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The value of travel time: a revealed preferences approach using exogenous variation in travel costs and automatic traffic count data

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Abstract
This paper suggests an alternative approach to estimate the value of travel time (VTT) savings, using a case study with exogenous variation in travel costs and data from automatic traffic counts (ATC). With this revealed preferences approach, we address a possible bias of VTT estimates because of self-selection. Compared to the VTT estimates used in transport appraisals, the results produce substantially higher estimates of VTT. Unfortunately, our analysis does allow us to distinguish the self-selection bias from other possible sources of bias. The cost of using ATC data is that there is no direct information regarding the motorists, and the analysis must be done using aggregated data at an hourly interval. Still, this alternative approach may complement the results with more detailed data.

Keywords Value of travel time · Revealed preferences · Stated preferences · Self-selection

Introduction

The value of travel time (VTT) savings is a crucial factor in transport appraisals. VTT is a key input in transport modeling, as it influences the route choice, mode, and number of trips. Additionally, VTT is essential in project appraisal, as it is used to calculate the value of travel time gains. VTT is typically estimated with a stated preference (SP) study, in which an individual's valuation is derived from answers to hypothetical and realistic choices. Another approach is a revealed preference (RP) study in which VTT is derived from observed behavior.

SP studies have some well-known challenges. The hypothetical nature of SP studies may be a source of bias (Brownstone and Small 2005; Shires and De Jong 2009; Hensher 2010; Wardman et al. 2016). Other challenges with SP studies are strategic behavior (Fosgerau et al. 2010), reference dependence (e.g., De Borger and Fosgerau 2008), or answering that reflect what those participating in the studies think is the "correct" answer, the "warm glow

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effect" (Johansson-Stenman and Svedsäter 2012). A possible approach to address these challenges is to use a RP approach and study observed behavior.

RP studies have, however, other challenges. First, there may be a self-selection bias due to the recruitment of participators (i.e., the ones participating in surveys are not random and are self-selected into the study group).[1] Rightfully, the self-selection problem also applies to most SP studies, where participants also need to be recruited. The bias from the recruitment process will be downward on VTT if individuals with a high income, who are presumably busy, have a lower probability of participating in the study (Kouwenhoven et al. 2013; Halse et al. 2019).[2] Another problem with RP studies appears if motorists base their decisions on the wrong travel costs. If this is the case, it might result in overestimating the VTT (Varotto et al. 2017; Varela et al. 2018).

Some of the issues with the RP approach can be addressed by using a suitable case study. Such a case study should include (at least) two nearly equal routes and exogenous changes in travel costs. The self-selection issue can be addressed by using a passive data collection approach, such as GPS signals or automatic traffic counts (ATC), instead of a typical interview- or survey-based recruitment. Although this approach cannot control the experimental setting and address individual-specific components, they are less costly than interview-based approaches and might solve some of the problems that come from hypothetical bias, self-selection, and strategic behavior.

In this paper, we attempt to address self-selection bias by estimating VTT using ATC data, together with a case study. To the best of our knowledge, this is the first attempt to use ATC data to estimate VTT. Admittedly, using toll-road decisions to measure VTT is not new (see Brownstone and Small 2005; Steimetz and Brownstone 2005 for earlier contributions), but these studies do not use a passive data collection approach. This analysis also differs from the existing literature by focusing on exogenous changes in trip costs, which makes it possible to separate individual-specific components (fixed effects) from travelers' time valuations. The focus on exogenous changes in travel costs is also, to the best of our knowledge, new.[3]

Specifically, we utilized a case study with two similar routes where the travel cost of one of the routes changed because of an unplanned change in tolls. This change derives from an opening of a new road which, due to an error with the ATC cameras, had an unplanned period without tolls. The change in tolls is used to estimate the share of motorists who changed routes after the toll changes. We argue that this share represents the motorists with a valuation below the boundary value of time (BVoT), which makes both routes equally attractive. After assuming the shape (normal or lognormal) and spread (the relative standard deviation) of the VTT distribution, we calculated the mean VTT, which is consistent with the observed route choice behavior.

[1] If the underlying process of self-selection is known, a non-representative sample could be adjusted using statistical techniques. This selection problem points to cases where there is selectivity on VTT across all groups.

[2] However, there is also evidence that people with higher education are more likely to participate in studies, and a high level of education and income are positively correlated (Carlsson et al. 2006; Demarest et al. 2012).

[3] In standard economics in the last decade, there has been a great focus on natural experimentation and causal analysis, and in 2021, the Nobel Prize in Economic Sciences was given for work in this area.

Literature review

This section reviews an often overlooked issue regarding RP estimates: the self-selection of participants. After a brief introduction to the literature, we discuss this issue in more detail.

What is the value of travel time savings?

The question of the valuation of time originates with Becker (1965), who introduced time as a resource. In contrast to ordinary markets, there is no market price for time, but people may still attach monetary value to their leisure time. The standard is to use the alternative cost approach and an individual's willingness to pay. Becker's model was further developed by Oort (1969) and DeSerpa (1971). In DeSerpa's model, the utility function depends directly on the attractiveness of the time allocated to activities, and the traveler maximizes utility subject to budget constraints. Using this approach, DeSerpa derives the VTT as the marginal value of leisure time minus the marginal utility of travel.

Several factors determine VTT. First, there are individual components, such as income (wages). Second, characteristics attached to the transport mode may affect valuation; for example, seating comfort, crowding, and safety. Third, situation-specific factors, such as time pressures at the specific time, trip purpose, weather conditions, and time of year, may influence the VTT. Hence, there are reasons to believe that valuation differs among people and settings and that no single value will accurately reflect the valuation of time.

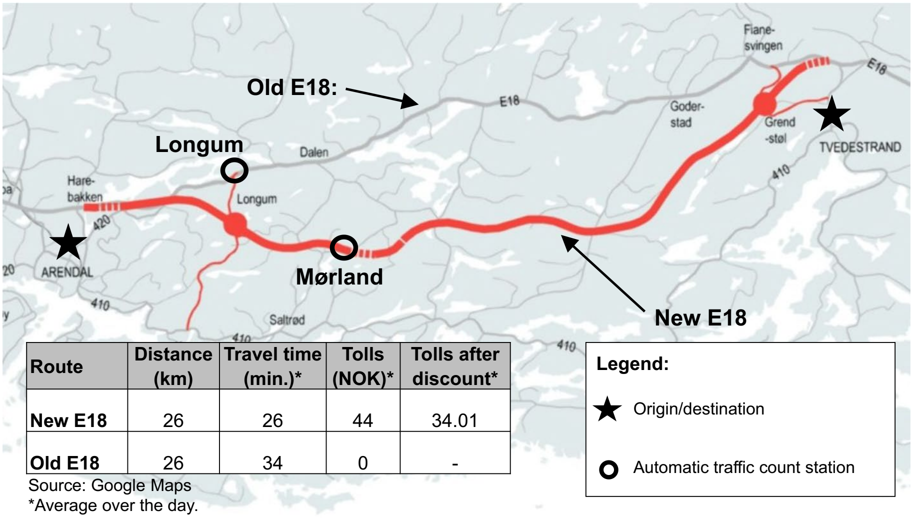
The value of time is usually measured in a money metric per time unit. In Norway, the typical value of an hour is approximately NOK 120 (1 NOK = 9.7 Eurocent in summer 2019), but around this value, there are large differences depending on the lengths and purposes of the trips. Currently, the official values in NOK 2019 prices for short trips (below 70 km) used in appraisals are NOK 77 per hour for leisure trips, NOK 512 per hour for business trips, and NOK 93 per hour for commuting trips. The average across purposes is NOK 99.[4] These values are estimated by SP methods using simple time–money trade-offs and are documented in Flügel et al. (2020b).

