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The Impact of Road Toll Removal on Light and Heavy Truck Demand: Evidence from Multi-Project Time-Series Analysis

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Abstract

Most empirical evidence on road toll elasticities is derived from studies of toll implementation or toll increases and typically relies on aggregate traffic or aggregated truck flows. Consequently, relatively little is known about how truck demand responds when tolls are removed, even though toll removal represents a clean pricing experiment that avoids the confounding effects often associated with new toll facilities or infrastructure upgrades. Moreover, existing studies rarely distinguish between different segments of truck traffic, despite the critical role heavy vehicles play in toll financing by contributing a disproportionately large share of toll revenues. This study addresses these gaps by examining how light and heavy trucks respond to road toll removal using revealed-preference data. The analysis draws on traffic observations from 14 toll road projects in Norway and focuses exclusively on road segments where tolls were removed without any accompanying changes in infrastructure. This multi-project time-series setting allows demand responses to be identified both over time and across projects. An autoregressive distributed lag (ARDL) model combined with an unrestricted error correction model (UECM) is employed to capture short-run dynamics and long-run equilibrium effects. The results reveal clear and systematic differences between light and heavy trucks. Short-run elasticities for light trucks typically range between − 0.2 and − 0.8 and are statistically significant in several cases, indicating an immediate response to toll removal. Long-run elasticities for light trucks are significant in fewer projects and typically lie between − 0.3 and − 1.0, suggesting that persistent demand adjustments occur only in a subset of cases. In contrast, heavy truck elasticities are substantially smaller, averaging around − 0.1 and frequently statistically insignificant in both the short run and the long run, indicating limited responsiveness to toll removal. Overall, the findings suggest that traffic responses to toll removal are primarily short-lived and concentrated among light trucks, while heavy truck demand remains largely insensitive to pricing changes. These results highlight the importance of distinguishing between truck categories in toll appraisal, revenue forecasting, and transport modeling, and suggest that toll revenues derived from heavy vehicles may be more stable over time than commonly assumed.

1 Introduction

In many countries, road tolls are a central instrument for financing road transport infrastructure. They are widely regarded as an effective means of generating revenue to supplement constrained public budgets and to support investment in road networks (Queiroz et al., 2016; Odeck, 2017; Welde et al., 2020). Evidence from Norway and elsewhere further highlights the importance of realistic demand assumptions in toll-financed projects, as inaccuracies in traffic forecasts and demand responses may result in revenue shortfalls and financial risk (Odeck, 2014; Odeck and Welde, 2017; Bain, 2009, 2011, 2024, 2025). Recent ex-post evidence further shows that tolling schemes are generally terminated on time or earlier than planned, largely because traffic volumes and revenues are sufficient to meet financing obligations within the postulated period (Odeck, 2026). Despite this extensive experience with toll-financed projects, empirical evidence on how traffic demand responds to toll changes remains uneven across policy contexts and vehicle types (Wardman, 2022).

Essential to the effective design of such financing schemes is an understanding of the relationship between tolls and transport demand, commonly expressed as the elasticity of transport demand with respect to road tolls. This elasticity measures the percentage change in transport demand resulting from a one-percent change in toll rates. Knowledge of these elasticities is important because it informs how toll levels influence road

usage, revenue, and associated externalities. However, much of the existing evidence is derived from studies of toll introduction or toll increases and typically relies on aggregate traffic measures, with limited attention paid to toll removal and to potential differences in responsiveness between light and heavy trucks. Among these effects, the revenue impact is often of primary concern to policymakers in contexts where tolls are implemented mainly to finance transport infrastructure.

While several studies have examined the elasticity of road transport demand with respect to tolls in general and over time (Odeck and Bråthen, 2008; Tsukada and Fukuda, 2013; Kweun, 2017; Bain, 2009, 2011, 2024, 2025; Wardman, 2012 and 2022; Wardman et al., 2018), relatively few contributions have focused specifically on elasticity estimates for heavy vehicles. This gap in the literature is noteworthy, as understanding the toll elasticity of heavy vehicles is essential for assessing how toll policies influence freight transport behavior. In this study, truck traffic is used as a proxy for road freight transport, consistent with common practice in the toll elasticity literature, given that the vast majority of road freight is carried by trucks. Heavy vehicles typically account for a relatively small share of total traffic, often around 10–20 percent, yet they face higher toll rates and contribute a substantial share of total toll revenues. Biased estimates of the relationship between heavy vehicle transport demand and toll rates may therefore lead to significant revenue losses and financial challenges for toll operators. A clear understanding of how heavy vehicles respond to changes in toll levels is thus crucial for policymakers, planners, and operators.

Despite its importance, empirical evidence on how tolls affect heavy vehicle transport demand remains limited (Ozbay et al., 2006; Bari et al., 2015). This limitation is particularly evident with respect to distinguishing between light trucks (7.6–16 m) and heavy trucks (greater than 16 m), two categories of freight vehicles that are likely to exhibit different price elasticities with respect to tolls (Ozbay et al., 2006; Wang and Zhang, 2017). Understanding how these vehicle types respond to toll levels is especially important given that they are often subject to the same toll rates. Variations in the composition of light and heavy trucks across toll facilities may therefore have important implications for aggregate toll revenues.

Elasticities of heavy vehicle transport demand are also key inputs in traffic forecasting and transport modeling. Although light and heavy trucks may respond differently to tolls, they are often treated as a homogeneous category in models used for traffic forecasting. Improving the understanding of behavioral differences between these vehicle types would support a more refined representation of freight traffic in future modeling efforts. This is particularly relevant in the route assignment stage, where toll costs tend to exert a strong influence on route choice. Similar considerations apply in cost–benefit analysis, where user benefit estimates derived from transport models play a central role. This focus on toll removal allows an assessment of whether pricing changes lead to persistent adjustments in truck traffic demand or primarily short-term responses.

This paper contributes to the limited empirical literature on how light and heavy trucks respond to road toll removals. Using observed traffic data from 14 toll stations in Norway, the study analyzes changes in traffic volumes for light and heavy trucks following toll removal. A key feature of the analysis is its exclusive focus on road segments where tolls were removed without any accompanying changes in infrastructure during the period the tolls were in place. This research design allows the effects of toll removal to be identified separately from confounding factors such as improvements in road quality or reductions in travel time, which frequently accompany the introduction of new toll roads (Matas and Raymond, 2003; Odeck and Bråthen, 2008). By

avoiding these sources of bias, the study provides cleaner estimates of toll elasticities associated with toll removal for light and heavy trucks.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and situates the contribution of the study. Section 3 describes the data, Section 4 outlines the empirical framework, and Section 5 presents the empirical results. Section 6 discusses the findings and their implications, while Section 7 provides concluding remarks.

