Transportation
DOI 10.1007/s11116-009-9199-7

Error and optimism bias in toll road traffic forecasts

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Abstract Traffic forecasts are employed in the toll road sector, inter alia, by private sector investors to gauge the bankability of candidate investment projects. Although much is written in the literature about the theory and practice of traffic forecasting, surprisingly little attention has been paid to the predictive accuracy of traffic forecasting models. This paper addresses that shortcoming by reporting the results from the largest study of toll road forecasting performance ever conducted. The author had access to commercial-in-confidence documentation released to project financiers and, over a 4-year period, compiled a database of predicted and actual traffic usage for over 100 international, privately financed toll road projects. The findings suggest that toll road traffic forecasts are characterised by large errors and considerable optimism bias. As a result, financial engineers need to ensure that transaction structuring remains flexible and retains liquidity such that material departures from traffic expectations can be accommodated.

Keywords Toll road · Traffic forecast · Optimism bias · Forecasting error

Introduction

The global trend for investor-financed toll road concessions brings traffic forecasts—and their predictive accuracy—into sharp relief. All too often, aggressive financial structuring leaves little room for traffic usage to depart from expectations before projects experience distress and debt repayment obligations become threatened. Thus the accuracy of traffic forecasts is of considerable interest to practitioners in the toll road sector yet, until recently, very little was published in the literature about the predictive performance of traffic and revenue forecasting models. That literature is reviewed here.

The review starts by examining an early, small-scale study of toll road traffic forecasting accuracy from the USA. Building on and extending this analysis, the majority of the paper is devoted to recent toll road traffic forecasting research conducted by the

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Published online: 28 February 2009

author—and its key findings. This is followed by an examination of traffic forecasting accuracy for toll-free roads. Towards the end of the paper, a comparison of the predictive accuracy of forecasts for toll roads and toll-free roads is made, and conclusions are drawn.

The new study reported here was conducted over a 4-year period (2002–2005) while the author worked for the credit rating agency Standard & Poor's.

The JP Morgan Study (1997)

In 1997 the investment bank JP Morgan published a study examining the predictive accuracy of traffic forecasts prepared for 14 recently constructed toll roads in the USA (Morgan 1997). The bank compared actual, early-year performance of the roads with the original forecasts. Banks (and other investors) are commonly most sensitive to early-year asset performance as a project's cumulative cash flow curve will be at its lowest point. All of the project debt has been drawn down yet project revenues are only just starting to be generated. The potential for project distress (and possibly default on debt repayments) is arguably at its greatest during the earliest years of project operations.

Of the 14 toll road projects evaluated, JP Morgan reports that only one exceeded its original revenue forecast. Three forecasts were wrong (optimistic) by up to 25% and, for four of the projects, revenue was lower than 30% of the forecasts. Commenting on the considerable error and marked optimism bias in the forecasts, JP Morgan concludes by stating that:

> "Reducing the uncertainty associated with these forecasts represents one of the major challenges for transportation agencies, traffic consultants, investment bankers and investors."

The Standard & Poor's Studies (2002–2005)

The traffic forecasting research undertaken by the author was conducted over a 4-year period. Standard & Poor's rates around 30 privately financed toll roads globally and actively monitors these projects. The continuous process of credit surveillance involves examining, among other business and financial performance indicators, traffic volumes on a quarterly basis—in comparison with forecasts—to provide early warnings of investor exposure to potential project distress.

Annual traffic projections were compiled alongside outturn traffic performance for this core sample of international road projects—however, the core sample (for which the agency maintains public credit ratings) was expanded using comparable traffic data made available by banks for the rating of collateralised debt obligations (CDOs).

CDOs—or collateralised loan obligations (CLOs)—are structured, asset-backed securities. Banks package their loans, such as those made to cash-generating infrastructure projects, into a portfolio and then sell-on the rights to the cash flows. However, CDO detail is not relevant here. The point of note is that CDOs require credit ratings. Therefore, Standard & Poor's analysts have access to bank-financed project credit monitoring documentation (such as performance reports) alongside the bond-financed ones more traditionally associated with credit rating agencies. As the majority of privately financed infrastructure projects globally are financed through bank lending (not bonds), CDOs expose credit rating agencies to a far broader universe and quality of assets—including road schemes—than otherwise would be the case.

CDO-related documentation contributed significantly to the expansion of the sample of road projects studied as part of this research; from the core sample of 30 rated projects to (at the end of the programme) over 100 international, privately financed toll roads, bridges and tunnels. Annual traffic volumes and the respective traffic forecasts were compiled for each project. The forecasts used (there can be a number of forecasts made at different times by different parties for the same project road) were the ones embedded in the models used at financial close—as these represented the basis for lending decision-making. These were the forecasts that investors had used to evaluate traffic risk.

The traffic risk research programme started with a sample of 32 projects in 2002. This sample gradually expanded over the 4-year study period—through a combination of new (full, public) project ratings and with considerable input from bank-financed road projects contained in CDO portfolios. The sample was analysed annually and the research results were published in a series of reports—see Bain and Wilkins (2002), Bain and Plantagie (2003, 2004), and Bain and Polakovic (2005). The analysis presented here does not follow this chronological sequence but, instead, looks back at the research programme—and its findings—as a whole.