Self-selection

A source of bias that has been little emphasized in the literature is the effect of the recruitment of participants. When looking at a broad range of studies, from the valuation of traffic safety to water quality and skin cancer risk, Lindhjem and Navrud (2011) find that although the recruitment process might be of substantial interest, it is generally given less attention than methodological choices by most studies.

Typically, data collection is conducted via web and phone panels, web surveys, computer-assisted personal interviewing (CAPI), or phone surveys. In a recent report from the Norwegian valuation study, the authors report that the individuals recruited from web panels have lower VTTs than those recruited from phone panels and by e-mail (Flügel et al. 2020b). A similar finding was found in Kouwenhoven et al. (2014) when comparing internet panels to en-route recruitment.

[4] The weights are commuting trips 26%, leisure 70%, and business 4%.



Route	Distance (km)	Travel time (min.)*	Tolls (NOK)*	Tolls after discount*
New E18	26	26	44	34.01
Old E18	26	34	0	-

Source: Google Maps
*Average over the day.

Fig. 1 E18 between Arendal and Tvedestrand (Norway). *Source*: Nye Veier and Google Maps

It is not clear to what extent self-selection is a problem regarding the groups that seldom participate in any voluntary study. If individuals who do not participate have a lower VTT than the general population, the resulting estimates will be downward biased. Ironically, participating in any kind of group requires people to sacrifice their time. It is then only a small conceptual step to conclude that self-selection exists because of the recruitment strategy. Hence, there might be limitations to any recruitment strategy that requires active participation.

Case study

Project background

A new trunk road on European Road 18 (hereafter E18) between the cities of Tvedestrand and Arendal in southern Norway opened for traffic on July 2, 2019. The new road (the thick red line in Fig. 1) replaced an older route (the gray line), which is still open to traffic. The objectives of the new road were fewer accidents, increased capacity, and reduced travel time. According to Google Maps, the new route reduces travel time by 7–11 min per trip compared to the existing road, with the largest travel time reduction occurring during rush hours. These travel times were collected from Google Maps by searching for the travel time between the points depicted on the map by stars. As Google Maps uses anonymously tracked user data, traffic sensors, and satellite data to calculate travel times, these travel times are the most accurate source of the travel time on this road (Xia et al. 2018).[5]

[5] The specific algorithm behind the travel times from Google Maps is a trade secret. The algorithm uses official speed limits and recommended speeds, likely speeds derived from road types, historical average speed data over certain time periods (sometimes just averages, sometimes at particular times of day), actual travel times from previous users, and real-time traffic information.

Table 1 Average generalized travel costs per vehicle in NOK by time and route

	Leisure		Commute	
	Before*	After*	Before*	After*
Old route	135	135	179	179
New route	122	157	157	191

*Before or after 1. September 2019, when the tolls were implemented at the new route

The costs are calculated between Tvedestrand–Arendal. Calculations of generalized travel costs are based on the standard procedure presented in NPRA (2018). Costs per km are set to NOK 3.22, and the value of travel time in hours is set to NOK 100 for commuters and NOK 85 for leisure trips (values for trips < 70 km from Table 5–11 in NPRA (2018)). The values are converted to 2019 prices using the consumer price index from Statistics Norway, with a nominal price change of 6.7% from 2016 to 2019

From Fig. 1, we see that the new E18 is similar in length to the old E18. The exact difference depends on the origin and destination of the travel; for example, whether the route follows E18 on a long trip or goes between the cities on either end of the route (Arendal and Tvedestrand). For simplicity, we treat the distances as equal.

What makes this case interesting is the existence of two routes and the change in tolls on the new route. The new route has tolls, but because of an error in the toll collection system, the new road opened on July 2, 2019, without tolls. After two months, the error was corrected, and after September 1, tolls were collected.[6] The period from July 2 to September 1, therefore, was an unintended period without tolls. The exogenous changes in costs enable us to separate the effects of travel time from other factors, which can be regarded as fixed effects and held constant in the analysis.

Including discounts, the average toll is 33.93 NOK during the workweek (Monday–Friday) and 34.25 NOK during the weekend, both for vehicles shorter than 5.6 m. The toll was used to finance the project and the toll level is therefore fixed throughout the day and the week. The variation in average tolls, including discounts, comes from a difference in the share of discount payments, which is slightly higher during the work week.[7]

Table 1 displays the generalized costs for the two routes. Using the standard VTT from NPRA (2018) in the calculation, we see that for the average motorist, the old route is most attractive if there are tolls on the new route, and the new route is most attractive when the tolls are removed. Both VTTs used here are for short trips, estimated as a national average, and the VTT is set equal for both passengers and drivers. In this case, the national averages are used because, since both the income and industry structures in this region are close to the national average. Without tolls, the new road generated the lowest travel costs for both leisure travelers and commuters. However, after tolls were introduced, the new road had higher generalized costs for the specific travel calculated here for both commuters and

[6] Using the Nordic news archive, information searches show that the error with the camera was publicly available from July 29, 2019 (Tvedestrandsposten 2019). The information regarding the date of collection of tolls is from July 1, when the newspaper wrote that tolls would be collected starting in September 2019 (Agderposten 2019).

[7] The payment data were made available by the toll-collecting company Ferde to the authors.

Table 2 Boundary value of time (BVoT) per hour. New vs. Old E18: Arendal–Tvedestrand

Period	Tolls	Load*	Difference in travel time, in minutes (ΔTT)	Boundary value of time (BVoT)
Morning (07–09, Mon.-Fri)	34.01	1.1	7	265
	34.01	1.1	8	232
	34.01	**1.1**	**9**	**206**
	34.01	1.1	10	186
	34.01	1.1	11	169
Evening/weekend (20–24 Mon-Fri & Sat-Sun)	34.01	1.9	7	153
	34.01	1.9	8	134
	34.01	**1.9**	**9**	**119**
	34.01	1.9	10	107
	34.01	1.9	11	98

BVoT is calculated using Eq. (1). *Load factors are taken from NPRA (2018). The bold font shows the chosen level used in the later baseline calculation

leisure travelers. The tolls increased the generalized cost of the new road by between 22 and 28%.

The share of the distance-related costs varies between 43 and 53% of the generalized costs. This component is also uncertain. However, when it comes to route choices, the literature points in the direction of a behavior consistent with a valuation of only 50% of the actual cost (Allcott 2013; Andor et al. 2020). Hence, it is likely that the route choices are based up on an underestimated distance cost. However, since the distance between the two routes is approximately equal, the value of the distance-related costs is of limited importance in our analysis.