2 Literature review

Road transport demand responds to changes in travel costs, including both monetary and non-monetary components (Ortúzar and Willumsen, 2011). In the context of road-based freight transport, these costs typically include fuel and vehicle operating costs, tolls, travel time, and the value of the goods being transported. Since the vast majority of inland freight transport on roads is carried by trucks, empirical analyses of road freight demand commonly rely on observed heavy vehicle traffic volumes as a proxy for freight transport demand.

Changes in tolls affect road freight demand primarily through adjustments in heavy vehicle travel, most notably route choice, as operators seek to minimize generalized travel costs. Tolls may also induce broader behavioral responses, including changes in departure time, delivery frequency, logistics organization, or modal choice. The ability of freight operators to adjust to toll changes depends on vehicle characteristics, shipment value, and contractual arrangements within the transport chain. While some carriers are able to pass toll costs on to shippers or receivers, others absorb these costs themselves, particularly smaller operators with limited bargaining power (Wang et al et al., 2023; Gómez and Vassallo, 2015). As a result, behavioral responses in road freight transport may differ from those observed for passenger travel.

A substantial literature has examined road pricing and toll elasticities in general. Reviews by Goodwin et al. (2004), Litman (2017), Wardman (2012, 2022), and Wardman et al. (2018) show that road traffic demand typically exhibits inelastic responses to price changes, although elasticity estimates vary across contexts, time horizons, and methodological approaches. Empirical studies using toll road data broadly confirm this pattern. Matas and Raymond (2003) estimate demand elasticities for Spanish tolled motorways, while Odeck and Bråthen (2008) analyze multiple Norwegian toll projects using before-and-after data. Evidence from Japan (Tsukada and Fukuda, 2013) and the United States (Burris, 2003; Kweun, 2017) similarly points to generally inelastic demand responses to tolls.

Several studies emphasize the importance of accurate elasticity assumptions for toll road appraisal and revenue forecasting. Bain (2009) documents systematic optimism bias in toll road traffic forecasts across a large international sample, showing that demand and revenue are frequently overestimated when user responses to tolls are insufficiently accounted for. Subsequent work confirms that such forecast errors persist over time and are closely linked to unrealistic assumptions about demand elasticities (Bain and Polak, 2010; Bain, 2011). Empirical evidence from toll road evaluations further highlights the sensitivity of revenues to traffic responses. Odeck and Welde (2017) show that deviations between forecast and realized traffic volumes in Norwegian toll projects have substantial implications for financial performance, while Vassallo (2006) demonstrate that demand risk, including uncertainty about traffic responsiveness to tolls, is a key determinant

of revenue outcomes in toll road concessions. These findings are particularly relevant in toll-financed systems where heavy vehicles, and thus road freight transport, account for a relatively small share of traffic volumes but a disproportionately large share of toll revenues.

Despite the extensive literature on toll elasticities, relatively few studies focus explicitly on road freight transport as distinct from passenger traffic. Where freight transport is considered, it is most often represented by aggregate heavy vehicle traffic, without differentiation between truck types. Ozbay et al. (2006) show that heavy vehicle demand tends to be less price-sensitive than passenger car demand on tolled facilities. Gómez and Vassallo (2015) estimate toll elasticities for heavy vehicles on Spanish toll roads, using truck volumes as a proxy for freight transport demand, but treat trucks as a single aggregated category. System-level analyses of heavy vehicle tolling in Europe also find measurable effects on freight traffic patterns, although responses vary across countries and network characteristics (Gómez and Vassallo, 2020).

Recent contributions by Bain and Sullivan (2024) and Bain and Cimon (2025) further emphasize the importance of demand elasticity assumptions for toll road appraisal and revenue forecasting, drawing on large international datasets of toll projects. While these reports provide valuable evidence and practitioner insights, they rely primarily on aggregate traffic measures and do not distinguish between different segments of freight traffic.

Only a very limited number of studies explicitly distinguish between different categories of heavy vehicles when estimating toll elasticities. Hirschman et al. (1992) is a notable exception, estimating separate toll elasticities for light, medium, and heavy trucks at major crossings in New York City and finding substantial differences across vehicle classes. Most subsequent studies aggregate all trucks into a single heavy vehicle category. The bulk of the empirical evidence on road freight demand responses to tolls is therefore based on aggregated heavy vehicle traffic, rather than disaggregated truck classes. Table 1 summarizes empirical studies that have estimated toll elasticities for road freight transport, highlighting the predominance of analyses based on aggregated heavy vehicle traffic and the scarcity of studies that distinguish between different truck sizes.

Table 1
Elasticities of road freight (heavy vehicle) traffic with respect to tolls reported in previous studies

Location / Facility	Heavy vehicle category (proxy for freight)	Elasticity	Scope of elasticity	Method / Data source	Reference
TBTA crossings, New York City:	- Light trucks	−0.54 to − 0.07	Freight (disaggregated)	Revealed preference, time series	Hirschman et al. (1992)
	- Medium trucks	−0.61 to − 0.29	Freight (disaggregated)	Revealed preference, time series	Hirschman et al. (1992)
	- Heavy trucks	−0.93 to -0.20	Freight (disaggregated)	Revealed preference, time series	Hirschman et al. (1992)
Brisbane	Trucks (all sizes)	−0.30 to − 0.20	Freight (aggregated)	Transport model estimates	Lake and Ferreira (2002)
Ohio Turnpike	Trucks (all sizes)	−0.15	Freight (aggregated)	Revealed preference, time series	Zhou et al. (2009)
Florida Turnpike	Trucks (all sizes)	0.00	Freight (aggregated)	Revealed preference, time series	Huang and Burris (2013)
Dallas North Tollway	Trucks (all sizes)	−0.60	Freight (aggregated)	Stated preference	Huang and Burris (2013)
12 U.S. toll facilities	Trucks (all sizes)	−0.35	Freight (aggregated)	Time series (ARDL)	Huang and Burris (2013)
SH 130, Austin	Trucks (all sizes)	−0.43	Freight (aggregated)	Revealed preference	Bari et al. (2015)
New York	Trucks (all sizes)	−0.37	Freight (aggregated)	Stated preference	Wang and Zhang (2017)
Spain	Trucks (all sizes)	−0.43 to − 0.19	Freight (aggregated)	Panel data	Gómez and Vassallo (2015)

Taken together, the studies summarized in Table 1 indicate that freight transport demand is generally inelastic with respect to road tolls, but that estimated elasticities vary substantially across contexts and methodologies. Most studies report negative elasticities, typically ranging from around − 0.1 to − 0.4 when freight or truck traffic is analyzed in aggregate, suggesting that higher tolls tend to reduce freight traffic but that the magnitude of the response is modest. Larger elasticities are often associated with urban corridors, shorter-distance trips, or stated preference approaches, while lower elasticities are commonly found in interurban settings or when revealed preference data are used. The wide dispersion of estimates also reflects differences in study design, including whether toll changes are analyzed in isolation or alongside infrastructure improvements, and whether short-run or long-run responses are captured. Importantly, the majority of existing studies treat freight traffic as a single homogeneous category, which may obscure heterogeneity across vehicle types. As a result, relatively

little is known about how different segments of freight traffic, particularly heavy trucks, respond to toll changes. This limitation motivates the disaggregated analysis undertaken in the present study.

