of credibility) may represent an equilibrium in the short-term. In fact, while candidates submit opportunistic bids to increase their probability of success, the more aggressive the bids, the better it would be for the public procuring authority, since it is more efficient in the short-term. Moreover, financial agencies and lenders, suspecting that traffic forecasts are strategically increased, find a risk-sharing agreement that cushions them against any losses.

This major feature of toll road concessions can strongly question the theoretical effects highlighted above to the extent that the bidder realizes that there is no point in internalizing the winner's curse (Milgrom and Weber, 1982). Thus, depending on the likelihood of renegotiation, bidders will more or less internalize the winner's curse as the number of bidders increases.

3.3 Bidding for Toll Road Concessions: A Simple Model

We now present a simple model of competitive bidding that takes into account the various features highlighted above.

3.3.1 Model Framework

For concreteness, let assume that firms bid on lowest toll (this is not essential). We assume that there exists a one-to-one, decreasing, relation between the traffic forecast and the toll included in the bid. First, this boils down assuming that the costs (global investments and operation costs) are independently identically distributed - this assumption is made by numerous papers on PPP (e.g. Engel et al. (2007)) -, and that costs underestimation cannot be used strategically; this seems realistic to the extent that concessionaires cannot complain ex post about cost underestimation since there are very few exogenous components in the cost estimation, and the uncertainty and information asymmetry between bidders and procuring authorities regarding construction costs are low. Second, this boils down assuming that rates of return are the same across firms. Again, this does not seem to be a too restrictive assumption since it is well-known that procuring authorities expect a range of values for the financial rate of return of a particular project.

Thus, the firm decides the toll it wants to bid, and then puts pressure on the forecaster so that she approves the traffic forecast consistent with this bid. As already discussed, it is possible for firms to have some margin to adjust the traffic forecasts since the uncertainty associated with forecasts (exogenous and methodological) makes it very easy to manipulate the forecasts. Forecasts rely upon so many assumptions that it is usually possible to adjust forecasts so that they meet such demands. For instance, considering that the project will produce higher time savings or using higher economic growth than actually expected are possible ways to overestimate demand, among many others.

Nevertheless, bidders do not have an unbounded margin to adjust traffic forecasts. As a matter of fact, the margin is first bounded by credibility. Procuring authorities have an expectation, though inaccurate, of what the future traffic can be, so the bidder is not able to manipulate indefinitely traffic forecasts. Second, the margin is bounded by the other bidders' tenders. Procuring authorities are able to compare the traffic forecasts of the different bidders and hence notice if one forecast is largely different from the others. For instance, there was a case in France where one bidder was asked for a particular audition to justify her overly high traffic forecasts compared to the others.

In addition, this above central assumption implies the implicit assumption that procuring authorities have information provided by the firms on costs, rates of return, traffic forecasts, so that they can check the consistency of the bid. This assumption seems to be realistic in the sense that, first, the financial model is most often required in the bids, second, when international development banks are involved, they have the responsibility to assess the bids, and third procuring authorities have internal resources to check the consistency of the bids [9].

Finally, this strategic bidding behaviour depends also on the possibility for bidders to renegotiate the contract. As already highlighted in the previous section, there is a high incidence of renegotiation in toll road concessions, made mainly possible by the claim that actual traffic does not meet the forecasts due to a change in the exogenous factors.

3.3.2 Model Setting

Consider the actual traffic D^A. This actual traffic is determined by nature. Each firm receives an estimate of this actual traffic defined as

[9] Discussions with experts (from France, Chile and Spain) and some independent regulatory authorities (Brazil, Portugal) also corroborate this assumption.

$$D^E = D^A \pm \varepsilon$$

where ε is i.i.d. with zero mean, so that bidders believe that the average of bidders' traffic forecasts is a good estimate of the actual traffic (a standard assumption in common-value models; see for example Bikhchandani and Riley (1991), Bulow et al. (1999), Goeree and Offerman (2003)). In addition, we assume that rational bidders believe that the variance of ε is increasing in the number of bidders.

Each firm chooses then a strategic traffic forecast D^S such as

$$D^S = D^E \pm s$$

As highlighted in the Section 2, the strategic bias s depends on the number of bidders, the degree of common uncertainty, and the likelihood of renegotiation. So we have

$$s = f(NB, CU, PR)$$

where NB is the number of bidders, CU the level of common uncertainty, and PR the likelihood of renegotiation.

Given D^S, each firm chooses the toll $p = g(D^S)$ with $g' < 0$ and $g'' < 0$. As highlighted in the previous section, g is the same for each firm and given ex ante. We then have $p = g(D^E \pm f(NB, CU, PR))$.

The net present value can be written as

$$NPV = -\int_{tt}^{t0} I_t e^{-rt} dt + \int_{t0}^{tf} [p_t D_t^A(p_t) - C(D_t^A)] e^{-rt} dt \tag{3.1}$$

where I is the initial investment and C the operation and maintenance costs.

We suppose that the demand is inelastic (with respect to both price and quality) and, as already discussed, that the main strategic variable is the demand, so that costs do not matter. Within this framework, only the gross benefit matters, which is

$$B = \int_{t0}^{tf} [p_t D_t^A] e^{-rt} dt \tag{3.2}$$

However, at the bidding stage, the demand included in the financial model is D^E . Thus, given r and B, the only way to reduce the price (toll) included in the bid is to increase the traffic forecast. The probability of winning can be then written as

$$P_{win} = P(D_i^S \geq D_j^S \; \forall j) \tag{3.3}$$

where i and $j, j \in 1, ..., NB - 1$ index the bidders.

3.3.3 Number of Bidders and Traffic Forecast Deviation

Let consider the forecast error e be the difference between the traffic forecast included in the bid and the actual traffic. So we have $e = \varepsilon + s$. The winner's forecast error can then be written as

$$e_i \mid D_i^S > D_j^S \forall j \neq i = D_i^S - \frac{1}{N} \sum D_j^S \tag{3.4}$$

As the variance of ε is increasing in the number of bidders, then $e_i \mid D_i^b > D_j^b \forall j \neq i$ is strictly increasing in the number of bidders;

$$e_i \mid D_i^S > D_j^S \forall j \neq i = k(NB); k' > 0, k'' < 0; \tag{3.5}$$

In addition, the probability of winning the bid for the bidder i is proportional to her own forecast D_i^S and inversely proportional to other bidders' forecasts $D_j^S \forall j$. So we have

$$Pr(D_i^S > D_j^S \forall j \neq i) = h(D_i^S, D_j^S \forall j \neq i) \tag{3.6}$$

where

$$\frac{\partial h}{\partial D_i^S} > 0, \frac{\partial h}{\partial NB} < 0, \frac{\partial h^2}{\partial^2 D_i^S} < 0, \frac{\partial h^2}{\partial^2 NB} < 0$$

The expected forecast error is then

$$E(e_i) = k(NB)h(D_i^S, D_j^S \forall j \neq i) \tag{3.7}$$

Since bidders are risk-neutral, they want the expected forecast error to be constant, let say equal to e_i^* . Thus, as the number of bidders increases, the probability of winning the bid has to decrease as much as the error term increases. Nevertheless, we assume that the impact of the increase in the number of bidders is weaker on the probability of winning than on the error term, *i.e.* the increase in the error term is not compensated by the decrease in the probability of winning. That is

$$-\frac{\partial h}{\partial NB} < \frac{\partial k}{\partial NB}$$

This assumption seems realistic as we expect a high variance of traffic forecasts in our particular case due to the magnitude of traffic uncertainty. Thus, they have to decrease their traffic forecast to keep the expected forecast error constant. This is the winner's curse effect.

This leads to the following proposition:

Proposition 1: *The greater the number of bidders, the more likely bidders will be conservative to correct for traffic overestimation, i.e. the greater the effects of the winner's curse. So*

$$\frac{\partial D_i^S}{\partial NB} < 0$$

3.3.4 Number of Bidders and Level of Common Uncertainty

Let now consider the winner's curse effect relative to the degree of common uncertainty. We assume that the higher the common uncertainty, the higher the variance of bids, that is

$$\frac{\partial D_i^S}{\partial CU} > 0 \tag{3.8}$$

Thus, the winning expected forecast error is a strictly increasing, concave function of the common uncertaity (CU). We can then write this winning forecast error as

$$e_i \mid D_i^S > D_j^S \forall j \neq i = k(NB, CU) \tag{3.9}$$

where

$$\frac{\partial k}{\partial NB} > 0, \frac{\partial k}{\partial CU} > 0, \frac{\partial k^2}{\partial^2 NB} < 0, \frac{\partial k^2}{\partial^2 CU} < 0$$

The expected forecast error is then

$$E(e_i) = k(NB, CU)h(D_i^S, D_j^S \forall j \neq i) \tag{3.10}$$

Equations 3.8 and 3.10 indicate that an increase in the common uncertainty may have two counteracting effects on bids. First, since the variance increases with the common uncertainty, the winning bid is an increasing function of the common uncertainty (Equation 3.8). Second, to keep the expected error constant, bidders should review their bids (forecasts) downwards (Equation 3.10). As a result, the winning bid may increase or decrease with the common uncertainty, depending on which of these two effects prevails.

Furthermore, repeating the same exercise as in the previous section, we obtain that the higher the common uncertainty, the more bidders will internalise the winner's curse as the number of bidders increases

$$\frac{\partial}{\partial CU} \frac{\partial D_i^S}{\partial NB} < 0$$

This leads to the following proposition:

Proposition 2: *The greater the degree of common uncertainty, the more likely bidders will be conservative as competition gets fiercer, i.e. the greater the effects of the winner's curse.*

3.3.5 Number of Bidders and Renegotiation

As already highlighted, toll road concessions observe a high incidence of renegotiation. This feature can impact the behaviour of bidders. They might anticipate a future renegotiation that will lead them to increase their expected forecast error ex ante to the limit of the outcome they expect of the renegotiation. In other words, some dynamic concerns are now involved in the bidding behaviour.

Thus, we can write the expected forecast error in case of anticipation of renegotiation as following:

$$E^R(e_i) \in [E(e_i), \bar{e}_i^{PR}] \tag{3.11}$$

with

$$\bar{e}_i^{PR} = E(e_i)\frac{1}{1 - PR} \tag{3.12}$$

where PR is the anticipated likelihood of renegotiation and $E^R(e_i)$ is the expected forecast error of the winning bidder i in case of anticipation of renegotiation. The expected forecast error is not constant anymore and as the probability of renegotiation increases, this expected forecast error increases, up to an upper bound, that is:

$$E^R(e_i) = k(NB, CU)h(D_i^S, D_j^S \forall j \neq i) \tag{3.13}$$

Then, as the probability of renegotiation increases, an increase of the number of bidders has a weaker impact on the correction of traffic forecast overestimation, that is

$$\frac{\partial}{\partial PR}\frac{\partial D_i^S}{\partial NB} > 0$$

This leads to the following proposition:

Proposition 3: *The lower the likelihood of contract renegotiation, the more likely bidders will be conservative as the number of bidders increases, i.e. the greater the effects of the winner's curse.*

The purpose of this analysis is to test this triple prediction. In other words, we will test first whether, overall, bidders in such auctions are cognizant of the winner's curse,*i.e.* whether their correction for the overestimation of future traffic is larger the larger is the number of bidders. Second, we will test whether bidders are more or less cognizant of the winner's curse according to the projects' differing levels of common-value components. Third, we will test the magnitude of the winner's curse effect relative to the likelihood of renegotiation.

3.4 Data on Road Concession Contract Auctions

We constructed a dataset consisting of 49 toll road concession contract auctions (highways, bridges and tunnels). They are from Australia, Brazil, Canada, Chile, France, Germany, Hungary, Israel, Jamaica, Portugal, South Africa, Thailand, and United Kingdom . The oldest auctions in the sample were awarded in 1989, whereas the latest was in 2003. Table 3.1 shows the distribution by country and by year. Most of data included in the database was provided by concessionaires and by regulators. Some others come from scientific and professional press. As far as we know,this database is the most exhaustive one on toll road concession auctions.

3.4.1 Dependent Variable: Traffic Forecast Deviation

In settings where bidders may be subject to the winner's curse, one often recommends that bidders be cautious: bidders need to correct for overestimation of future traffic and increase their correction on their estimate when competition gets fiercer. As already highlighted, a good measure for this correction is the relative discrepancy between the traffic forecast and the actual traffic.

We have data on the traffic forecasts included in the bids submitted by the **winning bidders**, and on actual traffic coming from traffic counts. The average ratio between them is called Traffic Forecast Deviation (TFD). Thus, we define our dependent variable as following:

$$TFD = \frac{1}{n} \sum_{t=t_0}^{t_0+n-1} \frac{forecast_t}{actual_t} \tag{3.14}$$

where $actual_t$ is the actual traffic observed in year t, $forecast_t$ is the traffic forecast for the year t and n is the number of years for which we could calculate this deviation. As data availability varies across projects, the variable *TFD* used in the regressions is the average deviation for the period for which we have both data on forecast and actual traffic. This period ranges up to 7 years. We take the average *TFD* because it captures the fact that bidders can manipulate either the traffic forecasts at the opening of the facility or the traffic growth forecasts, or both.

The interpretation of this variable is straightforward: when it tends to 1, it means that the traffic forecasts are very close to the actual one so that the winning bidders are less aggressive and conversely, when it increases, it means that the winning bidders submitted more aggressive bids. Thus, a positive impact on this variable implies a more aggressive bid and a negative impact on this variable implies a more conservative bidding behaviour.

Figure 3.2 gives the distribution of this TFD variable in the sample. One aspect of this contractual record draws immediate attention: the prevalence of traffic overestimation, as highlighted by the existing literature (e.g. Skamris and Flyvberg 1997, Estache 2001), since the average deviation is 1.25, i.e. an average overestimation of 25%.

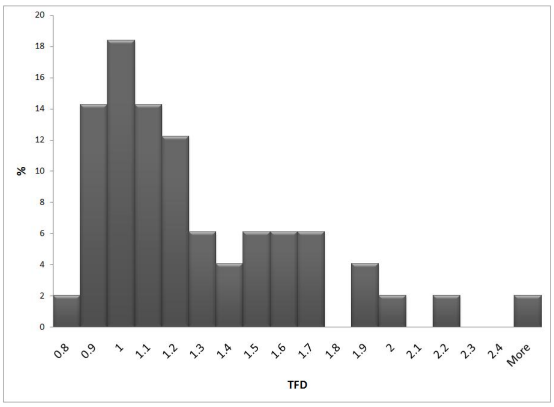

Figure 3.2: TDF.

3.4.2 Explanatory Variables

The propositions to be tested formulated above suggest three main factors that are likely to influence the bidding behaviour: the number of bidders, the degree of common uncertainty, and the likelihood of contract renegotiation.

The actual number of bidders accounts for the level of competition (it represents the number of bidders that actually bid after the prequalification stage). Figure 3.3 presents the distribution of the number of bidders in our sample. Most Auctions have between 2 and 4 bidders [10]. Table 3.2 reports that on average there were 3.9 bidders per contract, ranging from 1 to 9 bidders across contracts. The hypothesis is that bidders will be more conservative the larger is the number of bidders, *i.e.* we expect a negative impact of the *NUMBER OF BIDDERS* variable on our *TFD* variable.

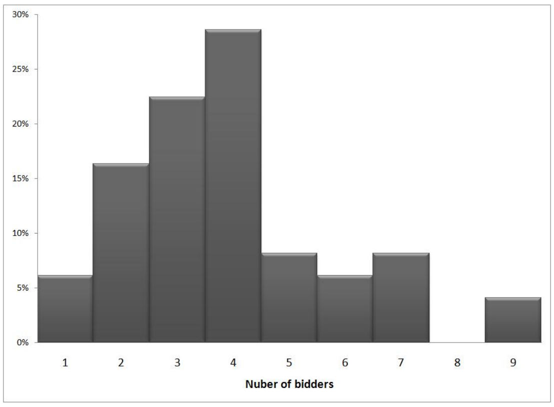

Figure 3.3: Number of Bidders.

The theoretical literature in auctions suggests that the winner's curse effect should be more pronounced in auctions where there is greater common uncertainty. As explained above, to examine the potential differences in the effect of the competition across projects, we look at the length of the facilities being auctioned. In order to capture the potential differences in the effect of the winner's curse across projects, we include in our regressions the variable *LENGTH*, reflecting the length of the facility in kilometres. Thus, the prediction is that each of these variables, interacted with the number of bidders, will

[10]It can be noticed here that for some auctions, only one bidder submitted a tender after the prequalification stage. We take into account these auctions because the tendering was competitive.

have a positive impact on the traffic forecast deviation.

So as to take into account a reputation effect of the procuring authority that could complement the release of her own traffic forecast, we interacted the variable *PUBLICINFO* not only with the number of bidders but also with *GOVLEARN* variable, which reflects the experience of the procuring authority in awarding concession contracts.

Regarding the likelihood of contractual renegotiation, Guasch et al. (2003) develop a model to accommodate renegotiations initiated by firms. This provides them with a set of predictions for the probabilities of renegotiation of concession contracts. They highlight the importance of having a regulator in place and an experimented procuring authority to limit renegotiations, the fragility of price caps, the relevance of economic shocks and political cycles, as well as the importance of good institutions (bureaucracy, rule of law, control of corruption) to reduce the incidence of renegotiations. Given the specificity of toll road concession contracts - absence of a regulator in most countries, all price-cap contracts, and consortiums composed most of time of both local and foreign companies - we introduced three variables to capture the reliability of contract enforcement. The first one, the variable *GOVLEARN*, reflects the experience of the procuring authority in awarding concession contracts. As a large number of prior concessions should decrease the probability of renegotiation Guasch et al. (2003); Guasch (2004), we expect a negative impact of this variable interacted with the number of bidders variable on our dependent *TFD* variable.

The second proxy for the likelihood of renegotiation is the indicator *HIGH INCOME COUNTRY* developed by the World Bank (2006). As highlighted by Laffont 2005, the prediction is that wealthier countries have more money to finance the functioning of the enforcement mechanism than poorer ones. In other words, the government's "tolerance for renegotiation" depends on the investment in enforcement. This is the reason why we expect stronger institutional framework in wealthier countries and hence a lower probability of contractual renegotiation in such countries. The hypothesis is therefore that greater numbers of bidders for projects taking place in wealthier countries will more likely lead to more conservative bidding behaviour at equilibrium than in poorer ones, i.e. to a negative impact of the crossed variable *HIC*NUMBER*

OF BIDDERS on our *TFD* dependent variable (highlighting a greater winner's curse effect in wealthier countries).

However, as discussed above, we also observe renegotiations in developed countries, even if it is at a lower incidence. The legal system may then serve as a useful guide for the probability of enforcing the agreed upon contract. There has been increased attention from economists and legal scholars directed to the question of what legal environments best promote economic growth and stability. Some have suggested that common law regimes outperform civil code regimes throughout the world (La Porta et al., 1999). More specifically, institutional features that traditionally characterize a common law regime make it more difficult to renegotiate under such a legal regime than under a civil law system. The reason is that in civil law countries, legislation is seen as the primary source of law. By default, courts thus base their judgments on the provisions of codes and statutes, from which solutions in particular cases are to be derived. Courts thus have to reason extensively on the basis of general rules and principles of the code, often drawing analogies from statutory provisions to fill lacunae and to achieve coherence. By contrast, in the common law system, cases are the primary source of law, while statutes are only seen as incursions into the common law and thus interpreted narrowly.

According to these features of the different legal regimes, we assume that the likelihood of renegotiation is higher in civil law regimes and expect therefore a lower winner's curse effect in civil law countries, i.e. a positive impact of the variable CIVILLAW interacted with the number of bidders on our TFD dependent variable.

The variables used in our estimations are summarized in the following Table 3.2 and their respective distribution is given in Appendices B.

3.5 Econometric Results

In order to test our three theoretical predictions, we have performed log-log regressions (so as to be able to interpret the results in terms of elasticity). Ten models were estimated. We first analyse the overall impact of the number of bidders on bidding behaviour (Model 1). We then examine the effects of the winner's curse on contract auctions with differing levels of common-value components (Models 2 to 6). Finally, we identify, in Models 7 to 10, if the theoretical effects still hold when we account for the possibility for bidders to renegotiate the contract [11]. Results are reported in Tables 3 and 4.

The first striking result we observe is that the number of bidders is clearly an important variable, driving the value of bidders' tenders. Model 1 shows that there is a negative impact of a fiercer competition on the traffic forecast deviation variable. This result corroborates our proposition 1, whatever the econometric model (at 1% significance level). It means that, overall, bidders are more conservative the more bidders there are, i.e. the effect of the winner's curse in toll road concession contract auctions is strong.

We also observe that this winner's curse effect is even larger for projects for which the common uncertainty is greater. In fact, the public release of information prior to bidding, regarding the procuring authority's internal forecast of the future traffic, has a positive impact on the traffic forecast deviation variable when interacted with the number of bidders. This result suggests, consistent with the theory, that one way to hinder the winner's curse effects is to reduce the information dispersion on the contract valuation by giving more contract information. This highlights the bid effects of uncertainty over the value of a contract, which has been largely ignored. Furthermore, we find that the impact of the public release of information on bidding behaviour is not stronger when accounting for procuring authority's experience, in contrast to Yin (2005).

These results then emphasize that the larger the relative size of the common-value component, the more cognizant of the winner's curse bidders are when competition increases. This result corroborates our proposition 2, whatever the econometric model.

Results of Models 7 to 10 show that the effects of the winner's curse are significantly higher when bidders expect a low likelihood of renegotiation. In particular, as predicted, Model 7 indicates that the effect of the variable *GOV-LEARN* interacted with the number of bidders is negative, though almost not

[11] As the public release of information may affect the number of bidders, we introduced the institutional variables only in the model with the length variable as a proxy for uncertainty, as it is truly exogenous.

significant, on the *TFD* variable. This may corroborate the result of Guasch (2004) of a negative impact of the experience of the public authority on the probability of renegotiation. Besides, the variable *CIVIL LAW* interacted with the number of bidders is positive on the traffic forecast deviation, implying that bidders anticipate a higher likelihood of renegotiation in civil law countries and therefore less internalize the winner's curse when bidding in such countries. This result, in contrast to what is often written on this topic, favours the approach which consists in relying on long concession-specific documents, trying to make the contract as complete as possible, i.e. trying to include every possible contingency to avoid leaving room for ex post renegotiations.

Finally, we obtain a similar result when we proxy for the likelihood of renegotiation by the wealth of the countries. In fact, we observe a negative impact of the *HIC* variable when competition gets fiercer on the traffic forecast deviation, meaning that bidders are more cognizant of the winner's curse in wealthier countries, i.e. in countries in which the probability of renegotiation is lower. These results are consistent with our proposition 3 and suggest that the effect of the winner's curse depends on the likelihood of renegotiation, and hence stress the necessity to improve the theoretical framework by considering the transaction as a whole, i.e. considering the impact of not only the ex ante but also the ex post conditions on bidding behaviour.

3.6 Robustness Analysis

One shortcoming of our work is that the true number of bidders may be unobserved and/or endogenously determined. Porter and Zona (1993) show that bid rigging may occur in construction contract auction settings. This can question our results. Nevertheless, as explained above, the bidders in our sample of contracts have little experience. Besides, toll road concession contracts are long-term contracts and Chong (2007) shows that collusion is hardly sustainable when contracts are long-term contracts. Thus, it seems uncertain that bid rigging and collusion may occur in such auctions. In addition, even if some bid rigging or collusion exists, it tends to mitigate the winner's curse effect. Yet, we still find statistical evidence of the winner's curse effect.

