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UNDERSTANDING AND ACCOMMODATING RISK AND UNCERTAINTY IN TOLL ROAD PROJECTS: A REVIEW OF THE LITERATURE

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The following paper is a pre-print and the final publication can be found in
Transportation Research Record No. 2132: 106-112, 2009.

Presented at the 88th Annual Meeting of the Transportation Research Board, January 2009

Key Words: travel demand forecasting, project risk, highway tolling, forecast uncertainty

ABSTRACT

Forecasting traffic and toll revenues for new highway projects involves great uncertainty due to the inherent uncertainty in the models used to make forecasts. As private investment becomes more common in project financing, quantifying the levels of risk and uncertainty associated with such projects becomes critical. This paper represents a review of many key studies and reports dealing with uncertainty in traffic and revenue forecasts for highway projects. These studies found that tolled projects tend to suffer from substantial optimism bias in forecasts, with predicted traffic volumes exceeding actual volumes by 30% or more about half of the time. Moreover, projects with greater uncertainty tend to overestimate year-one traffic volumes more and stabilize at lower final traffic volumes. But after controlling for added optimism bias in traffic forecasts (compared to non-tolled projects), there is little difference in uncertainty levels between tolled and non-tolled forecasts. A typical way to address uncertainty in traffic forecasts is through sensitivity testing, via variations in key inputs and parameters. A more extensive and less arbitrary version of this, Monte Carlo simulation, can provide probability distributions of future traffic and revenue, though it tends to require many simulations, which demand greater computational effort and time, unless networks are streamlined. Nonetheless, if reasonable assumptions for model input and parameter distributions can be made, Monte Carlo simulation generates a variety of useful information, and establishes the actual likelihood of loss (rather than more basic win/lose indicators from a limited set of “stress tests”).

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3 **INTRODUCTION**
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5 Considerable uncertainty exists in traffic forecasts for new highway projects. While such
6 uncertainty is not unexpected, in many projects it is largely ignored by designers and
7 transportation planners. Compounding the issue, rising congestion and scarcity of open space in
8 urban areas means that forecasting errors can be quite costly. Recently, Flyvbjerg et al. (2005
9 and 2006) sought to quantify and document the level and nature of uncertainty in traffic forecasts
10 using data from highway and transit projects across the globe. The absolute difference between
11 forecast and actual traffic is more than 20% for about half of the highway projects examined, and
12 about 40% for roughly one-quarter of projects. However, they did not consider uncertainty in
13 traffic predictions for tolled highways specifically.
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15 Uncertainty in demand for *tolled* roadways is compounded by the introduction of more unknown
16 variables. Yet such new understanding can be critical, since private investment generally
17 depends on cost recovery through toll collection. In order to begin to address this clear gap in
18 the literature, Standard & Poor's (Bain and Wilkins 2002, Bain and Plantagie 2003 and 2004,
19 Bain and Polakovic 2005) and Fitch Ratings (George et al. 2003 and George et al. 2007)
20 produced a series of studies that examine the risk and uncertainty of tolled highway projects.
21 This paper summarizes key elements of those results and investigates methods for
22 accommodating (or at least recognizing) uncertainty in the forecasting process. The resulting
23 synthesis is intended to offer guidance in planning and decision-making processes of tolled
24 roadway projects. The first section of this paper describes the observed frequency and
25 magnitude of traffic volume mispredictions (forecast versus actual), while the second explains
26 the various sources of risk and uncertainty in traffic forecasts and how these relate to project
27 financing. The third section describes methods for recognizing and incorporating uncertainty in
28 models of travel demand.
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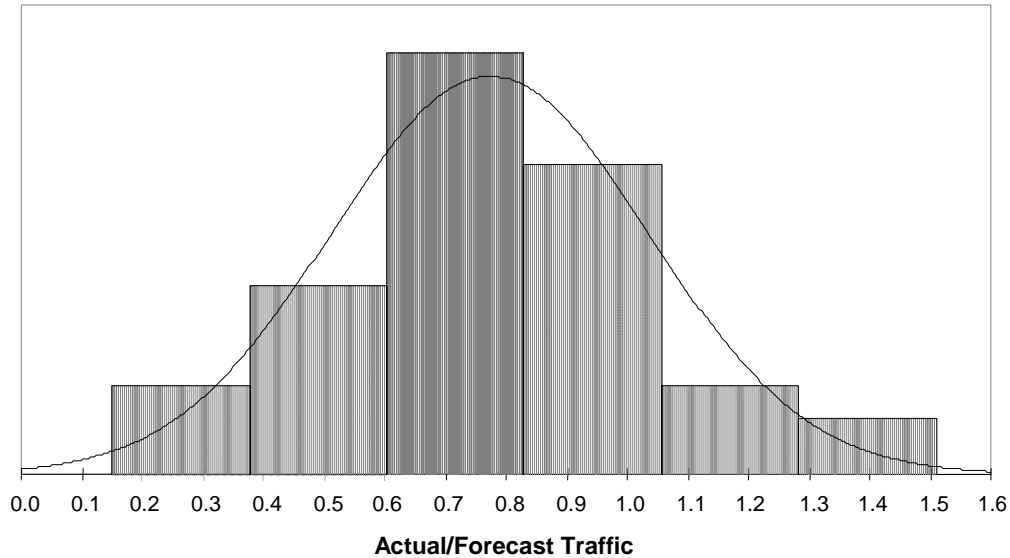
30 **FREQUENCY AND MAGNITUDE OF MISPREDECTIONS**
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32 Standard & Poor's (S&P's) study of traffic forecasts began in 2002 with data on 32 toll road
33 projects from around the world. The sample was then increased to 68 and 87 projects in 2003
34 and 2004, respectively. However, in both updates the conclusions remained largely the same.
35