The year 2005 marked the culmination of the traffic forecasting risk research programme. By this stage the number of international road, bridge and tunnel case studies compiled was over 100.[1] Throughout the programme, the research findings had been presented as ratios of actual/forecast traffic. Projects that had out-performed their forecasts therefore had ratios above 1.0. More commonly, performance ratios below 1.0 were observed—reflecting a trend of over-forecasting. The research results are summarised in Fig. 1. Figure 1 is based on Year 1 performance. The performance of traffic forecasts in subsequent years is considered later.

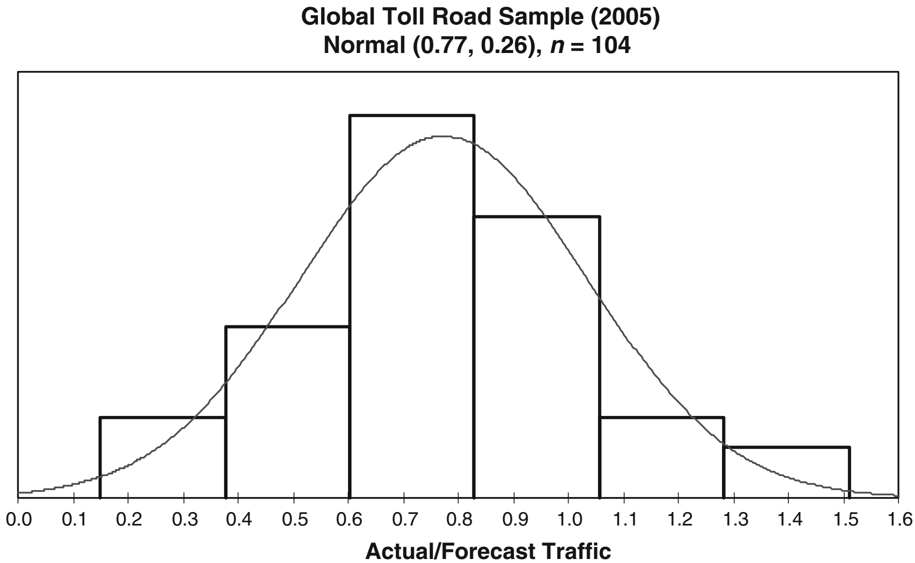

Fig. 1 2005 Full data-set forecast performance distribution

[1] The data set was anonymised. Commercial sensitivities prevented the individual roads, bridges and tunnels from being identified.

Figure 1 reveals traffic forecasting performance ranging from 0.14 to 1.51. In other words, actual traffic turned out to lie between 86% below forecast to 51% above forecast. This considerable error range illustrates the possible magnitude of uncertainty when traffic risk is passed to the private sector.

Distribution-fitting software (@RISK) suggested a normal distribution for the data with a mean of 0.77 and a standard deviation of 0.26. Goodness-of-fit was measured by the Chi Squared (χ^2) statistic. The existence of random errors in the data set would have resulted in a mean around 1.0 (reflecting an equal chance of forecast under- or over-prediction). A mean sitting to the left of unity is indicative of a tendency for over-forecasting. To assess the significance of this finding, a *t*-test was performed. The *t*-test statistic was calculated to be -9.02. $P(t \leq -9.02) = P(t \geq 9.02)$. The t distribution with 103 degrees of freedom was approximated by a t distribution with 100 degrees of freedom where $P(t \geq 9.02)$ was less than 0.0005. This result was significant at the 0.01 level and beyond and therefore the null hypothesis (that the mean was no different from 1.0) was rejected with confidence. The mean of 0.77 suggests that, on average, the respective forecasts were optimistic by some 23%.

These findings—a large range of error and systematic optimism bias—are consistent with those revealed from the earlier years' studies (based on smaller sample sizes). The general trend is also consistent with the JP Morgan study findings discussed earlier (see Table 1).

Returning to the Standard & Poor's data set, the banks' credit surveillance documentation made available to the rating agency typically provided reasons if the outturn traffic volumes departed from expectations. These explanations, together with similar information contained in the technical reports supporting projects with full public ratings, suggested common 'drivers' behind toll road traffic forecast inaccuracy.

Recession or economic downturn was cited in a number of cases, underscoring the positive—if somewhat complex—relationship between economic growth and traffic growth. A recent period of macro-economic downturn in Portugal, for example, has been accompanied by negative growth on the country's privatised toll road network. Land use scenarios that changed from those assumed by traffic forecasters were also highlighted. The closure of a major military installation led to an unanticipated reduction of traffic on a toll road in Southern California.

