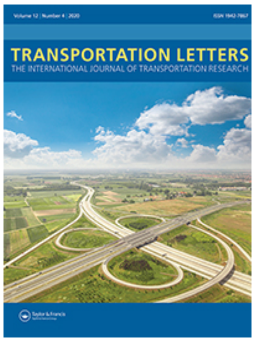

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Transportation Letters
The International Journal of Transportation Research

ISSN: 1942-7867 (Print) 1942-7875 (Online) Journal homepage: https://www.tandfonline.com/loi/ytrl20

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To cite this article: Askill Harkjerr Halse, Vegard Østli & Marit Killi (2020) Revealed and stated preferences for reliable commuter rail in Norway, Transportation Letters, 12:4, 288-292, DOI: 10.1080/19427867.2019.1586088

To link to this article: https://doi.org/10.1080/19427867.2019.1586088

TRANSPORTATION LETTERS
2020, VOL. 12, NO. 4, 288–292
https://doi.org/10.1080/19427867.2019.1586088

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Revealed and stated preferences for reliable commuter rail in Norway

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ABSTRACT

We study the effect of travel time reliability on passenger demand using a rich data set on period tickets and train delays over time for commuter trips in the Oslo capital region in Norway. We estimate the relationship between delays and demand using origin-destination fixed effects, which controls for any unobserved time-invariant heterogeneity across stations. The results show a negative effect of delays on demand, but smaller than the effect implied by stated preferences. As a possible explanation for this, we consider a reverse causal relationship, where high demand causes passenger crowding which again results in more delays. Splitting the sample into trips that start at crowded stations within the city-zone and trips that do not, we find evidence indicating that crowding is biasing the estimates towards zero.

KEYWORDS

Value of reliability; elasticity of demand; railway; stated preference; revealed preference

Introduction

Do rail commuters 'vote with their feet' and abandon the train if service reliability is low? Evidence from stated preference (SP) studies show that travelers are willing to pay for more reliable transport (Li, Hensher, and Rose 2010; Carrion and Levinson 2012). In this paper, we investigate to what extent this is also reflected in their actual choice of transport services, looking at the market for commuter rail in Norway.

In economic analysis of transport demand, the preferences of travelers can be inferred from either data on (1) their actual choices *(revealed preferences, RP)* or (2) data on choices between hypothetical alternatives *(stated preferences, SP)*. SP data is a useful supplement to RP data because the researcher can control the characteristics of the alternatives, which ensures that the parameters of interest can be identified. The drawback of SP data is its hypothetical nature.

Our study, therefore, serves as a validation of the existing SP evidence on the value of travel time reliability. It is made possible due to a rich disaggregated data set on period tickets and train delays for 412 origin-destination (O-D) station combinations for commuting into and out of the Oslo metropolitan area in Norway. Using monthly data covering 2010–2013, we estimate the effect of delays on demand using fixed effects estimation which accounts for unobserved time-invariant characteristics of each O-D. Our approach is similar to the one by Batley, Dargay, and Wardman (2011) from the UK and van Loon, Rietveld, and Brons (2011) from the Netherlands, except that the latter is based on yearly data. Wardman and Batley (2014) give a review of other similar studies from the UK.

We study a market in which there is tight competition between rail and other modes of transport (car and express coach). Hence, we expect commuters to have relatively high freedom in choosing their preferred mode of transport, and changing mode if service quality is not satisfactory. In the longer term, commuters could also adjust by moving or switching jobs to avoid the commute, which would result in even lower demand for rail services.

Our results show that the demand elasticity with respect to average delay is about -0.04. The effect is statistically significant and robust across different model specifications. Like Wardman and Batley (2014), we find that the estimated elasticity is substantially lower than the implicit elasticities we get when using evidence from SP studies and data for the relevant commuting trips.

The previous studies of this kind (Batley, Dargay, and Wardman 2011; van Loon, Rietveld, and Brons 2011) do not consider the possibility of a reverse causal relationship, where high demand causes passenger crowding which again results in delays. Crowding, defined as the number of travelers per square meter onboard or at the platform, could result in train delays because the train needs to spend more time at each station for people to be able to board and leave the train. We address this by looking at morning and return trips starting at stations within and outside the Oslo metropolitan area, exploiting that crowding is more severe within this area. We find evidence indicating that the effect of delays on crowded train lines is biased towards zero. This could explain part of the discrepancy between SP and RP results.