Much of the empirical work on auctions faces the problem of an endogenous number of bidders. The auction bidders who chose to bid may have been attracted by some aspect of the contract being auctioned that is not captured in the other regressors or is unobservable to the econometrician. If this aspect is correlated with traffic forecast deviation, then we need to instrument for the number of bidders. Nevertheless, employing potentially weak instruments may not yield more accurate estimates. Besides, our dependent variable is not the bid (or the price) itself but traffic forecast deviation, so that the potentiality of unobservable determinants of traffic forecast deviation is weak.

Nevertheless, in table 3.4, we introduce additional variables, not explicitly theoretically considered, that could potentially affect the traffic forecast deviation and alter the significance of our core variables. These are reputation effects, the duration of contract, the total construction costs, the political ideology of the public procuring authority and a trend variable.

So far, we assumed that the auction setting is static whereas auctions for toll road concessions are repeated. We could then expect a dynamic effect on bidding behaviour (Jofre-Bonet and Pesendorfer, 2003). More specifically, repeated interactions render reputational effects important in this toll road concession setting (Athias and Saussier, 2007). In fact, many of the concessionaires in these auctions bid on many contracts over time. The potential loss of future bidding eligibility may counteract concessionaires' incentives to submit opportunistic bids with high traffic forecasts, anticipating renegotiation. We then introduced the dummy variable *REPEATED* as a control variable, which takes the value 1 if the procuring authority and the winning bidder had contracted together at least once before.

The *DURATION* variable, defined as the number of months between the completion of the infrastructure construction and the end of the concession, captures the increasing uncertainty associated with long time horizons in forecasting future traffic growth. The hypothesis is that longer concession period increases uncertainty, leading to greater traffic growth forecast errors. The amount of investments - measured in terms of total construction costs - may affect the importance candidates will give to the production of a better traffic forecast and also the bidders' determination to win the auction.

It is possible that differences in political ideology (e.g. left or right leaning public authorities) might affect the number of bidders. In fact, private companies may show a lack of interest in bidding for contracts when the procuring authority is controlled by a particular political party (Athias and Saussier, 2007). We capture this effect in the control variable *LEFT*.

Finally, we include in the regressions a *TREND* variable so as to control for a temporal evolution of the traffic forecast practices for toll road concessions.

Model 11 of both estimation methods indicates that the results remain unaltered when controlling for dynamic considerations. In fact, while the variable *REPEATED* is weakly significant (15% significance level) and has a negative effect on the TFD - suggesting that reputational effect might play a role in such settings, *HIC*and *CIVILLAW* variables interacted with the number of bidders are still significant and of the expected sign (the impact of the legal regime is however less significant).

Models 12 indicate that results are not affected by the introduction of all the other additional variables and that none of these variables is significant. Thus, including control variables does neither diminish the coefficient of the competition variable, uncertainty variables and institutional variables, nor their sign and significance.

In addition, although our sample is non-random in the sense that we only have observations for which all information was available (especially regarding the traffic forecast), we cannot characterize a sample selection bias because our observations (and the observations we do not have) do not follow any selection rule; *i.e.* the function parameters of traffic forecast deviation are completely independent of the parameters of the function determining the probability of entrance into the sample. We could however suppose that a country fixed-effect can exist (determined by the institutional environment for example). Unfortunately, our within-country samples are not sufficiently large to estimate such possible effect.

Finally, to test the robustness of our results, it is also possible to perform some tests on the normality of the residuals. The Shapiro-Wilk test tests the null hypothesis that a sample came from a normally distributed population. In the Shapiro-Wilk test for normality, the p-value is based on the assumption that the distribution is normal. In our case, the p-value is extremely large (0.93) indicating that we cannot reject that residuals are normally distributed.

3.7 Conclusions

This chapter has studied the impact of the number of bidders on the effectiveness of the award process of toll infrastructure concession contracts. We first discuss what the economic theory says about this issue and the specificities of such auctions, leading to three propositions. We test these propositions using unique data gathered from a variety of sources. We show that the winner's curse effect is particularly strong in toll road concession contract auctions. More precisely, we show that bidders bid less aggressively in toll road concession auctions when they expect more competition. We also find, in agreement with the theory, that the winner's curse effect is even larger for projects for which the common uncertainty is greater. Thus, we highlight the bid effects of uncertainty over the value of a contract, which has been largely ignored.

Perhaps more interestingly, we show that, in concession contracts, the public authority is exposed to the risk of opportunistic behaviour on the part of the private subject during the execution phase of the contract. In fact, when we interact the number of bidders variable with the experience of the procuring authority, or with institutional variables, proxying for the likelihood of renegotiation, we observe that the effect of the winner's curse is weaker when the likelihood of renegotiation is higher (*i.e.* when the procuring authority is not experienced, the country is a low income country and the legal regime is a common law one). This means that bidders will bid more strategically in weaker institutional frameworks or in civil law countries, in which renegotiations are easier.

These results point out the necessity to improve the current theoretical framework for procurement policy and regulation by taking into account as a primary concern the impact of the perspective of later profitable renegotiation on equilibrium bidding behaviour. In other words, our results show that the classical assumption of auction models that bidders are able to commit with bidding promises is not satisfied and stress the necessity to improve the theoretical framework by considering the transaction as a whole, *i.e.* considering the impact of not only the ex ante but also the ex post conditions on bidding behaviour.

The policy implication of our results is not straightforward. In fact, while we show that asymmetric information overturns the common economic wisdom that more competition is always desirable, since we find a strong winner's curse effect in toll road concession auctions, we also show that there is a systematic traffic overestimation due to methodological and behavioural sources, so that in most cases bidders would know *ex post* very low or negative profit rates in they do not renegotiate the contractual terms. Thus, the short-term policy implication of our results would fit the standard view: governments should restrict entry, or favour negotiations over auctions, in toll road concession auctions to favour aggressive bidding. By contrast, the long-term policy implication of our results is that governments may wish to maintain the procedure as open as possible to the extent that the winner's curse effect reduces the systematic traffic overestimation and then reduces the likelihood that the procuring authority will have to renegotiate the contract, once eventual bidding competitors are gone.

In addition, we find that bidders less internalize the winner's curse when procuring authorities release publicly their own traffic forecast prior to bidding. Thus, procuring authorities interested in increasing the winner's curse effect, in order to incentive more conservative bids, should not release contract information that may reduce information dispersion in these toll road auction settings.

Table 3.1: Toll Road Concessions by Country and by Year

	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Total
Australia							1								1	2
Brazil						1	3		1							5
Canada					1						1					2
Chile				1		1	2	1								5
France		1							1				2			4
Germany								1			1					2
Hungary						2										2
Israel											1					1
Jamaica													1			1
Portugal						1				2	2	2	2	1		10
RS[a]										7						7
South Africa									1							1
Thailand	1															1
UK	1		1	1				1			1			1		6
Total	2	1	1	2	1	5	6	3	3	9	6	2	5	2	1	49

[a] RS means Rio Grande do Sul, the Brazlian southest state. It is presented as a different country since its concessions programme as well as its regulatory regime is completely independent.

Table 3.2: Data Definitions and Descriptive Statistics

Variable	Mean	Median	SD	Min	Max	Definition
TFD	1.25	1.10	0.45	0.80	3.40	Ratio forecast / actual traffic
NB	3.92	4.00	1.89	1.00	9.00	Number of bidders for the contract
Length	107.09	96.00	113.00	0.50	510.00	Length of the facility (km)
Civil Law	0.73	1.00	0.45	0	1	
HIC	0.53	1.00	0.50	0	1	1 if the country in question is a high income country; 0 otherwise.
Public Information	0.49	0	0.50	0	1	
Concessionaire Experience	1.92	1.00	2.89	0	13	Number of former toll road concessions of the winning bidder
Government Learning	2.53	1.00	3.05	0	10	Number of concessions the public authority had awarded before the present project
Trend	9.20	8.00	3.43	3.00	17.00	
Left	0.49	0	0.50	0	1	
Repeated Contract	0.49	0	0.87	0	4	
Duration	356.88	348.00	179.96	180.00	1164.00	Delay between the completion of the construction and the end of the concession (months)
Ivestment	445.77	259.00	430.26	10.00	1554.00	Total construction costs (M€)

Table 3.3: Econometric results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
number of	-0.220	-0.257	-0.373	-0.261	-0.678	-0.660	-0.682	-0.711	-0.863	-0.873
bidders (NB)	(-2.87)	(-3.33)	(-3.29)	(-3.36)	(-2.41)	(-2.43)	(-2.45)	(-2.72)	(-2.94)	(-3.17)
Publicinf			-0.284							
			(-1.39)							
Publicinf*NB		0.110	0.305							
		(1.92)	(2.01)							
Publicinf*				0.039		0.041				
Govlearn*NB				(1.90)		(2.14)				
Length					-0.182	-0.170	-0.198	-0.238	-0.207	-0.257
					(-2.36)	(-2.28)	(-2.58)	(-3.23)	(-2.71)	(-3.48)
Length*NB					0.103*	0.089	0.119	0.134	0.113	0.144
					(1.68)	(1.50)	(1.93)	(2.31)	(1.88)	(2.48)
Govlearn*NB							-0.014			-0.004
							(-1.49)			(-0.36)
HIC*NB								-0.159		-0.138
								(-2.93)		(-2.16)
Civillaw*NB									0.131	0.117
									(1.82)	(1.71)
Constant	0.452	0.435	0.609	0.474	1.229	1.194	1.266	1.453	1.381	1.570
	(4.37)	(4.31)	(3.79)	(4.67)	(3.48)	(3.51)	(3.63)	(4.33)	(3.90)	(4.62)
R2	0.149	0.212	0.244	0.210	0.299	0.365	0.333	0.414	0.348	0.452
Adjusted R2	0.131	0.178	0.194	0.176	0.252	0.308	0.272	0.360	0.289	0.373
N	49	49	49	49	49	49	49	49	49	49

(t-stats in parentheses)

Table 3.4: Econometric results - extended

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
number of	-0.220	-0.257	-0.373	-0.261	-0.678	-0.660	-0.682	-0.711	-0.863	-0.873	-0.979	-1.016
bidders (NB)	(-2.87)	(-3.33)	(-3.29)	(-3.36)	(-2.41)	(-2.43)	(-2.45)	(-2.72)	(-2.94)	(-3.17)	(-3.45)	(-3 .42)
Publicinf			-0.284									
			(-1.39)									
Publicinf*NB		0.110	0.305									
		(1.92)	(2.01)									
Publicinf*				0.039		0.041						
Govlearn*NB				(1.90)		(2.14)						
Length					-0.182	-0.170	-0.198	-0.238	-0.207	-0.257	-0.289	-0.307
					(-2.36)	(-2.28)	(-2.58)	(-3.23)	(-2.71)	(-3.48)	(-3.77)	(-3.82)
Length*NB					0.103	0.089	0.119	0.134	0.113	0.144	0.161	0.168
					(1.68)	(1.50)	(1.93)	(2.31)	(1.88)	(2.48)	(2.74)	(2.72)
Govlearn*NB							-0.014			-0.004	0.006	0.005
							(-1.49)			(-0.36)	(0.51)	(0.36)
HIC*NB								-0.159		-0.138	-0.148	-0.143
								(-2.93)		(-2.16)	(-2.32)	(-1.72)
Civillaw*NB									0.131	0.117	0.104	0.116
									(1.82)	(1.71)	(1.52)	(1.48)
Repeated											-0.132	-0.138
											(-1.47)	(-1.49)
Investment												0.01
												(0.25)
Duration												-0.07
												(-0.56)
Left												-0.057
												(-0.68)
Trend												-0.11
												(-1.02)
Constant	0.452	0.435	0.609	0.474	1.229	1.194	1.266	1.453	1.381	1.570	1.767	2.457
	(4.37)	(4.31)	(3.79)	(4.67)	(3.48)	(3.51)	(3.63)	(4.33)	(3.90)	(4.62)	(4.83)	(2.99)
R2	0.149	0.212	0.244	0.210	0.299	0.365	0.333	0.414	0.348	0.452	0.476	0.499
Adjusted R2	0.131	0.178	0.194	0.176	0.252	0.308	0.272	0.360	0.289	0.373	0.386	0.351
N	49	49	49	49	49	49	49	49	49	49	49	49

(t-stats in parentheses)

Chapter 4

Decreasing Long-Term Traffic Growth

-Estimating the Functional Form of Road Traffic Maturity- [1] [2]

> "A straight line may be the shortest distance between two points, but it is by no mean the most interesting." (Doctor Who)

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[2]A version of this chapter was accepted for publications in the Journal of Spatial and Network Economics.

Abstract

It has been observed that motorways with high traffic levels experience lower traffic growth than those with lower traffic (ceteris paribus). This phenomenon is known as traffic maturity; however, it is not captured through traditional time-series long-term forecasts, due to constant elasticity to GDP these models assume, leading overestimation in traffic forecasting for these motorways. In this chapter we argue that traffic maturity results from decreasing marginal utility of transport. The elasticity of individual mobility with respect to the revenue decreases after a certain level of mobility is reached. In order to find evidences of decreasing elasticity we analyse a cross-section time-series sample including 40 French motorways' sections. This analysis shows that decreasing elasticity can be observed in the long term. We then propose a decreasing function for the traffic elasticity with respect to the economic growth, which depends on the traffic level on the road. This model seems to well explain the observed traffic evolution and gives a rigorous econometric approach to time-series traffic forecasts, producing more accurate forecasts.

4.1 Introduction

The link, or coupling, between traffic and economic growth is a strong concept in transport and regional planning. In aggregated models of transport demand forecast, individual mobility and revenue are represented by traffic and gross domestic product (GDP). Mobility generates traffic and we suppose that growth in GDP leads to growth in purchase power. In economics, this link is represented by an elasticity of traffic with respect to the GDP, usually greater than one. We can observe that older high traffic motorways experience lower traffic growth than newer, low traffic, ones (*ceteris paribus*). This phenomenon is known as traffic maturity in analogy with market maturity, a well known stage of products lifecycle. This phenomenon is not captured through traditional time-series long-term forecasts, due to constant elasticity to GDP these models assume. However, the observation of long traffic growth series put in evidence a growth deceleration in the long term.

In this sense we argue that the application of traditional traffic forecast models using time series with constant elasticity of traffic with respect to the GDP produces high growth hypothesis, leading to traffic overestimation. This study aims at putting in evidence a decreasing relationship between the traffic lever and the elasticity of the traffic with respect to economic growth and proposes a new econometric formulation for the time-series traffic forecast which considers the elasticity of traffic with respect to the GDP as a function of traffic level. Results show that this new model produces more reliable and precise forecasts.

The chapter is organized as follows: section 2 presents the stages of traffic growth and the traditional econometric approach. Section 3 proposes that traffic maturity is a direct consequence of the decreasing marginal utility of transport. In section 4 we present the Partial Adjustment Model and the Error Correction Model. Section 5 puts in evidence the decreasing of elasticity over the traffic lever using data from 40 cross-sections time series sample. Section 6 proposes the new model and shows the impact in long term forecasts. Section 7 briefly concludes the chapter.

4.2 Traffic Growth

In transport demand forecast, whether for road, rail or air link, three growth stages are identified: the ramp-up, the traffic growth and the maturity. Ramp-up describes the delay traffic needs to reach its market share. The ramp-up period reflects the users' lack of familiarity with the new infrastructure and its benefits. It can also be due to reluctance to pay tolls or to information lags. The ramp-up period is characterized by a high traffic growth, from a level that is lower than expected as the equilibrium.

Another important phenomenon affecting the ramp-up is the induced traffic. Induced traffic is the increment of new vehicle traffic resulting from a road capacity improvement. It represents the latent demand, excluding shifts from other modes or routes, changing in departure time and longer distances (which account for induced travels) and exogenous factors (as growth in population and economy). New trips to existing locations, trips that would not have occurred otherwise, are the purest form of induced traffic (Goodwin, 1996; Mokhtarian et al., 2002).

As the short term impacts get over, the traffic evolution results from the growth in demand, which comes from the economic and population growths and the impact of monetary costs (toll, fuel and operating costs) on the route chosen and on alternative routes and modes. After a certain level is reached, traffic grows slower, giving evidence that the need for transport was satisfied. Disregarded in transport, market maturity is nevertheless a main issue in new products market analysis, for which the life cycle is shorter and concurrence stronger than in transport sector. In the transport sector, this phenomenon has been recognized and studied at first in the air transport for tourism (Department for Transport, 1997; Graham, 2000); the possibilities to go on holidays been constrained, we should expect traffic will not grow unlimitedly.

The volume of traffic on a motorway can be assumed to depend on the level of economic activity, on the monetary and time costs of the motorway and on those of the alternative route and modes, as well as on the transport system characteristics. Monetary cost is defined as the sum of three components: toll, fuel price and other vehicle operating costs. Besides, given that demand for transport is a derived demand, other variables that have an effect on traffic should also be included in the equation. In this case, traffic volume in a specific motorway section is assumed to depend on the capacity of traffic emission and attraction of origins and destinations. The model can therefore be expressed as follows (Matas and Raymond, 2003):

$$T_{it} = \alpha_{0i} + \alpha_{1i}GDP_t + \alpha_{2i}PF_t + \alpha_{3i}Toll_{it}^M + \alpha_{4i}VC_{it}^M + \alpha_{5i}TC_{it}^M + \alpha_{6i}VC_{it}^R + \alpha_{7i}TC_{it}^R + \alpha_{8i}E_i + \alpha_{9i}A_i + \varepsilon_{it} \quad (4.1)$$

where

T_{it} is the traffic volume at the motorway section i and period t,

GDP_t is the level of economic activity in period t,

PF_t is the fuel price in period t,

$Toll_{it}$ is the motorway toll in section i and period t,

VC_{it}^j are other vehicle operating costs, $j = M, R$ refers to motorway and alternative modes, respectively,

TC_{it}^j are the time costs in section i and period t,

E_i is the emission factor in section i,

A_i is the attraction factor in section i.

However, in the context where this estimation takes place it can be assumed that other vehicle operating costs and time costs remain constant over time. Thus, it is assumed that $VC_{it}= VC_i$ and $TC_{it}= TC_i$. Therefore, after substitution, we get:

$$T_{it} = [\alpha_{0i} + \alpha_{4i}VC_{it}^M + \alpha_{5i}TC_{it}^M + \alpha_{6i}VC_{it}^R + \alpha_{7i}TC_{it}^R + \alpha_{8i}E_i + \alpha_{9i}A_i] + \alpha_{1i}GDP_t + \alpha_{2i}PF_t + \alpha_{3i}Toll_{it}^M + \varepsilon_{it} \quad (4.2)$$

Thus, the demand equation can be re-written as:

$$T_{it} = \beta_{0i} + \alpha_{1i}GDP_t + \alpha_{2i}PF_t + \alpha_{3i}Toll_{it}^M + \varepsilon_{it}$$

where β_{0i} captures the terms in brackets in equation (4.2). This equation is usually applied on the log-log form. This transformation reduces heteroscedasticity and gives a convenient interpretation of results, which can be read directly as elasticities. The equation becomes:

$$lnT_{it} = \beta_{0i} + \alpha_{1i}lnGDP_t + \alpha_{2i}lnPF_t + \alpha_{3i}lnToll_{it}^M + \varepsilon_{it} \tag{4.3}$$

This model, henceforth called LTM, for long-term model, represents a long-term equilibrium between the variables. The elasticity of traffic with respect to the GDP in section i is α_1 because:

$$\varepsilon_{T/GDP} = \frac{GDP}{T}\frac{\delta T}{\delta GDP} = \frac{\delta lnT}{\delta lnGDP} = \alpha_1 \tag{4.4}$$

This constant elasticity specification is generally used in empirical studies but it is however questionable since we could expect the elasticity to be decreasing; this argument is developed in the next section.

4.3 Why does Traffic Grow Decreasingly?

The consumer theory, from its classic axioms, transforms preferences in utility. The law of decreasing marginal utility states that marginal utility decreases as the quantity consumed increases. In essence, each additional good consumed is less satisfying than the previous one. This law holds for most goods, and do so for transport. This principle supports the idea of decreasing transport growth since the utility of an additional travel depends on individual's mobility. Furthermore, time and money constraints limit transport possibilities.

New traffic comes from new users on the route or mode and from existent users making more or longer trips. The traffic increment due to new users results from population growth as well as changes in land use and in locations of economic activities. Furthermore, reductions in transport costs as well as increases in user's wealth allow people to travel more and more often. This is particularly evident in the case of the air transport sector, where price reductions due to competition in the last years had not only diverted users from other modes but also allowed less rich people to afford air travels.

For existing users, the reduction on generalized costs, increasing in wealth and reduction and flexibility in working time allow users to travel more often. The possibility of supplementary trips is however constrained by time (daily time and holidays) and money availability. Budget and time depend not only on transport itself but on time and money spent in all others activities. These constraints unequally affect different people and different population classes. A retired person is supposed to be more constrained by money than by time, inversely to a rich businessman.

In addition to budget and time constraints, there is the will to travel. We can reasonably suppose that the higher is the individual's mobility level, the lesser will be his inclination or necessity to make one more trip. Despite regular fluctuations in transport demand, i.e. seasonal peaks, it has been suggested (for example, by Thomson (1974)) that over time, there has been a remarkable stability in the demand for travel, with households, for example, on average making roughly the same number of trips during a day albeit for different purposes or by different modes. There may be more leisure travel, but there are fewer work trips and greater is now made of air transport and the motorcar at the expense of walking and cycle. It is suggested that this situation reflects the obvious fact that there is a limit to the available time people have for travel, especially if they are to enjoy the fruits of the activities at the final destinations (Button, 1993).

This phenomenon is formulated as the decreasing marginal utility of travel, which means that $U(t) > 0$, $U'(t) > 0$ and $U''(t) < 0$, where $U(t)$ is the utility of transport. The utility function and constraints compose the individual's utility maximization program, where individual make trade-offs between possible allocations of resources. Utility functions define choices which generate demand functions, from which elasticities can be derived. Elasticities give adimensional measures of sensibility of a variable with respect to another. Elasticities are then concise measures of preferences and reflect the sensibility to changes in a limited resources environment (figure 4.1).

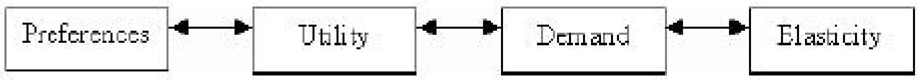


Figure 4.1: From preferences to elasticity.

The ordinary or Marshallian demand function is derived from consumers who are postulated to maximize utility subject to a budget constraint. As a good's price changes, the consumer's real income (which can be used to consume all goods in the choice set) changes. In addition the goods price relative to other goods changes. The changes in consumption brought about by these effects following a price change are called *income* and *substitution* effects respectively. Thus, elasticity values derived from the ordinary demand function include both income and substitution effects (Gillen et al., 2004).