Commonly reported forecast error drivers also included time savings that turned out to be lower than expected and over-estimations of drivers' willingness-to-pay tolls, particularly on facilities charging higher-than-average toll tariffs. Improvements to competitive (toll-free) routes, low off-peak or weekend traffic (periods not often modelled in detail) and truckers' resistance to paying tolls were also identified as contributing to forecasting error. Other error drivers included:

- The complexity of the project (and, in particular, its tolling regime). This was identified as compounding the forecasting challenge. This point was raised in connection with projects with complex toll schedules where tariffs varied by vehicle type (with many categories),

Table 1 Traffic forecasting studies: comparative results

	J P Morgan Study	Bain Study
Sample size (no. of road projects)	14	104
Location	USA	International
Forecasting performance (ratio of actual/predicted traffic)		
Minimum	0.18	0.14
Average	0.58	0.77
Maximum	1.17	1.51

by section of road and, in some cases, by time of day—requiring detailed, disaggregated traffic modelling in terms of the number of user classes and time slices employed.
- Underestimation of the severity and duration of ramp-up (the period between the start of tolling and steady-state operations). Some forecasts had assumed that ramp-up would be quick—instant, in a few cases—however, the actual data suggested that traffic patterns were still continuing to evolve some years later.
- Over-estimation of the value of time. Outturn data from some roads reflected the fact that fewer drivers than anticipated were prepared to pay tolls to enjoy the time savings on offer. Reports by lenders' technical advisers suggested that the use of single-point, average estimates for the value of time (in the original forecasting model) was an inadequate proxy for a key model input that was, in fact, characterised by a distribution. This, they suggested, contributed to predictive failure.
- Longer-term traffic forecasts and their critical dependence on macro-economic projections. A number of comments were recorded about the relationship between economic growth and traffic growth; concerns being raised about traffic forecasts—particularly over longer horizons—relying on strong and sustained economic growth assumptions that resembled policy targets rather than unbiased assessments of future economic performance.

The principal reasons behind forecast inaccuracy were compiled to become the basis of an empirically derived risk register for investors and financial analysts; Standard & Poor's Traffic Risk Index. (described later).

For a small number of the forecasting case studies, actual traffic volumes (and forecasts) were available by vehicle category. This allowed for a first-cut analysis of the data by light and heavy vehicles. 'Light vehicles' were mainly private cars. 'Heavy vehicles' were mainly trucks. In terms of the ratio of actual to forecast volumes, the means of the disaggregated data sets were broadly comparable, however, the standard deviation appeared to be larger for trucks (0.33) than for cars (0.26).

Although some caution should be taken with this finding—because of the small sample size—it accords with anecdotal evidence. A number of toll roads—including the UK's M6 Toll—have experienced much lower truck usage than predicted. The significance of this finding derives from the fact that the toll tariff differential between light and heavy vehicles is commonly considerable. Trucks often pay 4–10 times the respective car tariff. Although trucks represent less than 10% of vehicles using France's toll road network, for example, they contribute over 25% of the revenues (Bain and Polakovic 2005) and on some US toll roads they contribute around a half of revenues.[2] For this reason, toll road revenue projections that are reliant upon forecasts of high truck usage should be treated particularly cautiously by potential investors.

As the data set grew over the study period, it became possible to undertake further disaggregate analysis, the first of which looked at a binary division of the data into forecasts made in (a) host jurisdictions with a strong history of road tolls, and (b) host jurisdictions new to tolling. This data division suggested that two distinct (underlying) distributions were present (see Fig. 2).

The performance distribution of forecasts made in countries new to tolling ('Without Tolls') had a lower mean (0.58) and a marginally wider spread (standard deviation = 0.26) than those made in countries with a strong history of road tolls (mean = 0.81; standard deviation = 0.24). The tendencies towards predictive error and optimism bias appear to be greater in countries new to tolling. This finding has an intuitive appeal. Forecasts made in

[2] About 50% of the revenue from the Pennsylvania Turnpike is derived from trucks.

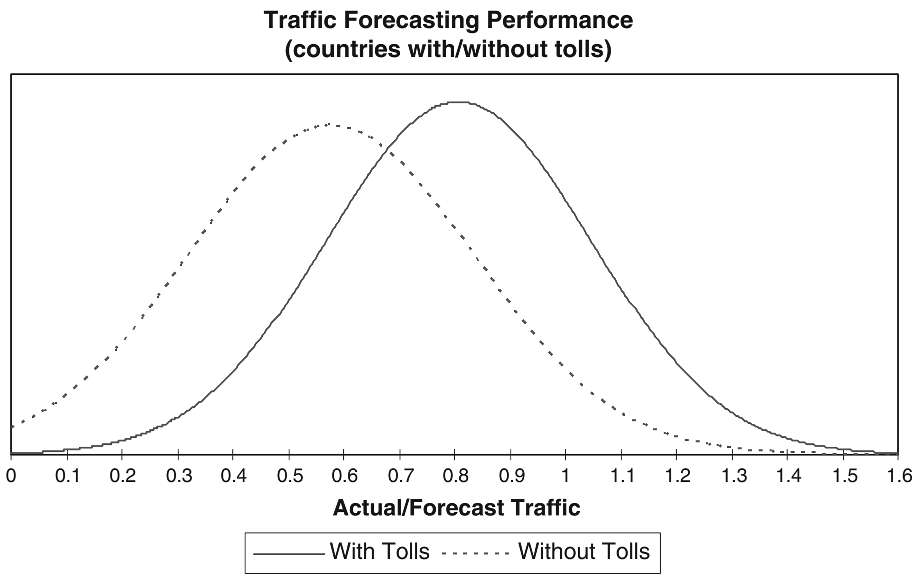

Fig. 2 Comparison of the predictive accuracy of forecasts

countries with a history of tolls have revealed preference information upon which to calibrate, benchmark or simply 'sense check' the predictive results from traffic models. A practical example of this effect is described in Panel 1.