Another important limitation concerns identification. Many studies examine toll introductions or toll level changes that coincide with infrastructure upgrades, capacity expansions, or reductions in travel time, making it difficult to isolate the causal effect of tolls on heavy vehicle and freight demand (Matas and Raymond, 2003; Odeck and Bråthen, 2008). Empirical evidence based on toll removals, particularly in settings without concurrent infrastructure changes, remains scarce.

Against this background, the present study contributes to the literature by providing new empirical evidence on how road freight transport, as proxied by heavy vehicle traffic, responds to toll removals. By exploiting toll removals on road segments without simultaneous infrastructure changes, the study offers cleaner identification of toll elasticities. Furthermore, by distinguishing explicitly between light and heavy trucks, it provides disaggregated elasticity estimates that improve the empirical basis for traffic forecasting, toll revenue assessment, and transport appraisal.

3 Data

This study uses traffic count data from the Norwegian national traffic count database, operated by the Norwegian Public Roads Administration (Statens vegvesen, 2024). The data consist of annual average daily traffic (AADT) observations and cover up to twelve years before toll removal and up to five years after toll removal, depending on the availability of data for each site.

Traffic volumes are disaggregated by vehicle length into two categories that serve as proxies for road freight transport: light trucks (7.6–16 m) and heavy trucks (greater than 16 m). These classifications are consistent with Norwegian traffic counting practice and allow the analysis to distinguish between different segments of heavy vehicle traffic.

The following subsections describe (I) the case selection, (II) key characteristics of toll removal, and (III) the explanatory variables used in the subsequent analysis.

(I) Case selection and study sample

The empirical analysis focuses on toll road projects in Norway where tolls were removed during the past ten years. An initial screening identified fourteen candidate cases. For each case, information was collected on toll rates prior to removal and traffic volumes for light and heavy trucks in the year immediately before and after toll removal. Table 2 summarizes the toll rates and traffic volumes for light and heavy trucks in the year immediately before and after toll removal for all identified cases.

Table 2 summarizes toll rates and truck traffic volumes for the identified toll road projects, together with descriptive statistics illustrating average levels and dispersion across cases. Toll rates prior to removal vary substantially, ranging from 20 to 475 NOK in nominal terms, reflecting differences in project characteristics and financing arrangements. Traffic volumes also differ markedly across sites, particularly for light trucks, indicating considerable heterogeneity in freight activity across the study corridors. This variation provides a

useful basis for the econometric analysis, as it allows the responsiveness of truck traffic to toll removal to be examined across a wide range of traffic and toll conditions.

Three cases were subsequently excluded from the analysis due to confounding factors unrelated to toll removal. Traffic volumes on FV303 Tønsberg were strongly affected by the closure of a nearby oil refinery, while traffic on the E39 Teisdalstunnelen and E39 Vatland sections was influenced by major infrastructure upgrades located outside but close to the study corridors. Excluding these cases helps ensure that observed traffic changes can be more confidently attributed to toll removal rather than to unrelated structural changes in demand or network conditions.

After these exclusions, the final dataset consists of eleven toll road projects. For all remaining cases, traffic data are available for several years before and after toll removal, allowing the estimation of short-run and long-run demand responses.

Table 2
Toll rates and truck traffic volumes before and after toll removal

Case no.	Road section	Toll rate (NOK)	AADT before (7.6–16 m)	AADT after (7.6–16 m)	AADT before (> 16 m)	AADT after (> 16 m)
1	FV 255	32	248	294	97	111
2	E18 Østfold / Smaalenene	20	1,161	1,194	728	716
3	FV 303 Tønsberg	38	866	910	103	79
4	RV 19 Horten	66	577	685	465	517
5	E6 Østfold (Melleby)	20	1,124	1,194	744	716
6	FV 64 Atlanterhavsveien	475	151	315	11	19
7	E136 Tresfjordbrua	270	266	349	212	234
8	E18 Kristiansand–Lillesand	50	1,385	1,449	702	734
9	FV 107 Folgefonntunnelen	51	118	126	31	31
10	RV 13 Svelgen (Vossapakka)	99	227	460	96	109
11	E16 Dalseide aust (Vossapakka)	99	503	533	306	290
12	FV 17 Tverland–Godøy	36	188	231	24	31
13	E39 Teisdalstunnelen	40	452	487	505	562
14	E39 Vatland	40	588	681	485	514
	Mean	90.4	520	601	322	347
	Std. dev.	132.7	417	438	273	284
	Minimum	20	118	126	11	19
	Maximum	475	1,385	1,449	744	734
	No. of cases	14	14	14	14	14

Notes:

AADT denotes annual average daily traffic. Traffic volumes are reported separately for light trucks (7.6–16 m) and heavy trucks (> 16 m). Summary statistics are calculated across all identified cases prior to exclusion of projects affected by confounding factors.

Toll rates are reported in nominal Norwegian kroner (NOK). For reference, 1 NOK ≈ 0.084 EUR and ≈ 0.10 USD as of December 2025.

(II) Characteristics of toll removal

A common feature of the selected projects is that toll removal applied simultaneously to the main route and to the most attractive alternative routes. This reflects a typical characteristic of Norwegian toll systems, where tolls are levied on both primary corridors and parallel routes to prevent traffic diversion and ensure revenue generation during the tolling period. Consequently, the observed changes in traffic following toll removal are unlikely to be driven primarily by route switching between tolled and non-tolled alternatives, strengthening the interpretation of the results as reflecting changes in overall heavy vehicle demand rather than redistribution of traffic within the network.