36 In the first study, Bain and Wilkins (2002) found that traffic forecasts for new toll roads suffer
37 from substantial optimism bias, a finding that is supported in the subsequent studies. The
38 average ratio of actual-to-forecast traffic volumes in the first year of operation was about 0.73
39 (versus 0.74, 0.76, and 0.77 in the 2003, 2004, and 2005 studies). Figure 1 shows the
40 distribution of forecasting errors in the 2005 update. (Comparisons to non-tolled projects are
41 drawn later in this section.) Of course, due to the nature of averaging ratios such as these, traffic
42 forecasts for toll roads may be over-predicting actual volumes by even more than 33% (implied
43 by an actual-to-forecast ratio of 0.75).¹ Moreover, the 2002 study found that 78% of actual-to-
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46 ¹ A volume-weighted average of ratios (essentially the sum of predicted values over the sum of actual values) yields
47 a much more robust indicator of the average percentage error, reflecting whether an investor will win (average >1)
48 or lose (<1) – on average, across projects. Essentially, the issue is that the ratios are non-negative and bounded by
49 zero, leaving a right-side skew that can tends to bias averages high. For instance, if predicted-to-actual ratios for two
50 projects are 0.5 and 2.0, the average is 1.25, suggesting predictions are biased high. If we invert the ratios first and
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3 forecast traffic volume ratios were less than 0.9 while only 12% were over 1.05. In the 2003
4 study, 63% of such ratios were less than 0.85, and 12% were over 1.05. Essentially three
5 quarters of first-year traffic forecasts for tolled facilities are overestimated by 10% or more,
6 suggesting that planners, bankers, and communities should be wary, and modelers need to
7 improve their methods.
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26 Figure 1: Distribution of actual-to-forecast traffic volumes (Source: Bain and Polakovic 2005,
27 Chart 1)

28
29 One of the main diagnostics to come out of the 2002 study was S&P's Traffic Risk Index (TRI).
30 While the exact details for its estimation are proprietary in nature (and thus not provided), the
31 index attempts to predict the amount of project risk based on many project attributes, as
32 discussed later in this paper. Based on the TRI, Bain and Wilkins (2002) determined a risk level
33 (low, average, or high) for each project, and divided its discussion by forecast source: those
34 commissioned by banks versus those commissioned by others.
35

36 The findings suggest that actual-to-forecast traffic volume ratios in the first year of operation
37 average about 0.9 for "low-risk" bank-commissioned projects, and 0.8 for "low-risk" projects
38 commissioned by others. Both types of low-risk projects had average ramp-up durations² of
39 about 2 years (after which actual volumes track forecasts, on average). For "average-risk"
40 projects, year one volume ratios were found to be 0.8 and 0.65 for bank- and non-bank-
41 commissioned projects, respectively. Ramp-up duration was about 5 years in both cases.
42 However, those commissioned by banks ramped-up to about 95% of forecast volumes over those
43 first five years, while others ramped-up to only 90%. For "high-risk" projects, the volume ratios
44 were just 0.7 and 0.45, respectively, and ramp-up durations were about 8 years. After ramp-up,
45 bank-commissioned projects reached about 90% of forecast volumes while other projects
46

47 then average, the result is again 1.25, but the interpretation is that predictions are biased low. Thus, one must use
48 caution when dealing with averages of ratios.

49 ² The ramp-up period is the period in which traffic volumes rise to a relatively stable or equilibrium level. This
50 period may require several years.
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4 reached approximately 80% of forecast. What this suggests is that projects with greater
5 uncertainty (and thus risk) overestimate initial traffic volumes by a greater amount, on average,
6 experience a longer ramp-up duration (to reach stable volumes), and stabilize at lower final
7 traffic volumes (versus predictions). Moreover, the magnitude of risk is greater for projects not
8 commissioned by banks, which is not so surprising given that banks are much more directly
9 accountable for investors' monies than are public agencies. Moreover, other project
10 commissioners (public agencies, interest groups, and bidders) may have interests that are best
11 served when predicted traffic volumes are high (Bain and Wilkins 2002).

12
13 With the 2003 study's increased sample size, Bain and Plantagie (2003) were able to conduct
14 several less aggregate analyses. Multiple factors were investigated, but only one with
15 significance was found, in distinguishing countries with and without a tolling history. The
16 findings suggest that actual-to-forecast volume ratios in the first year of operations averaged 0.81
17 in countries with a history of tolling, but just 0.58 in other countries. Thus, forecast risks appear
18 much higher in countries without a history of tolling. This is intuitive, given that user adoption
19 will be much faster (thanks to existing toll tag and manual payment experiences) and that
20 contractor and operator familiarity will be higher. In several U.S. regions (e.g., Florida,
21 Southern California, New York, and Houston), flat-rate tolling is already well-established; so, in
22 these regions it may be reasonable to expect first-year ratios in the neighborhood of 0.8.
23 However, most other U.S. regions may dramatically under-perform if more appropriate modeling
24 assumptions are not used (particularly for the ramp-up period).

25
26 In the 2004 update (Bain and Plantagie 2004), traffic forecasts along new tolled highways were
27 compared to those of new non-tolled facilities. The sample size was increased to 87 highway
28 projects, with all data for non-tolled facilities coming from Flyvbjerg et al.'s (2005 and 2006)
29 work. The comparisons suggest that new non-tolled roadways exhibit little optimism bias,
30 though the same amount of uncertainty or spread in the distribution (of volume ratios) remains.
31 Figure 2 shows how the two distributions appear similar, but with the distribution of tolled road
32 (forecast-to-actual) volume ratios shifted to the left by about 0.2 units (essentially indicating a
33 20-percent optimism bias). This suggests that, after controlling for the added optimism bias of
34 tolled projects, there may be little difference in the accuracy of traffic forecasts for tolled and
35 non-tolled projects.