The initial focus for the traffic forecasting risk research was on Year 1 data—for the reasons mentioned earlier. Some practitioners and academics, however, have suggested that opening year forecasts are the most difficult to make and that predictive performance over subsequent years improves—see, for example, Vassallo (2007). They maintain that a focus on Year 1 analysis over-estimates predictive failure. This hypothesis was tested using the full Standard & Poor's forecasting data set which was extended, as possible, to include comparative actual and forecasted traffic volumes for the case study roads in Years 2, 3, 4 and so forth.

Multi-year traffic data was available for a subset of the case studies reflecting, in part, the fact that in many countries privately financed road projects are still a relatively recent phenomenon. However, that subset appeared to contain sufficient data for the hypothesis to be tested through to Year 5, as shown in Fig. 3.

Panel 1 Countries with/without tolls: a Caribbean illustration

In Puerto Rico, road tolling was established in the early 1970s. The sector has subsequently grown considerably. By 2000, over one million toll transactions were processed every day on the Island (Bain 2000).

700 miles to the west of Puerto Rico lies Jamaica. Until recently, Jamaica had no toll roads. The Island's first facility (Highway 2000) was opened in 2003.

Preparing toll road traffic forecasts in Jamaica is considerably more challenging than preparing them in Puerto Rico. Demand forecasting in Puerto Rico is certainly not trivial, yet the consumer response to the imposition of point-of-use charging can be observed in Puerto Rico. In fact, there is over 30 years worth of toll road data which can be used to calibrate local traffic forecasting models.

Until very recently, the consumer response to road tolls in Jamaica could not be observed, and there was no local data upon which to calibrate forecasting models or assess their credibility. In the absence of such information, it seems reasonable to accept that the scope for predictive inaccuracy will tend to be greater—*ceteris paribus*—in Jamaica than in Puerto Rico.

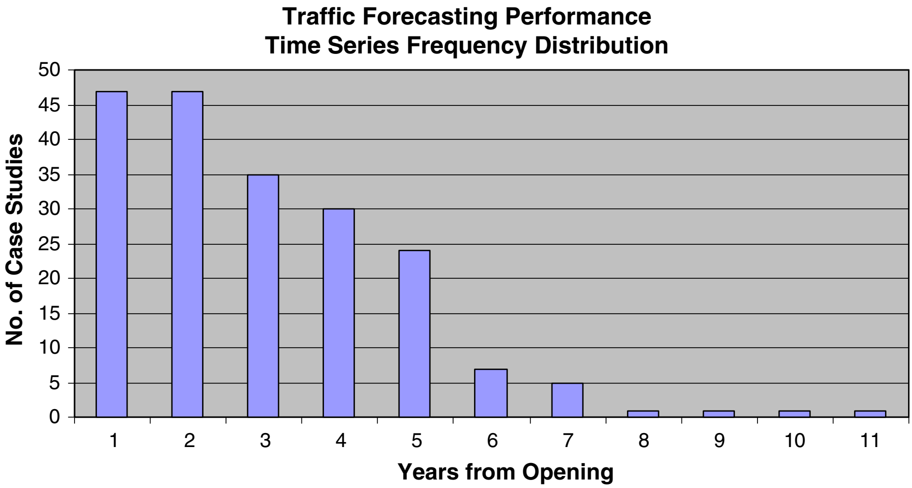

Fig. 3 Subset of case studies with multi-year data available

If the hypothesis was correct, the trend—in terms of individual forecast performance—should show a general improvement in predictive accuracy after Year 1. The results from the multi-year analysis of forecasting performance are presented in Fig. 4. The horizontal axis used in earlier figures (the ratio of actual to forecasted traffic) has been transposed to become the vertical axis, with 'Years from Opening' now defining the horizontal axis. Individual lines (plots) represent separate case studies. All things being equal, an improvement in predictive accuracy would be accompanied by plots with a tendency to converge towards a ratio of 1.0.