(III) Explanatory variables

Several factors may influence heavy vehicle traffic volumes on tolled road segments. In addition to toll charges, changes in truck traffic may reflect broader economic conditions, fuel costs, and developments in freight activity at the regional and national levels (Gómez and Vassallo, 2015; Bari et al., 2015). The model framework therefore considers a set of explanatory variables intended to capture changes in generalized travel costs and broader demand conditions for road freight transport.

In this study, changes in generalized travel cost are driven exclusively by the removal of toll charges. All road segments included in the analysis experienced toll removal without any accompanying changes in infrastructure, road standard, or traffic management. Travel distance and travel time therefore remained constant over the observation period. As a result, the change in generalized travel cost faced by truck drivers corresponds directly to the eliminated toll payment. This allows the estimated demand responses to be interpreted as reflecting a pure price effect of toll removal, without confounding influences from simultaneous changes in travel conditions.

To contextualize the magnitude of the toll removal relative to typical truck movements on each corridor, assumptions were made regarding representative trip lengths for light and heavy trucks. These assumptions were based on information from Statistics Norway and national travel time and distance studies (TØI, 2019). Projects located in or near major urban areas were assumed to involve shorter average trip lengths, while projects in more peripheral regions were assigned longer distances. Importantly, these assumptions are used to characterize typical travel conditions and to scale the toll component relative to overall travel costs; they do not imply that travel time or distance varied during the study period, nor that generalized travel cost was recalculated using multiple cost components in the empirical models.

Several variables were initially considered as proxies for regional economic activity, including population density, employment density, and county-level growth in heavy vehicle traffic. While this approach is consistent with earlier studies (Bari et al., 2015), population and employment variables were ultimately excluded due to inconsistencies arising from administrative boundary changes across counties during the study period. These changes made it difficult to construct reliable and comparable time series for demographic and employment indicators.

Average fuel costs and regional import and export volumes were also examined as potential explanatory variables. However, these variables were not statistically significant in any of the estimated model specifications and were therefore excluded from the final models. The final set of variables retained for

estimation is summarized in Table 3. All variables are measured on an annual basis. Observations for the years most affected by the COVID-19 pandemic (2020 and 2021) were excluded from the analysis to avoid distortions related to exceptional traffic conditions.

Table 3 provides an overview of the explanatory variables considered in the analysis, together with their definitions and time coverage.The table highlights the range of cost-related and demand-side factors examined, while also indicating which variables were ultimately excluded from the final model specifications.

Table 3
Explanatory variables considered in the analysis

Variable	Description	Time period
AADT	Annual average daily traffic of light trucks (7.6–16 m) or heavy trucks (> 16 m)	2008–2024
Generalized travel cost	Composite measure including toll charges, travel distance, and travel time	Varies by project
County truck traffic growth	Annual growth rate of trucks longer than 7.6 m at county level	2008–2024
Population density	Population per square kilometer at county level	2008–2024
Employment density	Number of workplaces per square kilometer at county level	2008–2024
Fuel costs	Annual average county-level fuel cost (Statistics Norway)	2008–2024
Import/export volumes	Annual road-based import/export volume ratio (Statistics Norway)	2000–2024
Household income	Average income per household at municipality level	2005–2024

Notes: Not all variables listed were retained in the final model specifications. Population density, employment density, fuel costs, import/export volumes, and household income were excluded from the final models due to data limitations or lack of statistical significance. All variables are measured on an annual basis. Observations for 2020 and 2021 were excluded due to abnormal traffic patterns during the COVID-19 pandemic.

4 Econometric framework

This study employs an autoregressive distributed lag (ARDL) time series framework to estimate the responsiveness of heavy vehicle traffic to toll removals. The ARDL approach is well suited for transport demand analysis because it allows short-run and long-run effects of explanatory variables to be estimated within a single specification and can be applied regardless of whether the variables are stationary in levels or first differences, provided none are integrated of order two.

An ARDL model of orders *p* and *n*, denoted ARDL(*p*,*n*), can be written as (Pesaran and Shin, 1999) :

$$y_t = c + \sum_{i=1}^{p} \alpha_i y_{t-1} + \sum_{j=0}^{n} \beta_j X_{t-j} + u_t \,, \quad (1)$$

where y_t is the dependent variable at time *t*, *c* is the constant term, and u_t is an error term assumed to have zero mean error term and constant variance. The vector $\varvec{X}_t$ contains the explanatory variables observed at time *t* and $\varvec{\beta}_j$ is the corresponding vector of coefficients. The parameters *p* and *n* denote the number of lags for the dependent and independent variables. The parameters α_i are scalar autoregressive coefficients capturing the dynamic dependence of the dependent variable on its own past realizations.

The ARDL model framework has been widely used in empirical studies of road pricing and toll demand because it captures both immediate (short-run effects) and delayed behavioral responses (long-run effects) to changes in toll levels (Odeck and Bråthen, 2008; Bari et al., 2015; Gómez and Vassallo, 2015).

To facilitate interpretation of the short-run and long-term dynamics, the ARDL specification is reparametrized as an unrestricted error correction model (UECM). This formulation expresses the model in first differences, for example $\Delta \varvec{X}_t = \varvec{X}_t - \varvec{X}_{t-1}$, while retaining lagged level terms that capture the long-run equilibrium relationship. The UECM framework allows short-run adjustment processes to be distinguished from long-run effects and provides a basis for testing for cointegration using the bounds testing approach developed by Pesaran et al. (2001). The short-run and long-run dynamics of the model, together with the diagnostic tests and the procedure used to estimate elasticities, are described below.

4.1 Short-run and long-run dynamics, diagnostics, and elasticity estimation

The ARDL–UECM framework allows short-run adjustments and long-run equilibrium relationships to be examined within a unified specification. While the differenced terms capture immediate responses of heavy vehicle traffic to changes in generalized travel cost following toll removal, the lagged level terms describe the speed and extent of adjustment towards a new long-run equilibrium.

The ARDL–UECM approach requires that the variables included in the model are stationary in levels or first differences, but not integrated of order two, and that the residuals exhibit stable variance and no serial correlation. These conditions were assessed using standard diagnostic procedures, including unit root tests and tests for residual autocorrelation.

Within this framework, the estimated coefficients are used to derive elasticities that summarize the responsiveness of heavy vehicle traffic to changes in generalized travel cost. Generalized travel cost includes travel time, distance, and toll charges. In the empirical setting considered here, toll removal constitutes the only change in generalized travel cost over the analysis period, while travel time and distance remain unchanged. Although travel time and distance may vary marginally in practice, this simplification is reasonable because the most relevant alternative routes were also tolled, limiting the scope for substantial changes in these components.