Apart from the studies mentioned above, the methods used in our paper are also related to studies of other modes of transport. Several studies have estimated travel demand elasticities for air transport with RP data using panel data approaches with origin-destination (O-D) combinations as observational units (Garín-Muñoz et al 2007; Tsekeris 2009; Rey, Myro, and Galer 2011). Similar methods have also been applied to investigate the competition between rail and air transport (Clewlow, Sussman, and Balakrishnan 2014). These studies find that factors such as ticket price, service frequency, income, population density, and travel time are important determinants of travel demand, while the role of travel time reliability is often neglected due to lack of available disaggregated travel time data for different O-D combinations over time.

Below, we first present our data on period tickets and train reliability. We then explain our empirical strategy and show the estimated effects of reliability on passenger demand. Finally, we compare our results with evidence from a Norwegian SP study and discuss our findings.

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Data: commuter rail in Norway

Revealed preferences can be estimated both based on data on the individual level and data on a more aggregate level. In this study, we rely on data aggregated on combinations of origin and destination (O-D), defined as the station of departure and arrival, respectively, on the morning trip (typically a work trip). We use data on reliability both for the morning trip (to work) and the return trip in the afternoon.

To measure passenger demand, we use period ticket data from the national publicly owned railway operator NSB. Our data cover all period tickets for trips between the Oslo metropolitan area (Oslo county and Akershus county) and the surrounding counties from 2010 to 2013.[1] The length of these trips is typically between 40 km (e.g. Drammen–Oslo) and 100 km (e.g. Tønsberg–Oslo). The advantage of using this data compared to data on shorter commuter trips within the Oslo area is that tickets are sold for one specific O-D combination, which allows us to use variation both between lines and stations on the same line for identification.

There is tight competition between modes of transport in this market. According to a survey by Engebretsen et al. (2012), about half of the commuters alternate between different modes, and 25% have used a different main mode previously. Fifty-six percent of commuters have railway as their main mode of transport. Travel time is similar by train and by car for those who live close to a railway station.

Our data on train reliability was extracted from the database of the National Railway Directorate, which includes the time of arrival of all trains at all stations. We have identified which trains are relevant for each (O-D) based on the train reporting number ('headcodes') of each train, assuming that trips are made during the morning and evening commute. The trains serve eight different lines running in two directions. We have data on 412 O-Ds with a direct train connection.

O-Ds can be segmented into *inward* commutes (to Oslo/Akershus from the counties outside), *outward* commutes (from Olso/Akershus to the outside) and *other* commutes (from and to a station outside Oslo/Akershus). Table 1 shows that O-Ds are very heterogeneous with respect to passenger volume. Volumes are particularly high for inward commutes to Oslo central station from near medium-sized cities like Drammen and Moss, while other O-Ds have months without any period ticket holders at all.

Delays are higher and vary more for return trips on inward commutes and morning trips on outward commutes. Average delays are within the range reported by Wardman and Batley (2014) for Great Britain (5.2 minutes for long-distance trains to and from London and 1.2 minutes for non-commuters within Greater London) and somewhat higher than the numbers reported by van Loon, Rietveld, and Brons (2011) for the Netherlands (1.4–1.8 minutes).

Effect of unreliability on demand

Our main objective is to identify how the level of train reliability affects whether people choose to commute by train. Using the data described in the previous section, we estimate the effect of reliability on demand using linear regression with O-D fixed effects (Wooldridge 2010, 300), which controls for any time-invariant characteristics of each O-D that could affect demand. Below, we explain our empirical strategy before showing our results.

Empirical strategy

We estimate the following relationship:

$$\begin{aligned}\ln(Q_{it}) &= \alpha_i + \theta_t + \beta ln(Delay_{it}) + \gamma_1 ln(Mtrains_{it}) \\ &\quad + \gamma_2 ln(Rtrains_{it}) + \varepsilon_{it} \qquad (1)\end{aligned}$$

where i indicates O-D and t indicates month. Q_{it} is the number of tickets, $Delay_{it}$ is the average delay (morning plus return trip) per day and $Mtrains_{it}$ and $Rtrains_{it}$ is the number of trains serving the O-D on the morning and return trip, respectively. The α_i are O-D fixed effects, and the θ_t are time fixed effects. The log-log specification implies that β can be interpreted as the elasticity of demand with respect to unreliability.