In this sense, the elasticity of individual mobility with respect to the revenue decreases after a certain level of mobility is reached. In aggregated terms, the superposition of individual behaviours results in an increment in traffic which is decreasing in the part of traffic generated by existing users and therefore for economic and population constant growth, globally decreasing.

Congestion also constrains traffic growth. It has a double effect, first it physically limits traffic growth and second it reduces the generation of traffic by increasing the generalised cost. Nevertheless, traffic maturity must be isolated of congestion. Traffic maturity is a pure demand effect while congestion comes from the interaction of a level of demand higher then infrastructure capacity. We argue that maturity do not depends on supply (while traffic does). This argument is valid if we consider that congestion is limited to special periods (holiday departure) or a particular OD pair, affecting at the individual level, while our analysis focuses in a more aggregated level.

4.4 Econometric Issues

4.4.1 Partial Adjustment

The model (4.3) implies a long-run relationship between the variables; in any given period, actual demand could only be expected to be in equilibrium with (and so to be completely explained by) the income and costs associated in each period. However, the persistence of habit, uncertainty and incomplete information are some reasons why complete adjustment could not be achieved in a single period. In this case, the desired demand in year t, T^*_{it} is not equivalent to the actual demand in t, T_{it}. Although behavioural adjustment is toward the equilibrium, only a proportion, θ, of the gap between the desired (equilibrium) demand and actual demand is closed each year. This can be written as:

$$T_{it} - T_{it-1} = \theta(T^*_{it} - T_{it-1}) \tag{4.5}$$

where θ $(0 \leq \theta \leq 1)$ is the adjustment coefficient, which indicates the rate of adjustment to long term equilibrium and reflects the inertia of economic behaviour. Rearranging (4.5) and substituting in (4.3) we obtain the following Partial Adjustment Model:

$$lnT_{it} = \theta\beta_{0i} + \theta\alpha_{1i}lnGDP_t + \theta\alpha_{2i}lnPF_t + \theta\alpha_{3i}lnToll^M_{it} + (1-\theta)lnT_{it-1} + \varepsilon_{it} \tag{4.6}$$

or equivalently:

$$lnT_{it} = \beta_{0i} + \alpha_{1i}lnGDP_t + \alpha_{2i}lnPF_t + \alpha_{3i}lnToll^M_{it} + \phi lnT_{it-1} + \varepsilon_{it} \tag{4.7}$$

where the short-run elasticities are given by the coefficients α's and the long-run elasticities are the ratio of the short-run value by 1-ϕ.

4.4.2 Integrated variables, Cointegration and Error-Correction

Most time-series techniques need data to be stationary, but this requirement is often not fulfilled by economic series, which tend to increase over time. Those problems were somehow ignored in applied work until important papers by Granger and Newbold (1974) and Nelson and Plosser (1982) alerted many to the econometric implications of non-stationarity and the dangers of running *nonsense* or *spurious* regressions.

A non-stationary series can be made stationary by detrending series. A convenient way of detrending is by using first differences rather than levels of the variables. A non-stationary series which can be made stationary by differencing d times is said to be integrated of order d, denoted $x_t\tilde{I}(d)$, a stationary series is a $I(0)$ series (Engle and Granger, 1987).

While removing trending by differencing can actually be a statistical satisfactory solution, it represents a lost of economic information about the long term relationship. However, for some time it remained to be well understood how both variables in differences and levels could coexist in regression models. (Granger, 1981), resting upon the previous ideas, solved the puzzle by pointing out that a vector of variables, all of which achieve stationarity after differencing, could have linear combinations which are stationary in levels. Later, (Engle and Granger, 1987), were the first to formalize the idea of integrated variables sharing an equilibrium relation which turned out to be either stationary or have a lower degree of integration than the original series. They denoted this property by *cointegration*, signifying co-movements among trending variables which could be exploited to test for the existence of equilibrium relationships within a fully dynamic specification framework. In this sense, the basic concept of cointegration applies in a variety of economic models. A humorous illustration of this concept is given by Murray (1994) and extended by Harrison and Smith (1995).

Before proceeding with the cointegration analysis, it is necessary to verify whether the variables under consideration are stationary, and if not, check their orders of integration. This can be accomplished using the unit-root test. The most widely used unit-root test is the Augmented Dicky-Fuller (ADF) test, which involves running (with constant, trend and p lags):

$$\Delta y_t = \mu + \beta_t + \gamma y_t + \sum_{j=1}^{p} \phi_j \delta y_{t-1} + \varepsilon_t \tag{4.8}$$

This test was applied for each section as well as for the independent variables. The null hypothesis of unit root was always non-rejected (tables 4.1 and 4.2).

Various methods have been suggested to test for cointegration. One method is to estimate the long-run relationship (as in (4.3)) by OLS and testing whether the residual is stationary. This can be done using the Durbin-Watson statistic, DF or ADF tests. The hypothesis of unit roots of residuals could always be rejected .

Table 4.1: ADF test - exogenous variables

	Variables (in logarithms)	
	adf	p-value
GDP	-3.3579	0.08363
Fuel	-2.8059	0.2654
Toll 1	-2.3442	0.4412
Toll 2	-4.1275	0.0188
Toll 3	-2.3482	0.4397
Toll 4	-1.8115	0.6442
Toll 5	-2.0474	0.5543
Toll 6	-3.3201	0.0888
Toll 7	-1.4157	0.7950

It should be stressed that unit-root tests in general do not produce unambiguous results. They are large sample tests and their behaviour in small samples is questionable. Moreover, the results of different tests are contradictory many times. Given these problems, any results regarding the stationarity or non-stationarity of a particular series must be treated with caution (Dargay et al., 2002). Furthermore, the link between the economic and traffic growth in not to be proved anymore.

According to the Granger Representation Theorem, cointegrated series can be represented by an Error Correction Model. The dependent variable in an Error-Correction Model (ECM) is specified in terms of differences, rather than levels. ECM are well suited in cointegrated relationships since they incorporate the long-run relationships as well as the dynamics implied by the deviations from this equilibrium path and the adjustment process to recover it. The ECM can be written as (Dargay et al., 2002):

$$\Delta T_t = \alpha_0 + (\varphi - 1)T_{t-1} + \beta_0 \delta X_t + (\beta_0 + \beta_t)X_{t-1} + \varepsilon_t \tag{4.9}$$

where X is the vector of explanatory variables. More general forms could include higher order lagged differenced terms of the independent variables and lagged differences of the dependent variables. The model (10) can alternatively be written as:

$$\Delta T_t = \alpha_0 + \beta_0 \delta X_t + (\varphi - 1)\left[T_{t-1} + \frac{(\beta_0 + \beta_t)}{X_{t-1}} X_{t-1}]\right] + \varepsilon_t \tag{4.10}$$

The parameter β_0 represents the short-term effect and $(1 - \varphi)$ is the feedback effect, which is similar to the adjustment coefficient, θ, in the Partial Adjustment Model. The long-run response is given by $(\beta_0 + \beta_1)/(1 - \varphi)$. The term in the square brackets in equation (A5) is called an "error-correction mechanism" since it reflects the deviation from the long run, with $1 - \varphi$ of this deviation being closed each period. The Error Correction Model allows estimation of both short- and long-run parameters simultaneously. If the error-correction term $\varphi - 1$ is significantly different from zero and negative (since $0 < \varphi < 1$) the variables are cointegrated and the estimated parameters of the lagged level variables define the long-run relationship. The estimated model then takes the following form:

$$\begin{aligned} \Delta lnT_{it} = {} & \beta_{0i} + \beta_{1i}\Delta lnGDP_t + \beta_{2i}\Delta lnPF_t + \beta 3i \Delta lnToll_{it}^M + \\ & \alpha_{1i} lnT_{it-1} + \alpha_{2i} lnGDP_{t-1} + \alpha_{3i} lnPF_{t-1} + \alpha_{4i} lnToll_{it-1}^M + \varepsilon_{it} \end{aligned} \tag{4.11}$$

4.5 Data and Estimation

The data used in this analysis comes from the ASFA (Federation of French motorways concessionaires). Our sample includes 40 French motorway's sections with traffic series longer than 15 years, in different French regions and including all the main concessionaires (ASF, APRR, COFIROUTE, SANEF and SAPN). The GDP series comes from the INSEE (National Institute for Statistics and Economic Studies). The series of toll prices for all concessionaires were provided by the the Department of Traffic and Economic Studies of COFIROUTE.

For each section and each model (LTM, PAM and ECM), we begin with a general specification which includes all explanatory variables, and proceed to exclude those which are either implausible because of magnitude or sign or insignificant in a statistical sense. All estimates and statistical tests presented in this chapter were computed using *SAS* v9.

4.6 Evidences of Decreasing Growth

A concavity can be observed for the last periods in many long term traffic series. Figure (4.2) and Figure (4.3) show this decreasing of growth in two French motorways. The issue here is to understand whether this deceleration of the growth indicates that the maturity had been reached or it results from an economic deceleration, an increasing in fuel costs or other factors.

In order to find evidences that this decreasing growth results from a decreasing elasticity we proceed to a three steps analysis. First, we estimate the long-run elasticity of traffic with respect to the GDP using the three models presented earlier. Second, we test for the statistical stability of parameters on these sections using the CUSUM2 tests. Finally, we segment the sample in order to observe the evolution of elasticities.

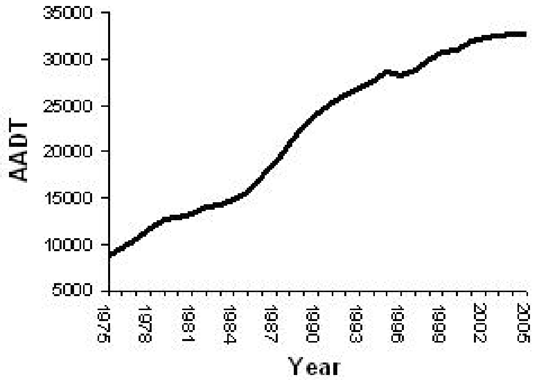


Figure 4.2: Traffic on the A10 motorway.

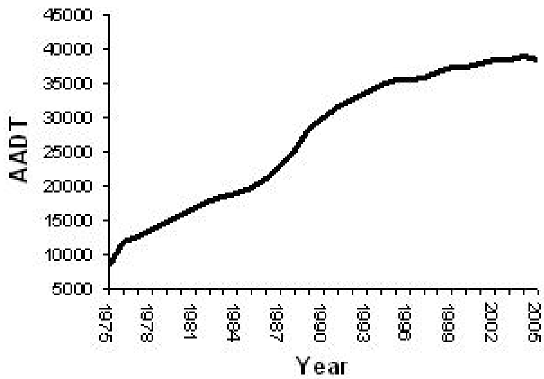


Figure 4.3: Traffic on the A11 motorway.

4.6.1 Cross-section Time Series Analysis

We applied the LTM, PAM and ECM for the 40 sections in order to determine the (constant) elasticity of traffic with respect to the GDP (results are presented in appendix 1). Plotting the long-run elasticity of the traffic with respect to the GDP over the traffic level in the first period (max(1980, opening date)) we can observe a clear decreasing relationship, i.e. sections with a high traffic at opening present a lower elasticity.

This result is however much less evident for the short-run elasticities. Some decreasing relationship can be found using the ECM but not with the PAM, moreover, many short-run elasticities are not statistically significant. This

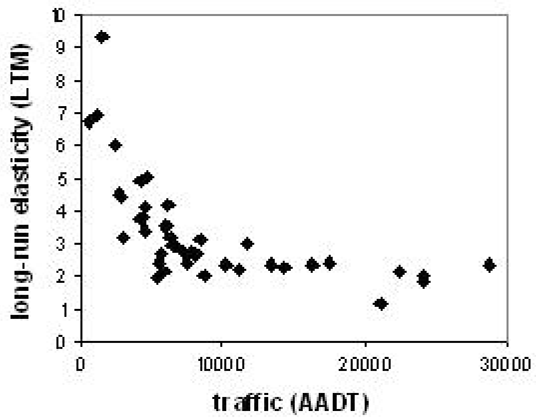


Figure 4.4: LTM long-run elasticities.

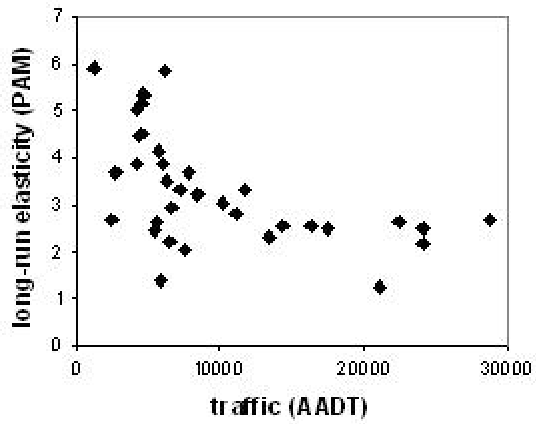


Figure 4.5: PAM long-run elasticities.

result can be viewed in figures 4.7 and 4.8 .

An interesting issue here is to see whether the three models produce comparable elasticities. Comparing the statistical significant (at 90% level) long-run elasticities estimated by the LTM, PAM and ECM (appendix 1) we can see that (i) results are quite close in the three models for most sections and (ii) it seems that, in average, the PAM tends to produce slightly higher elasticities than the other models. Despite its incapacity of estimating short-run elasticities the LTM has the strong advantage of allowing for more robust estimates. It is the only model which produces statistical significant elasticities for every

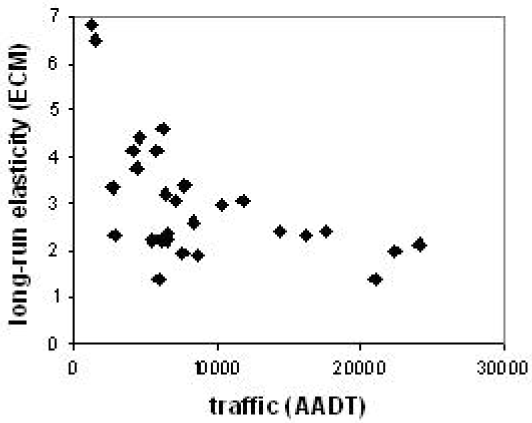


Figure 4.6: ECM long-run elasticities.

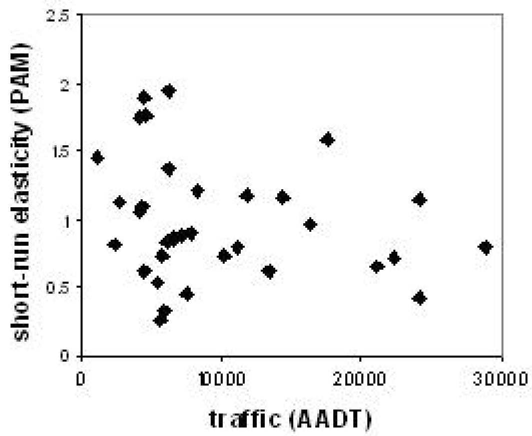


Figure 4.7: PAM short-run elasticities.

section.

4.6.2 Testing for Parameter Stability

Proposed by Brown et al. (1975) the CUSUM^2 (or CUSUM of squares) test for the constancy over time of the coefficients of a linear regression model. This tests is based on recursive residuals. The technique is appropriate for time series data and might be used if one is uncertain about when a structural change might have taken place (contrary to the Chow test). The null hypothesis is

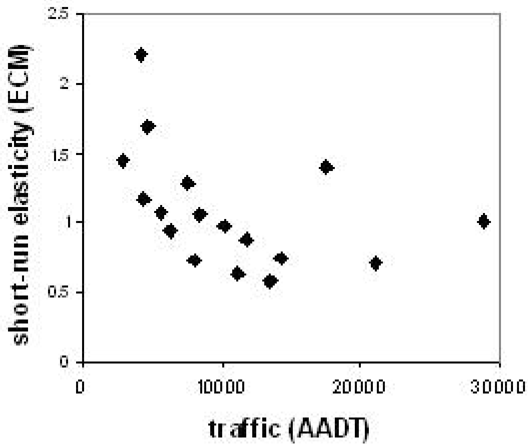


Figure 4.8: ECM short-run elasticities.

that the coefficient vector β is the same in every period; the alternative is simple that it (or the disturbance variance) is not. The test is quite general in that it does not require a prior specification of when the structural change takes place and is preferred to the CUSUM due to its higher power.

Suppose that the sample contains a total of T observations. The tth recursive residual is the ex-post prediction error for y_t when the regression is estimated using only the first $t-1$ observations. Since it is computed for the next observation beyond the sample period, it is also labeled a one step ahead prediction error;

$$e_t = y_t - x_t'\hat{\beta}_{t-1}$$

where x_t is the vector of regressors associated with the observation y_t and $\hat{\beta}_{t-1}$ is the least square coefficients computed using the first $t-1$ observations. The forecast variance of this residual is:

$$\sigma_{ft}^2 = \sigma^2[1 + x_t'(X_{t-1}'X_{t-1})^{-1}x_t]$$

Let the rth scaled residual be

$$w_r = \frac{e_r}{\sqrt{1 + x_r'(X_{r-1}'X_{r-1})^{-1}x_r}}$$

The CUSUM of squares test uses

$$S_t = \frac{\sum_{r=K+1}^{t} w_r^2}{\sum_{r=K+1}^{T} w_r^2} \tag{4.12}$$

Since the residuals are independent, each of the two terms is approximately a sum of chi-square variables each with one degree of freedom. Therefore, $E[S_t]$ is approximately $(t - K)/(T - K)$. The test is carried out by constructing confidence bounds for $E[S_t]$ at the values of t and plotting S_t and these bounds against t. The appropriate bounds are $E[S] \pm c_0$, where c_0 depends on both $(T - K)$ and the significance level desired. As before if the cumulated sum strays out the confidence bounds, doubt is cast on the hypothesis of parameters stability. This test was applied in the fits provided by (4). Results are shown in table 1 where 0 represents the validity of the null hypothesis (constancy of parameter) and 1 indicates that coefficients do not remain constant during the full sample period at 95% of significance. The null hypothesis of stability was rejected in 29 cases.

4.6.3 Moving Regressions

The relationship between long-run elasticities and the traffic level shows that high traffic level motorways tend to have smaller elasticities and the cusum of squares test show that parameters may be varying over time. The link between these two results will be to show that within each section, the elasticity is decreasing. A simple diagnostic test to detect the decreasing of the parameter is to partition the sample into subsamples of approximated equal number of observations each. We set 2 subsamples of approximately 15 years (with overlapping). Results in table 4.5 (ss_1 and ss_2 for subsamples 1 and 2 respectively) show that a globally decreasing elasticity can be observed in all but 2 sections, and in most cases, the elasticity in the second period is also smaller than the lower bound (95%) of the first subsample.

4.7 A Functional Form for Decreasing Elasticity

There are different ways to specify declining elasticities. Some studies (as in Dargay et al. (2002) propose "inconditional" declining elasticites by replacing the log of GDP by the inverse of some function of GDP (GDP, $ln(GDP)$, or other). Dargay et al. (2002) find that declining elasticities are more arguable and provide statistically better fits.

Precedent results and the theoretical arguments explained before lead us to consider a variable relation between traffic and economic growths by an elasticity depending on the traffic level. To take in account the asymptotically decreasing put in evidence, we propose the following formulation:

$$\varepsilon_{T/GDP}(T) = \frac{\frac{\delta T}{T}}{\frac{\delta GDP}{GDP}} = kT^{\gamma} \tag{4.13}$$

where k is a positive constant and γ is a negative constant. The parameter γ may be interpreted as the elasticity of the - elasticity of traffic with respect to the GDP - with respect to the traffic level, since:

$$\varepsilon_{\varepsilon_{T/GDP}/T} = \frac{\delta\varepsilon_{T/GDP}}{\delta T}\frac{T}{\varepsilon_{T/GDP}} = \gamma kT^{\gamma-1}\frac{T}{kT^{\gamma}} = \gamma$$

The differential equation (4.13) is separable and its solution (for $\gamma \neq 0$) is:

$$T = (-\gamma(klnGDP + c))^{-\frac{1}{\gamma}} \tag{4.14}$$

Where c is the constant from the integration. Assuming that this relation holds for the first period (T_1, GDP_1) and both T_1 and GDP_1 are normalized to one then T becomes:

$$T = (1 - \gamma klnGDP)^{-\frac{1}{\gamma}} \tag{4.15}$$

The equation (4.3) can be therefore rewritten as:

$$lnT_{it} = \beta_{0i} - \frac{1}{\gamma_i}ln(1 - \gamma_i k_i lnGDP_t) + \alpha_{2i}lnPF_t + \alpha_{3i}lnToll^M_{it} + \varepsilon_{it} \tag{4.16}$$

This approach sets up an intrinsic relation between the traffic level and its reactivity to economic growth, as wanted; it allows for a good representation of the phenomenon and an easy interpretation of results at the cost of introducing a non-linearity in the transport demand equation.

Estimated γ and k are reported in appendix 1. Results provide very good fits and proper values, except in two cases, for which we estimated positives values for γ (for the same sections where the moving regressions indicated a growth instead of a decreasing of the elasticities), indicating that the maturity has not been reached; these values shall be used with care for forecast purposes. Figure 4.9 compares the constant and the variable elasticity for section 40; the vertical line represents the ratio between the traffic in the last and in the first periods.

Figure 4.9: Comparing elasticities.

We could expect lower traffic motorways to have higher k's and higher γ's, this result is confirmed in our analysis; it can be graphically viewed in figures 4.10 and 4.11(we do not include the two positive values of γ and their respective k). We can observe also that the dispersion of γ increases with the traffic level. This result means that high traffic motorways may be at different stages of maturity, as we could expect.

The same principle can be applied to the PAM and to the ECM. For these models we can apply two different approaches. The first one consists in setting a decreasing parameter for the GDP, as for the LTM. This will nevertheless imply a decreasing short-run elasticity for the PAM. The second approach is,

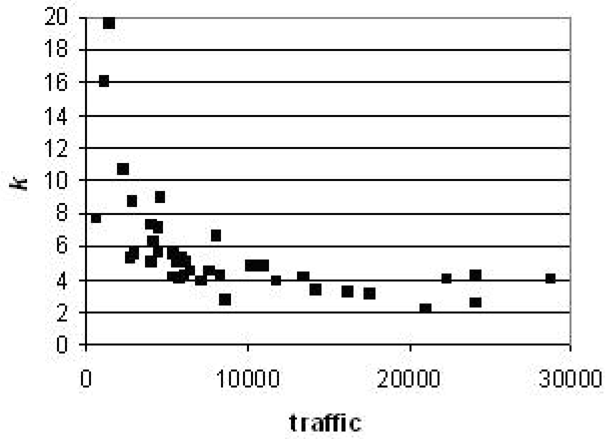


Figure 4.10: k versus traffic.