Short-run elasticities reflect the immediate response of heavy vehicle traffic to toll removal and are derived from the estimated short-run coefficients on generalized travel cost. For each vehicle category iii (light or heavy trucks), the short-run elasticity is calculated as:

$$E_i^{SR} = \beta_{GC} \bullet \frac{X_{GC_{before}} - X_{GC_{after}}}{\overline{Y_i}} \quad , \qquad (2)$$

where E_i^{SR} denotes the the short-run(SR) elasticity for vehicle type i, β_{GC} denotes the estimated short-run coefficient on generalized travel cost, GC_{before} and GC_{after} represent generalized travel cost before and after toll removal, respectively, and $\overline{Y_i}$ is the mean traffic volume for vehicle category i.

Long-run elasticities capture the full adjustment of heavy vehicle traffic once the system has converged to a new equilibrium. These are obtained from the estimated long-run relationship between traffic volumes and generalized travel cost in the ARDL model and are calculated as:

$$E_i^{LR} = \sum_{j=0}^{n} \beta_j / \left[1 - \sum_{k=0}^{p} \alpha_k\right] \bullet \frac{X_{GC_{befor}} - X_{GC_{after}}}{\overline{Y_i}} \qquad (3)$$

where β_j are the coefficients on current and lagged generalized cost terms and α_k are the coefficients on the lagged dependent variable. Both short-run and long-run elasticities are reported in the results section and interpreted in light of the toll removal context.

Standard diagnostic tests were used to assess the validity of the estimated ARDL–UECM models. One key requirement in time-series modelling is that the residuals are not serially correlated, as residual autocorrelation may indicate model misspecification and can bias inference. Residual autocorrelation was assessed using the Durbin–Watson statistic, which tests the null hypothesis of no first-order serial correlation in the error term. Values of the Durbin–Watson statistic close to two indicate the absence of autocorrelation, while values substantially below or above two suggest positive or negative serial correlation, respectively.

In addition, the existence of a long-run equilibrium relationship between heavy vehicle traffic and generalized travel cost was examined using the bounds testing approach for ARDL models proposed by Pesaran et al. (2001). The bounds test is based on a joint F-statistic for the lagged level terms in the unrestricted error correction model. If the computed F-statistic exceeds the upper critical bound, the null hypothesis of no long-run relationship is rejected, indicating cointegration. Values below the lower bound imply no cointegration, while values between the bounds are inconclusive. Evidence of cointegration supports the interpretation of the estimated long-run elasticities reported in the results section.

5 Empirical results

This section presents the empirical results from the final ARDL–UECM specifications estimated to analyze the response of light and heavy truck traffic to toll removal. Based on the variable selection summarized in Table 3, the final models include generalized travel cost and county-level truck traffic growth as explanatory variables, together with lagged dependent variables to capture dynamic adjustment.

The estimated specification for each vehicle category i (light or heavy trucks) can be written as:

$$y_{i,t} = c + \sum_{k=1}^{p} \alpha_i y_{i,t-k} + \sum_{j=0}^{n} \beta_{1j} GC_{t-j} + \sum_{j=0}^{n} \beta_{2j} Growth_{t-j} + u_{i,t} \quad , \qquad (4)$$

where $y_{i,t}$ denotes annual average daily traffic for vehicle category i, $\sum_{k=1}^{p} \alpha_i y_{i,t-k}$ captures autoregressive dynamics and adjustment over time, GC_t is generalized travel cost, and $Growth_{t-j}$ is county-level truck traffic growth, and $u_{i,t}$ is an error term.

The results are presented in two parts: (i) the ARDL and unrestricted error correction model (UECM) estimation results, including short-run dynamics, long-run relationships, and diagnostic statistics; and (ii) the implied short-run and long-run elasticities of truck traffic with respect to generalized travel cost, derived from the estimated coefficients.

(i) ARDL and UECM estimation results

Tables 4 and 5 report the estimation results from the autoregressive distributed lag (ARDL) and unrestricted error correction model (UECM) specifications, respectively, estimated separately for light and heavy trucks across the study sites. Table 4 presents the ARDL results, capturing long-run relationships between truck traffic volumes and the explanatory variables, while Table 5 reports the UECM results, describing short-run dynamics and the speed of adjustment towards long-run equilibrium. Together, these models provide a comprehensive picture of how truck traffic responds to changes in generalized travel cost following toll removal.

The estimated coefficients on the lagged dependent variable indicate substantial persistence in truck traffic volumes. Across most cases and vehicle categories, the lag coefficients are positive and statistically significant, with values typically ranging between 0.6 and 1.0 in the ARDL specifications. This suggests that current traffic levels are strongly influenced by past realizations, implying that adjustments to changes in tolls occur gradually over time rather than instantaneously.

The coefficients associated with generalized travel cost generally display the expected negative sign in both the ARDL and UECM estimations and are statistically significant in most cases. These results indicate that reductions in generalized travel cost following toll removal are associated with increases in truck traffic volumes. While this pattern holds across most projects, the magnitude and statistical significance of the estimated coefficients vary across sites and vehicle categories, reflecting heterogeneity in traffic conditions and freight activity. In general, the estimated cost coefficients tend to be larger in absolute terms for light trucks than for heavy trucks, indicating stronger immediate responses among lighter freight vehicles.

Table 4
ARDL estimation results

Case	Vehicle	Lag (AADT)	Gen. cost	County growth	DW	Bounds test (p)
Atlanterhavsveien	7.6–16 m	0.12	−0.33**	5.82	1.48	0.02
	> 16 m	0.23	−0.01**	0.29	1.94	0.06
FV255 Fåberg kirke	7.6–16 m	0.99**	−0.71**	2.48*	3.01	0.08
	> 16 m	0.86**	−0.21**	1.56**	1.56	0.44
E136 Tresfjordforbindelsen	7.6–16 m	0.79**	−0.21**	2.21*	1.25	0.42
	> 16 m	0.38*	−0.07**	−0.05	1.44	0.18
RV19 Horten	7.6–16 m	0.62**	−2.03*	7.13	1.96	0.02
	> 16 m	0.39	−1.38	16.48*	2.1	0.12
E6 Østfold – Melleby	7.6–16 m	0.71**	−3.96**	12.41**	2.55	0.08
	> 16 m	1.11**	−2.60**	1.60**	2.89	0.79
E18 Kristiansand–Lillesand	7.6–16 m	0.27	−4.21**	−9.77	2.44	0.03
	> 16 m	0.14	−2.08	−9.99	2.27	0.00
FV107 Folgefonntunnelen	7.6–16 m	0.75**	−0.83**	1.12	2.28	0.02
	> 16 m	0.94**	−0.04	0.11	1.56	0.69
Vossepakka (Svelgen)	7.6–16 m	0.27	−1.74**	10.59	2.67	0.01
	> 16 m	0.14	−0.17	0.8	1.64	0.09
Vossepakka (Dalseide)	7.6–16 m	0.83**	−0.29	2.3	1.81	0.13
	> 16 m	0.74**	−0.09	0.96	1.67	0.71
FV17	7.6–16 m	0.63**	−2.30*	7.13	2.07	0.63
	> 16 m	0.61**	−0.10**	−0.03	1.67	0.66