Average delay is chosen as the measure of reliability because it is a relatively simple and intuitive measure. When using month-to -month variation, alternative measures are likely to show a similar pattern. Preliminary results based on a model that instead included the share of long delays (10 minutes or more) gave results similar to those reported below (Halse et al. 2015).

As seen in the previous section, passenger volume varies greatly between O-Ds. O-Ds with very few commuters will have high relative changes in volume, resulting in very heteroscedastic error terms and low precision in an unweighted regression model. We, therefore, weight the observations by the average number of period ticket holders for each O-D.

Table 1. Period ticket holders and train delays (average minutes per train) for each origin and destination.

Variable	Obs	Mean	Std. Dev.	Min	Max
Inward commutes (to Oslo/Akershus):					
Period tickets	6,486	34.9	84.0	0.0	973.0
Delay, morning	6,486	2.2	1.5	0.1	11.1
Delay, return	6,486	3.7	2.2	0.1	16.0
Outward commutes (from Oslo/Akershus):					
Period tickets	5,657	11.2	22.8	0.0	245.0
Delay, morning	5,657	2.9	1.9	0.1	14.2
Delay, return	5,657	2.6	1.8	0.1	15.1
Other (outside Oslo/Akershus):					
Period tickets	5,679	6.6	12.5	0.0	127.0
Delay, morning	5,679	2.4	1.9	0.1	14.2
Delay, return	5,679	3.4	2.1	0.0	14.8
All commutes:					
Period tickets	17,822	18.3	54.2	0.0	973.0
Delay, morning	17,822	2.5	1.8	0.1	14.2
Delay, return	17,822	3.3	2.1	0.0	16.0

Note: Morning trips are defined as trips starting and ending between 4 AM and 10 AM. Return trips are trips starting and ending between 3 PM and 7 PM.

The identifying assumption is that there are no omitted variables that are correlated with the error term ε_{it}. Controlling for the number of trains is important because the timetable involves a trade-off between service frequency and reliability. Not controlling for frequency could, therefore, bias the estimated effect of delays on demand. Ticket price is not included since we do not have data on prices for each O-D over time. This is unlikely to be a big problem in our case since all O-Ds are operated by the same train operator (NSB), which sets prices mainly based on distance and not strategically as a reaction to local demand.

If crowding onboard or at the station causes the train to spend more time at each station, there could be a reverse causal link going from demand to reliability. In our case, since passenger volumes are much higher close to Oslo city center, passengers who commute to Oslo/Akershus from the outside ('inward commuters') contribute very little to crowding during the morning commute. However, they do contribute during the afternoon commute. Equivalently, those who commute out of Oslo ('outward commuters') contribute to crowding in the *morning*,[2] but hardly in the afternoon. We, therefore, investigate whether the estimated effect of delays differs between morning and return trips and by commuting direction.

Obviously, commuters do not only choose travel mode based on the quality of service. How convenient it is to use a particular mode also depends on where one lives and works, type of occupation, family situation, health, etc. We do not expect such characteristics to show a very different development for different O-Ds during the sample period, but this cannot be ruled out completely.

Results

Table 2 shows that the effect of train delays on passenger demand is negative and statistically significant. The results are similar when only controlling for season fixed effects and a linear time trend (column 2) and a full set of time fixed effects (column 3), and when adding different trends for each of the eight lines (column 4). When not controlling for season fixed effects (column 1), the estimated effect of delays on demand is somewhat higher, reflecting that reliability is correlated with seasonal variation.

Column (5) shows the results of a specification including both delays in the current and previous month. The disadvantage of this approach is that observations are lost if the previous month is missing for the same O-D. Since delays in the current and previous month are highly correlated, the estimated effect of the former decreases when we include both. The total effect is however similar to the one in the model without a lagged term.

The results from the preferred specification in column (3) shows that a 1% increase in average delay results in a 0.04% drop in demand. This is the same as reported by Wardman and Batley (2014) for commuters in their meta-analysis of UK evidence, when both significant and non-significant results are included. In standardized terms, this implies that a one standard deviation increase in delays (0,47 log units) causes about 1/24 standard deviations (0,02 log units) lower demand, when standard deviations are based on time variation within each O-D.