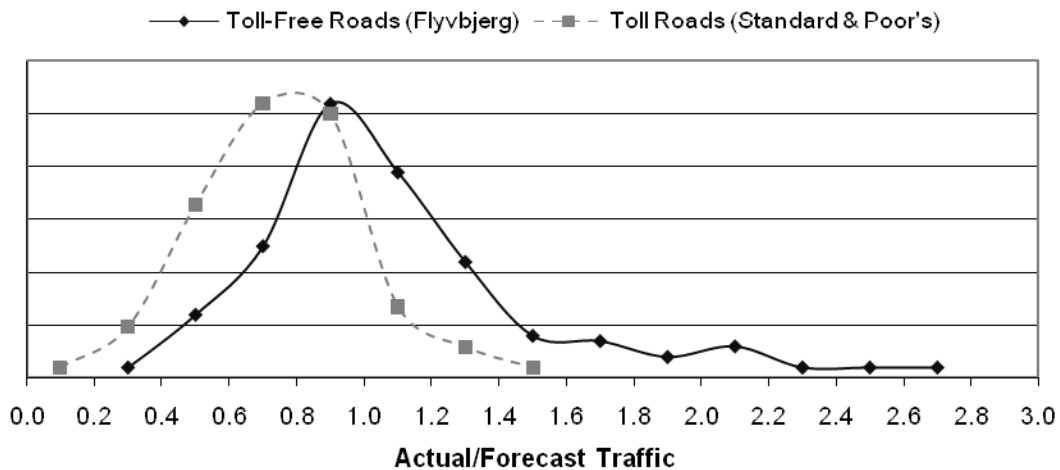


Figure 2: Distribution of actual-to-forecast traffic volumes for tolled and non-tolled projects (Source: Bain and Plantagie 2004, Chart 3)

Of course, S&P's uncertainty estimates for tolled roads were not exactly those published by Flyvbjerg et al. (2005 and 2006). Flyvbjerg et al. (2006) looked at 183 road projects (tolled and non-tolled), about half of which had actual-to-forecast volumes less than 0.8 or greater than 1.2 in their first year of operation (whereas S&P's studies [Bain and Wilkins 2002, Bain and Plantagie 2003 and 2004] found that roughly 65% of toll road projects fall into these two tails), and 25% had actual-to-forecast ratios less than 0.6 or greater than 1.4 (about 30% for tolled projects, according to S&P [Bain and Wilkins 2002, Bain and Plantagie 2003 and 2004]). Flyvbjerg et al. (2005 and 2006) found that the average actual-to-forecast ratio for non-tolled roads is 1.09 (with a 95% confidence interval on this value lying between 1.03 and 1.16). Of course, this average ratio is higher than if a weighted average were taken (as discussed previously). A weighted average ratio would likely be very close to zero since there appears to be approximately the same number of projects falling above and below the break even ratio of 1.0 (this corresponds to the 0% difference shown in Figure 3). Figure 3 shows Flyvbjerg et al.'s distribution of actual-to-predicted volumes.

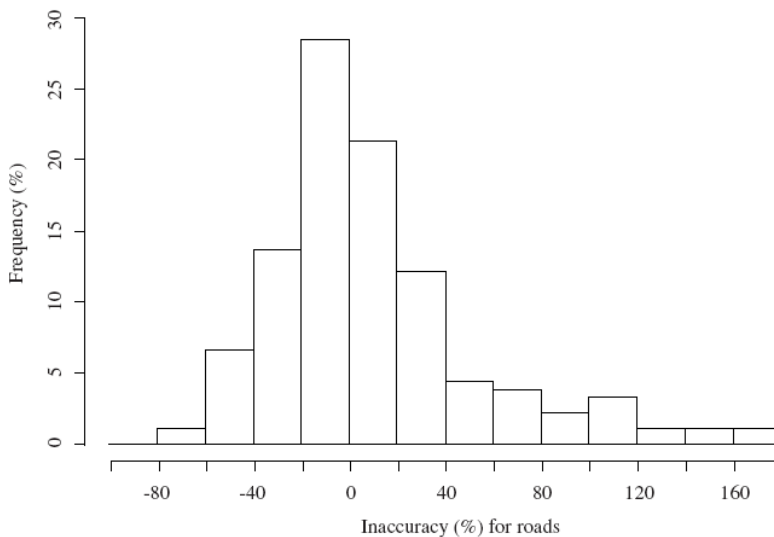


Figure 3: Distribution of actual-to-forecast traffic volume ratios for non-tolled road projects (Source: Flyvbjerg et al. 2006, Figure 1)

In Standard & Poor's 2005 update (Bain and Polakovic 2005), the uncertainty in project ramp-up years³ was investigated in greater depth. The expectation is that uncertainty falls slightly from opening year forecasts, since traffic demand would have an opportunity to stabilize, as drivers learn of route alternatives and obtain toll accounts, for example. The sample size was just 25 projects for years 1 through 5, and the hypothesis was not supported (Bain and Polakovic 2005). The mean ratio (of actual-to-forecast traffic volumes) was 0.77 in year 1, and 0.79 (negligibly higher) in year 5. These results suggest that traffic performance generally remains much less than forecast, even into year 5 of operation. While Vassallo and Baeza's (2007) much smaller sample (of Spanish toll roads) identified similar optimism biases, forecast ratios generally

³ Ramp-up years are those immediately following opening year.