Notes:

Lag (AADT) denotes the coefficient on the lagged dependent variable. DW denotes the Durbin–Watson statistic. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

The county-level truck traffic growth variable plays a more limited role in explaining traffic changes across the estimated models. In several cases, the coefficient is statistically insignificant or small in magnitude. When statistically significant, the coefficient typically has the expected positive sign, suggesting that broader regional growth in freight activity contributes positively to local truck traffic volumes. Overall, however, the results indicate that changes in generalized travel cost are the primary driver of observed traffic responses following toll removal.

Table 5
UECM estimation results (short-run dynamics)

Case	Vehicle	Δ Gen. cost	Δ County growth	ECT_{t-1}	DW	Adj. R^2
Atlanterhavsveien	7.6–16 m	−0.41**	−1.76	−1.39**	2,32	0,84
	> 16 m	−0.01**	0,16	−0.78**	2,26	0,55
FV255 Fåberg kirke	7.6–16 m	−0.59*	−0.78	−0.63*	1,24	0,32
	> 16 m	−0.12	1.37**	−0.35	1,73	0,42
E136 Tresfjordforbindelsen	7.6–16 m	−0.28**	−0.19	0,16	1,37	0,72
	> 16 m	−0.09**	0,11	−0.41	1,9	0,25
RV19 Horten	7.6–16 m	−3.20**	8.87**	−0.64**	1,57	0,74
	> 16 m	−0.59	4,41	−1.01**	1,97	0,38
E6 Østfold – Melleby	7.6–16 m	−2.76	−0.24	−0.85	1,17	0,22
	> 16 m	0,57	5,05	−0.23	0,63	0,00
E18 Kristiansand–Lillesand	7.6–16 m	−2.45	−6.12	−0.83**	1,07	0,29
	> 16 m	−1.22	−14.18	−1.16**	1,86	0,56
FV107 Folgefonntunnelen	7.6–16 m	0,28	−1.05	−0.69**	1,43	0,15
	> 16 m	0,04	0,2	0,1	1,65	0,08
Vossepakka (Svelgen)	7.6–16 m	−1.07**	−1.17	−1.32**	1,24	0,77
	> 16 m	−0.25**	0,49	−0.89*	1,57	0,34
Vossepakka (Dalseide)	7.6–16 m	−0.11	−1.90	−0.41	1,76	0,00
	> 16 m	0,12	0,24	−0.14	1,95	0,04
FV17	7.6–16 m	−1.01*	−0.19	−0.18	1,58	0,23
	> 16 m	−0.21**	−0.03	0,15	1,18	0,46

Notes:

Δ denotes first differences. ECT_{t-1} is the lagged error-correction term. DW denotes the Durbin–Watson statistic. ** and * indicate statistical significance at the 5% and 10% levels, respectively.

Model diagnostics suggest that the estimated specifications are generally well behaved. The Durbin–Watson statistics reported in Tables 4 and 5 mostly fall within the range of 1.5 to 2.5, indicating limited evidence of residual autocorrelation. Although a small number of models exhibit values slightly below this range, these deviations are not systematic and do not appear to affect the overall results.

Evidence on long-run relationships is assessed using bounds tests within the ARDL framework. Statistically significant bounds test results are obtained for the majority of the light truck models, indicating the presence of stable long-run relationships between traffic volumes and the explanatory variables. For heavy trucks (> 16 m), the bounds test results are more often insignificant, suggesting weaker or less consistent long-run relationships. This heterogeneity across vehicle categories motivates a separate examination of short-run and long-run elasticities in the next subsection.

(ii) Short-run and long-run elasticity estimates

This section presents short-run and long-run elasticities of truck traffic with respect to generalized travel cost following toll removal. Long-run elasticities reflect the equilibrium response of traffic demand after full adjustment and are derived from the estimated ARDL relationships presented earlier. Short-run elasticities capture the immediate response to toll removal and are derived from the unrestricted error correction model (UECM) specifications. Elasticities are reported only for cases in which the estimated effect of generalized travel cost is statistically significant.

To aid interpretation, it is important to note that short-run and long-run elasticities need not coincide in dynamic demand models. Short-run elasticities capture the immediate response of traffic volumes to changes in generalized travel cost, while long-run elasticities reflect the cumulative equilibrium response once adjustment processes have worked through the system. Differences between short-run and long-run estimates therefore provide information on the speed and persistence of traffic responses to toll removal.

The long-run elasticities reported in Table 6 summarize the cumulative effect of toll removal once traffic demand has converged to a new steady state. To ensure consistency between short-run and long-run measures, the short-run elasticities are evaluated at the same proportional change in generalized travel cost as applied in the long-run calculations. Rather than recomputing this proportional change separately, the short-run elasticities are derived using a scaling approach that links the UECM and ARDL estimates directly.

Specifically, for each case and vehicle category, the short-run elasticity is obtained by scaling the UECM coefficient on the change in generalized travel cost by the ratio between the long-run elasticity and the corresponding ARDL generalized travel cost coefficient. Formally, the short-run elasticity is given by

$$E_i^{SR} = \beta_{\Delta GC} \bullet \frac{E_i^{LR}}{\beta_{GC}}, \qquad (5)$$

where $\beta_{\Delta GC}$ denotes the estimated coefficient on the change in generalized travel cost in the UECM specification, β_{GC} is the corresponding generalized travel cost coefficient from the ARDL model, and E_i^{LR} is the long-run elasticity as defined in the econometric framework section. This formulation ensures that short-run and long-run elasticities are directly comparable and evaluated at the same toll-induced change in generalized travel cost.