The boundary value of time

The previous section showed that the new road was less attractive for the average motorist under the assumption that the route choice is based on generalized travel costs. The attractiveness of the new route is essentially determined by whether the valuation of the eight minutes saved by using the new road exceeds the toll. From this observation, we can also calculate the VTT that makes the two routes equally attractive; we refer to this value as the boundary value of time (BVoT). Thus, we can calculate BVoT as the ratio of tolls relative to saved travel time minutes (ΔTT):

$$BVoT = 60 \times (Tolls/\Delta TT)/Load \tag{1}$$

Table 2 displays different BVoT values. For morning traffic, we assume a load factor of 1.1, meaning that, on average, there is one passenger, in addition to the driver, for every 10 cars. Accounting for differences in travel time savings between the routes causes BVoT to vary between 169 and 265 NOK. A similar calculation was made for evening/weekend trips but with a higher load factor. The load factors are admittedly uncertain and are therefore addressed in a later robustness analysis. For evening/weekend trips, BVoT varies between 98 and 153 NOK. The difference in travel time varies slightly. In the morning, the difference varies by two to three minutes, depending on the traffic. The differences in travel

Table 3 Hourly traffic. New E18: Arendal–Tvedestrand. ATC: Mørland. Period August 1–October 16, 2019

Route	Obs	Average	Standard deviation	Min	Max
New E18	1848	361.5	295.9	5	1438
Old E18	1848	148.6	127.8	0	600

Only vehicles < 5.6 m are included

time reported in Table 2 is at the upper bound of these differences. In the evening and over the weekend, there is less variation in traffic according to estimated delays from Google Maps.

Data from automatic traffic counts

The main data used in this paper comes from automatic traffic counts (ATCs). This contrasts with almost all other studies on VTT that consider different types of survey/interview data. The traffic count data are automatic registrations of vehicles passing induction loops on the road surface. Passing these cables registers the vehicle length, speed, and distance to other vehicles, and the registrations cover all vehicles that have passed the ATC in the period. This differs from survey data, which capture, to varying degrees, only a sample of vehicles that have traveled along a route in each period. The cost of using ATC data is that no direct information about motorists is available.

Specifically, this paper uses the number of registered vehicles passing in hourly intervals. These data are publicly available from NPRA (2021). An observation in our dataset is, therefore, the number of passing vehicles per hour. In this paper, we consider only personal vehicles (shorter than 5.6 m).

The data is collected from two ATC stations: Mørland (the new route) and Longum (the old route). For the old route, we have data from January 1, 2018, to October 16, 2019. For the new E18, the dataset includes data after the opening in July 2019 to October 16, 2019. In the analysis, we used only observations after August 1 2019, to remove some of the possible sightseeing effects on the new route and for the motorists to get a more accurate perception of the travel costs on the new route.

Table 3 displays the main characteristics of the traffic data for the period used in the estimations. The data consist of 1848 hourly observations from August 1 to October 16, 2019 (77 days with 24 hourly observation each day). We see that, on average, 362 vehicles are registered each hour on the new route, and 149 vehicles are registered per hour on the old route. The variation in hourly traffic is substantial, which is evident by the fact that the standard deviation is relatively high compared to the mean. The main reason for this is that the traffic load varies throughout the day, as is evident in Fig. 2.

Figures 2 and 3 shows the hourly and monthly variations in vehicles per hour. Only data for the old route the last year before the opening of the new route (2018) is included. In Fig. 2, the distribution for January and July is also included (the dashed line). Figure 3 displays traffic over the year for the old route. The traffic follows an inverted U-shape, with low traffic at the start of the year, increasing until July and dropping thereafter. Note how traffic falls between August and September (the time when the toll was removed) from 541 to 458 vehicles per hour, a decrease of 15%.

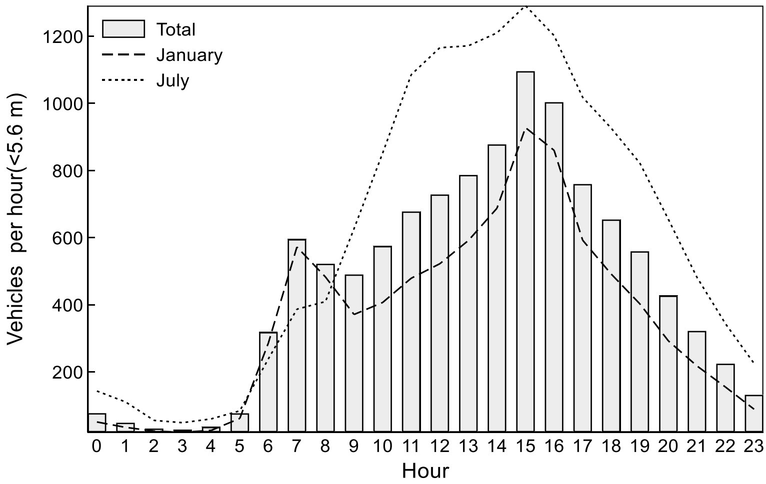


Fig. 2 Vehicles per hour over the day. New E18 (ATC: Mørland). Year = 2018

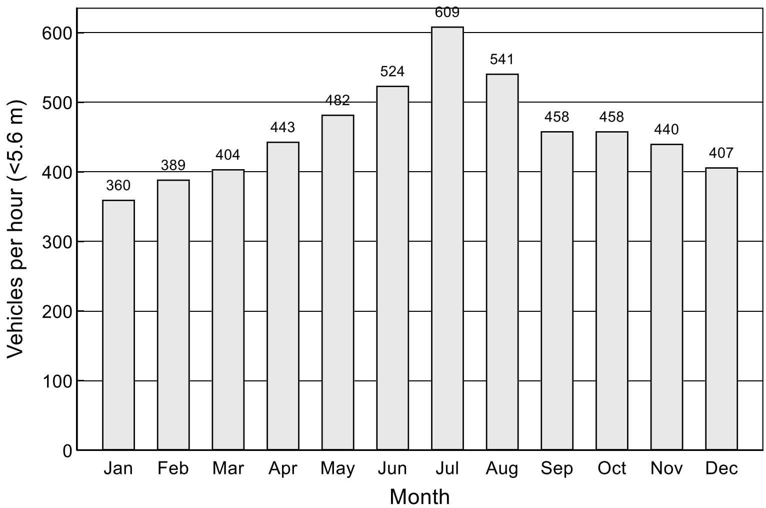


Fig. 3 Average vehicles per hour by month. Old E18 (Longum). Year = 2018

Descriptive evidence of route choice

The change in route choice because of the tolls is visually apparent. Figure 4 shows the number of passing vehicles in the months before and after the opening of the new route in 2019. On the new route, traffic decreased from 454 vehicles per hour to 304 vehicles per hour after the tolls were introduced in September, amounting to a reduction of 33%. If we correct for the normal reduction of 13% from August to September for the years