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3 improved following year one. So there is room for differences in average results, due to regional
4 economic conditions, marketing campaigns or other factors.
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6 **SOURCES OF RISK AND UNCERTAINTY IN TRAFFIC FORECASTS**

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8 While significant uncertainty in traffic forecasts clearly exists, the causes of such uncertainty
9 vary. Numerous studies have identified and examined several sources of forecast error (see e.g.,
10 Flyvbjerg et al. 2006 and 2006, Bain and Wilkins 2002, George et al. 2003, George et al. 2007),
11 and for the most part, these are similar for tolled and non-tolled highways, but differences do
12 exist.
13

14 Flyvbjerg et al. (2005 and 2006) interviewed project managers who identified a variety of
15 sources, including several travel demand modeling components. The two top-stated sources of
16 error for toll-free road projects are estimates of trip generation and land development, though trip
17 distribution and the forecasting model are close runners-up. Flyvbjerg et al. (2005 and 2006)
18 attribute much of the modeling uncertainty to dated data used in model calibration. Land
19 Transport New Zealand (2006) also notes the importance of quality and relevance of data used in
20 the forecasting model.
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22 Zhao and Kockelman (2002) tracked the propagation of uncertainty through a four-step travel
23 demand model. They controlled the uncertainty of model inputs and parameters, and performed
24 100 simulations of the model. Assuming coefficients of variation (CoVs) of 0.3 in all model
25 inputs and parameters, Figure 4 illustrates the range of CoVs in intermediate and final model
26 outputs (across the 100 simulations), including 5% and 95% bounds on these. Figure 6 suggests
27 that modeling error in effect “grows” through the application of trip generation, trip distribution,
28 and mode choice models (as one’s scale of resolution gets finer, essentially – to the number of
29 trips by mode between each origin-destination pair). However, the final step of traffic
30 assignment enjoys a drop in uncertainty (at the link-flow level), thanks to overlap in different
31 trips’ routings and mode and trip distribution choices across all travelers, along with congestion
32 feedbacks (which moderate the presence of high link-demand values). Overall, Zhao and
33 Kockelman’s (2002) work suggests that link-flow estimates enjoy the same level of uncertainty
34 as inputs and parameters, and simple regressions of outputs on inputs (and aggregations of
35 inputs) offer very high predictive power, suggesting that prime sources of forecast uncertainties
36 can be rather quickly deduced – and exploited, for better prediction.
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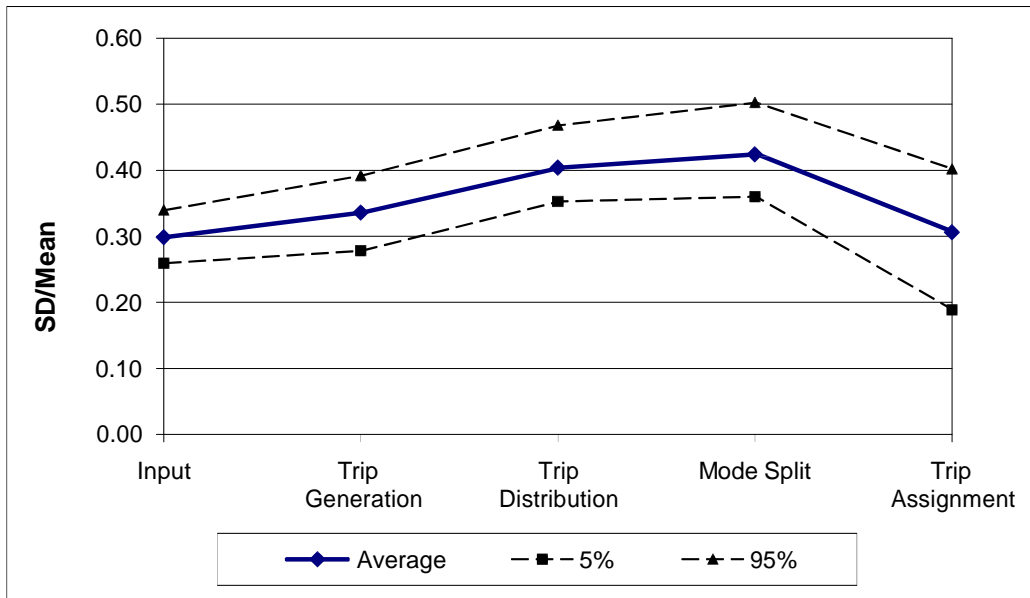


Figure 4: Uncertainty propagation through a four-step travel demand model (Source: Zhao and Kockelman 2002, Figure 5)

Zhao and Kockelman (2002) also point out that models are abstractions of reality and the entire modeling paradigm is a source of error in traffic forecasts. While their study did not consider tolled roads, one can imagine that output variability may rise, as toll-technology adoption rates and heterogeneity in value of travel time savings introduce more uncertainty. In fact, for tolled roads, Bain and Wilkins (2002) noted the importance of data used to calibrate travel demand models, both in terms of currency (more recent is better) and the ease with which data were collected (affecting data quality and quantity).

Network attributes can also play a key role in forecast reliability. Analysts do not know the actual future network, and coded networks are significant simplifications of actual networks (generally ignoring local streets, signal timing plans, turning lane presence and lengths, etc.). Forecasts that depend on future network changes (such as nearby highway extensions) tend to be less reliable (Bain and Wilkins 2002). Traffic congestion is also key. As noted by Bain and Wilkins (2002) and Zhao and Kockelman (2002), uncongested networks often are more difficult to anticipate flows on, since congestion feedbacks distribute traffic more evenly over space and time while establishing something like an upper bound (due to inherent capacity limitations) on all links. Thus, low-volume corridors tend to have greater uncertainty in their forecasts (Bain and Wilkins 2002).

Another key source of error in traffic forecasts comes from uncertainty in land development patterns (Rodier 2003, Flyvbjerg et al. 2005 and 2006, Land Transport New Zealand 2006). Rodier's (2003) application of the Sacramento, California travel demand model for year 2000 conditions found that about half of the 11-percent overestimation of VMT was due to demographic and employment projections, which serve as inputs to the demand models. The other half was due to the model itself. With forecasts anticipating demand 10-plus years out,

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3 Flyvbjerg et al. (2005 and 2006) suggest that more of the error may stem from uncertainty in
4 coming land development patterns. For tolled roads, Bain and Wilkins (2002) argue
5 convincingly that land development forecasts are regularly critical, and the more stable a
6 region's economy, the better its land-use (and, thus, its travel demand) forecasts. Such forecasts
7 are generally based on land use plans and expert judgment, which are simply educated guesses
8 and tend to evolve over time. Another option is land use modeling, which, of course, is also
9 fraught with a variety of uncertainties (see e.g., Pradhan and Kockelman 2002, Rodier and
10 Johnston 2002, Krishnamurthy and Kockelman 2003, Rodier 2005, Clay and Johnston 2006,
11 Sevcikova et al. 2007, and Kockelman et al. 2008).