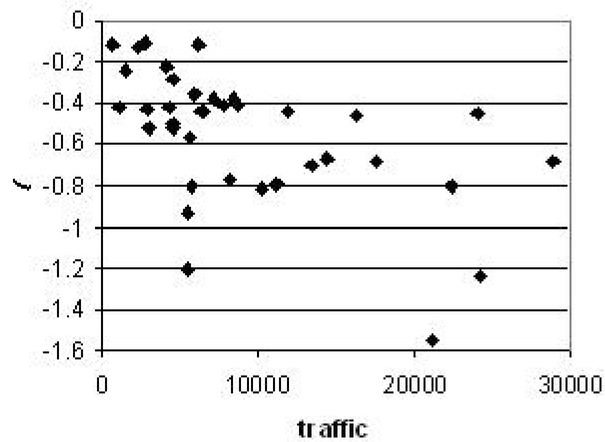


Figure 4.11: γ versus traffic.

instead of setting a decreasing coefficient with respect to the GDP, consider a growth of the adjustment coefficient (θ in the PAM and -1 in the ECM) following the same pattern. This formulation leads to the same results in terms of long-run elasticities and is consistent with the economic intuition behind the hypothesis of decreasing elasticity.

Writing $\phi = kT^{\gamma}$ in the PAM, equation (4.7) becomes:

$$lnT_{it} = \beta_{0i} + \alpha_{1i}lnGDP_t + \alpha_{2i}lnPF_t + \alpha_{3i}lnToll_{it}^M - \frac{1}{\gamma_i}ln(1 - \gamma_i k_i lnT_{t-1}) + \varepsilon_{it} \tag{4.17}$$

and the long-run elasticities will be given by the ration of the short-run value by $1 - k_i T^{\gamma_i}$, where $0 < k_i < 1$ and $\gamma_i < 0$.

Making $\varphi - 1 = kT^\gamma$ (where k will be negative and γ positive) the ECM (4.11) can be re-written as:

$$\begin{aligned} \Delta lnT_{it} &= \beta_{0i} + \beta_{1i}\Delta lnGDP_t + \beta_{2i}\Delta lnPF_t + \beta 3i\Delta lnToll_{it}^M \\ &- \frac{1}{\gamma_i}ln(1 - \gamma_i k_i lnT_{t-1}) + \alpha_{2i}lnGDP_{t-1} + \alpha_{3i}lnPF_{t-1} + \alpha_{4i}lnToll_{it-1}^M + \varepsilon_{it} \end{aligned} \tag{4.18}$$

The long-run elasticities will be given by $\alpha / -k_i T^{\gamma_i}$ or equivalently, $-\alpha k_i T^{-\gamma_i}$.

4.7.1 Impact on Long-Term Forecasts

As we can see in figure 4.12, if the elasticity decreases with the traffic growth, the assumption of a constant elasticity will tend to overestimate the future traffic. Consider the hypothetical case in figure 4.12 where both initial traffic is GDP are normalized to 1, the constant elasticity is 2.0, $k = 2.5$ and $\gamma = -0.5$. We can see that in the short term results from both models are very close. As the GDP increases the difference becomes more important; the classic model presents a globally convex profile while the new model produces a concave evolution.

This approach was applied in a large scale forecast traffic until 2030 to the main French private motorways. One example is given in the figure 4.13; both models presented very good fits ($R^2 > 0.98$). Results show that the variable elasticity model produces more conservative forecasts. Moreover, estimating both models using data until 1999 and comparing the forecasts between 2000 and 2005 with the actual traffic we can see that the variable elasticity model was twice more precise.

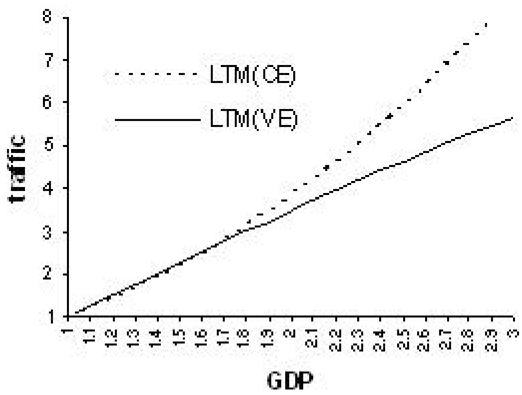


Figure 4.12: A hypothetical example.

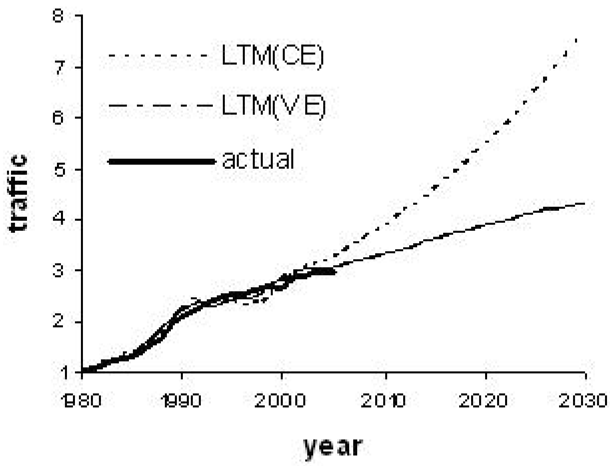


Figure 4.13: Application on the A11 motorway.

This method is however very data greedy. If no information on parameters is inferred, a quite long data series is needed to calibrate the model but it confers a significant advantage in terms of results for very long term forecasts for which the constant elasticity seems to be an unrealistic and overoptimistic hypothesis.

4.8 Conclusions

In this chapter we put in evidence the decreasing of the elasticity of traffic with respect to the GDP, which characterises the traffic maturity and have shown that the hypothesis of constant elasticity assumed by classic models is unrealistic and leads to traffic overestimation. A new model of decreasing elasticity is proposed setting up an intrinsic relation between the traffic level and its reactivity to economic growth. This model allows for a good representation of the phenomenon, a good interpretation of results and gives a rigorous econometric approach to time-series traffic forecasts, at the cost of introducing a non-linearity in the equation. In the short term the model results are closer to that given by the classical constant elasticity model; in the long term, where classic models tend to produce linear or convex profiles, this model reproduces the observed concavity. This model allows for a better interpretation of the coupling between traffic and economic growth, and a more accurate long-term forecast.

Table 4.2: ADF test - traffic

	Variables (in logarithms)		LTM residuals	
	adf	p-value	adf	p-value
section 1	-2.4394	0.405	-1.3287	0.8281
section 2	-1.3288	0.828	-1.5716	0.7356
section 3	-2.9603	0.2065	-2.228	0.4855
section 4	-1.1303	0.9014	-1.467	0.7754
section 5	-1.7939	0.6509	-1.1409	0.8997
section 6	-0.6814	0.9599	-1.371	0.812
section 7	-5.9499	0.01	-1.7975	0.6495
section 8	-2.2077	0.4933	-3.1229	0.1446
section 9	-1.7048	0.6848	-3.3294	0.08758
section 10	-2.9225	0.2209	-2.0562	0.551
section 11	-0.6509	0.9624	-2.3594	0.4355
section 12	-1.9304	0.5989	-1.4336	0.7882
section 13	-2.9601	0.2066	-2.4367	0.406
section 14	-2.2191	0.4889	-2.3243	0.4489
section 15	-1.8089	0.6452	-2.8079	0.2646
section 16	-2.4413	0.4043	-2.4306	0.4083
section 17	-1.3369	0.825	-1.464	0.7766
section 18	-1.6953	0.6885	-1.9466	0.5927
section 19	-1.7911	0.652	-3.184	0.1213
section 20	-2.4587	0.3977	-2.6592	0.3213
section 21	-2.3947	0.422	-1.8303	0.637
section 22	-1.552	0.743	-2.4978	0.3828
section 23	-2.756	0.2844	-1.8363	0.6348
section 24	-2.1455	0.5169	-2.2191	0.4889
section 25	-3.2599	0.09723	-2.5728	0.3542
section 26	-2.235	0.4828	-1.5475	0.7448
section 27	-2.4379	0.4056	-1.9891	0.5765
section 28	-1.1658	0.8902	-1.8397	0.6334
section 29	-3.2201	0.1076	-1.1729	0.8875
section 30	-2.5795	0.3516	-1.8774	0.6191
section 31	-2.156	0.513	-1.7083	0.6835
section 32	-2.5759	0.353	-1.6994	0.6869
section 33	-1.4993	0.7631	-1.4238	0.7919
section 34	-2.133	0.5217	-3.3224	0.08856
section 35	-1.3087	0.8357	-1.7997	0.6487
section 36	-1.0752	0.9095	-1.6362	0.711
section 37	-1.5235	0.7539	-2.1963	0.4976
section 38	-0.9742	0.9244	-1.4389	0.7861
section 39	-1.1471	0.8973	-1.6602	0.7018
section 40	-0.6956	0.9587	-2.2377	0.4818

Table 4.3: Summary of descriptive statistics

ID	L	year0	traffic0	elt(LTM)	esr(PAM)	elr(PAM)	esr(ECM)	elr(ECM)
1	25	1980	21090	1.15	0.65	1.24	0.71	1.38
2	18	1987	2362	6.03	0.82	2.69	(1.03)	(2.86)
3	25	1980	24164	1.84	0.42	2.50	(-0.07)	(0.42)
4	25	1980	6177	4.17	1.95	5.84	(1.41)	4.60
5	25	1980	5499	1.95	0.54	2.44	(0.16)	(1.37)
6	22	1983	4630	5.02	1.76	5.34	1.69	(3.39)
7	22	1983	662	6.71	(1.26)	(9.56)	(0.66)	(7.86)
8	20	1985	1532	9.35	(0.39)	(1.27)	(1.02)	6.48
9	25	1980	13456	2.37	0.62	2.32	0.58	(1.47)
10	25	1980	7541	2.43	0.45	2.01	1.29	1.94
11	25	1980	6002	3.54	0.83	3.88	(0.19)	2.23
12	25	1980	6296	3.23	1.37	3.48	0.95	3.20
13	25	1980	4505	4.11	1.90	5.17	(0.95)	4.40
14	25	1980	24111	2.00	1.15	2.18	(0.68)	2.15
15	25	1980	4332	3.76	1.09	4.47	1.18	3.78
16	25	1980	16252	2.35	0.96	2.52	(0.56)	2.34
17	25	1980	8709	2.04	(0.38)	(1.95)	(0.63)	1.89
18	25	1980	2917	4.43	(0.26)	(2.09)	1.44	2.32
19	25	1980	2768	4.51	1.13	3.69	(0.81)	3.33
20	25	1980	6565	2.94	0.86	2.93	(0.75)	2.37
21	24	1981	8370	3.11	1.21	3.23	1.05	2.60
22	18	1987	6494	2.97	0.86	2.22	(-0.90)	2.22
23	25	1980	28854	2.34	0.80	2.67	1.01	(2.55)
24	25	1980	11130	2.19	0.79	2.81	0.63	(2.47)
25	25	1980	4146	3.70	1.07	3.85	2.21	(4.27)
26	25	1980	10236	2.33	0.73	3.02	0.98	2.95
27	25	1980	4159	4.92	1.75	5.03	3.04	4.11
28	25	1980	5507	2.40	0.26	2.62	(0.32)	2.25
29	25	1980	17540	2.42	1.59	2.47	1.39	2.42
30	25	1980	14332	2.28	1.16	2.51	0.75	2.41
31	19	1986	5835	2.14	0.32	1.37	(-0.54)	1.41
32	25	1980	22402	2.19	0.72	2.63	(0.55)	2.00
33	25	1980	7162	2.73	0.88	3.33	(0.42)	3.07
34	25	1980	3074	3.18	(0.46)	(3.88)	(-0.19)	(2.35)
35	23	1982	1138	6.94	1.45	5.89	(1.31)	6.83
36	25	1980	8130	2.67	(0.34)	(3.21)	0.73	(-0.18)
37	25	1980	4496	3.37	0.62	4.49	(0.59)	(0.44)
38	25	1980	7777	2.73	0.90	3.70	(1.00)	3.38
39	25	1980	5700	2.71	0.74	4.15	1.07	4.15
40	25	1980	11834	3.04	1.17	3.33	0.87	3.04

Table 4.4: CUSUM of squares test

section	$cusum^2$	section	$cusum^2$
1	1	21	1
2	1	22	0
3	1	23	1
4	0	24	1
5	1	25	0
6	1	26	1
7	1	27	1
8	0	28	1
9	1	29	1
10	0	30	1
11	0	31	1
12	1	32	1
13	0	33	0
14	1	34	1
15	1	35	1
16	0	36	1
17	0	37	1
18	1	38	1
19	0	39	1
20	1	40	1

Table 4.5: Subsamples Elasticities

section	e_{ss1}	e_{ss2}	$e_{ss2} < e_{ss1}$	section	e_{ss1}	e_{ss2}	$ess2 < ess1$
1	1.39	0.42	1	21	3.36	1.98	1
2	9.36	2.09	1	22	2.05	2.26	0
3	2.26	0.59	1	23	2.89	1.03	1
4	4.29	1.77	1	24	3.05	0.91	1
5	2.43	1.42	1	25	3.46	2.02	1
6	5.08	3.62	1	26	3.13	0.88	1
7	9.26	3.98	1	27	5.34	1.53	1
8	11.31	2.19	1	28	3.41	0.87	1
9	2.44	1.51	1	29	2.60	2.35	1
10	2.26	2.54	0	30	2.52	2.17	1
11	4.08	1.68	1	31	2.64	1.40	1
12	3.94	2.16	1	32	2.49	1.26	1
13	5.07	1.87	1	33	2.98	1.34	1
14	2.21	1.65	1	34	3.64	1.55	1
15	4.44	2.44	1	35	7.17	2.11	1
16	2.58	2.01	1	36	3.36	1.24	1
17	2.18	2.15	1	37	4.12	1.55	1
18	5.33	2.22	1	38	3.16	1.52	1
19	4.81	2.73	1	39	3.15	1.33	1
20	3.29	2.26	1	40	2.84	1.55	1

Chapter 5

Estimating the Value of Travel Time Savings

-Application to the Freight Transport in France-

Abstract

In this study we apply the Logit, the Mixed Logit and the Bayesian Mixed Logit models to estimate the value of time in freight transport in France. We discuss the importance of the value of time and its particular role in the case of private motorways. We present the econometric models currently used to estimate it, giving a special attention to the Bayesian procedures, since it is a relatively new method with only a few results in the literature. We also discuss the main challenges in estimating the value of travel time savings. We then describe the revealed preference survey we realized, including 1027 vehicles in order to study the trade-off between the free road and the tolled motorway. Results show that the Bayesian procedures represent an interesting alternative to the optimization problems the maximum likelihood faces. Also, in line with recent works, we find that using a constant value, representative of an average, can lead to traffic overestimation. Finally, we found average values around €45 per vehicle and per hour, suggesting that the current French standard value should be reviewed upwards.

5.1 Introduction

The value of travel time savings (VTTS) is at the heart of transport projects and transport policies evaluation. It plays a central role in the socio-economic evaluation since time savings usually are the dominant factor in the users' benefit. Despite the importance of the freight transport in the economy, its representativeness in terms of volume of traffic and its contribution for the socio-economic benefits of a new motorway, relatively few studies, in France or abroad, are devoted to the study of the value of time in freight transport.

In order to estimate the welfare produced by the time saving generated by a new infrastructure, econometric models were developed to estimate the value of time. These models are mainly based on discrete choices evaluation of the trade-off between time and money. In models of choice among discrete alternatives, the assumption is made that individual choices are based on perceptions of the relative characteristics of the alternative options; in this way, implicit equivalences are subjectively established. This subjective value of time has concentrated the attention of researchers and policymakers within the industrialized countries. Given this importance, one would like to achieve estimates of subjective value of time that are robust and ideally independent from the functional form of the models used to estimate them (Gaudry et al., 1989).

With the introduction of private finance (and tolling) in transport, willingness to pay is applied to estimate actual out-of-pocket money and then the optimal toll levels and the financial profitability of a project. So, in recent years, an increasingly important application of discrete choice models has been to calculate the potential revenue for tolled roads, and networks with user charges, which offer higher speeds at a higher price. Here the important issue is not the hypothetical willingness to pay, but the actual money that will be handed over. It changes focus from hypothetical to bankable value of time (Hensher and Goodwin, 2004).

In this context, one of the main issues regarding the value of time is its distribution over the population. Heterogeneity in population comes from tastes, revenue, journey characteristics, distance and purpose. In freight transport, it will depend also on the firm's market and financial structures, on the characteristics of the goods, own account or hire transport, among other factors.

While in project evaluation the VTTS is usually taken as constant, for equity reasons (but this practice varies according the current national recommendation, and this social value usually differ from those issued from econometric estimations, representing a more "social" value of time), in revenue forecasts, and so for toll setting, the assumption of a constant VTTS may be very restrictive and lead to significant forecast errors. In fact, if an average value, virtually representative of a symmetric distribution, is taken as representative of a skewed distribution, there will be tendency to overestimate revenue. As a consequence, the value of time represents a main source of uncertainty. Moreover, in the VTTS modelling process, data quality, model structure and statistical or behavioural hypothesis play together; in this way VTTS may be used as a strategic variable, allowing to "adjust" the traffic and revenue levels.

Logit is by far the most applied model in discrete choice analysis. The logit model derives from the random utility model, which separates the total utility into deterministic and random components, under the assumptions of independent and identically distributed Gumbel disturbances. Its popularity is due to the fact that the formula of choice probabilities takes a closed form and is readily interpretable with good results related in literature[1]. In this model, heterogeneity, unobserved attributes and measurement errors are captured by the random disturbance and the coefficients of the utility function are fixed, leading to a constant value of time, representative of a virtual average individual.

Advances in simulated estimation techniques have enabled analysts to use increasingly complex models that allow one to define broader behavioural patterns, overshadowing the classic Multinomial Logit (Train, 2003). In the random coefficient random utility model, both coefficients and error term are represented by some PDF (Probability Distribution Function), this model is usually called Mixed Logit (ML) because it can be viewed as a logit with mixtures. ML is a high flexible model than can approximate any random utility model, and it is considered the most promising discrete choice model currently available (Hensher and Goodwin, 2004); it has been known for many years but has only become applicable with the development of simulation techniques. This model do not presents the restrictive properties of logit and allows for a

[1]probably accompanied by less good ones, less released

different PDF for each parameter, but results are also sensitive to the specification of the PDF shape. However, in practice, many difficulties challenge the application of this model, as the choice of the distribution, the starting values and convergence problems in maximum simulated likelihood.

Furthermore, the introduction of prior knowledge is intrinsic even to the classic analysis. First, the analyst usually has some priors about the result (i.e. one should expect that the value of travel time to be positive and to lay within a reasonable set) and second, the set of hypothesis and parameters need to the estimation of mixed logit models like the form of the distributions, eventual constraints and the starting values indirectly represent prior hypothesis.

Bayesian estimations have some strong advantages compared to the classical techniques; they allow for distributed coefficients but the estimation does not require any maximization, rather, draws from the posterior are taken until convergence is achieved, avoiding convergence problems and sample sizes necessary to achieve the convergence are substantially smaller. Moreover, they can properly integrate a priori knowledge on the parameters.

In order to determine the value of time in freight transport in France, an important but misunderstood parameter in project evaluation, and study the impact of model specification a revealed preference survey was conducted, interviewing 1027 truck drivers about their origin, destination and freight characteristics. The survey was conducted in four points; in two tolled motorways and their respective free parallel roads in the north-west of France. This configuration allows to the analysis of the trade off between rapid and more expensive links, and slower free roads.

In this chapter we discuss a number of issues related to the estimation and the interpretation of results in practical estimations of the value of time in transport (i) we analyse the role of model specification in the VTTS estimation, (ii) we identify sources of systematic and random taste variations; (iii) we propose a comparison of the different methods without using relevant prior information; (iv) we measure the benefit of integrating a prior distribution of VTTS and finally (v) we provide a robust estimation of the value of travel time for the freight transport in France. Results show that Bayesian estimations based on a prior knowledge leads to more sound and robust results; furthermore we find that values used currently in France should be reviewed upwards.

The contributions of this study are twofold. First, at the theoretical level, we discuss the importance of estimating distributed value of time in evaluating the willingness to pay for toll roads and show the impact of model structure on the evaluation of the real willingness to pay. Second, at the practical level, we estimate the value of time in freight transport in France and show the sensibility of estimations with respect to the model.

The rest of the chapter is organized as follows. Section 2 briefly discusses the notion and the importance of the value of travel time as well as the scarcity of empirical results in freight transport. Section 3 presents the most used econometric models applied to the VTTS estimation. Section 4 presents the Bayesian procedures and its application to estimate discrete choice models. Section 5 discuss some challenges in estimating the value of travel time savings. Section 6 presents the survey conducted for this study. Section 7 presents the econometric results and compares the different models. Section 8 discusses the results and section 9 concludes the chapter.

5.2 The Value of Time in Transport

The willingness to pay for a unit change in a certain attribute can be computed as the marginal rate of substitution (MRS) between income and the quantity expressed by the attribute, at constant utility levels (Gaudry et al., 1989). The concept is equivalent to computing the compensated variation (Small and Rosen, 1981), as one usually works with linear approximation of the indirect utility function. Thus, the point estimates of the MRS represent the slope of the utility function for the range where this approximation holds. Furthermore, as income does not enter in the truncated indirect utility function, the MRS is calculated with respect to minus the cost variable (Jara-Diaz, 1990). In this way, the WTP in a linear utility function simply equals the ration between the variable of interest and the cost variable. The willingness to pay to save time is usually called the value of time, or, related to the travel time, the value of travel time savings, VTTS.

The value of travel time is certainly the most important number in transport economics. Time savings use to account for the main part of the socio-economic benefit of a new infrastructure. Moreover, it allows the estimation of the market share of a new infrastructure or service and the estimation of the optimal pricing.

The distribution of the VTTS over the population is a fundamental issue. We can classify heterogeneity in the population in two groups, systematic and random. Systematic variations depend on socio-economic and trip specific characteristics. They are estimated either by segmenting the population of by interacting variables. This heterogeneity left is due to factors which can not be observed or are difficult to measure. In these cases, this heterogeneity can take form of a random parameter.

The proportion of a population who will choose to pay a toll t is given by the proportion whose value of the time saved is greater than the toll. The analyst, according to taste, convenience and internal evidence, will select among a number of appropriate analytical distributions in order to find a satisfactory representation of the "true" empirical distribution. The number of people whose value of time savings exceeds the toll charged, who will therefore pay it is then the integral, from toll price to infinite, of that distribution. This is then the measure of revenue to be received by the charging agency. In the case of a symmetric distribution, e.g. normal, in general representing the distribution by its mean will be able to produce the correct revenue. In the case of a substantially skewed distribution (e.g. lognormal) the average will not be in the centre of the distribution, and there will be fewer people in the population actually ready to pay the toll. In this situation revenue will be overestimated for low toll levels.

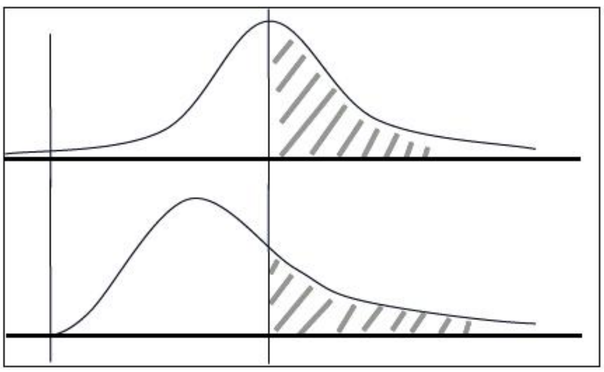


Figure 5.1: Comparison of VTTS distributions.