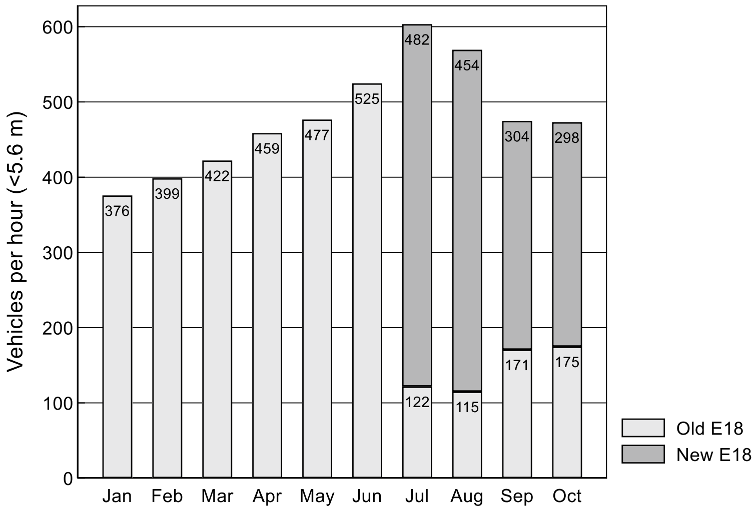


Fig. 4 Monthly traffic per hour. Old E18 and new E18. Jan. 2019–Nov. 2019

2015–2018, this implies that the toll decreased traffic on the new route by approximately 23%.[8]

Overall traffic, in contrast, seems to be little affected. The traffic on both routes together have been reduced by approximately 1% because of the toll. Looking at the numbers on each bar, we see that traffic declined by 15.3% from August to September 2018, but in 2019, total traffic declined by 16.5%.[9] Hence, a rough estimate of the total traffic effect because of the tolls is a reduction of 1.2%. On the new road, traffic decreased from 454 to 304, which amounts to 33%. Since traffic decreased by 15% the previous year, before the change in the infrastructure, a rough estimate is that approximately 21% of the motorists changed their route after the introduction of the tolls.[10]

Empirical strategy

Estimation framework

The estimation strategy is based on the observation that the expected *VTT* can be inferred from the share of motorists changing route after the exogenous change in travel costs. Although the data do not include observations at the individual (motorist) level, we start at this level when describing the estimation framework. Formally, inspired by the framework from Small et al. (2005),[11] individual i chooses the new E18 (toll route) whenever the random utility U_i is positive

[8] $\frac{(1-0.33)}{(1-0.13)} = 1 - 0.23$.

[9] We sum the two bars in Fig. 4 and calculate the percentage decrease: $(304 + 171)/(454 + 115) - 1 = 0.165$

[10] $\frac{(1-0.33)}{(1-0.15)} = 1 - 0.21$.

[11] The similarity with this paper only applies for the presentation of the random utility model, but not in any sense the estimation part of the model.

$$U_i = c + VTT_i \times TT + \epsilon_i \tag{2}$$

where c is a constant, VTT_i the value of travel time, TT travel time, and ϵ_i a random unexplained component. In our case study, the distances on the new and old roads are equal, and the distance-related costs are therefore omitted from the random utility specification (included in the constant term). The most heroic assumption in our analysis is that preferences for the express route (the comfort component) are included in the constant term. Only if the comfort component is nonessential for route choice and uncorrelated with VTT can this assumption be maintained. However, if comfort is important for route choice, it will affect the estimates as an omitted variable.

Given that the random utility, as an approximation, could be regarded as a function of only VTT and a constant, we can express the random utility with an index function:

$$\mathbf{1}_{U_i}(VTT) = \begin{cases} 1 & \text{if } U_i > 0 \\ 0 & \text{else} \end{cases} \tag{3}$$

Let Eq. (3) represent the choices in the pre toll period. The observations of motorists in the pre-toll period consists of the motorists that will remain at the route after implementing tolls and those that will change route. The share of motorists that change route is thus the motorists with a VTT below BVoT. This share is formally defined as

$$\int_0^{BVoT} \mathbf{1}_U(VTT)dP = P[VTT \leq BVoT] = \omega \tag{4}$$

Hence, ω represents the share of motorists with a VTT below BVoT. Next, let $z(\omega)$ be a fractile defined by $P[Z \leq z(\omega)] = \omega$. Using Eq. (4), we can write the fractile as

$$z(\omega) = \frac{BVoT - \overline{VTT}}{\sigma} \tag{5}$$

where $\overline{VTT}$ is the expected travel time and σ the standard deviation. Solving Eq. (5) for $\overline{VTT}$, we get

$$\overline{VTT} = BVoT - \sigma z(\omega) \tag{6}$$

Hence, if we know ω, the statistical distribution, and the standard deviation, we can calculate the expected VTT. Note that $z(\omega)$ is negative at the left-hand side of the distribution. Hence, $z(\omega)$ is negative if less than 50% of the motorist's changes route. We assume that this is the case in the following interpretations. Equation (7) tells us the following: (i) Higher $BVOT$ is associated with higher $\overline{VTT}$. (ii) Higher values of ω result in lower VTT. In particular, a value of ω close to 0.5 entails that the expected VTT is close to BVoT. For example, in the extreme case where 50% of motorists change routes, there will be no difference between $BVoT$ and $\overline{VTT}$. (iii) All else being equal, a larger σ is associated with higher values of VTT.

In the later analysis, we use a standard normal distribution and a lognormal distribution. We choose these distributions because they do not require additional parameters after normalization, although they are not the optimal choice, according to Fosgerau (2006).

Parameter estimation of the route change

The key parameter identified in "Estimation framework" section is ω: the share of motorists with a VTT below BVoT. We suggest identifying ω by estimating the share of motorists that changed route after the toll was introduced. This is achieved by estimating a time series model for traffic with a dummy for the introduction of tolls, using a log-lin formulation. The log-lin formulation is chosen for the estimate of the effect of toll removal to be interpreted as a percentage change in traffic (the estimated effect refers to the share of motorists with a VTT below the BVoT cut-off). Empirically this decrease includes both a route choice effect and a demand effect. But if the demand effect is negligible, the estimated coefficient for the toll dummy provides an estimate of ω.

The modeling approach is based on the interrupted time series (ITS) approach, which is used for quasi-experimental designs (Cook et al. 2002). For a recent application within transport, see Andreana et al. (2021). The ITS approach is advisable when the intervention begins at a known time, the outcome changes quickly after the intervention, and the intervention lasts long enough to be measured. Hence, the ITS approach is suitable in our case study. We use the following specification

$$\ln\left(vehicles_t\right) = c_0 + \alpha_{day} + \alpha_{hour} + \beta_1 t + \beta_2 t^2 + \omega \times Tolls_t + u_t \tag{7}$$

where t denotes the time of the day for different dates. $\ln\left(vehicles_t\right)$ is the logarithm of hourly registered vehicles, c_0 is a constant, α_{day} are day dummies, and α_{hour} are hour dummies. These two sets of dummies explain the variations in traffic during the day and across the week.[12] The next two terms, which include β, define a flexible time trend. The time trend is presented as a polynomial of order two and captures seasonal effects and overall traffic growth. However, estimates made using a lower order are also provided. The next term gives the effect of the route change from the change in tolls. The term $Tolls_t$ equals zero in the period without tolls and one afterward. The effect of this variable identifies the parameter of interest ω. Finally, u_t is the unexplained variation in traffic. The principle behind this specification is to estimate a flexible model that explains the time-series variation in traffic.