Before turning to the elasticity estimates, it is useful to clarify their interpretation. Short-run elasticities capture the immediate response of truck traffic to changes in generalized travel cost following toll removal, while long-run elasticities reflect the cumulative equilibrium response after full adjustment has taken place. In dynamic models such as the ARDL–UECM framework used here, short-run and long-run elasticities need not coincide, as adjustment may be gradual and incomplete. The elasticity estimates reported below therefore allow an assessment of both immediate and longer-term demand responses to toll removal.

The elasticity estimates reported in Table 6 reveal clear differences both across vehicle categories and between short-run and long-run responses.

Table 6
Short-run and long-run elasticities of truck traffic with respect to generalized travel cost

Case	Light trucks (SR)	Light trucks (LR)	Heavy trucks (SR)	Heavy trucks (LR)
Atlanterhavsveien	−0.83	−0.80	−0.32	−0.32
FV255 Fåberg kirke	n.s	n.s	n.s	n.s.
E136 Tresfjordforbindelsen	−0.25	−0.40	n.s	n.s.
RV19 Horten	−0.24	n.s.	n.s.	n.s.
E6 Østfold – Melleby	n.s	n.s.	n.s	n.s.
E18 Kristiansand – Lillesand	−0.14	n.s.	−0.19	−0.16
FV107 Folgefonntunnelen	n.s	−1.00.	n.s.	n.s.
Vossepakka (Svelgane)	−0.27	n.s.	−0.59	n.s.
Vossepakka (Dalseide)	n.s.	n.s.	n.s.	n.s.
FV17	n.s.	n.s.	−0.17	n.s.
Average	−0.40	−0.70	−0.23	−0.24

Notes: SR elasticities are derived from the UECM ΔGC coefficient and are reported only when the ΔGC coefficient is statistically significant. LR elasticities are those previously reported in Table 4 and are reported only when the ARDL generalized cost effect and Bounds test is statistically significant. n.s. denotes not statistically significant. Averages exclude n.s. cases.

For light trucks (7.6–16 m), short-run elasticities are negative and statistically significant in several cases, typically ranging from about − 0.14 to − 0.83. These estimates indicate that toll removal induces an immediate increase in light truck traffic, reflecting a moderate short-term sensitivity to changes in generalized travel cost. In contrast, long-run elasticities for light trucks are statistically significant in fewer cases. Where significant, they range from approximately − 0.40 to − 1.00, suggesting that the cumulative long-run response can be larger in magnitude than the initial short-run effect, but that such persistent responses are not uniform across projects. The limited number of statistically significant long-run elasticities indicates that, for many road segments, the traffic response to toll removal does not persist once traffic demand has fully adjusted.

For heavy trucks (> 16 m), both short-run and long-run elasticities are generally smaller in magnitude and are frequently statistically insignificant. Where statistically significant, short-run elasticities are modest, and long-run elasticities typically lie in the range of − 0.16 to − 0.32. In the majority of cases studied, toll removal does not lead to a statistically significant long-run change in heavy truck traffic. This suggests that heavy vehicle demand exhibits limited responsiveness to changes in generalized travel cost, both immediately following toll removal and after full adjustment.

Although long-run elasticities represent cumulative equilibrium effects, they need not be larger than short-run elasticities. In the present context, the smaller and often statistically insignificant long-run elasticities indicate that initial traffic responses to toll removal tend to dissipate over time rather than accumulate. This implies that toll removal primarily induces temporary adjustments in truck traffic, while long-run demand levels remain largely unchanged, particularly for heavy vehicles.

An important implication of this finding is that toll removal does not appear to fundamentally alter long-run freight traffic patterns on the studied road segments. Instead, observed demand responses seem to reflect short-term behavioral adjustments—such as route switching, rescheduling, or temporary changes in trip frequency—rather than persistent changes in underlying freight demand. This contrasts with much of the existing literature based on toll implementation or toll increases, where estimated elasticities may partly capture the effects of simultaneous infrastructure improvements or broader network changes. By isolating toll removal without accompanying infrastructure upgrades, the present results suggest that pure price effects, particularly for heavy vehicles, are more limited and short-lived than commonly inferred from aggregate or implementation-based studies.

The weaker and less consistent response observed for heavy trucks is consistent with the operational characteristics of larger freight vehicles. Heavy trucks often operate under fixed logistics arrangements, tighter scheduling constraints, and limited routing flexibility, and tolls typically constitute a relatively small share of their total generalized travel costs. As a result, demand in this segment appears relatively insensitive to toll changes.

Overall, the elasticity results highlight both heterogeneity across vehicle categories and differences in adjustment over time. Light truck traffic exhibits moderate short-run sensitivity to toll removal, with evidence of stronger long-run responses in a subset of cases, while heavy truck traffic appears largely inelastic. These findings underscore the importance of distinguishing between truck types when assessing the traffic and revenue implications of toll policies and provide new empirical evidence on how toll removal affects different segments of freight traffic.

The implications of these elasticity estimates and their consistency with findings from earlier studies are discussed in the following section.

6 Discussion and implications

The results reveal clear and systematic differences in cost sensitivity between light and heavy trucks, both in the short run and in the long run. Across the cases analyzed, a 10% increase in generalized travel cost is estimated to reduce light truck traffic by approximately 7% in the long run, whereas the corresponding

reduction for heavy trucks is around 2.4%. This pattern indicates consistently lower cost sensitivity among heavy vehicles and is robust across both the ARDL and UECM specifications.

The estimation results further show that toll removal generally leads to an increase in light truck traffic, with relatively high autoregressive coefficients indicating strong persistence and gradual adjustment over time. The negative and statistically significant generalized cost coefficients are consistent with theoretical expectations, confirming that reductions in travel costs stimulate higher demand. The combined use of ARDL and UECM models proves effective in capturing both short-run dynamics and long-run equilibrium responses to toll changes. In contrast, for heavy trucks, the estimated cost coefficients are weaker and often statistically insignificant, suggesting limited responsiveness to toll removal.

The lower sensitivity observed for heavy trucks likely reflects structural and operational characteristics of this vehicle category. Heavy trucks typically operate on longer routes, often under fixed logistics contracts, and the toll component constitutes a relatively small share of their total generalized travel costs compared to lighter freight vehicles. In addition, long-distance freight operators may face fewer viable routing alternatives and have less flexibility to adjust behavior in response to toll changes. In contrast, lighter trucks are more often engaged in local or regional distribution, where route choice and delivery scheduling may be more adaptable.