Hensher and Goodwin (2004) argue that financial institutions have two interests in their negotiations with public agencies on a public-private partnership. First, there is an interest in the best and most reliable possible estimate of the expected revenue. Second, there is interest in figures that strengthen their bargaining position in relation to the case for the scheme to go ahead at all, and on what basis of risk apportionment.

Consider the case where there is a well-established convention, used by the public agency for many years, to represent the distribution of VTTS by the average, partly for reasons of adequacy for purpose in previous applications, and partly because the models and consultants available find it convenient to do so. Then estimates made using the average, other things being equal, will tend to overestimate the revenue. In this case, the financial agency has the choice to go along with the standard procedure, or to "rock the boat" by suggesting using a distribution. The effect of doing so many well put the whole project at risk. So the perceived best interests of the agency are served by accepting the standard procedure, which strengthens the case for the project, but suspecting that it overestimates the revenue, finding a risk-sharing agreement, explicit or implicit, which cushions them against the likely result.

Conversely, the public agency's perceived best interests are served by using the standard practice, since this will increase the probability of raising the funding, anticipating that the public benefits in terms (for example) of congestion and pollution relief will be higher than calculated, and seek to ensure that the risk will be wholly born by the funders.

The paradoxical case is that each will be better served by using the distributions themselves, for internal, confidential reasons, but using the average (or preferably the median) value for public discussion, and hoping that the other party believes. But it is not a long-term solution, since it is almost bound to lead to later disputes, attempts to renegotiate, or collapse of confidence in such deals. There are signs that this can happen. The dilemma is obvious – will the financial advisers prefer to go with an overestimate to secure patronage and the contract (in a bid setting) knowing the likelihood (from previous contractual arrangements) that the risk can be transferred to government, or act as good corporate citizens and promote the more appropriate VTTS across the distribution.

In practice, this question is either ignored, or not expressed in this language (though accepting the underlying significance). The great majority of patronage studies around the world use simple averages for VTTS, so this provides an almost unquestioned benchmark as an always available fallback position, and a handy defensive (but not necessary defensible) instrument.

In this sense, distribution of the value of time in the population represents a number of issues including the choice of behavioural models and estimation procedures as well as the interpretation results will be subject to.

5.2.1 VTTS in Freight Transport

While for passengers transport there is a large literature and an important scientific activity on this topic, for freight transport both scientific and professional studies are very scarce. This little attention given to freight transport is mainly due to the information scarcity in the sector, where the competitiveness is very strong and information on costs play a strategic role. Furthermore, the logistic chain is very complex and has multiple decision takers. In passenger transport the decision maker is the passenger himself; but goods cannot decide, as notes DeJong (1996).

Ortuzar and Willumsen (2001) point out four reasons for the little research in freight transport modelling compared to passenger modelling:

- There are many aspects of freight demand that are more difficult to model than passenger movements.
- For some time urban congestion has been highest in the political agenda of most industrialised countries and in this field passenger play a more important role than freight.
- The movement of freight involves more actors than the movement of passengers; we have the industrial firm or firms sending and receiving the goods, the shippers organising the consignment and modes, the carrier(s) undertaking the movement and several others running transhipment, storage and custom facilities. In some cases two or more of these may coincide, for example in own-account operators, bur there is always scope for conflicting objectives which are difficult to model in detail in practice.

- Recent trends in freight research have emphasised the role it plays in the overall production process, inventory control and management of stocks. These trends are a departure from more traditional passenger modelling techniques and share little in common (Regan and Garrido, 2002).

The value of time of transport is defined as the marginal rate of substitution between travel time and travel cost. While in passenger's transport it comes from the Lagrange multiplier associated to the time constraint in the individual utility maximization, in freight transport time savings enter the financial optimization as they allow to reduce other costs like labour and capital costs and improve productivity.

In France, few studies were devoted to the empirical estimation of the value of time in freight transport; the main studies were realized by Fei Jiang (Jiang, 1998) who utilises revealed preference and Laura Wynter (Wynter, 1994), applying revealed and stated preference of shippers, by phone surveys, both studies in the context of their respective doctoral thesis. Their results range from 27 to 74 €/hour. Massiani (2005, pp.151-155) presents a review of the estimations of the value of time for freight transport in Europe found in literature. Governmental recommendation for the value of time for freight transport in France is 30 €(2000)/hour (Commissariat Général du Plan, 2001).

5.3 Discrete Choice Models

5.3.1 The Multinomial Logit

The most common theoretical base for generating discrete choice models is the random utility theory (Domencich and McFadden, 1975; Williams, 1977)[2]. In random utility models (RUM) the utility that the decision maker n obtains from alternative j is defined by

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{5.1}$$

[2]For the hypothesis underlying the model see also Ortuzar and Willumsen (2001) and Ben-Akiva and Lerman (1994)

where U_{nj} is a non-stochastic utility function (called *systematic* or *representative* component of the utility) and ε_{nj} is a random component (or disturbance) which captures the factors that affect utility but the researcher does not or can not observe. The deterministic part is usually assumed to be linear, so that

$$V_{nj} = \beta' x_{nj}$$

.

The individual selects the maximum-utility alternative so that user n chooses alternative i if and only if

$$U_{ni} \geq U_{nj} \; \forall j \neq i$$

From this perspective, the choice probability of alternative i is equal to the probability that the utility of alternative i is greater than or equal to the utilities of all other alternatives in the choice set. This can be written as

$$P_{ni} = Prob(U_{ni} \geq U_{nj} \; \forall j \neq i)$$

Using the random utility model in expression (5.1), this can be rewritten as

$$P_{ni} = Prob(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj} \; \forall j \neq i)$$

To derive a specific random utility model, we require an assumption about the joint probability distribution of the full set of disturbances $\varepsilon_{nj}, \forall j$. The issues therefore are what distribution is assumed for each model, and what is the motivation for these different assumptions.

The logit model is derived under the assumptions of independent and identically distributed Gumbel (IID) disturbances, which means that the unobserved factors are uncorrelated over alternatives and have the same variance for all alternatives. The density for each unobserved component of utility is

$$f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}} \tag{5.2}$$

and the cumulative distribution is

$$F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}} \tag{5.3}$$

The variance of this distribution is $\pi^2/6$. By assuming the variance is $\pi^2/6$ we are implicitly normalizing the scale of the utility. If ε_{ni} and ε_{nj} are independent and identically Gumbel (or type I extreme value) distributed, then $\varepsilon_n = \varepsilon_{nj} - \varepsilon_{ni}$ is logistically distributed

$$F(\varepsilon_n) = \frac{e^{\varepsilon_n}}{1 + e^{\varepsilon_n}}$$

If ε_{ni} is considered given, the choice probability is the cumulative distribution for each ε_{nj} evaluated at $\varepsilon_{ni} + V_{ni} - V_{nj}$, which, according to (5.3) is $exp(-exp(-(\varepsilon_{ni} + V_{ni} - V_{nj})))$. Since the ε's are independent, this cumulative distribution over all $j \neq i$ is the product of the individual cumulative distributions:

$$P_{ni}|\varepsilon_{ni} = \prod_{j \neq i} e^{-e^{-(\varepsilon_{ni} + V_{ni} - V_{nj})}}$$

Of course, ε_{ni} is not given, and so the choice probability is the integral of $P_{ni}|\varepsilon_{ni}$ over all values of ε_{ni} weighted by its density (5.2):

$$P_{ni} = \int (\prod_{j \neq i} e^{-e^{-(\varepsilon_{ni} + V_{ni} - V_{nj})}}) e^{-\varepsilon_{ni}} e^{-e^{-\varepsilon_{nj}}} \tag{5.4}$$

Some algebraic manipulation of this integral (Domencich and McFadden, 1975) results in a succinct, closed-form expression:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} \tag{5.5}$$

which is the logit choice probability.

Limitations of Logit

In addition to the well know property of independence of irrelevant alternatives (IIA) and it's inability to deal with correlated choices over time (panel data), the constant parameters represents a restrictive assumption. If one or more characteristics (parameters) vary randomly across the population, the assumptions of the standard logit calibration are not satisfied, and the error term is no longer distributed independently of the explanatory variables. Thus the coefficients estimates from the calibration will be biased.

Another problem due to heterogeneity arises because the estimation produces estimates of time and cost parameters that are averages over the sample, and they are then used in ratio form to give the value of time (Fowkes and Wardman, 1988). The true value of time would be the average over the sample of individuals' value of time, these values being the ratio of their individual time and cost coefficients. It is easy to demonstrate that the ratio of the means and the means of the ratio are not necessary equal (unless the denominator is constant or the ratios are constants).

Moreover, as the parameters for time and cost are estimates from the model, they are not really constants but random variables with a certain probability density function (PDF). For this reason the value of time (calculated as the ratio between the time and cost parameters in a linear in parameters model) is also a random variable with an unknown PDF. We know the maximum likelihood parameters are asymptotically distributed multivariate Normal. Consequently the VTTS point estimate is a random variable governed by an unknown PDF, the probability function for the ratio between two Normally distributed variables is unknown a priori); only some things are known is special cases. For example, the ratio between two independently distributed standard Normal variables follows a Cauchy PDF (Arnold and Brockett, 1992), but this is unstable since it has an infinite variance and its mean does not have an analytical expression.

However, some econometric methods were developed in order to estimate confidential intervals for the value of time calculated as the ratio between the time and cost parameters, say β_t and β_c. The most applied is the asymptotic t-test.

The asymptotic t-test is generally used to prove if a normally distributed parameter is significant different from zero. Ben-Akiva and Lerman (1994) present an extension of this test for a linear combination of the parameters. As β_t and β_c are asymptotically distributed normal, the following null hypothesis can be postulated:

$$H_0 : \beta_t - VT\beta_c = 0,$$

where VT represents the value of time point estimate. The confidence interval is given by the set of VT values for which it is not possible to reject H_0 at a given level of significance. The corresponding test statistic is (Armstrong et al., 2001):

$$t = \frac{\beta_t - VT\beta_c}{\sqrt{Var(\beta_t - VT\beta_c)}}$$

This expression distributes normal for linear models and asymptotically normal for non-linear models like the MNL (see Ben-Akiva and Lerman (1994)). Armstrong et al. (2001) also derive the upper and lower bounds for the interval as follows:

$$V_{S,I} = (\frac{\beta_t}{\beta_c}\frac{t_c}{t_t})\frac{(t_t t_c - \rho t^2)}{(t_c^2 - t^2)} \pm (\frac{\beta_t}{\beta_c}\frac{t_c}{t_t})\frac{\sqrt{(\rho t^2 - t_t t_c)^2 - (t_t^2 - t^2)(t_c^2 - t^2)}}{(t_c^2 - t^2)} \tag{5.6}$$

where t_t and t_c correspond to the t-statistic for β_t and β_c, respectively; t is the critical value of t given the degree of confidence required and sample size and ρ is the coefficient of correlation between both parameter estimates. Expression (5.6) is a real number only if the radical argument is non-negative; it can be shown that this condition is met when the parameters β_t and β_c are statistically significant (so that t_t and t_c are greater than t). This condition assures positive upper and lower bounds.

It can be observed that the confidence interval derived from this formulation is not symmetrical with respect to the VT point estimate (β_t/β_c), and that the interval's mid-point is greater than β_t/β_c as well. Another feature is that the value of ρ has a strong influence on the size of the interval. In fact, the bigger the value of ρ the narrower the interval and vice versa, all other things being equal. In addition, the more significant the t-statistics are, the narrower the intervals (for details, Armstrong et al. (2001)).

5.3.2 The Mixed Logit Model

The specification of the random coefficients logit model (or mixed logit)[3] is the same as for the standard logit except that varies over decision makers rather than being fixed. As in the MNL the utility of person n from alternative j is specified as

$$U_{nj} = \beta_n' x_{nj} + \varepsilon_{nj} \tag{5.7}$$

where x_{nj} are observed variables that relate to the alternative and decision maker, β_n is a vector of coefficients of these variables for person n representing that person's tastes, and ε_{nj} is a random term that is iid extreme value. The coefficients may vary over decision makers in the population with density $f(\beta)$. This density is a function of parameters θ that represent, for example, the mean and variance of the β's in the population.

The decision maker knows the value of his own β_n and ε_{nj}'s for all j and chooses the alternative i if and only if $U_{ni} \geq U_{nj} \forall j \neq i$. The researcher observes the x's but not β_n or the ε_{nj}'s. If the researcher observed β_n, then the choice probability would be standard logit, since the ε_{nj}'s are iid extreme value. That is, the probability *conditional* on β_n is

$$L_{ni}(\beta_n) = \frac{e^{\beta_n' x_{ni}}}{\sum_j e^{\beta_n' x_{ni}}}$$

However, the researcher does not know β_n and therefore can not condition on β. The unconditional choice probability is therefore the integral of $L_{ni}(\beta_n)$ over all possible variables of β_n.

$$P_{ni} = \int \frac{e^{\beta_n' x_{ni}}}{\sum_j e^{\beta_n' x_{ni}}} f(\beta) d\beta$$

[3]Random coefficients is the most widely used derivation of mixed logit models, but not the only one; each derivation provides a particular interpretation (Train, 2003).

which is the random coefficients probability.

The researcher specifies a distribution for the coefficients and estimates the parameters of that distribution.

McFadden (2000) show that any random utility model can be approximated to any degree of accuracy by a mixed logit with appropriated choice of variables and mixing distribution.

The researcher specifies the functional form $f(\cdot)$ and wants to estimate the parameters θ. The choice probabilities are

$$P_{ni} = \int L_{ni}(\beta) f(\beta|\theta) d\beta f(\beta) d\beta.$$

where

$$L_{ni}(\beta) = \frac{e^{\beta_n' x_{ni}}}{\sum_j e^{\beta_n' x_{ni}}}$$

The probabilities are approximated through simulation for any given value of θ:

(1) Draw a value of β from $(\beta|\theta)$, and label it β^1 with the superscript r=1 referring to the first draw.

(2) Calculate the logit formula $L_{ni}(\beta^r)$ with this draw.

(3) Repeat steps 1 and 2 many times, and average the results.

This average is the simulated probability:

$$\check{P}_{ni} = \frac{1}{R} \sum_{r=1}^{R} L_{ni}(\beta^r),$$

where R is the number of draws. $\check{P}_{ni}$ is an unbiased estimator of P_{ni} by construction. Its variance decreases as R increases. It is strictly positive, so that $ln\check{P}_{ni}$ is defined, which is useful for approximating the log-likelihood function below. $\check{P}_{ni}$ is smooth (twice differentiable) in the parameters θ and variables x, which facilitates the numerical search for the maximum likelihood function and the calculation of elasticities. And $\check{P}_{ni}$ sums to one over alternatives, which is useful in forecasting.

The simulated probabilities are inserted into the log-likelihood function to give a simulated log-likelihood:

$$SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} y_{nj} ln \check{P}_{nj},$$

where $y_{nj} = 1$ if n chose j and zero otherwise. The maximum simulated likelihood estimator is the value of θ that maximizes SLL. Usually, different draws are taken for each observation. This procedure maintains independence over decision makers of the simulated probabilities that enter SLL.

5.4 Bayesian Procedures

This section aims at introducing the bayesian procedures used to estimate mixed logit models. As they represent relatively new procedures they are described in more details than the precedent procedures, drawn on material in Train (2003).

A powerful set of procedures for estimating discrete choice models has been developed within the Bayesian tradition. The breakthrough concepts were introduced by Albert and Chib (1993) and McCulloch and Rossi (1994) in the context of probit, and by Allenby and Lenk (1994) for mixed logits with normally distributed coefficients. These authors showed how the parameters of the model can be estimated without needing to calculate the choice probabilities. Their procedures provide an alternative to the classical estimation methods. Rossi et al. (1996) and Allenby and Rossi (1999) showed how the procedures can also be used to obtain information on individual-level parameters within a model with random taste variation. Train (2001) extended the Bayesian procedure for mixed logit to nonnormal distributions of coefficients, including lognormal, uniform, and triangular distributions.

Two important notes are required regarding the Bayesian perspective. First, the Bayesian procedures, and the term “Hierarchical Bayes” that is often used in the context of discrete choice models, refer to an estimation method, not a behavioural model. Probit, mixed logit, or any other model that the researcher specifies can, in principle, be estimated by either classical or Bayesian procedures. Second, the Bayesian perspective from which these procedures arise provides a rich and intellectually satisfying paradigm for inference and decision making. Nevertheless, a researcher who is uninterested in the Bayesian perspective can still benefit from Bayesian procedures: the use of Bayesian procedures does not necessitate that the researcher adopt a Bayesian perspective on statistics. The Von-Misses theorem shows that the Bayesian procedures provide an estimator whose properties can be examined and interpreted in purely classical ways.

5.4.1 Overview of Bayesian Concepts

Consider a model with parameters θ. The researcher has some initial ideas about the value of these parameters and collects data to improve this understanding. Under Bayesian analysis, the researcher's ideas about the parameters are represented by a probability distribution over all possible values that the parameters can take, where the probability represents how likely the researcher thinks it is for the parameters to take a particular value.

Prior to collecting data, the researcher's ideas are based on logic, intuition, or past analyses. These ideas are represented by a density on θ, called the prior distribution and denoted $K(\theta)$ [4].

The researcher collects data in order to improve her ideas about the value of θ. Suppose the researcher observes a sample of N independent decision makers. Let y_n denote the observed choice (or choices) of decision maker n, and let the set of observed choices for the entire sample be labeled collectively as $Y = y_1, \ldots, y_N$. Based on this sample information, the researcher changes, or updates, her ideas about θ. The updated ideas are represented by a new density on θ, labeled $K(\theta|Y)$ and called the posterior distribution. This posterior distribution depends on Y, since it incorporates the information that is

[4] In the traditional literature we often find phrases such as "x is random" or "we shall treat w as random" or even "we shall treat x as fixed, i.e. as not random" where "random" means that the object in question will be assigned a probability distribution. In the Bayesian approach all objects appearing in a model are assigned probability distributions and are random in this sense. The only distinction between objects is whether they will become known for sure when the data are in, in which case they are data (!); or whether they will not become known for sure, in which case they are parameters. Generally, the words "random" and "fixed" do not figure in a Bayesian analysis and should be avoided (Lancaster, 2006).

contained in the observed sample.

There is a precise relationship between the prior and posterior distribution, established by Bayes' rule. Let $P(y_n|\theta)$ be the probability of outcome y_n for decision maker n. This probability is the behavioural model that relates the explanatory variables and parameters to the outcome, though the notation for the explanatory variables is omitted for simplicity. The probability of observing the sample outcomes Y is

$$L(Y|\theta) = \prod_{n=1}^{N} P(y_n|\theta)$$

This is the likelihood function (not logged) of the observed choices. Note that it is a function of the parameters θ.

Bayes' rule provides the mechanism by which the researcher improves her ideas about θ. By the rules of conditioning,

$$K(\theta|Y)L(Y) = L(Y|\theta)k(\theta) \tag{5.8}$$

where $L(Y)$ is the marginal probability of Y, marginal over θ:

$$L(Y) = \int L(Y|\theta)k(\theta)d\theta.$$

Both sides of equation (5.8) represent the joint probability of Y and θ, with the conditioning in opposite directions. The left-hand side is the probability of Y times the probability of θ given Y, while the right-hand side is the probability of θ times the probability of Y given θ. Rearranging, we have

$$K(\theta|Y) = \frac{L(Y|\theta)k(\theta)}{L(Y)} \tag{5.9}$$

This equation is Bayes' rule applied to prior and posterior distributions. In general, Bayes rule links conditional and unconditional probabilities in any setting and does not imply a Bayesian perspective on statistics. Bayesian statistics arises when the unconditional probability is the prior distribution (which reflects the researcher's ideas about θ *not* conditioned on the sample information) and the conditional probability is the posterior distribution (which gives the researcher's ideas about θ conditioned on the sample information).

We can express equation (5.9) in a more compact and convenient form. The marginal probability of Y, $L(Y)$, is constant with respect to θ and, more specifically, is the integral of the numerator of (5.9). As such, $L(Y)$ is simply the normalizing constant that assures that the posterior distribution integrates to 1, as required for any proper density. Using this fact, equation (5.9) can be stated more succinctly by saying simply that the posterior distribution is proportional to the prior distribution times the likelihood function:

$$K(\theta|Y)\alpha L(Y|\theta)k(\theta).$$

Intuitively, the probability that the researcher ascribes to a given value for the parameters after seeing the sample is the probability that she ascribes before seeing the sample times the probability (i.e., likelihood) that those parameter values would result in the observed choices. The mean of the posterior distribution is

$$\overline{\theta} = \int \theta K(\theta|Y)d\theta \tag{5.10}$$

This mean has importance from both a Bayesian and a classical perspective. From a Bayesian perspective, $\overline{\theta}$ is the value of θ that minimizes the expected cost of the researcher being wrong about θ, if the cost of error is quadratic in the size of the error (Lancaster, 2006; Train, 2003). From a classical perspective, $\overline{\theta}$ is an estimator that has the same asymptotic sampling distribution as the maximum likelihood estimator.

5.4.2 Drawing from the Posterior

Usually, the posterior distribution does not have a convenient form from which to take draws. For example, we know how to take draws easily from a joint untruncated normal distribution; however, it is rare that the posterior takes this form for the entire parameter vector. Importance sampling can be useful for simulating statistics over the posterior. Geweke (1992, 1997) describes the approach with respect to posteriors and provides practical guidance on appropriate selection of a proposal density. Two other methods are particularly useful for taking draws from a posterior distribution: Gibbs sampling and the Metropolis-Hasting algorithm. These methods are often called Monte Carlo Markov chain, or MCMC, methods. Formally, Gibbs sampling is a special type of Metropolis-Hasting algorithm (Gelman, 1992).However, the case is so special, and so conceptually straightforward, that the term Metropolis-Hasting (MH) is usually reserved for versions that are more complex than Gibbs sampling. That is, when the MH algorithm is Gibbs sampling, it is referred to as Gibbs sampling, and when it is more complex than Gibbs sampling, it is referred to as the MH algorithm.

As stated, the mean of the posterior is simulated by taking draws from the posterior and averaging the draws. Instead of taking draws from the multidimensional posterior for all the parameters, Gibbs sampling allows the researcher to take draws of one parameter at a time (or a subset of parameters), conditional on values of the other parameters (Casella and George, 1992). Drawing from the posterior for one parameter conditional on the others is usually much easier than drawing from the posterior for all parameters simultaneously. In some cases, the MH algorithm is needed in conjunction with Gibbs sampling. The MH algorithm is particularly useful in the context of posterior distributions because the normalizing constant for the posterior need not be calculated. Recall that the posterior is the prior times the likelihood function, divided by a normalizing constant that assures that the posterior integrates to one. The MH algorithm can be applied without knowing or calculating the normalizing constant of the posterior. In summary, Gibbs sampling, combined if necessary with the MH algorithm, allows draws to be taken from the posterior of a parameter vector for essentially any model.

Gibbs Sampling

For multinomial distributions, it is sometimes difficult to draw directly from the joint density and yet easy to draw from the conditional density of each element given the values of the other elements. Gibbs sampling can be used in these situations. A general explanation is provided by Casella and George (1992).