Figure 4 is a challenging graph to interpret, in terms of tracing the evolution of forecasting performance for individual road case studies. However, that is not its primary

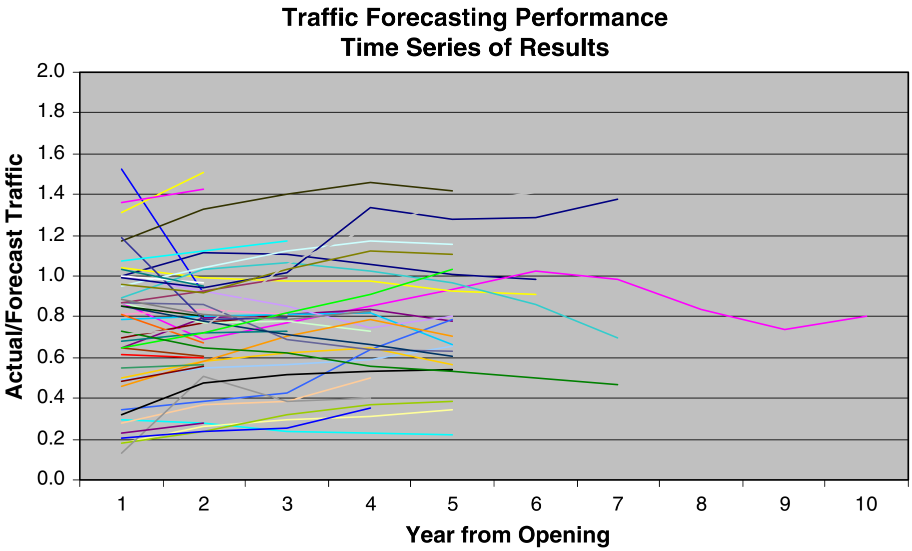

Fig. 4 Time series of traffic forecasting accuracy

Table 2 Time series distribution analysis

Years from opening	Mean	Standard deviation
Year 1	0.77	0.26
Year 2	0.78	0.23
Year 3	0.79	0.22
Year 4	0.80	0.24
Year 5	0.79	0.25

purpose. It is presented for the purpose of overall trend analysis and, at that aggregate level, there appears to be no clear or obvious trend towards convergence on 1.0. The means and the standard deviations of the time-series data subset are presented in Table 2, by year. After Year 5, the sample size becomes too small for meaningful analysis.

From this data it would appear that there is no evidence to support the hypothesis that there is any systematic improvement in toll road traffic forecasting accuracy after Year 1.

The Flyvbjerg Study (2005)

In 2005 a team of researchers led by Professor Bent Flyvbjerg compiled and published traffic forecasting performance data from a large, international sample of public (un-tolled) roads (Flyvbjerg et al. 2005). This presented the opportunity to compare the predictive accuracy of forecasts made for privately financed toll roads with those made for publicly provided toll-free ones. Flyvbjerg's findings are summarised in Fig. 5.

Flyvbjerg summarised his forecasting results in terms of 'percentage inaccuracy', however, this data can easily be converted to the form of ratio analysis presented earlier (−20% inaccuracy is 0.8, in terms of the ratio of actual to forecasted traffic). Recast as ratios, his findings are shown in Fig. 6. This format allows for a direct comparison of his toll-free data set with the toll road data reported earlier.

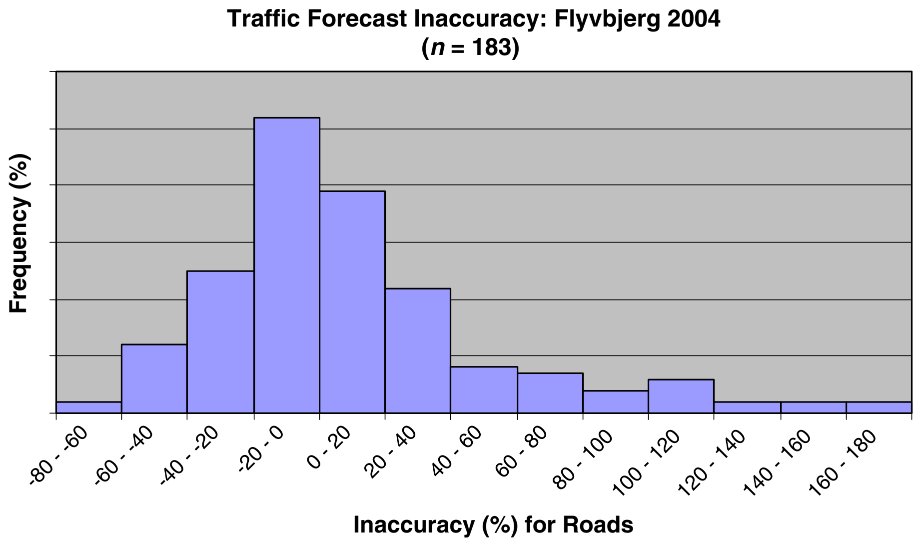

Fig. 5 The predictive accuracy of forecasts (toll-free roads)