Estimation results of route change

Main results

The estimated ω in Eq. (7) should be interpreted as the short-term response by motorists with a short trip length. The dependent variable in the estimation is the logarithm of hourly traffic. The estimation period was August 4 to October 16 (76 days), with hourly observations of traffic. The variation in the number of observations across the columns comes from differences in the number of hours included in each time segment. For example, there are 108 observations in Column 3 because the time segment "Morning" includes three hours, giving 108 observations over the 36 working days.

[12] The standard method of using dummies to capture seasonal effects is not used because the seasonal effect of September will be highly confounded by toll changes, since both are changed on the same day (September 1, 2018).

Table 4 OLS estimates of the reduction in trips on New E18: Tvedestrand–Arendal after introducing tolls

	Dependent variable: Log vehicles per hour							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tolls (ω)	– 0.22	– 0.31	– 0.39	– 0.17	– 0.26	– 0.29	– 0.10	– 0.18
	(0.04)	(0.07)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)
Period	Total	Night	Morning	Day	Afternoon	Evening	Weekend	Evening/weekend
Observations	1848	378	108	324	108	379	528	907
Adj. R-squared	0.92	0.90	0.77	0.85	0.90	0.94	0.94	0.94

Standard errors in parentheses. The parameter estimate of tolls refers to the estimate of ω from Eq. 7. Estimation period: August 1, 12 pm–October 16, 12 pm, 2019 (76 days). The models in Columns 1–8 are estimated separately. Night: 00–07 Mon-Fri; Morning: 07–09 Mon-Fri, Day: 09–17 Mon-Fri, Afternoon: 17–20 Mon-Fri, Weekend: Sat-Fri

Table 5 OLS estimates of the reduction in trips on both New and Old E18 (total traffic): Tvedestrand–Arendal after introducing tolls

	Dependent variable: Log vehicles per hour							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tolls (ω)	– 0.04	– 0.00	– 0.17	– 0.03	– 0.07	– 0.08	0.01	– 0.03
	(0.04)	(0.06)	(0.04)	(0.03)	(0.02)	(0.02)	(0.05)	(0.03)
Period	Total	Night	Morning	Day	Afternoon	Evening	Weekend	Afternoon/ weekend
Observations	1,848	378	108	324	108	378	528	906
Adj. R-squared	0.84	0.93	0.79	0.83	0.91	0.89	0.85	0.86

Standard errors in parentheses. The parameter estimate of tolls refers to the estimate of ω from Eq. 7. Estimation period: August 1–October 16, 2019 (76 days). The models in Columns 1–8 are estimated separately. Night: 00–07 Mon-Fri; Morning: 07–09 Mon-Fri, Day: 09–17 Mon-Fri, Afternoon: 17–20 Mon-Fri, Weekend: Sat-Fri

Table 4 shows the OLS estimates of the percentage reduction in hourly traffic on the new E18 (see Table 8 in Appendix for a full list of covariates). Columns 1–8 display estimates of ω for different hours of the day and shows that the estimated reduction in traffic is in the range of 10–39%. The greatest decline in traffic is in the morning (Column 3), which we interpret as comprising mainly commuting trips. The trips in the evening and on weekends are reduced between 10 and 29%. Thus, during these times, travelers are less affected than morning traffic. Combining the evening and weekend periods (Column) resulted in an estimated trip reduction of 18%.

The relatively high effect on morning trips is consistent with a lower value of time for these trips. A possible interpretation of the results is that 39% of the trips have a VTT such that the old route is more attractive. There are several possible explanations for why the estimated effect on morning traffic is the greatest. First, it could be that trips in the evening are, on average, longer than in the morning. Second, morning travelers may be better informed about cost differences, as they probably travel more regularly. Third, the load factor is perhaps the lowest for morning trips. If the driver considers the time value of the passengers, this should result in higher total values for the vehicle as a whole. This is a possible explanation since the observation unit, in this case, are vehicles and not individuals.

To adjust these coefficient estimates for the demand effect, we also regressed Eq. (7) using traffic on both routes. The results are reported in Table 5. We see that the overall effect on traffic is insignificant, but with a point estimate of a reduction of 4%. However, the effects in the morning and evening periods of interest show significant effects. The effects of morning traffic (Column 3) show a reduction in traffic of 17%. If we take this as an estimate of the effect on overall demand, the isolated effect on route choice reduces to 22%. For evening trips, the parameter estimates from Column (6) indicate a reduction in traffic of 8%. For the estimate where we combine both the evening and the weekend, the demand effect is far from significant, implying no adjustment.

Robustness analysis of estimates

The estimation period included in this analysis is only a few months, with data from August 4 to October 16. Although it seems reasonable that route choices will materialize quickly, we investigate the effect of the period of analysis on our estimates. Therefore, we have estimated the effects with even shorter periods. The results are presented in Tables 9 and 10 in the Appendix. Table 9 displays the results from using one month of data before and after the tolls were implemented, while Table 10 displays the results from using data from the two weeks before and after the tolls were implemented. The shorter the period, the lower the estimated effects, but they are not qualitatively different.

As the parameters should be interpreted as short-term effects, they will probably underestimate the long-term effects. The corresponding values of time will therefore be higher when estimating long-term effects. However, the difference between long- and short-term impacts in this context is small, as it mainly relates to route choices. The demand effect is also likely to be small, as the roads were without tolls for only two months, so there was never any long-term adjustment to having a toll-free E18 between Tvedestrand and Arendal.

In the results of the analysis reported in the Appendix (Table 11), we also vary the definitions of morning and evening. We changed the morning period to 0600–0900, while evening traffic was adjusted to 1800–2300. Both of these robustness checks had little effect on the parameter estimates.

Another possible source of bias is the log-lin formulation in Eq. (7). Using vehicles per hour instead of log vehicles resulted in an estimated decrease in traffic of 66 cars. Compared to the average hourly traffic the week before the toll removal of 385, this represents a 19% reduction.[13] Hence, the result is three percentage points lower than the main estimate of 22%.

The final sensitivity analysis investigates the choice of the time trend in Eq. (7). The default specification uses both linear and quadratic terms. However, there are no strong arguments in favor of this specification. An alternative specification with only a linear time trend (where $\beta_2 t^2$ is omitted) is therefore presented in Tables 12 and 13 in the Appendix. As the results show, the overall effect on morning trips falls, but it increases for evening/weekend trips. The final column shows the effect of using an estimated time trend from a later period and estimating the model on trend-adjusted data. Using the detrended data

[13] $\log(385)/\log(385-66) = 0.188$.