Consider two random variables ε_1 and ε_2. Generalization to higher dimension is obvious. The joint density is $f(\varepsilon_1, \varepsilon_2)$, and the conditional densities are $f(\varepsilon_1|\varepsilon_2)$ and $f(\varepsilon_2|\varepsilon_1)$. Gibbs sampling proceeds by drawing iteratively from the conditional densities: drawing ε_1 conditional on a value of ε_2, drawing ε_2 conditional on this draw of ε_1, drawing a new ε_1 conditional on the new value of ε_2, and so on. This process converges to draws from the joint density. To be more precise:

1. Choose an initial value for ε_1, called ε_1^0 Any value with nonzero density can be chosen.

2. Draw a value of ε_2 called ε_2^0, from $f(\varepsilon_2|\varepsilon_1^0)$.

3. Draw a value of ε_1, called ε_1^1 from $f(\varepsilon_1|\varepsilon_2^0)$

4. Draw ε_2^1 from $f(\varepsilon_2|\varepsilon_1^1)$, and so on.

The Metropolis-Hastings Algorithm

If all else fails, the Metropolis-Hastings (MH) algorithm can be used to obtain draws from a density. Initially developed by Metropolis et al. (1953) and generalized by Hastings (1970), the MH algorithm operates as follows. The goal is to obtain draws from $f(\varepsilon)$.

1. Start with a value of the vector ε, labeled ε^0.

2. Choose a trial value of ε^1 as $\tilde{\varepsilon}^1 = \varepsilon^0 + \eta$, where η is drawn from a distribution $g(\eta)$ that has zero mean. Usually a normal distribution is specified for $g(\eta)$.

3. Calculate the density at the trial value $\tilde{\varepsilon}^1$, and compare it with the density at the original value ε^0. That is, compare $f(\tilde{\varepsilon}^1)$ with $f(\varepsilon^0)$. If $f(\tilde{\varepsilon}^1) \geq f(\varepsilon^0)$, then accept $\tilde{\varepsilon}^1$, label it ε^1, and move to step 4. If $f(\tilde{\varepsilon}^1) = f(\varepsilon^0)$, then accept $\tilde{\varepsilon}^1$ with probability $f(\tilde{\varepsilon}^1)/f(\varepsilon^0)$, and reject it with probability $1 - f(\tilde{\varepsilon}^1)/f(\varepsilon^0)$. To determine whether to accept or reject $\tilde{\varepsilon}^1$ in this case, draw a standard uniform μ. If $\mu \leq f(\tilde{\varepsilon}^1)/f(\varepsilon^0)$, then keep $\tilde{\varepsilon}^1$. Otherwise, reject $\tilde{\varepsilon}^1$. If $\tilde{\varepsilon}^1$ is accepted, then label it ε^1. If $\tilde{\varepsilon}^1$ is rejected, then use ε^0 as ε^1.

4. Choose a trial value of ε^2 as $\tilde{\varepsilon}^2 = \varepsilon^1 + \eta$, where η is a new draw from $g(\eta)$.

5. Apply the rule in step 3 to either accept $\tilde{\varepsilon}^2$ as ε^2 or reject $\tilde{\varepsilon}^2$ and use ε^1 as ε^2.

6. Continue this process for many iterations. The sequence et becomes equivalent to draws from $f(\varepsilon)$ for sufficiently large t.

The draws are serially correlated, since each draw depends on the previous draw. In fact, when a trial value is rejected, the current draw is the same as the previous draw. This serial correlation needs to be considered when using these draws. The MH algorithm can be applied with any density that can be calculated. The algorithm is particularly useful when the normalizing constant for a density is not known or cannot be easily calculated. Suppose that we know that ε is distributed proportional to $f^*(\varepsilon)$. This means that the density of ε is $f(\varepsilon) = \frac{1}{k} f^*(\varepsilon)$, where the normalizing constant $k = \int f^*(\varepsilon) d\varepsilon$ assures that f integrates to 1. Usually k cannot be calculated analytically, for the same reason that we need to simulate integrals in other settings. Luckily, the MH algorithm does not utilize k. A trial value of et is tested by first determining whether $f(\tilde{\varepsilon}^t) > f(\tilde{\varepsilon}^{t-1})$. This comparison is unaffected by the normalizing constant, since the constant enters the denominator on both sides. Then, if $f(\tilde{\varepsilon}^t) \leq f(\tilde{\varepsilon}^{t-1})$, we accept the trial value with probability $f(\tilde{\varepsilon}^t)/f(\tilde{\varepsilon}^{t-1})$. The normalizing constant drops out of this ratio. The MH algorithm is actually more general than described here, though in practice it is usually applied as described. Chib and Greenberg (1995) provide an excellent description of the more general algorithm as well as an explanation of why it works. Under the more general definition, Gibbs sampling is a special case of the MH algorithm, as Gelman (1992) pointed out. The MH algorithm and Gibbs sampling are often called Markov chain Monte Carlo (MCMC, or MC-squared) methods; a description of their use in econometrics is provided by Chib and Greenberg (1996). The draws are Markov chains because each value depends only on the immediately preceding one, and the methods are Monte Carlo because random draws are taken.

5.4.3 Posterior Mean as a Classical Estimator

The Bayesian procedure provides draws from the joint posterior of the parameters. In a Bayesian analysis, these draws are used in a variety of ways depending on the purpose of the analysis. The mean and standard deviation of the draws are simulated approximations to the mean and standard deviation of the posterior. These statistics have particular importance from a classical perspective, due to the Bernstein-von Mises theorem. Consider a model with parameters θ whose true value is θ^*. The maximum of the likelihood function is $\widehat{\theta}$, and the mean of the posterior is $\overline{\theta}$ for a prior that is proper and strictly positive in a neighbourhood of θ^*. Three interrelated statements are established in different versions of the theorem (e.g., Rao (1987); Cam and Yang (1990); Lehmann and Casella (1998); Bickel and Doksum (2000)

1. The posterior distribution of θ converges to a normal distribution with covariance B^{-1}/N around its mean, where B is the information matrix. Stated more precisely: $\sqrt{N}(\theta - \overline{\theta}) \xrightarrow{d} N(0, B^{-1})$, where the distribution that is converging is the posterior rather than the sampling distribution.

2. The posterior mean converges to the maximum of the likelihood function: $\sqrt{N}(\overline{\theta}) - \widehat{\theta} \xrightarrow{p} 0$. This result is a natural implication of statement (1). Asymptotically, the shape of the posterior becomes arbitrarily close to the shape of the likelihood function, since the posterior is proportional to the likelihood function times the prior and the prior becomes irrelevant for large enough N. The mean and mode of a normal distribution are the same.

3. The asymptotic sampling distribution of the posterior mean is the same as for the maximum of the likelihood function: $\sqrt{N}(\overline{\theta}) - \theta^* \xrightarrow{d} N(0, B^{-1})$. This result is obvious from statement (2).

The third statement says that the mean of the posterior is an estimator that, in classical terms, is equivalent to MLE. The first statement establishes that the standard deviations of the posterior provide classical standard errors for the estimator. The true mean and standard deviation of the posterior cannot be calculated exactly except in very simple cases. These moments are approximated through simulation, by taking draws from the posterior and calculating the mean and standard deviation of the draws. For fixed number of draws, the simulated mean, denoted $\breve{\theta}$, is consistent and asymptotically normal, with variance equal to $1 + (1/R)$ times the variance of the non-simulated mean, where R is the number of (independent) draws. If the number of draws (whether independent or not) is considered to rise with N at any rate, the simulation noise disappears asymptotically such that $\breve{\theta}$ is efficient and asymptotically equivalent to MLE. In contrast, MSLE is inconsistent for a fixed number of draws. For consistency, the number of draws must be considered to rise with N, but even this condition is not sufficient for asymptotic normality. The number of draws must be considered to rise faster than $\sqrt{N}$ for MSLE to be asymptotically normal, in which case it is also equivalent to MLE. Since it is difficult to know in practice how to satisfy the condition that the number of draws rises faster than $\sqrt{N}$, $\breve{\theta}$ is attractive relative to MSLE, even though their non-simulated counterparts are equivalent.

The researcher can therefore use Bayesian procedures to obtain parameter estimates and then interpret them the same as if they were maximum likelihood estimates. A highlight of the Bayesian procedures is that the results can be interpreted from both perspectives simultaneously, drawing on the insights afforded by each tradition. This dual interpretation parallels that of the classical procedures, whose results can be transformed for Bayesian interpretation as described by Geweke (1989). In short, the researcher's statistical perspective need not dictate her choice of procedure.

5.4.4 Posteriors for the Mean and Variance

The posterior distribution takes a very convenient form for some simple inference processes. We describe two of these situations, which, as we will see, often arise within more complex models for a subset of the parameters. Both results relate to the normal distribution. We first consider the situation where the variance of a normal distribution is known, but the mean is not. We then turn the tables and consider the mean to be known but not the variance. Finally, combining these two situations with Gibbs sampling, we consider the situation where both the mean and variance are unknown.

Result A: Unknown Mean, Known Variance

We discuss the one-dimensional case first, and then generalize to multiple dimensions. Consider a random variable β that is distributed normal with unknown mean b and known variance σ. The researcher observes a sample of N realizations of the random variable, labeled β_n, $n = 1, \ldots, N$. The sample mean is $\overline{\beta} = (1/N) \sum_n \beta_n$. Suppose the researcher's prior on b is $N(b_0, s_0)$; that is, the researcher's prior beliefs are represented by a normal distribution with mean b_0 and variance s_0. Note that we now have two normal distributions: the distribution of β, which has mean b, and the prior distribution on this unknown mean, which has mean b_0. The prior indicates that the researcher thinks it is most likely that $b = b_0$ and also thinks there is a 95 percent chance that b is somewhere between $b_0 - 1.96\sqrt{s_0}$ and $b_0 + 1.96\sqrt{s_0}$. Under this prior, the posterior on b is $N(b_1, s_1)$ where

$$b_1 = \frac{\frac{1}{s_0} b_0 + \frac{N}{\sigma} \overline{\beta}}{\frac{1}{s_0} + \frac{N}{\sigma}}$$

and

$$s_1 = \frac{1}{\frac{1}{s_0} + \frac{N}{\sigma}}$$

The posterior mean b_1 is the weighted average of the sample mean and the prior mean[5].The weight on the sample mean rises as sample size rises, so that for large enough N, the prior mean becomes irrelevant. Often a researcher will want to specify a prior that represents very little knowledge about the parameters before taking the sample. In general, the researcher's uncertainty is reflected in the variance of the prior. A large variance means that the researcher has little idea about the value of the parameter. Stated equivalently, a prior that is nearly flat means that the researcher considers all possible values of the parameters to be equally likely. A prior that represents little information is called *diffuse*.

The multivariate versions of this result are similar. Consider a K-dimensional random vector $\beta \tilde{N}(b, W)$ with known W and unknown b. The researcher observes a sample β_n, $n = 1, \ldots, N$, whose sample mean is $\overline{\beta}$. If the researcher's

[5]For the proof, see Train (2003)

prior on b is diffuse (normal with an unboundedly large variance), then the posterior is $N(\overline{\beta}, W/N)$. To take draws from this posterior let L be the Choleski factor of W/N. Draw K iid standard normal deviates, $\eta_i, i = 1, \ldots, K$, and stack them into a vector $\eta = \langle \eta_1, \ldots, \eta_K \rangle'$. Calculate $\tilde{b} = \overline{\beta} + L\eta$. The resulting vector $\tilde{b}$ is a draw from $N(\overline{\beta}, W/N)$.

Result B: Unknown Variance, Known Mean

Consider a (one-dimensional) random variable that is distributed normal with known mean b and unknown variance s. The researcher observes a sample of N realizations, labeled β_n, $n = 1, \ldots, N$. The sample variance around the known mean is $\overline{s} = (1/N) \sum_n (\beta_n - b)^2$. Suppose the researcher's prior on s is inverted gamma with degrees of freedom v_0 and scale s_0. This prior is denoted $IG(v_0, s_0)$. The density is zero for any negative value for s, reflecting the fact that a variance must be positive. The mode of the inverted gamma prior is $s_0 v_0/(1 + v_0)$. Under the inverted gamma prior, the posterior on σ is also inverted gamma $IG(v_1, s_1)$, where

$$v_1 = v_0 + N,$$

$$s_1 = \frac{s_0 v_0 + N\overline{s}}{v_0 + N}.$$

The inverted gamma prior becomes more diffuse with lower v_0. For the density to integrate to one and have a mean, v_0 must exceed 1. It is customary to set $s_0 = 1$ when specifying $v_0 \to 1$. Under this diffuse prior, the posterior becomes $IG(1 + N, (1 + N\overline{s})/(1 + N))$. The mode of this posterior is $(1 + N\overline{s})/(2 + N)$, which is approximately the sample variance $\overline{s}$ for large N. The multivariate case is similar. The multivariate generalization of an inverted gamma distribution is the inverted Wishart distribution. The result in the multivariate case is the same as with one random variable except that the inverted gamma is replaced by the inverted Wishart. A K-dimensional random vector $\beta\tilde{N}(b, W)$ has known b but unknown W. A sample of size N from this distribution has variance around the known mean of $\overline{S} = (1/N) \sum_n (\beta_n - b)(\beta_n - b)'$. If the researcher's prior on W is inverted Wishart with v_0 degrees of freedom and scale matrix S_0, labeled $IW(v_0, S_0)$, then the posterior on W is $IW(v_1, S_1)$ where

$$v_1 = v_0 + N,$$

$$S_1 = \frac{S_0 v_0 + N\overline{S}}{v_0 + N}.$$

The prior becomes more diffuse with lower v_0, though v_0 must exceed K in order for the prior to integrate to one and have means. With $S_0 = I$, where I is the K-dimensional identity matrix, the posterior under a diffuse prior becomes $IW(K+N, (KI+N\overline{S})/(K+N))$. Conceptually, the prior is equivalent to the researcher having a previous sample of K observations whose sample variance was I. As N rises without bound, the influence of the prior on the posterior eventually disappears. Consider first an inverted gamma $IG(v_1, s_1)$. Draws are taken as follows:

1. Take v_1 draws from a standard normal, and label the draws $\eta_i, i = 1, \ldots, v_1$.
2. Divide each draw by $\sqrt{s_1}$, square the result, and take the average. That is, calculate $r = (1/v_1)\sum_i(\sqrt{1/s_1}\eta_i)^2$, which is the sample variance of v_1 draws from a normal distribution whose variance is $1/s_1$.
3. Take the inverse of $r : \tilde{s} = 1/r$ is a draw from the inverted gamma.

Draws from a K-dimensional inverted Wishart $IW(v_1, S_1)$ are obtained as follows:

1. Take v_1 draws of K-dimensional vectors whose elements are independent standard normal deviates. Label these draws $\eta_i, i = 1, \ldots, v_1$.
2. Calculate the Choleski factor of the inverse of S_1, labeled L, where $LL' = S_1^{-1}$.
3. Create $R = (1/v_1)\sum_i(L\eta_i)(L\eta_i)'$. Note that R is the variance of draws from a distribution with variance S_1^{-1}.
4. Take the inverse of R. The matrix $\tilde{S} = R^{-1}$ is a draw from $IW(v_1, S_1)$.

Unknown Mean and Variance

Suppose that both the mean b and variance W are unknown. For neither of these parameters does the posterior take a convenient form. However, draws can easily be obtained using Gibbs sampling and results A and B. A draw of b is taken conditional on W, and then a draw of W is taken conditional on b. Result A says that the posterior for b conditional on W is normal, which is easy to draw from. Result B says that the posterior for W conditional on b is inverted Wishart, which is also easy to draw from. Iterating through numerous cycles of draws from the conditional posteriors provides, eventually, draws from the joint posterior.

5.4.5 Hierarchical Bayes for Mixed Logit

In this section we show how the Bayesian procedures can be used to estimate the parameters of a mixed logit model. We utilize the approach developed by Allenby (1997), implemented by Software (2000), and generalized by Train (2001). Let the utility that person n obtains from alternative j in time period t be

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt},$$

where ε_{njt} is iid extreme value and $\beta_n \tilde{N}(b, W)$.

Giving β_n' a normal distribution allows us to use results A and B, which speeds estimation considerably. The researcher has priors on b and W. Suppose the prior on b is normal with an unboundedly large variance. Suppose that the prior on W is inverted Wishart with K degrees of freedom and scale matrix I, the K-dimensional identity matrix.

Note that these are the priors used for results A and B. More flexible priors can be specified for W, using the procedures of, for example, McCulloch and Rossi (2000), though doing so makes the Gibbs sampling more complex.

A sample of N people is observed. The chosen alternatives in all time periods for person n are denoted $y_n' = \langle y_{n1}, \ldots, y_{nT} \rangle$, and the choices of the entire sample are labelled $Y = \langle y_1, \ldots, y_T \rangle$. The probability of person n's observed choices, conditional on β, is

$$L(y_n|\beta) = \prod_t \frac{e^{\beta' x_{n y_{nt} t}}}{\sum_j e^{\beta' x_{njt}}}.$$

The probability not conditional on β is the integral of $L(y_n|\beta)$ over all β:

$$L(y_n|b, W) = \int L(y_n|\beta) f(\beta|b, W) d\beta,$$

where $f(\beta|b, W)$ is the normal density with mean b and variance W. This $L(y_n|b, W)$ is the mixed logit probability. The posterior distribution of b and W is, by definition,

$$K(b, W|Y) \alpha \prod_n L(y_n|b, W) k(b, W), \tag{5.11}$$

where $k(b, W)$ is the prior on b and W described earlier (i.e., normal for b times inverted Wishart for W).

It would be possible to draw directly from $K(b, W|Y)$ with the MH algorithm. However, doing so would be computationally very slow. For each iteration of the MH algorithm, it would be necessary to calculate the right-hand side of (5.11). However, the choice probability $L(y_n|b, W)$ is an integral without a closed form and must be approximated through simulation. Each iteration of the MH algorithm would therefore require simulation of $L(y_n|b, W)$ for each n. That would be very time-consuming, and the properties of the resulting estimator would be affected by it. Recall that the properties of the simulated mean of the posterior were derived under the assumption that draws can be taken from the posterior without needing to simulate the choice probabilities. MH applied to (5.10) violates this assumption.

Drawing from $K(b, W|Y)$ becomes fast and simple if each β_n is considered to be a parameter along with b and W, and Gibbs sampling is used for the three sets of parameters b, W, and $\beta_n \forall n$. The posterior for b,W, and $\beta_n \forall n$ is

$$K(b, W, \beta_n \forall n|Y) \alpha \prod_n L(y_n|\beta_n) f(\beta_n|b, W) k(b, W).$$

Draws from this posterior are obtained through Gibbs sampling. A draw of each parameter is taken, conditional on the other parameters:

1. Take a draw of b conditional on values of W and $\beta_n \forall n$.

2. Take a draw of W conditional on values of b and $\beta_n \forall n$.

3. Take a draw of $\beta_n \forall n$ conditional on values of b and W.

Each of these steps is easy, as we will see. Step 1 uses result A, which gives the posterior of the mean given the variance. Step 2 uses result B, which gives the posterior of the variance given the mean. Step 3 uses an MH algorithm, but in a way that does not involve simulation within the algorithm. Each step is described in the following.

1. $b|W, \beta_n \forall n$. We condition on W and each person's β_n in this step, which means that we treat these parameters as if they were known. Result A gives us the posterior distribution of b under these conditions. The β_n's constitute a sample of N realizations from a normal distribution with unknown mean b and known variance W. Given our diffuse prior on b, the posterior on b is $N(\overline{\beta}, W/N)$, where $\overline{\beta}$ is the sample mean of the β_n's. To take draws from this posterior proceed as Result A described in section 5.4.4.

2. $W|b, \beta_n \forall n$. Result B gives us the posterior for W conditional on b and the β_n's. The β_n's constitute a sample from a normal distribution with known mean b and unknown variance W. Under our prior on W, the posterior on W is inverted Wishart with $K + N$ degrees of freedom and scale matrix $(KI+NS_1)/(K+N)$, where $S_1 = (1/N)\sum_n(\beta_n-b)(\beta_n-b)'$is the sample variance of the β_n's around the known mean b. It is easy to take draws from inverted gamma and inverted Wishart distributions, as shown before.

3. $\beta_n|b, W$. The posterior for each person's β_n, conditional on their choices and the population mean and variance of β_n, is

$$K(\beta_n|b, W, y_n) \alpha L(y_n|\beta_n) f(\beta_n|b, W), \tag{5.12}$$

There is no simple way to draw from this posterior, and so the MH algorithm is used. Note that the right-hand side of (5.12) is easy to calculate: $L(y_n|\beta_n)$ is a product of logits, and $f(\beta_n|b, W)$ is the normal density. The MH algorithm operates as follows:

(a) Start with a value β_n^0.

(b) Draw K independent values from a standard normal density, and stack the draws into a vector labeled η^1.

(c) Create a trial value of β_n^1 as $\tilde{\beta}_n^1 = \beta_n^0 + \rho L \eta^1$, where ρ is a scalar specified by the researcher and L is the Choleski factor of W. Note that the proposal distribution is specified to be normal with zero mean and variance $\rho^2 W$.

(d) Draw a standard uniform variable μ^1.

(e) Calculate the ratio

$$F = \frac{L(y_n|\tilde{\beta}_n^1)\rho(\tilde{\beta}_n^1|b, W)}{L(y_n|\tilde{\beta}_n^0)\rho(\tilde{\beta}_n^0|b, W)}.$$

(f) If $\mu^1 \leq F$, accept $\tilde{\beta}_n^1$ and let $\beta_n^1 = \tilde{\beta}_n^1$. If $\mu^1 > F$, reject $\tilde{\beta}_n^1$ and let $\beta_n^1 = \beta_n^0$.

(g) Repeat the process many times. For high enough t, β_n^t is a draw from the posterior.

We can know draw from the posterior for each parameter conditional on the other parameters. We combine the procedures into a Gibbs sampler for the three sets of parameters. Start with any initial values b^0, W^0, and β_n^0. The tth iteration of the Gibbs sampler consists of these steps:

1. Draw b^t from $N(\tilde{\beta}^{t-1}, W^{t-1}/N)$, where $\tilde{\beta}^{t-1}$ is the mean of the β_n^{t-1}'s.

2. Draw W_t from $IW(K+N, (KI + NS^{t-1})/(K+N))$, where $S^{t-1} = \sum_n (\beta_n^{t-1} - b^t)(\beta_n^{t-1} - b^t)'/N$.

3. For each n, draw β_n^t using one iteration of the MH algorithm previously described, starting from β_n^{t-1} and using the normal density $f(\beta_n|b^t, W^t)$.

These three steps are repeated for many iterations. The resulting values converge to draws from the joint posterior of b, W, and $\beta_n \forall n$. Once the converged draws from the posterior are obtained, the mean and standard deviation of the draws can be calculated to obtain estimates and standard errors of the parameters. Note that this procedure provides information about β_n for each n, similar to the procedure using classical estimation.

5.5 Challenges in Estimating VTTS

The value of time in transport has usually been estimated though classical multinomial logit which, assuming homogeneous tastes, can derive a single value of time for a fictitious average individual. Recently, the mixed logit model has been applied with different specifications and various degrees of sophistication. Although the theory is in general relatively clear, practical specification and estimation represent real challenges. Some important topics are discussed here focusing in the objective of estimating the VTTS.