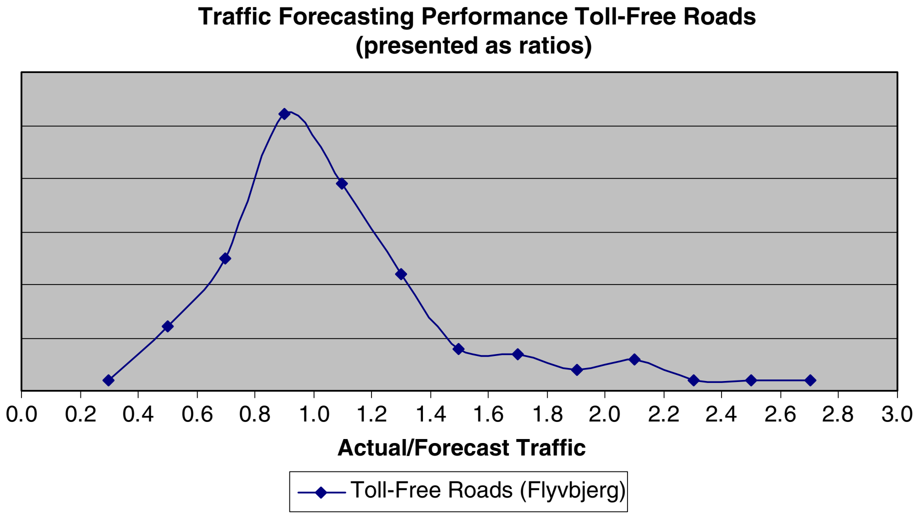

Fig. 6 Toll-free road forecast accuracy (ratios)

The Flyvbjerg distribution has two striking features. It resembles a normal distribution with an extended right-hand tail. The mean of the bell-shaped portion of the distribution sits near 1.0 (certainly nearer 1.0 than that observed from the toll road forecasting analysis). This suggests that forecasts for toll-free roads do not display the strong systematic tendency towards optimism bias identified earlier. Forecasts for toll-free roads appear to have a more equal chance of over- and under-prediction.

The long right-hand tail represents actual traffic that exceeded its respective forecasts by some margin (over twice). A possible explanation for this finding—and the fact that it is not observed in the toll road data—is that toll road forecasts are subjected to more rigorous, multi-party scrutiny than traditional public sector (toll-free) road forecasts. Much of that scrutiny is focussed precisely upon the potential for traffic usage to be high—as this represents a safety cushion for lenders and upside for equity investors. As such, there is less of a chance for toll road forecasters to have failed to capture the possibility of high traffic usage. That possibility will have been fully explored and embedded in most toll road forecasts. Indeed, the focus on upside traffic potential undoubtedly contributes to the optimism bias findings discussed earlier.

Notwithstanding, the right hand tail represents a relatively small number of roads in the Flyvbjerg sample. The majority of the sample is captured by the bell-shaped distribution to the left; centred around unity. Figure 7 shows a comparison of the two data sets.

The substance of the two distributions looks similar, albeit that the toll road distribution sits to the left. The presence of systematic optimism bias appears to be a characteristic that differentiates the two data sets. Optimism bias does not appear to be a defining attribute of toll-free road traffic forecasts. However, the standard deviation—measuring predictive error—looks broadly similar. This is illustrated in Fig. 8, in which explicit allowance has been made for the optimism bias in the toll road forecasts by adding 20% to the actual toll road traffic volumes.

After allowing for optimism bias, the spreads of the two distributions do, indeed, appear to be broadly comparable. The key lessons from this comparative analysis can be summarised as follows:

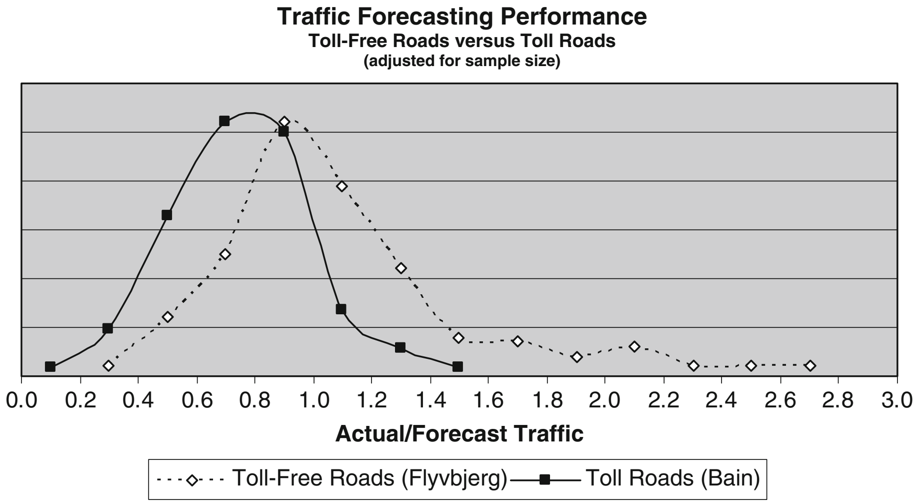

Fig. 7 Forecasting accuracy: toll roads and toll-free roads

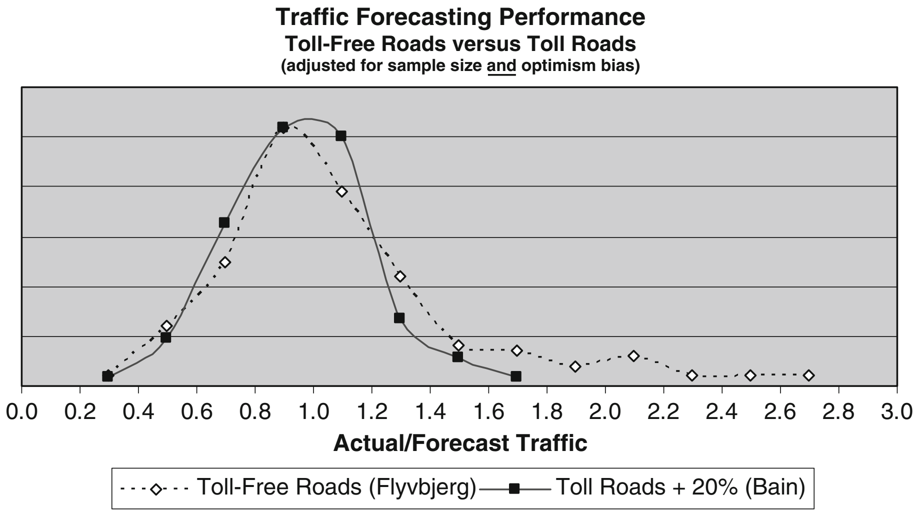

Fig. 8 Toll-free road and toll road forecasts (adjusted)

- Toll and toll-free road traffic forecasting accuracy appears to differ in terms of optimism bias.
- Toll and toll-free road traffic forecasting accuracy appears similar in terms of absolute error.

These findings are important in the context of privately financed shadow toll road projects.[3] Scheme sponsors have strived to promote shadow toll roads as less risky prospects for

[3] Shadow tolls are payments made by the government—not road users—to the private sector operator of a road based on the number of vehicles using the road.

private investors than user-paid toll roads. Arguments in support point to the fact that (a) assessing the consumer response to point-of-use charging (drivers' willingness-to-pay tolls) is a major challenge for traffic forecasters and so, (b) in situations where this challenge is removed—such as the preparation of shadow toll road projections—forecast reliability is enhanced. The potential for error, it is argued, is automatically reduced.

This argument does not appear to be supported by the data presented above. There is no evidence to support the notion that predictive error inevitably reduces in situations where drivers are not required to pay tolls.

Research Summary

The primary motivation for undertaking the traffic forecasting research presented in this paper was the somewhat surprising recognition—back in 2002—that very little cross-sectional data was published that would permit a comparison of toll road traffic forecasts with outturn figures. In fact, save for the JP Morgan study of 14 US toll roads, nothing had been published. The research presented in this paper represents the largest toll road traffic forecasting study of its type ever compiled. Given the body of demand forecasting research which has been conducted internationally—aimed at revising and fine-tuning the forecasting process—it is surprising that predictive accuracy has traditionally attracted such little attention.

Despite the absence of comparative data, however, there has been a history of considerable scepticism about traffic forecasting accuracy among private financiers. A key reason for this is that often a number of traffic forecasts are made by different parties for the same project road, with very little consistency among the results. Figure 9 shows four base-case forecasts for a well-known toll road, made by internationally recognised traffic consultants within months of each other. As the data was released to the author on a

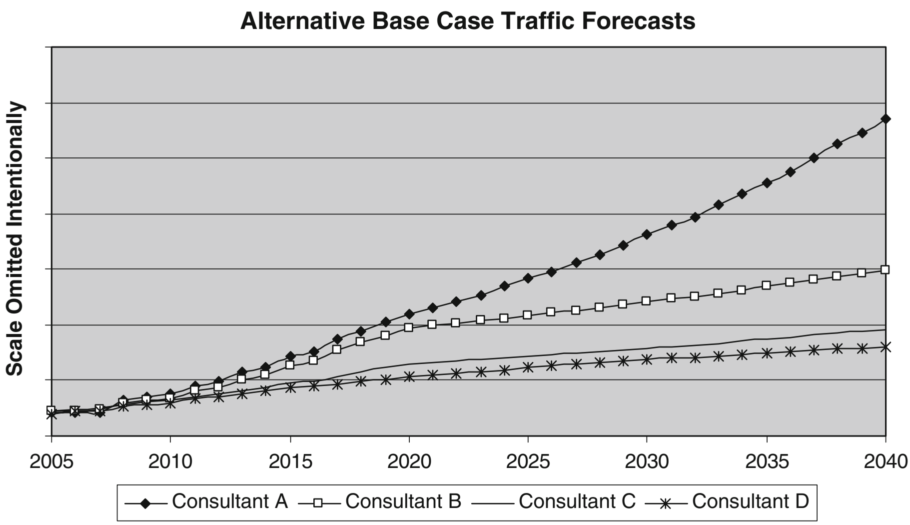

Fig. 9 Same toll road, different traffic forecasts

Table 3 Alternative traffic forecasts

Forecast period (from project opening) (years)	Difference between the highest and lowest base-case forecast (%)
5	26
10	66
15	106
20	130
25	164
30	204
35	255

confidential basis, the vertical axis scale is omitted to preserve project anonymity. This omission does not detract from the message, however. These 'base case' forecasts are significantly different from each other—as is highlighted in Table 3.

Even over the short to medium-term, the forecasts depart significantly (by 100% over 15 years). In terms of forecast reliability, this real-world example is all the more alarming when one considers that the different forecasts result from different input variable assumptions, yet these assumptions are themselves drawn from an entirely plausible (and relatively narrow) range.