12
13 While the sources of error described above apply for projects of any type, there are many others
14 that are rather specific to tolled roads. One such source identified by Bain and Wilkins (2002)
15 and George et al. (2007) is tolling design – i.e., whether shadow tolls or user-paid tolls⁴ are used.
16 With shadow tolls, the government pays the concessionaire an amount based on toll road use. So
17 from the user perspective, it is very similar to a toll-free road. With user-paid tolls, the toll
18 charge is quite transparent to the user. Since driver willingness to pay is more complex and
19 difficult to understand, projects with user-paid tolls carry more forecasting risk. Moreover,
20 George et al. (2007) suggest that user fees make a tolled road more susceptible to changes in
21 demand caused by economic downturns/recessions, toll rate increases, and escalating fuel costs.
22 Other special or relatively rare events (e.g., natural disasters or acts of terrorism among other
23 events) are often key sources of uncertainty as well (George et al. 2007). Of course, such events
24 are difficult to predict, though HLB Decision Economics (2004) suggests that the number and
25 duration of recessions in the forecast period should be considered in investment grade studies.
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28 Another important consideration in understanding project risk is the “tolling culture” of a region
29 (Bain and Wilkins 2002). This is essentially the degree to which tolls have been used in the past.
30 In nations and regions where tolling has not previously been used, there is greater uncertainty
31 surrounding traffic forecasts. If travelers are accustomed to paying tolls for other road facilities,
32 forecasts tend to be much more reliable. As noted earlier, this appears to result in 20% greater
33 average optimism bias (Bain and Plantagie 2003).

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35 Of course, travel demand model imperfections are a key source of error in traffic forecasts. For
36 instance, the robustness and heterogeneity (across travelers and trip types) of value of travel time
37 (VOTT) estimates are generally ignored, but may be crucial in producing accurate forecasts. The
38 use of imported parameters (calibrated for other regions or even other countries) can also cause
39 much error (Bain and Wilkins 2002). Another important issue in modeling deals with how the
40 actual tolls are modeled. If a complex tolling regime is to be used (e.g., variable tolls or HOT
41 lanes that are free at certain hours), models fully recognizing such complexity can be quite
42 difficult to specify and calibrate (Bain and Wilkins 2002), introducing further uncertainty.

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44 Facilities enjoying a competitive advantage of some sort also tend to offer more reliable forecasts
45 (Bain and Wilkins 2002, George et al. 2007). For instance, forecasts for projects in dense, urban
46 networks (with many alternative routes) generally will be less certain than those for projects with
47 a clear competitive advantage over alternatives (e.g., a corridor with the only river crossing in a
48 region). Moreover, many privately financed projects rely on protection against competition in

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50 ⁴ Only 4 of the 32 projects investigated in the 2002, Bain and Wilkins study had shadow tolls.

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3 the future. If protection is provided (via non-compete clauses, for example), long-run traffic
4 forecasts tend to be more reliable (Bain and Wilkins 2002). Of course, such clauses may be
5 contentious, as discussed in Perez and Sciara (2003), Poole (2007), and Ortiz et al. (2008).
6 However, non-compete clauses generally do not ban planned improvements (Ortiz et al. 2008)
7 and typically do not prohibit new free roads. But they may allow for compensation when toll
8 revenues fall due to improvements on nearby non-tolled facilities (Poole 2007).
9

10 Meaningful distinctions can also arise in the context of user attributes. Bain and Wilkins (2002)
11 assert that toll facilities serving mostly a small market segment of travelers allow for more
12 reliable traffic forecasts. This is because smaller markets are easier to model than more
13 heterogeneous populations (Bain and Wilkins 2002). For example, beltways (orbital style
14 facilities) are likely to carry more forecasting risk than radial facilities (which typically carry a
15 high share of commuters into and out of the city center, for work purposes). In addition, if there
16 is a single origin-destination (O-D) pair that constitutes the majority of trips made on the facility,
17 forecasts errors fall, as a result of the relatively homogeneous makeup of such travelers.
18 However, George et al. (2007) warn that, when only a small market segment constitutes the
19 majority of toll road users, the road's traffic and revenues will be more susceptible to any forms
20 of downturn affecting that small segment.
21