5.5.1 Identifying Preference Heterogeneity

The most popular way of acknowledging systematic variations on preferences (or systematic taste variations) has been (within a specific trip purpose) to segment a sample based on exogenous criteria such as income, trip length and time of day for passengers and in length, type of commodity and ownership (own account or hire) for freight. This segmentation is achieved through estimating separate models for each segment or by interacting the travel time with an individual socio-economic or specific trip characteristics (Gaudry et al., 1989; Revelt and Train.K., 1998; Ortuzar and Willumsen, 2001; Amador et al., 2004). Hensher and Goodwin (2004) note that in practice, the selection of the number and dimensions of discrimination is not usually driven by questions of statistical diagnostics, research hypothesis and evidence. It is constrained by the specific properties of the forecasting and appraisal models within which the empirical values will be used.

However, even after controlling for observable characteristics, there is a lot of heterogeneity left. This heterogeneity is due to factors which can not be observed or are difficult to measure. In these cases, this heterogeneity can take form of a random parameter. One disadvantage of specifying random parameters is that information is not provided about factors determining these variations. To maximise the explanatory power of the model, one should explain as much systematic variation as possible, and allow for a random variation where it is significant.

5.5.2 Selecting Random Parameters

McFadden (2000) propose a Lagrange Multiplier test as a basis for accepting/rejection the preservation of fixed parameters in the mode. Brownstone (2001) provides a succinct summary of the test. These tests work by constructing artificial variables as in equation (5.13):

$$z_n = (x_{in} - \overline{x}_i)^2,\ with\ \overline{x}_i = \sum_j x_{jn} P_{jn}, \tag{5.13}$$

and P_{jn} is the conditional choice probability. The conditional logit is then re-estimated including these artificial variables, and the null hypothesis of no random coefficients on attributes x is rejected if the coefficients of the artificial variables are significantly different from zero. The actual test for the joint significance of the variables can be carried out using either a Wald or Likelihood Ratio test statistics. Brownstone (2001) suggests that these tests are easy to calculate and appear to be a quite powerful omnibus test; however they are not as good for identifying which error components to include in a more general mixed logit specification. Another test (Hensher and Greene, 2003) is to assume all parameters are random and then examine their estimated standard deviations, using a zero-based t-test for individual parameters and the likelihood ratio test to establish the overall contribution of the additional information. While appealing, this is very demanding for a large number of explanatory variables and might be problematic in establishing the model with a full set of random parameters.

5.5.3 Selecting the Distributions of the Random Parameters

If there is one single issue that can cause much concern it is the influence of the distributional assumptions of random parameters (Hensher and Greene, 2003). Except for the sign of VTTS, we appear to have no theoretical arguments to support one distribution or another. However, there is evidence of a left skewed distribution of VTTS. Abraham and Blanchet (1973) proposed a lognormal distribution in analogy with the income distribution. In effect, it is quite intuitive that there is substantially more individuals with relatively low value of time and not prepared to pay much to save time; in contrast a smaller number of individuals are willing to pay high tolls. This evidence has been being validated by non-parametric studies (Fosgerau, 2007) and by good fits provided by left skewed distributions (lognormal, but also Sb, Raylagh and others).

The lognormal distribution is very popular for the following reasoning (Hensher and Greene, 2003). The central limit theorems explain the genesis of a normal curve. If a large number of random shocks, some positive, some negative, change the size of a particular attribute, x, in an additive fashion, the distribution of that attribute will tend to become normal as the number of shocks increases. But if these shocks act multiplicatively, changing the value of x by randomly distributed proportions instead of absolute amounts, the central limit theorems applied to $y = ln(x)$ tend to produce a normal distribution. Hence x has a lognormal distribution.

The substitution of multiplicative for additive random shocks generates a positively skewed, leptokurtic, lognormal distribution instead of a symmetric, mesokurtic normal distribution. The degree of skewness and kurtosis of the two-parameter lognormal distribution depends only on the variance, and so if this is low enough, the lognormal approximates the normal distribution. Lognormals are appealing in that they are limited to the non-negative domain; however they typically have a very long right-hand tail which is a disadvantage (especially for willingness-to-pay calculations). It is this large proportion of "unseasonable" values that often casts doubt on the appropriateness of the lognormal. Moreover, in parameter estimation, experience has demonstrated that entering an attribute in a utility expression specified with a random parameter that is lognormally distributed, and which is expected a priori to produce a negative mean estimate, typically causes the model either not converge or converge with unacceptable large mean estimates. The trick to overcome this is to reverse the sign of the attribute prior to model estimation.

The simplest way to derive VTTS is to take the ratio of the means of the parameter distributions involved. This is not the mean of the VTTS, but the VTTS derived from coefficients of the "average individual" for each parameter. If the denominator is a constant, as in our case, both values are identical. If it is distributed, the distribution of the ratio can be computed by simulation, as in Sillano and Ortuzar (2005). Revelt and Train.K. (2001) cites three reasons for fixing the cost coefficient: (1) As Ruud (1996) points out, mixed logit models have a tendency to be unstable when all coefficients are allowed to vary. Fixing the price coefficient resolves this instability. (2) If the price coefficient is allowed to vary, the distribution of willingness to pay is the ratio of two distributions, which is often inconvenient to evaluate. With a fixed price coefficient, willingness to pay for an attribute is distributed the same as the coefficient of the attribute. (3) The choice of distribution to use for a price coefficient is problematic. The price coefficient is necessarily negative, such that a normal distribution is inappropriate. With a lognormal distribution (which assures that the price coefficient is always negative), values very close to zero are possible, giving very high (implausibly high) values for willingness to pay.

However, as noted by Train and Weeks (2004), this restriction is counter-intuitive as the marginal utility of money can vary across respondents according to factors that can be independent of observed socio-economic covariates. A fixed price coefficient implies that the standard deviation of unobserved utility, which is called the scale parameter, is the same for all observations; if the price coefficient is constrained to be fixed when in fact scale varies over observations, then the variation in scale will be erroneously attributed to variation in willingness to pay.

In this context the choice of the distribution is dictated not only by the researcher's preferences but also by the model characteristics and uses. Number of recent works (for example Hensher and Greene (2003); Hess et al. (2005)

demonstrate that the choice of distributional assumptions have a significant impact on estimation results, particularly and predictably, in the inferences that can potentially be drawn regarding extreme values. Although selecting distributions for individual parameters is challenge enough, it is compounded when interest focuses on ratios of random parameters, as in the derivation of estimates of willingness to pay (WTP).

5.5.4 Revealed Preference Data

The main advantage of revealed preference data is that it represents the actual choices. Flyvbjerg et al. (2003) for example, point the stated preference approach as a main source of errors in forecasting due to divergences between the stated and the actual behaviour. However, one of the main problems with revealed data is that it usually does not provide a high variation in the choice set (usually no more than two or three options) and in the attributes of these options, making the identification of random variations very difficult.

5.5.5 Optimization Problems

With mixed logit models (especially those with lognormal distributions), maximization of the simulated likelihood function can be difficult numerically. Often the algorithm fails to converge for various reasons. The choice of starting values is often critical, with the algorithm converging from starting values that are close to the maximum but not from other starting values. The issue of local versus global maxima complicates the maximization further, since convergence does not guarantee that the global maximum has been attained. This fact emphasizes the importance of appropriate starting values. In effect in the mixed logit model, the use of inadequate starting points may cause the model not converge or stop in a local maximum.

5.5.6 Imposing Constraints

This point is directly related to the choice of the distributions. In practice we often find that any one distribution has strengths and weaknesses. The weakness is usually associated with the spread or standard deviation of the distribution at its extremes including behaviourally unacceptable sign changes for the symmetrical distributions. One appealing 'solution' is to constrain the distribution in terms of domain (for instance, a truncated normal) or dispersion (constraining the coefficient of variation). Hensher and Greene (2003) simulated the resulting VTTS with lognormal distributions and derived and unusually high mean. They managed to lower it to more plausible values by truncating the simulated distribution, but found it very sensitive to this kind of constraint.

5.5.7 Priors

The introduction of prior knowledge is intrinsic to even the classic analysis. First, the analyst usually has some priors about the result (i.e. one should expect that the value of travel time to be positive and to lay within a reasonable set) and second, the set of hypothesis and parameters need to the estimation of mixed logit models like the form of the distributions and the starting values indirectly represent a prior hypothesis.

5.5.8 Advantages and Problems of Bayesian Procedures

The Bayesian procedures avoid two of the most prominent difficulties associated with classical procedures. First, the Bayesian procedures do not require maximization of any function. Second, desirable estimation properties, such as consistency and efficiency, can be attained under more relaxed conditions with Bayesian procedures than classical ones. Maximum simulated likelihood is consistent only if the number of draws used in simulation is considered to rise with sample size; and efficiency is attained only if the number of draws rises faster than the square root of sample size. In contrast, the Bayesian estimators that we describe are consistent for a fixed number of draws used in simulation and are efficient if the number of draws rises at any rate with sample size.

Nevertheless, to simulate relevant statistics that are defined over a distribution, the Bayesian procedures use an iterative process that converges, with a sufficient number of iterations, to draws from that distribution. This convergence is different from the convergence to a maximum that is needed for classical procedures and involves its own set of difficulties. The researcher cannot easily determine whether convergence has actually been achieved. Thus, the Bayesian procedures trade the difficulties of convergence to a maximum for the difficulties associated with this different kind of convergence. The researcher will need to decide, in a particular setting, which type of convergence is less burdensome.

As we have shown, the Bayesian procedures provide an estimator whose properties can be examined and interpreted in purely classical ways. The researcher can therefore use Bayesian procedures to obtain parameter estimates and then interpret them the same as if they were maximum likelihood estimates. From an estimation perspective, for some behavioural models and distributional specifications, Bayesian procedures are far faster and, after the initial learning that a classicist needs, are more straightforward from a programming perspective than classical procedures. For other models, the classical procedures are easier. The differences can be readily categorized, through an understanding of how the two sets of procedures operate. The researcher can use this understanding in deciding which procedure to use in a particular setting.

However, the use of Bayesian procedures within a Bayesian perspective provides the fascinating opportunity of properly integrating prior beliefs in the analysis. The use of bayesian estimation with a bayesian perspective, which means that the researcher wants to update his prior information based on the new data (and do not use a diffuse prior), also rise some questions.

5.5.9 The Role of the Alternative Specific Constant

The alternative specific constant in a logit-like model assures that the market share estimated by the model corresponds to the actual (sample) market share, for each alternative. It captures the captive market share (which is not affected by the concurrent modes) and also the deterministic part of the utility function which is not explained by the explanatory variables. While this property is very suitable in many market analysis, in traffic forecasting it can poses a major problem. Suppose we could include all the decision variables (usually cost, time, alternative specific variables and decision maker specific variables), there are few reasons to believe that users have a preference for a road or another (behaviour effects like habit can affect the choice in the short term but have few implications in the long term). Affecting a bonus for one option reduces the part of the population willing to change of mode. This characteristic is few realistic and is not compatible with traditional assignment procedures which computes the generalized cost for each route and allocate traffic based on it.

5.6 The Survey

Our empirical analysis relies on a Revealed Preference study based on an Origin-Destination survey. The approach given is the concurrence between a tolled motorway and a free national road (autoroute and route nationale, in French, respectively), in order to compare the trade-off between a faster and tolled and a slower free option. This survey was realized in two pairs Motorway/National Route:

- A28 (Toll bridge of Alençon Nord) and N138, direction Le Mans-Alençon ;
- A11 (Toll bridge of Ancenis) and N23, direction Angers-Nantes ;

These points are illustrated in figure 5.2. We interviewed 1173 truck drivers about:

- The origin and the destination of the trip (last and next points of loading/ unloading);
- OD's frequency;
- Own account or hired;
- Number of employees of the transport company;
- Kind of product transported;
- Type of vehicle (visual observation).

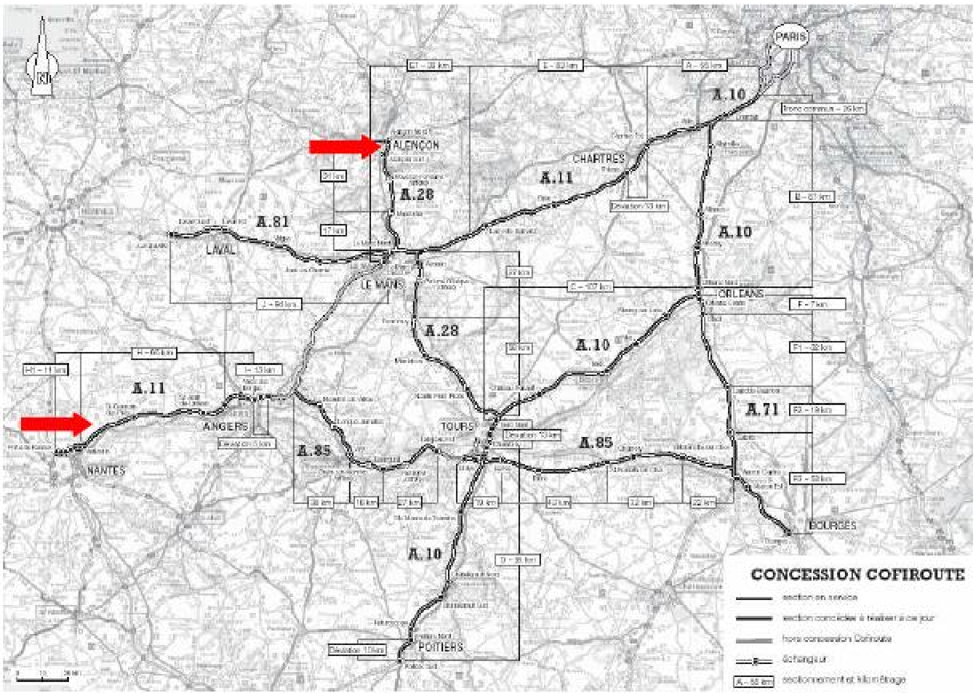


Figure 5.2: Survey's Location.

The traditional econometric approach to estimate the parameters of the discrete choice model is the maximum likelihood, producing the value of the parameters for which the observed sample is most likely to have occurred. Assuming that the observations in the sample are drawn independently at a random from the population, the likelihood of the sample is the product of individual likelihoods.

In an Origin-Destination survey, observations are collected based on their *ex-ante* choice, which characterizes a choice-based sample. The problem of finding tractable estimation procedure possessing desirable statistical properties is not an easy one, and the state of the art is provided by the papers of Coslett (1981) and Manski and McFadden (1981).

It has been found in general that maximum likelihood estimators specific to choice-base sampling are impractical, except in very restrict circumstances, due to computational intractability. However, if the analyst knows the fraction of the decision making population selecting each alternative then a tractable method can be introduced. The approach modifies the familiar maximum likelihood estimator of random sampling by weighting the contribution of each observation to the log-likelihood by the ratio Q_i/S_i, where the numerator is the fraction of the population and the denominator the fraction, of the sample selecting option i. This approach is applied in this study. Sample sizes and count data for the motorway (M) and free road (R), are reported in table 5.1.

Table 5.1: Sample and traffic count data
Sources: Cofiroute; Service des Routes de la DDE de la Sarthe; Service des Routes de la DDE de Loire Atlantique.

		sample	Count	Weight	Integer Weight
Ancenis	M	400 (50%)	2412 (76%)	6.03	6
	R	395 (50%)	767 (24%)	1.94	2
Alençon	M	183 (48.5%)	962 (50%)	5.25	5
	R	195 (51.5%)	954 (50%)	4.89	5
Total	M	583 (50%)	3374 (66%)	-	-
	R	590 (50%)	1721 (34%)	-	-

Once the sample has been weighed, we remove from the analysis those observations presenting one of the following characteristics:

- No real choice, i.e. the other alternative is too expensive or inexistent;
- Local traffic, distance shorter than 25 km;
- Recorded OD pair disconnected to the site of survey.

After removing these observations, the sample was reduced to 1027 observations, shared as shown in table 5.2.

Table 5.2: Final Sample

		sample	Weighted Sample
Ancenis	M	385	2310
	R	343	686
Alençon	M	170	850
	R	129	645
Total	M	555	3160
	R	472	1331

Table 5.3 presents the summary statistics for the main variables in the sample.

Table 5.3: Summary of descriptive statistics

Variable	Mean	Median	Std dev	Min	Max	Definition
Travel Cost (TC)	34.49	23.01	31.27	0.87	290.68	Toll in €
Travel Time (TT)	-1.24	-0.93	1.19	-8.02	7.92	Δ time in hours
distance	343.96	249.50	317.45	25.80	2227.40	distance in km
loaded	0.91	1	0.28	0	1	1 if loaded
hire	0.75	1	0.43	0	1	1 if for hire

5.7 Econometric Results

5.7.1 Maximum Likelihood estimations

We introduce the variables "hire" and "loaded" as sources of systematic variation as we could imagine that transport for hire (against own account) and loaded vehicles (against empty) have higher values of time. The variable distance was also tested as a source of systematic variation but not kept in the model due to a high correlation (0.81) with the travel cost. This fact represents a weakness of the revealed preference approach as discussed before. Using the Lagrange Multiplier test presented before, we have found that the travel time parameter was the only one presenting a significant random variation over the population.

As pointed by many authors, the simplicity of the MNL represents an strong advantage due to its properties and well-known estimation procedure; in this sense, the classic MNL shall be the starting point of any discrete choice estimation. We first estimate the model without the sources of systematic heterogeneity. The results of this model are shown in model MNL(1) in table 5.4. The value of time estimated by this model is €52 /h.

We then add the interaction between the travel time and the variables "loaded" and "for hire" in the model MNL(2). We can see that these factors strongly affect the value of time, which can be whiten as:

$$VTTS_{MNL} = 46 + 10loaded + 16hire \tag{5.14}$$

The average in the sample using MNL (2) is €67.1, ranging from €46 for empty and €72 for hire and loaded.

Results estimated by MNL are extremely close to those find by Alvarez et al. (2007) in Spain (€64.1) using the same model, but far higher than the national standard values used in both countries.

We then estimate models with distributed coefficients. We tested the Matlab code developed by Kenneth Train [6] and the *R* code developed by Ryuich Tamura. The Matlab code of Kenneth Train was kept for the final estimations.

We first estimated, as usual, considering the travel time parameter as lognormally distributed. Model 5.15 uses only time and cost as explanatory variables. Model 5.16 includes interactions. Note that in the models using lognormal distributions, the travel time was multiplied by -1 to get positive coefficients.

$$VTTS_{ML} = \frac{1}{0.0017} e^{2.87+1.99N(0,1)} \tag{5.15}$$

$$VTTS_{ML} = \frac{1}{0.024} e^{1.98+0.10loaded+0.21hire+1.80N(0,1)} \tag{5.16}$$

Results show unacceptable mean and variance. This result confirms the difficulty in estimating mixed logit models with lognormal distributions discussed before.

We tried also to estimate the model using the cost variable following a lognormal PDF and the cost normally distributed and the time lognormally distributed. In both cases we failed to achieve convergence. There is a folk concept floating among researchers in the field that the variance of random coefficients are identified empirically only if with repeated choices for each person. This concept is probably too severe, but it indicates the difficulty we face.[7]

5.7.2 Bayesian Estimations

Within the Bayesian approach, instead of proceeding adding constraints or changing the PDF in order to find more reasonable values, we include our

[6] Available at http://elsa.berkeley.edu/t̃rain/software.html

[7] based in a discussion with Kenneth Train.

beliefs as “priors”.

As a prior distributions for the Bayesian estimations we adopt as mean the current value used in France. Jiang (1998) finds an average VTTS of 195 FF, or approximately €30, which is also the value adopted as the governmental recommendation in the “Rapport Boiteux” (Commissariat Général du Plan, 2001). Since the VTTS from a linear in parameters utility function is the ration between the time and cost estimates, we decided to keep the cost parameter from the model (ML); the mean of the prior distribution for time becomes the mean of the value of time used today (€30) inflated by the economic growth between 2000 and 2005 (€32.3) multiplied by 0.01. We specify a large standard deviation (3.0) in order to diffuse the prior. The result of this estimation is shown in model HB. The estimation was performed using the Matlab code developed by Kenneth Train. It should be noted that the HB reproduces the maximum likelihood estimations when the coefficients are considered fixed and when the prior information is very diffuse and the simulation is long enough. We have used a very large number of draws in order to be able to identify the variance.

Note that the approach adopted to represent the real market share, weighting observations (and then the likelihood function) was derived and is usually applied for maximum likelihood estimations. Although we believe the same approach can be applied to Bayesian estimations without further concerns, we did not find any application or theoretical discussions on this point.

We first estimate the model considering the cost coefficient as fixed and the time as lognormally distributed. Results show that the VTTS distibution (in €/h) can be written as:

$$VTTS_{HB} = \frac{1}{0.03} e^{0.294+0.083 loaded+0.175 hire+0.0059 N(0,1)} \tag{5.17}$$

Even after a very high number of draws, the bayesian algorithm was unable to get apart from the initial solution and to identify the heterogeneity (small variance). The average value of time in the population is 54.6€. Figure 5.3 shows the VTTS distribution when both loaded and hire dummy variables are equal to zero.

We then estimate the model with the cost coefficient following a normal

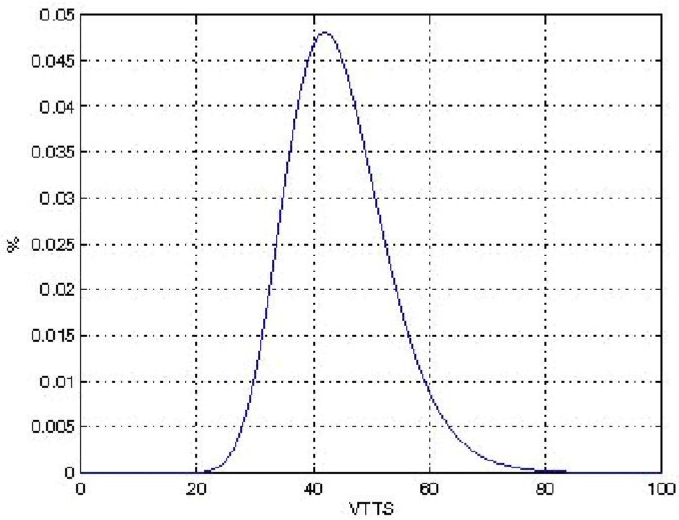


Figure 5.3: VTTS Distribution for empty and own account by ML

distribution and the time coefficient following a lognormal PDF.

$$VTTS_{HB} = \frac{1}{N(0.303, 0.027)} e^{2.207+0.256loaded+0.196hire+0.297N(0,1)} \tag{5.18}$$

Although the ratio of a lognormal by a normal distribution is not a trivial analytical issue, we can use simulation to calculate the ratio of points the both distributions and then derivate the resulting distribution, taking in account the correlation among the coefficients (-0.0136). We used the trial version of @Risk to perform this simulation (Latin Hypercube sampling with 10000 iterations). The resulting distribution when both load and own account dummy variables are one is given in figure 5.4 and the resulting distribution when both load and own account dummy variables are null is given in figure 5.5. Figure 5.6 shows the distribution for the average values of load and own account dummy variables in the sample.

This result seems to be much more reliable than the previous since the solution obtained is quite far from the priors and it accommodates the variations of the utility of money in the sample.