Table 6 Baseline value of time savings based on indirect valuation

	(1) $\widehat{\omega}$	(2) $z(\widehat{\omega})$	(3) $BVoT$	(4) $\widehat{\sigma}$	(5) $\widehat{VTT}$
Morning	– 22%	– 0.77	186	31	210
Evening/Weekend	– 18%	– 0.92	119	18	135

$\overline{VTT}$ is calculated using Eq. (6). The VTTs are in 2019 NOK

results in slightly higher effects: the overall traffic is reduced by 29%. In total, the different specifications of the time trend resulted in lower and higher estimates of the reduction in traffic. This variation reflects that the estimate is uncertain and depends on the specification of this element, but there is no reason to believe that the main estimates are biased in any particular direction.

Estimates of the value of travel time savings

Main results

Combining the estimates of ω, $BVoT$, an assumed standard deviation, and a given statistical distribution, we can calculate the estimate of VTT using Eq. (6).

Table 6 displays the input and the resulting VTT estimates for the morning and evening weekend trips. Column 1 displays the main estimates of the route choice effect. The values in Column 2 are the fractiles from a standard normal distribution, using the values from Column 1. The next Column shows the BVoT, and Column 4 displays the standard deviation ($\widehat{\sigma}$). The standard deviation is set such that the coefficient of variance (CV) matches the CV from the distribution of wages in Norway, as reported by Statistics Norway (2020), which is currently 0.16.[14] Hence, the calculated $\widehat{VTT}$ are 210 NOK for morning trips and 135 NOK for evening/weekend trips.

These results are not directly comparable to the "official" values used in transport appraisals in Norway. Although not directly comparable, a comparison with existing SP estimates provides a reality check of whether the values are different. A justification for why the national average could be used as a comparison is that both the income level and the industry structure in the area do not differ significantly from the national average.[15] This comparison shows that the estimated VTT for morning trips is twice as high as the weighted VTT for commuting trips, while the VTT for evening/weekend trips is approximately 60% higher than that for leisure trips.[16] Even if we assume that all trips are longer than 70 km, where the share of business trips is higher than for short trips (11% in the last

[14] Since total traffic is a broad category, we hypothesize that the main factor that determines the distribution is the alternative cost of travel, which should be correlated by earnings. This is, however, a strong assumption.

[15] The wage level in the county where the road is situated (Agder) is 3–4% above the national average, while the wage at the municipality level (Tvedestrand and Grimstad) is 15% below the national average, according to monthly earnings from Statistics Norway from 2020 (Table 12,852).

[16] In the morning, the share of commuter trips was 80%, the share of leisure trips was 17%, and the share of business trips was 3%, according to the last Norwegian travel survey. In the evening, the shares were 10% commuting trips, 88% leisure trips, and 2% business trips.

Table 7 Factors varied in the sensitivity analysis

Period	Sensitivity factor		Unit	Baseline value	Sensitivity value (High/Low)
Morning	(1)	Standard deviation (σ)	NOK	31	46.5/15.5
	(2)	Route change (ω)	Percent	− 22	− 30/− 45
	(3)	$z(\omega)$ = Log norm. distribution	Quantile	− 0.77	− 0.46
	(4)	Passenger factor	Persons per vehicle	1.1	1
	(5)	The boundary of value of time (*BVOT*)	NOK	186	169/265
	(6)	Omitted comfort factor	Percent	0	− 20
Evening/Weekend	(1)	Standard deviation (σ)	NOK	18	27/9
	(2)	Route change (ω)	Percent	− 18	− 20/− 35
	(3)	$z(\omega)$ = Log norm. distribution	Quantile	− 0.92	− 0.40
	(4)	Passenger factor	Persons per vehicle	1.9	1
	(5)	The boundary of value of time (*BVOT*)	NOK	119	98/153
	(6)	Omitted comfort factor	Percent	0	− 20

Each factor is changed one by one in the evaluation of Eq. (6)

survey of Grue et al. 2021), than the weighted average is well below the estimated VTT. Although the exact difference is open to discussion, the results, especially for morning trips, seem to be higher than the "official" VTT used in appraisals.

Sensitivity analysis

To investigate the robustness of the results, we vary all the factors determining *VTT* in Eq. (6). The following factors are changed: the standard deviation (σ), the estimated trip change (ω), the distribution $z(.)$, the *BVoT*, the load factor, and the possibly omitted comfort factor. Each component is varied by setting a higher and lower value than the baseline values used in Table 6, and the components are varied one by one to isolate the effect.

Table 7 displays the input for the sensitivity analysis. First, the standard deviation was changed by 50% in both directions. Second, we varied the estimates of the share of trips that changed routes. For this factor, we used the estimated coefficients reported in Table 4 and added two standard deviations in each direction to obtain an upper and lower bound estimate of the effects. These bounds imply that we varied the estimates within the 95% confidence interval of the coefficient estimates. Third, we used a standardized lognormal distribution instead of a standardized normal distribution in the calculation. Fourth, we set the passenger factor to unity. Fifth, we changed the *BVoT*. These values were set based on a range of different travel time reductions during the day, as presented in Table 2. Sixth, we accounted for the possible omitted comfort factor. This factor could be interpreted as being included in the fixed component c in Eq. (2). According to a study looking at exactly the same route, comfort might explain 20% of the difference in preferences for the new route

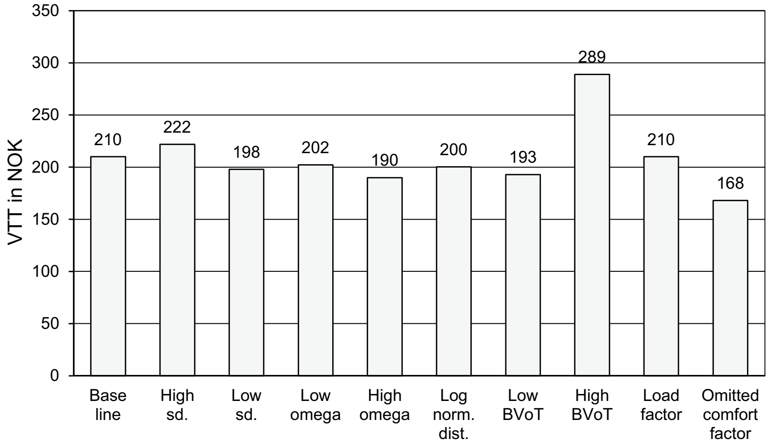


Fig. 5 Sensitivity analysis of VTT for morning trips

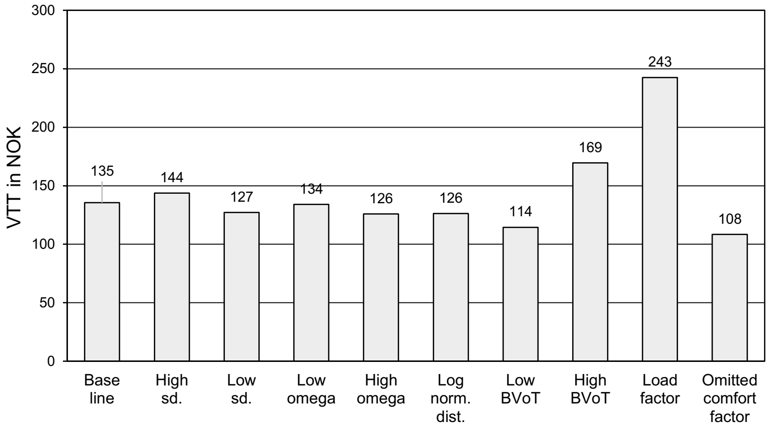


Fig. 6 Sensitivity analysis of VTT for evening/weekend trips

(Flügel et al. 2020a). Using this result, the estimates could be upward biased by approximately 20% because of the comfort factor component.