The findings of this study are broadly consistent with earlier empirical literature, which generally reports negative elasticities between toll levels and freight traffic demand. Previous studies have estimated toll elasticities for freight transport in the range from approximately − 0.1 to − 0.9 (e.g. Hirschman et al., 1992; Bari et al., 2015; Wang and Zhang, 2017). The long-run elasticity estimates for light and heavy trucks in the present study fall within this range. However, the estimates for heavy trucks are frequently insignificant. By explicitly distinguishing between light and heavy trucks, the analysis highlights heterogeneity that is often obscured in studies treating all trucks as a single aggregated category.

An important aspect of the present study is that it examines demand responses to toll removal rather than toll introduction or increases, which dominate the existing literature. Elasticities derived from toll removal need not be symmetric to those associated with toll implementation. Behavioral responses to new tolls may be stronger due to loss aversion, initial route adjustment, or concurrent infrastructure improvements, whereas toll removal may trigger more gradual or incomplete reversals, particularly in freight transport where routing decisions and logistics contracts are often fixed over longer periods. As a result, elasticities estimated from toll removal may be smaller in absolute value than those reported in studies of toll implementation. The relatively low and frequently insignificant elasticities estimated for heavy trucks in this study are consistent with this interpretation and suggest that demand responses to toll removal may be more muted than those observed following the introduction of tolls.

This heterogeneity also helps to interpret findings from influential studies that estimate toll elasticities using aggregate traffic measures. Studies such as Odeck and Bråthen (2008), together with large-sample analyses and practitioner-oriented syntheses by Bain (2009, 2011, 2024, 2025), emphasize the importance of elasticity assumptions for toll road appraisal and revenue forecasting but do not distinguish between different segments of freight traffic. The present results suggest that elasticity estimates derived from aggregate traffic data are likely driven primarily by the behavior of light vehicles and lighter freight vehicles rather than by heavy trucks. Given the consistently lower and often insignificant elasticities estimated for heavy trucks in this study,

aggregate toll elasticities may therefore overstate the responsiveness of heavy vehicle demand to toll changes, while still providing a reasonable approximation for overall traffic and revenue outcomes.

A further contribution of the study lies in its exclusive focus on toll removal rather than toll introduction. Many previous studies analyze new toll facilities or toll increases, often in conjunction with infrastructure upgrades that confound price effects with improvements in travel time or road quality. By examining toll removals on road segments without accompanying infrastructure changes, the present analysis isolates the pure price effect of tolls more clearly. This strengthens the causal interpretation of the estimated elasticities and provides a useful complement to the existing literature based on toll introductions and stated preference data.

These findings are consistent with recent ex-post evaluations of toll-financed road projects, which show that tolling schemes are generally terminated once financing objectives have been met, and often earlier than initially planned (Odeck, 2026). This suggests that toll removal typically reflects sufficient revenue performance rather than declining demand. In this context, the relatively low and often insignificant demand responses estimated for heavy trucks help explain why toll revenues can remain robust up to the point of toll removal, despite changes in toll levels.

The results have important implications for toll policy and revenue forecasting. The relatively low and often insignificant elasticities for heavy trucks suggest that toll revenues derived from heavy vehicles may be more stable than commonly assumed. Given that heavy trucks account for a disproportionately large share of toll revenues due to higher toll rates, overestimating their responsiveness could lead to biased revenue forecasts and unnecessary adjustments to toll levels or collection periods. The findings therefore underscore the importance of distinguishing between truck types in toll road appraisal, traffic forecasting, and cost–benefit analysis.

Overall, the results emphasize that freight traffic is not homogeneous in its response to toll changes. Light trucks exhibit moderate sensitivity to generalized travel cost, with stronger responses in the long run than in the short run, while heavy trucks appear relatively inelastic. Recognizing these differences is essential for designing effective toll policies, improving revenue forecasts, and developing transport models that more accurately represent freight behavior.

7 Concluding remarks

This paper examined how road toll removal affects freight traffic by estimating short-run and long-run elasticities of light and heavy truck demand with respect to generalized travel cost. Using revealed-preference traffic data from multiple Norwegian toll stations and applying autoregressive distributed lag (ARDL) and unrestricted error correction models, the study isolated the price effect of toll removal on road segments without concurrent infrastructure changes. This design allowed for a cleaner identification of demand responses than is typically possible in studies of toll introduction or toll increases.

The results reveal clear and systematic differences in cost sensitivity between light and heavy trucks. Light trucks exhibit moderate responsiveness to toll removal, with statistically significant short-run effects in several cases and stronger responses in the long run where persistence is observed, reflecting gradual behavioral adjustment over time. In contrast, heavy trucks display substantially lower elasticities that are frequently

statistically insignificant, indicating limited responsiveness to changes in toll levels. These findings suggest that freight transport demand, particularly for larger vehicles, is relatively inelastic with respect to toll pricing.

Although long-run elasticities represent cumulative equilibrium effects, they need not exceed short-run elasticities. In the present context, the smaller and often statistically insignificant long-run elasticities indicate that initial traffic responses to toll removal tend to dissipate over time rather than accumulate. This pattern suggests that toll removal induces temporary adjustments in truck traffic, while long-run demand levels remain largely unchanged, especially for heavy vehicles operating under fixed logistical and contractual constraints.

A central contribution of the study is the explicit distinction between light and heavy trucks. Much of the existing literature relies on aggregated truck or freight traffic, which may obscure important heterogeneity in behavioral responses. The results indicate that commonly reported aggregate toll elasticities are likely driven primarily by the behavior of light vehicles and lighter freight trucks, while the responsiveness of heavy trucks is considerably lower. This distinction helps explain why toll revenues often remain relatively stable despite observable traffic adjustments following pricing changes.

The findings have important implications for toll policy, revenue forecasting, and transport modeling. Given that heavy trucks contribute a substantial share of toll revenues while exhibiting low price sensitivity, toll revenues may be more stable than commonly assumed. At the same time, failure to account for differences between truck types may lead to biased traffic forecasts and misinformed policy decisions. Incorporating vehicle-specific elasticities into toll road appraisal, traffic forecasting, and cost–benefit analysis could therefore improve the accuracy of demand projections and user benefit estimates.

Several limitations should be acknowledged. The analysis is based on a limited number of toll removal cases and relatively short post-removal observation periods. In addition, the set of explanatory variables is constrained by data availability, and broader economic or logistical factors influencing freight demand may not be fully captured. Future research could extend this work by examining additional toll removal cases, using longer time series, and exploring further heterogeneity within freight traffic, such as differences by commodity type, contract structure, or trip purpose.

From a policy perspective, the results suggest that toll appraisal and revenue forecasts should explicitly distinguish between light and heavy trucks, as assuming uniform freight elasticities risks overstating heavy vehicle responsiveness and misjudging the stability of toll revenues.

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