Although the issue of traffic forecasting risk has received some attention in the literature, little consideration appears to have been given to the nature and scale of the risk itself. The implications of the research reported here are that, in terms of error, the predictive accuracy of traffic models—used for toll or toll-free road forecasts—is poor. Turning to bias, it is difficult to delink the observed systematic tendency for over-forecasting from the fact that privately financed toll road concessions are commonly awarded to bidding teams submitting the highest traffic (and hence revenue) projections. In summary, errors arise from the not insignificant yet commonly understated forecasting challenge. Bias derives from strategic game-playing designed to win potentially lucrative long-term contracts.

Throughout the 4-year research programme, the reasons attributed to toll road traffic forecasting errors were compiled. These reasons (error drivers) are summarised in Table 4; the Traffic Risk Index. The idea behind the Index was to identify specific project and transaction characteristics—based on solid, empirical evidence—that could increase (or decrease) exposure to forecasting error. For the first time, the Index offers investors and financial analysts a way of systematically evaluating forecasting risk—by subjectively scoring projects—in a logical, comprehensive and consistent fashion. The Traffic Risk Index has since been adopted by a number of toll road traffic and revenue consultants for presentations to procuring agencies, scheme sponsors, potential investors and rating agencies.

The principal conclusion to be drawn from the research reported in this paper is that toll road investors need to be aware of the considerable potential for error and bias to influence future projections of asset usage. Transaction structures need to retain sufficient flexibility, liquidity and liquidity support to accommodate the potential for often-observed and commonly large departures from performance expectations.

Table 4 The Traffic Risk Index

Project attributes	Good — Traffic Risk Index: Scores 0 1 2 3 4	5 6 7 8 9 10 — Bad
Tolling culture	Toll roads well established—data on actual use available	No toll roads in the country—uncertainty over toll acceptance
Tariff escalation	Flexible rate setting/escalation formula; no government approval	All tariff hikes require regulatory approval
Forecast horizon	Near-term forecasts required	Long-term (30 year+) forecasts required
Toll facility details	Facility already open	Facility at the very earliest stages of planning
	Estuarial crossing	Dense urban network
	Radial corridor into urban area	Ring-road/beltway round urban area
	Extension of existing road	Greenfield site
	Alignment—strong rationale (inc. tolling points & intersections)	Confused/unclear road objectives (not where people want to go)
	Alignment—strong economics	Alignment—strong politics
	Clear understanding of future highway network	Many options for network extensions exist
	Stand-alone (single) facility	Reliance on other proposed highway developments
	Highly congested corridor	Limited/no congestion
	Few competing roads	Many alternative routes
	Clear competitive advantage	Weak competitive advantage
	Only highway competition	Multi-modal competition
	Good, high capacity connectors	Hurry-up-and-wait
Surveys/data collection	Active competition protection (e.g. traffic calming, truck bans)	Autonomous authorities can do what they want
	Easy to collect (laws exist)	Difficult/dangerous to collect
	Experienced surveyors	No culture of data collection
	Up-to-date	Historical information
	Locally calibrated parameters	Parameters imported from elsewhere (another country?)
	Existing zone framework	Develop framework from scratch
Users: private	Clear market segment(s)	Unclear market segment(s)
	Few, key origins & destinations	Multiple origins & destinations
	Dominated by single journey purpose (e.g. commute, airport)	Multiple journey purposes
	High income, time-sensitive market	Average/low income market
	Tolls in line with existing facilities	Tolls higher than the norm (extended ramp up)?
	Simple toll structure	Complex toll structure (discounts, frequent users, variable pricing etc.)
	Flat demand profile (time-of-day, day-of-week etc.)	Highly seasonal or 'peaky' demand profile

Table 4 continued

Project attributes	Good — Traffic Risk Index: Scores (0–4)	Bad — Traffic Risk Index: Scores (5–10)
Users: commercial	Fleet operator pays toll	Owner-driver pays toll
	Clear time/operating cost savings	Unclear competitive advantage
	Simple route choice decision-making	Complicated route choice decision-making
	Strong compliance with weight restrictions	Overloading of trucks is commonplace
Micro-economics	Strong, stable, diversified local economy	Weak/transitioning local/national economy
	Strict land-use planning regime	Weak planning controls/enforcement
	Stable, predictable population growth	Population forecast dependent on many exogenous factors
Traffic growth	Driven by/correlated with existing, established and predictable factors	Reliance on future factors, developments, structural change etc.
	High car ownership	Low/growing car ownership

Source: compiled by the author

Acknowledgement I would like to thank the editor and several anonymous referees for their useful suggestions about and helpful comments on an earlier draft of this paper. I would also like to thank Standard & Poor's for giving me permission to present material in the paper which was compiled while I worked full-time for the credit rating agency.

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Author Biography

Robert Bain spent the first 15 years of his career as a traffic and transportation consultant before joining the infrastructure team at Standard & Poor's in 2002. He is currently retained by the rating agency on a freelance basis and, separately, provides transport-related technical support services to infrastructure funds, insurance companies and institutional investors. Robert recently completed a PhD at the Institute for Transport Studies—hence his affiliation with the University of Leeds.