Figures 5 and 6 display the results of the sensitivity analysis. The height of the bars shows the calculated VTT for the different scenarios. The baseline estimates from Table 6 are displayed as the first bar, and the bars to the right show the results using the alternative specifications

Overall, the sensitivity analysis shows that the most crucial assumptions are the *BVoT* value, the possibly omitted comfort factor, and the load factor. Comparing the two figures, it is evident that the value of time is more uncertain for the evening/weekend period than for the morning period. In particular, party size (passenger factor) is a crucial element. It is reasonable to assume that the party size is approximately one in the morning, but for the other periods, the size will probably vary much more. Varying the other factors typically results in differences of approximately 10–20%. The VTT calculated in this paper is higher than the most relevant comparisons (VVT estimates of commuting and leisure from Flügel et al. (2020b), for short trips). For morning trips, the estimates are approximately 80–100% higher in most cases, while the difference for the valuation of evening/weekend trips is approximately 40–60% higher. Some of this difference is likely due to the inclusion of both business and commuting trips in our estimates; although such travels are few in the evening and weekend, they are certainly not zero.

In the empirical framework laid out in this paper, rational agents are assumed to choose routes. This hypothesis entails that all motorists know the generalized costs of the different routes and choose the route that minimizes the costs of the trips made. However, the literature shows that individuals make poor estimates of the total cost of road usage. Andor et al. (2020) show that while fuel costs are accurately predicted (this is also shown by Allcott 2013), the other components are underestimated, making the total vehicle cost underestimated. Moreover, the perceived travel time might be different from the "true" travel time (Varotto et al. 2017; Varela et al. 2018). Hence, we cannot know which travel costs the motorists base their decision on and how these costs affect behavior. These errors may affect both the questionnaire-based calculations and the observationally based calculations presented in this paper. In SP studies, however, there is no error in calculating the correct costs for each cost element. It may also be true in such cases that individuals make errors in calculating the generalized costs—that is, in the mental task of calculating generalized costs correctly—for each alternative.

The results of the analysis in this paper are only directly applicable to the context of similar situations. That is, the valuation of travel time applies for short trips on a major highway (trunk road). The valuation of other modes of transport (e.g., public transport) in other settings (e.g., within dense city areas) may be very different.

Conclusion

This paper has suggested an alternative approach for estimating the value of travel time savings. The approach uses a case study with exogenous changes in travel costs and data from automatic traffic counts. The existence of two alternative routes and exogenous changes in tolls results in a situation that is used to calculate the value of time that balances the costs of choosing either of the routes. The identification of travel time valuation is achieved through the assumption that motorists with a travel time valuation below the BVOT are those who change routes. This approach provides a framework that could reduce bias from strategic behavior or self-selection from an interview-based evaluation. To the best of our knowledge, the framework suggested in this paper is the first to use data from automatic traffic counts when studying travel-time valuations.

The approach of estimating VTT in this paper differs from the standard approach in Norway in several respects. Although not directly comparable the current estimates from Flügel et al. (2020a) these are the most relevant comparison to be made. Compared to the estimates of VTT in Flügel et al. (2020a), the result in this paper shows estimates that are substantially higher. If we compare the valuation of the morning trips with the commuting VVTs from Flügel et al. (2020a) they are roughly twice the size, while comparing the weekend VTTs to the leisure VTTs the estimates in this paper are roughly 50 percent higher. Since this comparison is far from exact, the quantification of the difference should be interpreted with cautiousness, but the comparison shows a non-negligible difference. Admittedly, the source of the bias could also come from other sources, such as response errors, but we cannot separate these sources from each other.

Of course, using passive data instead of interview-based data collection also has disadvantages. In particular, this implies that data on individual-specific components are unavailable. These components include trip purpose, wealth (income), and the use of discounts on a toll road, to mention a few. The advantage, however, is that there was no self-selection into the RP study. Undoubtedly, the approach taken in this paper can be improved, as it represents a first attempt to use traffic registration and a case study to infer the value of travel time savings. An important future research approach would be to separate out the effects of differences in comfort levels between different routes. Hopefully, this paper will inspire other researchers to refine the methodology and make use of the rapidly increasing number of new data sources available.

Appendix

Back-of-the-envelope calculation of traffic reduction

To calculate the reduction given by tolls, in addition to the reduction given by the season, we start with the definition of the reduction in traffic caused by tolls:

$$\frac{T_1}{T_0} - 1 = \omega$$

where T_1 is the observed traffic in September with tolls and T_0 is the counterfactual traffic in September without tolls. T_1 is 427. For unobserved traffic in September, we use the observed values from August of 667, which we adjust for the seasonal difference between traffic in August and September, which on average was 13% for the years 2015–2018 with available registration. Hence, $T_0 = \frac{667}{1.13} = 590$. Plugging the traffic values into the equation, we obtain.

$$\omega = \frac{427}{590} - 1 = 0.28.$$

Hence, the traffic reduction because of tolls is 28%.

Additional table from robustness analysis

.

Table 8 Estimates of the reduction in trips on New E18: Tvedestrand–Arendal after introducing tolls

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time	− 5.07e − 08	− 2.14e − 08	9.05e − 08	− 8.42e − 08	− 2.81e − 08	− 6.16e − 08	− 7.43e − 08	− 6.85e − 08
	(1.15e − 08)	(2.27e − 08)	(1.18e − 08)	(9.20e − 09)	(1.09e − 08)	(1.28e − 08)	(1.57e − 08)	(1.07e − 08)
Time^2	1.35e − 20	5.68e − 21	− 2.40e − 20	2.23e − 20	7.45e − 21	1.63e − 20	1.97e − 20	1.82e − 20
	(3.04e − 21)	(6.03e − 21)	(3.14e − 21)	(2.44e − 21)	(2.90e − 21)	(3.39e − 21)	(4.16e − 21)	(2.83e − 21)
Hour = 1	− 0.53	− 0.54					− 0.50	− 0.49
	(0.06)	(0.06)					(0.09)	(0.08)
Hour = 2	− 0.99	− 1.05					− 0.87	− 0.87
	(0.06)	(0.06)					(0.09)	(0.08)
Hour = 3	− 1.05	− 1.02					− 1.12	− 1.12
	(0.06)	(0.06)					(0.09)	(0.08)
Hour = 4	− 0.59	− 0.45					− 0.94	− 0.94
	(0.06)	(0.06)					(0.09)	(0.08)
Hour = 5	− 0.03	0.29					− 0.83	− 0.83
	(0.06)	(0.06)					(0.09)	(0.08)
Hour = 6	1.29	1.91					− 0.22	− 0.22
	(0.06)	(0.06)					(0.09)	(0.08)
Hour = 7	1.80						0.33	0.33
	(0.06)						(0.09)	(0.08)
Hour = 8	1.85		− 0.06				0.63	0.63
	(0.06)		(0.02)				(0.09)	(0.08)
Hour = 9	1.97						1.22	1.23
	(0.06)						(0.09)	(0.08)
Hour = 10	2.16			0.09			1.63	1.64
	(0.06)			(0.02)			(0.09)	(0.08)
Hour = 11	2.31			0.18			1.94	1.94
	(0.06)			(0.02)			(0.09)	(0.08)