22 Of course, road location and configuration also affect levels of forecast error. When the
23 preferred alignment of a new tollway is constrained by external factors (e.g., land use patterns,
24 nature and location of existing development, land/right-of-way availability, topography,
25 geological sensitivities, engineering limitations, and politics), traffic forecasts become more
26 uncertain (Bain and Wilkins 2002). Bain and Wilkins (2002) also assert that facilities with
27 proper connectors to the rest of the network have more reliable estimates. If the toll road
28 terminates in the downtown area and long queues await travelers joining the local network and/or
29 if travelers must take circuitous routes to enter the tollway, the competitive advantage of the toll
30 road can be compromised, and greater forecast errors can emerge. Demand variations over times
31 of day and days of the year also affect forecast reliability. If a road serves a stable demand
32 profile, forecasts tend to be more reliable (Bain and Wilkins 2002). Commercial users of the
33 tolled facility also can play an important role. In particular, if most commercial vehicles are
34 independent truckers, there is added risk in traffic forecasts since their behavior is less well
35 understood. However, if most commercial truckers work for fleet owners, the opposite is true.
36 (Bain and Wilkins 2002) Moreover, dependence on commercial travel carries more risk since
37 commercial travel is more susceptible to economic downturns (George et al. 2007)
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39 Overall, Bain and Wilkins (2002) indicate seven top drivers of forecast failure: poorly estimated
40 VOTTs, economic downturns, mis-prediction of future land use conditions, lower-than-predicted
41 time savings, added competition (e.g., improvements to competing roads or the addition of new
42 roads), lower than anticipated truck usage, and high variability in traffic volumes (by time-of-day
43 or day of the year). Bain and Plantagie (2003) added several other top drivers: complexity of
44 the tolling regime, underestimation of the duration and severity of the ramp-up period, and
45 reliance on a single VOTT (as opposed to segmenting user groups). However, it did not offer
46 any information regarding the magnitude of added uncertainty for each of these features.
47 Another rating agency, Fitch Ratings (George et al. 2003), also suggested several of these same
48 drivers, but added that the use of a regional travel demand model developed for other planning
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3 purposes also can cause great error in traffic forecasts. (Such was the case for the San Joaquin
4 toll road forecast in Orange County, California. [George et al. 2003]) This suggests, to some
5 extent, that a comprehensive, regional model may not perform as well as simpler estimation
6 techniques (e.g., OD pair trend analysis), if the regional model lacks appropriate specification for
7 the project scenario. Clearly, there is a great deal of uncertainty in traffic and revenue forecasts
8 of tolled roads stemming from various sources. The next section discusses methods that can be
9 used to measure and evaluate this uncertainty in forecasting models.
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11 **METHODS OF ACCOMMODATING RISK IN TDM AND REVENUE ESTIMATION** 12 **ANALYSES** 13

14 Accommodating risk and uncertainty in demand and revenue forecasts is an important component
15 of any toll road study. While a single “best” statistical forecast is useful, it lacks the information
16 needed for making long-term financial decisions. With the great number of assumptions, inputs,
17 and estimated parameters entering travel demand models, model outputs can be highly uncertain
18 and inaccurate. Neglecting this uncertainty (or equivalently, assuming determinism) can invite
19 scrutiny from stakeholders, since not all will agree with assumed inputs and parameter values
20 (Duthie 2008). As noted in the previous sections, the magnitude of error in demand forecasts
21 (and, thus, revenue forecasts) can be substantial, and tends to be biased in
22 favor of toll road projects. Even with advances in model designs over the past couple decades,
23 Flyvbjerg’s review of the data suggests that forecast accuracy has not improved and may have
24 worsened (Flyvbjerg et al., 2006). Most analysts, policy-makers, and investors agree that it is
25 imperative that modelers quantify forecasting risk in a meaningful way (Rodier 2007), and while
26 the financial community has understood the need to address risk in toll road studies, Kriger et al.
27 (2006) believe that very few practitioners conduct any sort of risk assessment. Some simply
28 verify results by use of “reality checks” (e.g., comparing to older forecasts and using simple
29 intuition to verify whether results seem reasonable) while others use no verification methods at
30 all.
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32 One key component of risk assessment in model outputs lies in explicitly stating all modeling
33 assumptions (Kriger et al., 2006), making the model specification as transparent as possible. If
34 modelers and users understand the implications of alternative assumptions, the uncertainty in the
35 forecasting process will be better understood. Of course, other options for understanding and
36 communicating forecast uncertainty also exist, as discussed here now.
37

38 A relatively common and reasonably effective method for accommodating risk in demand and
39 revenue forecasts is the use of sensitivity analyses or “stress tests” (Kriger et al., 2006). Most
40 sensitivity analyses rely on the exploration of a very limited set of different values for key
41 variables, such as a region’s or neighborhood’s population growth rate, values of travel time, and
42 planned tolls (Kriger et al., 2006). Though such analyses can provide key insights, many
43 practitioners and financial analysts feel that they inadequately reveal the range of possible
44 outcomes (see, e.g., HLB Decision Economics 2003 and Kriger et al. 2006). As their name
45 implies, stress tests seek to understand the outcomes of relatively extreme conditions – generally
46 to anticipate worst- (and best-) case investment scenarios. In this way they help analysts
47 anticipate lower (and upper) bounds on project outcomes, but certainly not a distribution of
48 outcomes, or probability of financial loss.
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4 Model validation studies offer another method for quantifying uncertainty, by examining how
5 well model forecasts match observed data not used in model calibration (Rodier 2007). Such
6 studies measure forecast uncertainty directly from observed data, and thus require data from two
7 points in time: the older data set is used for model estimation and calibration while the newer one
8 is used for validation. It can be impossible to conduct such tests of models developed from
9 recent data, but at least one obtains a sense of the magnitudes of errors that can emerge from
10 transferring behavioral parameters calibrated on old data to current-year contexts. Such
11 validation tests are a valuable complement to sensitivity tests. And such results assist analysts in
12 communicating of the size and relevance of uncertainty to decision makers and the public
13 (Rodier 2007).
14

15 Of course, sensitivity testing and model validation studies have their limitations. For example,
16 sensitivity tests are quite constrained, to typically three or four scenarios. In contrast, Monte
17 Carlo simulation techniques more fully explore the range of possible outcomes, by defining and
18 drawing from probability distributions for key inputs. Moreover, such techniques are not new:
19 Ashley (1980) and Lowe et al. (1982) investigated the sensitivity of forecast traffic volumes to
20 model inputs and parameters using Monte Carlo methods; and, more recently, Lam and Tam
21 (1998), Boyce and Bright (2003), Zhou and Kockelman (2002), Beser Hugosson (2005), and de
22 Jong et al. (2007) performed similar analyses. Of course, such techniques also exhibit
23 limitations: They require assumptions of input distributions (and their covariances), when these
24 are often unknown, and generally more sophisticated programming techniques (to ensure rapid
25 run times for testing a high number of scenarios). And as model complexity increases, model
26 run times invariably grow. Under fixed time constraints, an increase in model complexity
27 generally implies fewer Monte Carlo simulations. Nonetheless, these simulation methods can be
28 invaluable for a proper understanding of uncertainty in traffic and revenue forecasts.
29