Estimation results are given in table 5.4. TT is the travel time and TC is the travel cost; standard errors are given in parentheses. Note that the

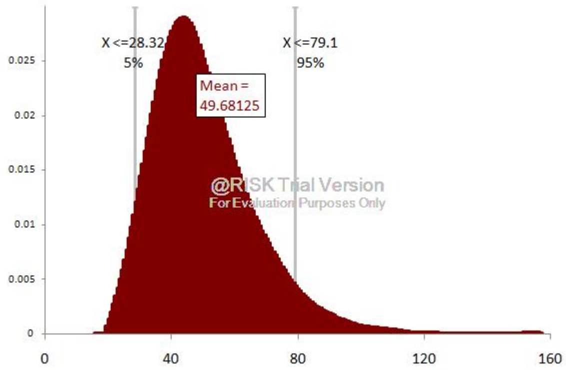


Figure 5.4: VTTS Distribution for loaded and hire by HB.

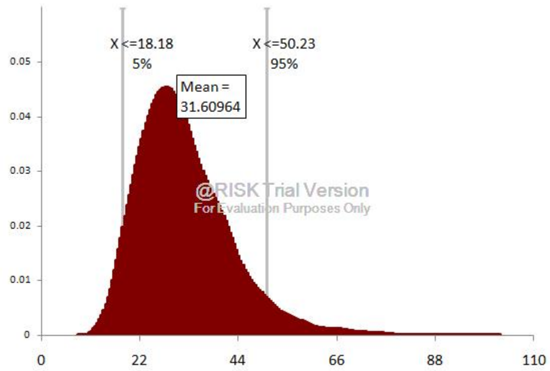


Figure 5.5: VTTS Distribution for empty and own account by HB.

log-likelihood for the Bayesian estimations is simulated, in order to be able to compare models in a single base.

5.8 Discussion

In line with many recent studies in this field, we faced here many difficulties in estimating the VTTS, especially when the mixed logit model is applied; we faced many convergence problems and even when convergence was achieved, the values provided were unrealistic. The Bayesian estimation provides a very attractive way of avoiding these optimization problems, accommodating both cost and time variables following PDFs, most in line with the theory.

Two points are of particular interest in our study. The differences between

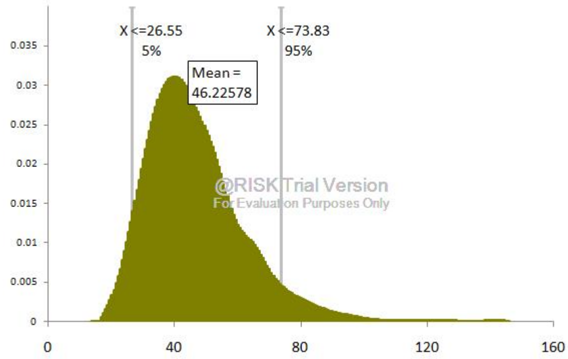


Figure 5.6: VTTS Distribution for average load and hire dummies by HB.

the constant and the distributed values of time in forecasting demand and the magnitude of the value itself.

It is easy to see that if the researcher believes that the average value of time is €52 (from model MNL(1)), but in fact it follows the distribution represented in figure 5.6 than instead of 50%, only 29,7% of the population will be willing to pay more than €52, leading to a rude demand overestimation. However if the atual values are given by the distribution in figure 5.6 but the researcher applies the current value used in France (€32) then most of users will actually be willing to pay more than this value, and the demand will be underestiamted.

Many recent results in the literature converge to the conclusion that using constant instead of distributed values of time tends to overestimate the demand. Two effects have to be isolated. First the skewness of the distribution. If the means are roughly the same, the constant value (or symmetrical distribution) will tend to overestimate the market share. Another point is whether the classic logic model and the distributed parameters model tend to produce different means. International experience suggests that this is not a general conclusion but depends on the nature of the data and specifications used in each study. For example Algers et al. (1998) and Gaudry et al. (1989) also found that more restrictive models lead to higher average values. However Amador et al. (2004) and Hensher (2001a,b) conclude that more restrictive models tend to underestimate the value of time; finally, other authors have found no significant differences between the values produced by different models (Train, 1998; Carlsson, 1999).

Table 5.4: Econometric results

		MNL (1)	MNL (2)	ML(1)	ML(2)	HB(1)	HB(2)
PDF TT			fixed	Lognormal	Lognormal	Lognormal	Lognormal
PDF TC			fixed	fixed	fixed	fixed	Normal
TT	Mean	0.541	0.461	2.879	1.983	0.294	-2.207
		(0.053)	(0.061)	(0.720)	(0.244)	(0.004)	(0.928)
	Sdt Dev			1.9933	1.8072	0.0059	0.2968
				(0.156)	(0.125)	(0.001)	(0.060)
TC	Mean	-0.0104	-0.01	-0.0017	-0.0238	-0.0302	0.3029
		(0.002)	(0.003)	(0.006)	(0.006)	(0.003)	(0.066)
	Sdt Dev						0.0267
							(0.011)
Loaded			0.1004		0.1079	0.0833	0.2557
			(0.021)		(0.045)	(0.024)	(0.081)
Hire			0.163		0.2103	0.1746	0.1966
			(0.020)		(0.043)	(0.021)	(0.071)
Intercept		0.0300	-0.1347	-4.3057	-2.411	-0.270	-3.2377
		(0.052)	(0.057)	(2.4688)	(0.395)	(0.063)	(0.300)
LL		-2510	-2467	-2359	-2338	-2529	-2242

(standard errors in parentheses)

Using wrong national standard values, of course, can lead to either over or underestimation. This point lead us to discuss the magnitude of the value of time in freight transport in France. Our results suggest that they should be reviewed upwards. Recent studies in other European countries have found similar results. Alvarez et al. (2007) found €64.1 in Spain, Fowkes et al. (2004) obtain values ranging from €55 to €200 in UK. We can conclude that the current standard French value can be on a downward bias.

5.9 Conclusions

The value of travel time savings is a fundamental concept in transport economics and its size strongly affects the socio-economic evaluation of transport schemes. Financial assessment of tolled roads rely upon the value of time as the main (or even the unique) willingness to pay measure. Values of time estimates, which primarily represent behavioural values, as then increasingly been used as measures of out-of-pocket money. In this setting, one of the main issues regarding the value of time is its distribution over the population.

Logit is by far the most applied discrete choice model used in estimations of values of time. Its popularity is due to its easy closed form. However, using a single value (representative of a mean or median) may lead to significant errors in evaluating the optimal toll and the revenue from a tolled road. In this perspective, the generalised used of logit models in the context of tolled infrastructure may lead to consequent traffic and revenue forecast errors.

The ambition of using distributed values for the parameters of discrete choice models associated with the recent progresses in hardware and software performances lead researchers to focus in more flexible structures. In this way a partial simulation partial closed form discrete choice model called mixed logit has been developed, allowing for distributed coefficients, estimated by simulated likelihood. In practice, however, the use of such models has been limited to cases where the kind of data associated with the choice of the distribution lead to model convergence and coherent results. Researchers and practitioners usually want to estimate lognormal distributed values of time, which in practice present convergence problems and tend to produce unacceptable high values for some share of the population. In this context, the use of constraints under the form of censure or caps for the standard deviation has been the solution find to overcome such problems. These constraints are then set according to the researcher's beliefs and prior works. The introduction of à priori knowledge is intrinsic to the econometric analysis. First, the analyst usually has some à priori about the result (i.e. one should expect that the value of travel time to be positive and to lay within a reasonable set) and second, the set of hypothesis, constraints and starting values of mixed logit models represent a priori hypothesis.

Bayesian estimations have some strong advantages compared to the classical techniques; they allow for distributed coefficients but the estimation does not require any maximization, rather, draws from the posterior are taken until convergence is achieved, avoiding convergence problems and sample sizes necessary to achieve the convergence are substantially smaller. Moreover, they can properly integrate a priori knowledge on the parameters.

In this chapter we present the main econometric models currently used for VTTS estimation. We apply these methods to the estimation of the value of travel time savings in freight transport in France. For this analysis a revealed preference study on two couple of tolled motorways and free roads was conducted. For the Bayesian estimation, we conjugate the data from this survey with the precedent studies guiding the current value used in France.

Estimations with mixed logit faced many difficulties, as expected. These difficulties could be avoided using the Bayesian procedures, providing also the opportunity of properly integrating a priori beliefs.

Results show that 1) using a single constant value of time, representative of an average, can lead to demand overestimation, 2) the estimated average value of time of freight transport in France is about €45, depending on the load/empty and hire/own account variables, which implies that 3) the standard value recommended in France should be reviewed upwards.

General Conclusions

We focused here on four important issues on traffic forecasting for toll roads under concessions schemes, sources of errors and biases. We analysed the forecasters' behaviour, the bidders' behaviour, the aggregated and the disaggregated users' behaviour.

Regarding the forecasters' behaviour, we presented the results of the first large sample survey on forecasters' characteristics and their opinions about forecasting demand for transport projects, based on an on-line survey. Results describe which are their main characteristics, details about their latest forecast, the models they apply, the forecast errors they declare and the main sources of errors according to them and the environment these forecasts take place in terms of pressure forecasters receive. These unique results provide a picture of the world of forecasters and forecasts, allowing for a better understanding of them.

Results show that the distribution of errors transport forecasters state has a smaller average magnitude and a smaller variance than those found in literature. Comparing forecasters perception of their own competence with the results found in literature about drivers skill self-evaluation, however, we could not find a significant difference, meaning that the forecasters' overconfidence is in line with what could be viewed as a normal human overconfidence level.

The pressure for results forecasters receive and the strategic manipulation they affirm exist merit a special attention. They imply that while forecasters' behavioural biases may exist and should be take in account when evaluation forecasts, the project promoter may influence forecasts by pressuring the forecasters to produce results which better fit his expectancies. Moreover, the forecast error tends to increase as the perception of the importance of strategic manipulation of results increases. This result corroborates recent studies pointing out that traffic forecasts are strategic variables subject to manipulation.

We modeled bidders behaviour using a unique, self-constructed, dataset of 49 worldwide road concessions. We show that the winner's curse effect is particularly strong in toll road concession contract auctions. Thus, we show that bidders bid less aggressively in toll road concession auctions when they expect more competition. Besides, we observe that this winner's curse effect is even larger for projects where the common uncertainty is greater. Moreover, we show that the winner's curse effect is weaker when the likelihood of renegotiation is higher, i.e. bidders will bid more strategically in weaker institutional frameworks, in which renegotiations are easier.

The policy implication of our results is not straightforward. In fact, while we show that asymmetric information overturns the common economic wisdom that more competition is always desirable, since we find a strong winner's curse effect in toll road concession auctions, we also show that there is a systematic traffic overestimation due to methodological and behavioural sources, so that in most cases bidders would know *ex post* very low or negative profit rates in they do not renegotiate the contractual terms. Thus, the short-term policy implication of our results would fit the standard view: governments should restrict entry, or favour negotiations over auctions, in toll road concession auctions to favour aggressive bidding. By contrast, the long-term policy implication of our results is that governments may wish to maintain the procedure as open as possible to the extent that the winner's curse effect reduces the systematic traffic overestimation and then reduces the likelihood that the procuring authority will have to renegotiate the contract, once eventual bidding competitors are gone.

Modelling aggregated users' behaviour, we put in evidence a decreasing function for the traffic elasticity with respect to the economic growth, which depends on the traffic level on the road. A new model of decreasing elasticity is proposed setting up an intrinsic relation between the traffic level and its reactivity to economic growth. This model allows for a good representation of the phenomenon, a good interpretation of results and gives a rigorous econometric approach to time-series traffic forecasts, at the cost of introducing a non-linearity in the equation. In the short term the model results are closer to that given by the classical constant elasticity model; in the long term, where classic models tend to produce linear or convex profiles, this model reproduces the observed concavity. This model allows for a better interpretation of the coupling between traffic and economic growth, and a more accurate long-term forecast.

We modeled the individual choice most important variable, the value of time, in the particular case of road freight transport in France. We find that the bayesian procedures represent many advantages compared to traditional maximization; that the standard use a single constant value of time, representative of an average, can lead to demand overestimation. We find a distributed value of time with mean about €45, depending on the load/empty and hire/own account variables, which indicates that the standard value recommended in France should be reviewed upwards.

Appendix A

Forecasters' survey questions

N	Question	Possible answers if closed question
1	In which country do you work?	
2	You have been working mainly on forecasts for projects	in the country in which you work|abroad
3	In which sector(s) do you work?	Private Company (Construction, concessionaire, operator,...)|Public Company|Government|Consultancy firm/ independent consultant|Academic /Research
4	You have a degree in	Engineering|Economics|Statistics|Geography|No Degree|Other, specify :
5	Do you have a post-graduate degree?	Not any|Master, MBA or equivalent|PhD or equivalent
6	Age	< of 25|25-35|35-45|45-55|55-65|> of 65
7	Gender	Man|Woman
8	How many traffic forecast studies have you conducted (or participated in)?	between 1 and 3|between 3 and 7|between 7 and 10|between 10 and 20|more than 20
9	Has the project for which you did your last traffic forecast been launched?	Yes|No, it will not be|No, but it will be|No and I don't know if it will be
10	Your last traffic forecast study for a project which has already been launched was for	No launched projects |Road / Motorway|Rail|Waterways|Air|Underground / Tramway/ Bus|Bicycles|Other, specify :
11	Financing	Public|Private|Mix
12	Operation	Public|Private
13	When was this forecast made?	less than 1 year ago|between 1 and 3 years ago|between 3 and 5 years ago|between 5 and 10 years ago|more than 10 years ago
14	What is your estimation of the deviation between the forecast and the actual (ex-post) traffic in your last traffic forecast? (where -10% means that traffic was 10% below the forecast)	<-50%|-50%|-40%|-30%|-25%|-20%|-15%|-10%|-5%|0%|5%|10%|15%|20%|25%|30%|40%|50%|>50% No launched projects|I don't Know
15	Comparing your forecasts with ex-post traffic you consider your results to be:	excellent|Very Good|Good|Fair|Poor|Very poor|extremely poor
16	In general, what was the tendency of deviations between your forecasts and actual traffic?	Forecast traffics where mostly **below** the real traffic|Forecast traffics where mostly **above** the real traffic|Forecast traffics were **equally distributed** below and above the real traffic
17	You apply mainly	"Tendencies" (time-series extrapolation, estimation of elasticities)|"Sequential models"(four-stage model)|Activity Based Approach|Other, specify :
18	With modal choice models	Aggregated|Disaggregated
19	And values of time	Constant|Distributed
20	In your opinion, which is the more difficult to forecast with accuracy?	The initial traffic|The traffic growth
21	Do you feel under pressure (explicit or implicit) to produce forecasts in accord with the expectations of the client?	Always|Usually|Occasionally|Rarely|Never
22	Do you believe you could make better forecasts in the absence constraints on the results?	Yes|No|I don't know
23	In your forecasts, did you know, with a good precision, the minimum traffic level necessary to attain the requested level of return:	Always|Usually|Occasionally|Rarely|Never
24	Between the technical study and the final forecast adopted for decision, the client can modify the results (directly or by influencing the forecaster) in order to suit its own interests. This is called strategic manipulation. Do you think it plays a role :	Insignificant|Somewhat important|Important|Very important
25	It goes mainly in the sense of:	Underestimation (reduce forecast traffic)|Overestimation (increase forecast traffic)
26	In your opinion, the influence of the technical study on the final decision is (a strong influence means that most of projects with high traffic levels are launched and most of projects with low traffic levels are not)	Absolute (decision takers always follow forecasts)|Strong|Moderate|Weak (decision takers rarely follows forecasts)
27	What is, in your opinion, the main source(s) of errors in traffic forecasts?	
28	Comparing yourself with forecasters in transport known to you, class youself according your level of competence (in a percentile scale, where higher percentiles represent better forecasters)	0 to 10 (best 10%)|11 to 20|21 to 30|31 to 40|41 to 50|51 to 60|61 to 70|71 to 80|81 to 90|91 to 100
29	Comments	

Figure A.1: Questions in the survey of forecaster's behaviour.

Appendix B

Distributions of variables in chapter 3

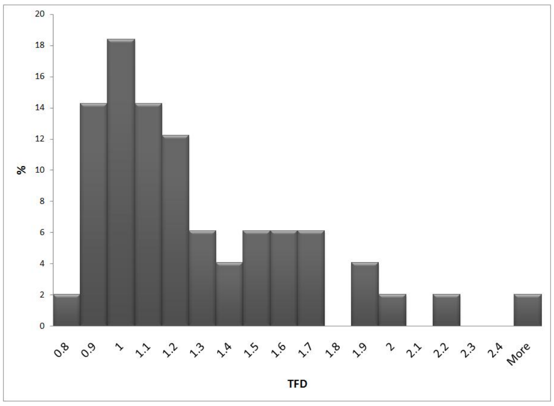


Figure B.1: TDF.

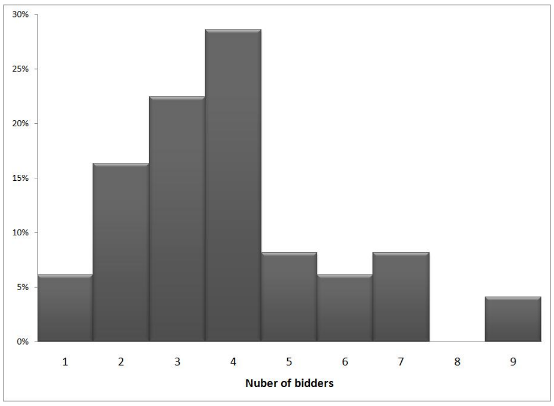


Figure B.2: Number of Bidders.

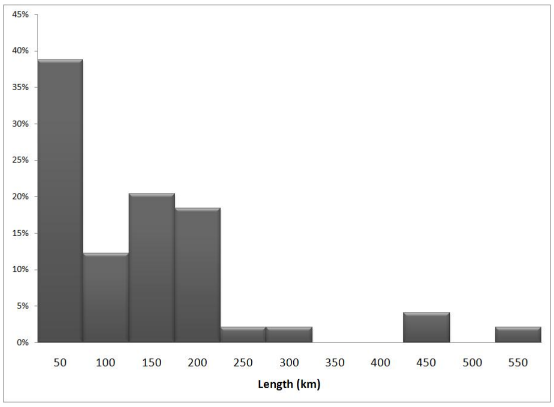


Figure B.3: Length.

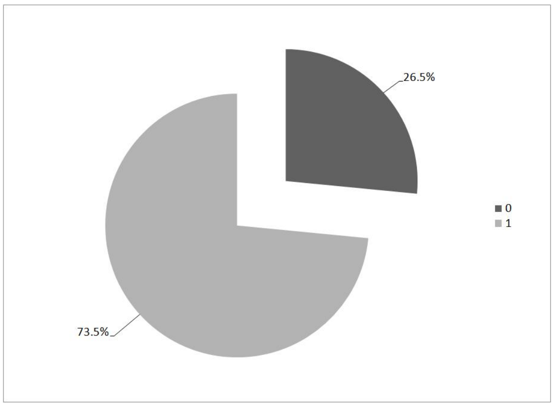


Figure B.4: Civil Law.

Figure B.5: HIC.

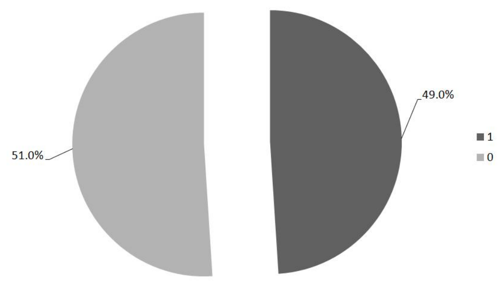


Figure B.6: Public Information.

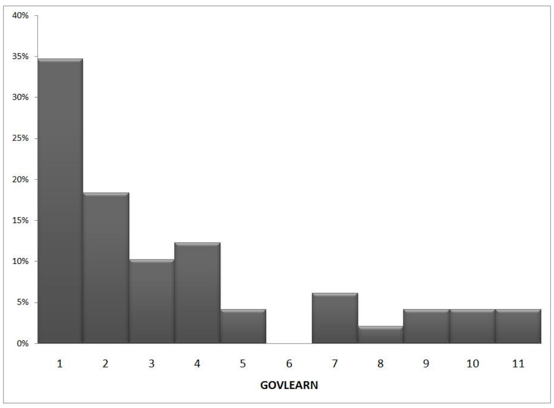


Figure B.7: Government Learning.

Appendix C

VTTS survey form

Local : Sorigny (barrière – vers Tours)	Ancenis (barrière – vers Nantes)	
N10 (vers Tours)	N138 (Alençon – sens Sud-Nord)	N23 (Ancenis – vers Nantes)
Enquêteur :		

Présentation de l'enquête…..

Quel était votre dernier lieu de chargement ou déchargement ?
(where are you comming from ? donde ha usted empezado este viaje ? de onde procede esta viagem ?)

Quel sera votre prochain lieu de chargement ou déchargement ?
(where are you going to ? donde va usted? Para onde vai ?)

Avec quelle fréquence vous faites ce trajet ? **_____ fois par semaine** **______ fois par mois**
(with what frequecy do you make this journey ?
con que frenquencia hace usted este trayecto ?
com qual frequência você realiza este trajeto ?)

Votre entreprise travaille pour :	**Compte d'autrui**	**Compte propre**
(your company works mainly for	Hire	Own account
su empresa trabaja mas por	cuenta ajena	cuenta propia
sua empresa trabalha principalmente por)	conta de outrém	conta propria

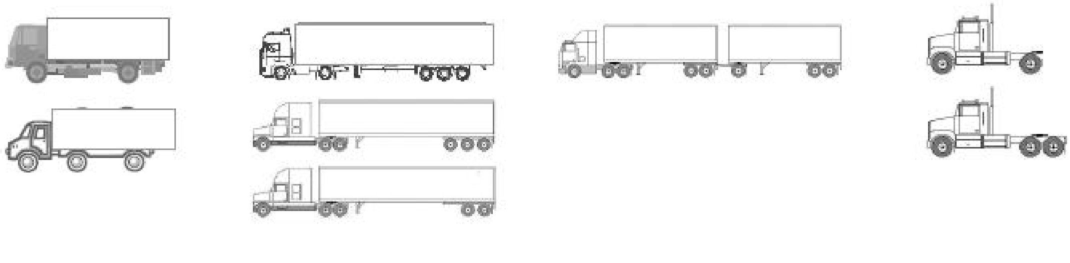
Combien d'employés compte votre entreprise (number of employees, numero de empleados, numero de empregados)

moins de 5   entre 5 et 10   entre 10 et 50   entre 50 et 100   plus de 100

Quel type de marchandise transportez-vous ? (class or kind of commodity, tipo de mercancia, tipo de mercadoria)

	Vide		Minerais et déchets
	Ne sait pas		Produits métallurgiques
	Produits agricoles et animaux vivants		Matériaux de construction et minéraux
	Produits Alimentaires / boissons		Engrais
	Produits périssables / réfrigérés		Produits chimiques
	Combustibles / produits pétroliers		Matériel de transport / agricole/ machines
	Electroniques/électroménager/informatique/		Papier
	Vêtement/chaussures		Autres

Camion   Semi-remorque   ensemble avec remorque   Tracteur



Pays d'immatriculation : FR   autre :_______________________

Figure C.1: VTTS survey form

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