Table 8 (continued)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hour = 12	2.39			0.24			2.07	2.08
	(0.06)			(0.02)			(0.09)	(0.08)
Hour = 13	2.47			0.32			2.14	2.15
	(0.06)			(0.02)			(0.09)	(0.08)
Hour = 14	2.57			0.45			2.19	2.19
	(0.06)			(0.02)			(0.09)	(0.08)
Hour = 15	2.74						2.19	2.19
	(0.06)						(0.09)	(0.08)
Hour = 16	2.66				− 0.10		2.16	2.16
	(0.06)				(0.02)		(0.09)	(0.08)
Hour = 17	2.44						2.06	2.16
	(0.06)						(0.09)	(0.06)
Hour = 18	2.29					− 0.20	2.02	2.00
	(0.06)					(0.04)	(0.09)	(0.06)
Hour = 19	2.11					− 0.36	1.82	1.83
	(0.06)					(0.04)	(0.09)	(0.06)
Hour = 20	1.85					− 0.63	1.56	1.57
	(0.06)					(0.04)	(0.09)	(0.06)
Hour = 21	1.60					− 0.88	1.32	1.32
	(0.06)					(0.04)	(0.09)	(0.06)
Hour = 22	1.13					− 1.35	0.86	0.85
	(0.06)					(0.04)	(0.09)	(0.06)
Hour = 23	0.52					− 1.99	0.32	0.24
	(0.06)					(0.04)	(0.09)	(0.06)

Table 8 (continued)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tolls (ω)	− 0.22	− 0.31	− 0.39	− 0.17	− 0.26	− 0.29	− 0.10	− 0.18
	(0.04)	(0.07)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)
Monday	− 0.00							− 0.46
	(0.03)							(0.04)
Tuesday	− 0.17	− 0.45	− 0.06	− 0.13	− 0.01	− 0.01		− 0.47
	(0.03)	(0.05)	(0.03)	(0.02)	(0.03)	(0.03)		(0.04)
Wednesday	− 0.12	− 0.48	− 0.07	− 0.05	0.09	0.12		− 0.34
	(0.03)	(0.05)	(0.03)	(0.02)	(0.03)	(0.03)		(0.04)
Thursday	− 0.03	− 0.39	− 0.10	0.01	0.17	0.25		− 0.20
	(0.03)	(0.06)	(0.03)	(0.02)	(0.03)	(0.03)		(0.04)
Friday	0.11	− 0.37	− 0.23	0.21	0.40	0.52		0.07
	(0.03)	(0.05)	(0.03)	(0.02)	(0.03)	(0.03)		(0.04)
Saturday	− 0.11						− 0.10	− 0.11
	(0.03)						(0.03)	(0.02)
Period	Total	Night	Morning	Day	Afternoon	Evening	Weekend	Evening/weekend
Observations	1848	378	108	324	108	379	528	907
Adjusted R^2	0.92	0.90	0.77	0.85	0.90	0.94	0.94	0.94

Full list of covariates

Standard errors in parentheses. The parameter estimate of tolls refers to the estimate of ω from Eq. 6. Estimation period: August 1–October 16, 2019. The models in Columns 1–8 are estimated separately. “h” denotes the time of day

Table 9 Robustness check: Estimates of the reduction in trips on New E18: Tvedestrand–Arendal after introducing tolls. Short sample I

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tolls	− 0.24	− 0.34	− 0.36	− 0.20	− 0.27	− 0.32	− 0.10	− 0.20
	(0.04)	(0.08)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)
Period	Total	Night	Morning	Day	Afternoon	Evening	Weekend	Evening/weekend
Observations	1465	301	86	258	86	302	432	734
Adjusted R-squared	0.92	0.90	0.82	0.87	0.90	0.93	0.95	0.94

Standard errors in parentheses. Estimation period: August 1–October 1, 2019

Table 10 Robustness check: Estimates of the reduction in trips on New E18: Tvedestrand–Arendal after introducing tolls. Short sample II

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tolls	− 0.15	− 0.07	− 0.24	− 0.19	− 0.20	− 0.19	− 0.09	− 0.15
	(0.06)	(0.13)	(0.04)	(0.04)	(0.04)	(0.07)	(0.10)	(0.06)
Period	Total	Night	Morning	Day	Afternoon	Evening	Weekend	Evening/weekend
Observations	673	140	40	120	40	140	193	333
Adjusted R-squared	0.91	0.90	0.91	0.87	0.94	0.93	0.93	0.94

Standard errors in parentheses. Estimation period: August 18–September 15, 2019

Table 11 Robustness check: Estimates of the reduction in trips on New E18: Tvedestrand–Arendal after introducing tolls. Alternative definitions of times of day

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tolls	− 0.22	− 0.28	− 0.38	− 0.18	− 0.21	− 0.29	− 0.10	− 0.18
	(0.04)	(0.08)	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.04)
Period	Total	Night 23–06	Morning* 06–09	Day* 09–15	Afternoon* 15–18	Evening* 18–23	Weekend	Evening / week-end
Observations	1848	324	184	400	130	347	440	787
Adjusted R-squared	0.92	0.71	0.98	0.87	0.93	0.93	0.95	0.94

Standard errors in parentheses. Estimation period: August 1–October 16, 2019

*Different definitions of time of day

Table 12 Robustness check: Estimates of the reduction in trips on New E18: Tvedestrand–Arendal after introducing tolls. Specification without quadratic time term

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tolls	− 0.30	− 0.34	− 0.26	− 0.30	− 0.30	− 0.38	− 0.20	− 0.27
	(0.03)	(0.07)	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.03)
Period	Total	Night	Morning	Day	Afternoon	Evening	Weekend	Evening/weekend
Observations	1848	378	108	324	108	379	528	907
Adjusted R-squared	0.91	0.90	0.63	0.81	0.90	0.93	0.94	0.94

Standard errors in parentheses. Estimation period: August 1–October 16, 2019

Table 13 Robustness check: Estimates of the reduction in trips on New E18: Tvedestrand–Arendal after introducing tolls. Dependent variable: Vehicles per hour

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tolls	− 65.97	− 28.31	− 200.22	− 68.64	− 204.68	− 59.77	− 37.64	− 46.94
	(11.93)	(5.68)	(17.37)	(19.01)	(28.63)	(16.14)	(22.39)	(14.79)
Period	Total	Night	Morning	Day	Afternoon	Evening	Weekend	Evening/weekend
Observations	1848	378	108	324	108	379	528	907
Adjusted R-squared	0.84	0.93	0.79	0.83	0.91	0.89	0.85	0.86

Standard errors in parentheses. Estimation period: August 1–October 16, 2019

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