30 Monte Carlo techniques are at the heart of the four-step risk analysis process (RAP) used by
31 HLB Decision Economics (2003). In step 1, HLB defines a “structure and logic” model, in order
32 to forecast traffic and revenue on the basis of an array of inputs and parameters. In step 2,
33 central estimates and probability ranges are assigned to each relevant input and parameter. In
34 step 3, expert opinions regarding the results of step 2 are obtained, and probability ranges and
35 central estimates are revised. In the final step, Monte Carlo simulation techniques are employed,
36 drawing inputs and parameters from their respective probability distributions, and traffic and
37 revenue probability ranges are derived based on the simulation outcomes. (HLB Decision
38 Economics 2003) This approach allows firms like HLB to determine the likelihood that revenue
39 cannot cover the debt service, an important criteria for issuance of debt.
40

41 As discussed earlier, Zhao and Kockelman (2002) performed a similar analysis (for a non-tolled
42 case), using a four-step travel demand model for a sub-network of the extensive Dallas-Fort
43 Worth region with 118 variable input and parameter values. Due to typical time constraints on
44 their research, only 100 runs were undertaken (using TransCAD software). Using more
45 streamlined networks or hands-on programming would have allowed for more runs, which can
46 be critical in cases of many uncertain inputs (assuming there is a potential for highly nonlinear
47 model behaviors, for example), since the parameter space grows exponentially with added
48 inputs. In practice, most toll road studies use highly streamlined networks and simplified model
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3 specifications (see e.g., Lam and Tam 1998, HLB Decision Economics 2003), to facilitate
4 computation while recognizing that the majority of a region's network is largely irrelevant when
5 evaluating a relatively short new, tolled corridor. Nonetheless, Zhao and Kockelman's analysis
6 provides useful insights into the degree of uncertainty in link- and region-level traffic forecasts.
7 They assigned density functions to the 18 random model parameters (13 in trip generation, 1 in
8 trip distribution, 2 in mode choice, and 2 in assignment) and four major model inputs for each of
9 25 zones (household counts along with basic, retail, and service job counts). Each of the
10 uncertain parameters and inputs were assumed to follow log-normal distributions with
11 coefficients of variation⁵ (CoVs) of 0.3, 0.1, and 0.5. After performing 100 simulation runs (for
12 each of the 3 CoVs), two network links were examined in detail for the case of CoVs equal to
13 0.3. On both links, flows ranged from around 400 vehicles per hour to over 2000, with CoVs of
14 0.31 and 0.32. Zhao and Kockelman (2002) also performed a regression analysis of standardized
15 input and parameter values on system-level VMT results. This analysis indicated that inputs and
16 trip generation parameter values were the most important factors in forecasts of total VMT. It
17 seems evident that traffic forecasts can exhibit a great deal of variation and depend greatly on
18 parameter and input assumptions used in model calibration and application. When tolls are
19 present, results could exhibit even greater variation. However, Zhao and Kockelman (2002)
20 observed similar uncertainty levels in model inputs and outputs suggesting that opportunities for
21 errors in one part of the model to offset errors in another can have a dampening effect on overall
22 uncertainty. Thus, adding more uncertain inputs and/or parameters may not amplify forecast
23 uncertainty.
24

25 Lam and Tam (1998) also performed a study of uncertainty using Monte Carlo draws in traffic
26 and revenue forecasts for a toll road project connecting Hong Kong to an adjacent region
27 separated by a body of water. No actual travel demand model was used, however, since only one
28 other reasonable route existed between the two regions and a detailed travel study was deemed
29 unnecessary. Instead, trip generation and routing shares were assigned distributions, and allowed
30 to vary across simulation runs in order quantify forecast uncertainty. A total of 10,000
31 simulations were performed, and overall revenues were found to hit or exceed the base forecast
32 approximately 52% of the time. This is not so surprising, since the base forecast represents a
33 simulation based on the mean values for all 12 unknowns. They also estimated that the standard
34 deviation of forecast revenues rose from just 17% of the mean in the first forecast year to 28% of
35 the mean after 20 years (Lam and Tam, 1998). It is useful to note the smaller coefficients of
36 variation found here, in comparison to Zhao and Kockelman's (2002) study. For instance, the
37 total population and trip generation rates were both assumed to have CoVs of 0.05. Lam and
38 Tam investigated a particular scenario with arguably much less risk. Since their bridge facility
39 enjoyed a clear advantage over competing routes, there was a specific traveler group being
40 serviced, and a single origin-destination pair making up the majority of travel.
41

42 As noted earlier, land use is an important determinant of long-run traffic levels, particularly
43 when new highways are provided in largely undeveloped locations. Land use change can be
44 more difficult to predict and more variable in the long run than traffic volumes, and new work is
45 emerging in this area. For example, Sevcikova et al. (2007) recently compared Bayesian
46 Melding techniques and standard sampling approaches to analyze uncertainty in projections of
47 household counts using UrbanSim. And Kockelman et al. (2008) used an antithetic sampling
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49 ⁵ The coefficient of variation is defined as the ratio of the standard deviation to the mean.
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3 technique to analyze uncertainty in an integrated land use-transportation setting. Methods like
4 these, for sampling thoughtfully and performing estimation rapidly, could potentially aid in
5 obtaining output distributions from complex models relatively quickly.
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8 Consistent with such analyses, the National Federation of Municipal Analysts (NFMA 2005)
9 formally recommends that a range of possible road project and policy outcomes should be
10 explored based on different scenarios (or assumptions), and that varying variables or parameters
11 one at a time is insufficient. By assigning realistic probability distributions to parameter values
12 and inputs, the probability of a given scenario can be understood. The NFMA's (2005)
13 guidelines for traffic and revenue studies include several highlights: a no-build traffic forecast
14 should be produced, a baseline traffic and revenue forecast should be produced, sensitivity
15 analyses should be performed on inputs (including population, employment, and income growth,
16 toll elasticity by consumers, and acceleration of the planned transportation network), and debt
17 service analysis should be performed.

18
19 Of course, just as neglecting uncertainty is equivalent to assuming determinism, neglecting
20 covariance in inputs is equivalent to presuming their independence. Thus, it is important to
21 recognize the co-dependence of input distributions due to correlated response under various
22 conditions and as introduced in parameter distributions via the estimation process. For example,
23 economic boom/bust cycles can affect land development and thus population and job growth
24 across zones similarly, along with trip generation rates, vehicle ownership, and income levels.
25 This can result in wider uncertainty bounds than univariate input and parameter distributions
26 would indicate. For example, Zhao and Kockelman (2002) used multivariate distributions for
27 their population and employment input values with +0.30 correlations, but relied on independent
28 distributions for all model parameters.

29
30 Another approach is "reference class forecasting," as described by Flyvbjerg et al. (2005). This
31 method essentially relies on past experiences with a sample of similar projects in order to
32 estimate outcome distributions and thus the probability of various events occurring. By
33 comparing the forecasts with past experience, judgments can be made regarding the validity of
34 results. Of course, this is difficult to do without good data on a variety of reasonably comparable
35 projects. But it is a useful strategy when such data exist.

36
37 To determine an investment's credit rating, credit agencies and financial analysts use varied
38 approaches to account for revenue forecast risk. For example, Fitch Ratings (George et al. 2003,
39 George et al. 2007) claims to study the key assumptions and inputs of the travel demand model
40 used in creating future forecasts, and then considers a range of possible outcomes associated with
41 each factor in order to develop a "stress" scenario alongside a base scenario (essentially
42 sensitivity testing, but with relatively extreme scenarios). The base case is generally more
43 conservative than the base case developed by the project sponsor, eliminating any evident
44 forecast optimism. The stress case is developed to determine the project's ability to withstand
45 rather severe (but not unreasonable) circumstances in which the ability to pay debt service is
46 stressed. Based on the results of the stress scenario, an investment rating is assigned to the
47 project. For credit analysis of longer-term traffic forecasts, Bain et al. (2006) suggest taking a
48 conservative approach, reducing growth rate expectations and carefully examining future toll
49 schedule increases. They also suggest that long-term growth rates exceeding 1% and toll
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3 increases beyond those suggested by reasonable correction for inflation should be viewed with
4 caution. While these techniques simplify uncertainty testing dramatically and help investors
5 understand the real possibility of loss, they do not illuminate the variety (and likelihood) of
6 futures that truly exist, and associated investment risk cannot be fully understood using such
7 methods.
8

9 **SUMMARY AND RECOMMENDATIONS**

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11 As discussed in this paper, a great deal of uncertainty exists in traffic forecasts. Flyvbjerg's
12 analyses (2005 and 2006) suggest that traffic forecast errors exceed 20% roughly half the time
13 across all roadway projects and more than 40% of the time for a quarter of projects. This
14 situation is compounded when traffic forecasts of *tolled* projects are considered, since more
15 unknowns exist. S&P's analysts (Bain and Wilkins 2002, Bain and Plantagie 2003 and 2004)
16 found that, on average, tolled traffic volumes are well below forecasts (on the order of 25% or
17 more) in their first year of operation, suggesting considerable optimism bias, and that this bias
18 does not fade over time. As transportation agencies look more closely at tolling options as a way
19 to fund highway capacity expansion and manage demand, it becomes even more important that
20 models provide reliable traffic forecasts.
21

22 Traditionally, travel demand models have been used to provide a single projection of future
23 conditions. Though the models become more sophisticated, the future remains unknown, and
24 model forecasts should be presented as such. It is critical that the uncertainty implicit in travel
25 demand models be communicated to planners and policy makers. Of course, quantifying such
26 uncertainty is not a trivial task. While the sources of misprediction vary, designers and
27 transportation planners have found a number of methods to accommodate forecast uncertainty
28 (or at least quantify it).
29

30 Sensitivity testing allows for greater understanding of the magnitudes of uncertainty in the
31 model. By allowing key model inputs and parameters to vary simultaneously, creating multiple
32 possible scenarios, uncertainty in traffic and revenue forecasts can be better bounded. Indeed,
33 this appears to be the most common method for dealing with uncertainty by credit agencies.
34 However, sensitivity testing generally does not provide a probability of particular outcomes
35 occurring. Therefore, it can be difficult for policy makers to truly understand inherent risks.
36 When feasible, comparisons with similar, past projects is a meaningful tool for anticipating
37 potential outcomes.
38

39 Monte Carlo simulation may be most appropriate to identify a more comprehensive set of
40 possible futures. By drawing parameters and inputs from reasonable sets of distributions, the
41 probability of particular outcomes can be understood. Of particular importance for projects
42 where financial backing is dependent on toll revenues is the probability that toll revenues will
43 cover debt service, and whether additional revenues will remain (over and above debt service).
44 Moreover, since most toll road studies use rather streamlined model systems, computing time is
45 typically not an issue. Thus, the recommended best practice for dealing with uncertainty in toll
46 road projects is the use of Monte Carlo simulation. Sensitivity testing is valuable in some cases
47 where simulation may be too computationally expensive, though more thoughtful sampling
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3 methods, such as Bayesian melding and antithetic sampling, can reduce such computational
4 burden in many cases.
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7 **ACKNOWLEDGEMENTS**

8
9 The authors thank several anonymous reviewers, Mr. Peter Vovsha of Parsons Brinckerhoff, Inc.
10 (PB), Robert Bain at the University of Leeds, and Jennifer Duthie for their useful suggestions
11 and Ms. Annette Perrone for editorial assistance. We also want to thank the National
12 Cooperative Highway Research Program (NCHRP) for financially supporting this study under
13 Project HR 08-57, titled “Improved Framework and Tools for Highway Pricing Decisions.”
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