A positive reverse causal relationship between demand and delays due to crowding would cause the estimated (negative) effect of delays on demand to be biased towards zero. This bias should be more severe for morning or return trips starting at a downtown station where crowding is an issue. In Table 3, we, therefore, show the estimated effects of morning and return delays separately for different trip directions.

When only considering inward commuting (column 2), we find no effect of delays on return trips, but a negative effect of delays on morning trips, although not statistically significant (p = 0.13). When looking at outward commutes (column 3), we find exactly the opposite: The effect of delays on return trips is negative, and in this case also statistically significant. This is consistent with a bias caused by crowding at downtown stations on the *return* trips of *inward* commuters and on the *morning* trips of *outward* commuters. The effects on other trips (column 4) are less precise, possibly reflecting the low passenger volumes in this sample.

If the true effect of a 1% increase in delays in *one direction* is 0.03 or 0.05, as indicated by the results in columns (2) and (3) of Table 3, the effect of a 1% increase delay in *both directions* should be between approximately 0.06 and 0.10. This is higher than the point estimate in column (3), but still a modest effect, as discussed in the next section. There could also be other explanations for the differences in the effects observed here.

Comparison with stated preferences

Above, we have shown that time-variation in train delays and period ticket holders within O-Ds can be used to identify the effect of reliability on passenger demand. The estimates show that the demand elasticity with respect to delays is between

Table 2. The effect of train delays on demand for period tickets.

	(1)	(2)	(3)	(4)	(5)
Delay, morning+return	−0.09***	−0.05***	−0.04***	−0.05***	−0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Delay, morning+return (t-1)					−0.03**
					(0.01)
No. of trains, morning	−0.19	0.05	0.11	0.01	0.11
	(0.13)	(0.12)	(0.12)	(0.10)	(0.12)
No. of trains, return	−0.11	−0.05	−0.00	0.08**	−0.00
	(0.07)	(0.05)	(0.05)	(0.04)	(0.05)
Time trend	0.01***	0.01***			
	(0.00)	(0.00)			
Observations	17,822	17,822	17,822	17,822	15,701
R-squared	0.08	0.50	0.57	0.58	0.59
Season fixed effects	No	Yes	No	No	No
Time fixed effects	No	No	Yes	Yes	Yes
Line-specific trends	No	No	No	Yes	No

Note: All variables except time are in logarithms. All specifications include origin-destination (O-D) fixed effects. Each column indicates which explanatory variables are included and whether the model includes additional fixed effects or time trends. The number of observations is lower in column (5) because average delay in the previous month is missing for some observations. Observations are weighted based on the average number of period ticket holders. Standard errors clustered on origin and destination. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 3. The effect of train delays on morning and return trips on demand for period tickets, by travel direction.

	(1)	(2)	(3)	(4)
	All	Inward	Outward	Other
Delay, morning	−0.00	−0.03	−0.00	0.01
	(0.01)	(0.02)	(0.01)	(0.02)
Delay, return	−0.03***	−0.00	−0.05***	0.03
	(0.01)	(0.02)	(0.02)	(0.02)
No. of trains, morning	0.12	0.34*	−0.01	0.08
	(0.12)	(0.18)	(0.08)	(0.24)
No. of trains, return	−0.01	−0.06	−0.09	0.07
	(0.05)	(0.04)	(0.08)	(0.27)
Observations	17,822	6486	5657	5679
R-squared	0.57	0.70	0.45	0.38
Season fixed effects	No	No	No	No
Time fixed effects	Yes	Yes	Yes	Yes
Line-specific trends	No	No	No	No

Note: All variables are in logarithms. All specifications include origin-destination (O-D) fixed effects. The different columns show results for (1) all commuting trips, (2) trips to Oslo/Akershus from the regions outside, (3) trips from Oslo/Akershus to the regions outside and (4) trips with both origin and destination outside Oslo/Akershus. Observations are weighted based on the average number of period ticket holders. Standard errors clustered on origin and destination. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Demand elasticities with respect to delays, based on stated preferences (SP).

Trip	VTTS	RR	Delay (min.)	Price (NOK 2017)	Price elasticity (η_P)	Delay elasticity (η_D)
Drammen – Oslo	103	2.05	5.1	69.2	−0.65	−0.17
Tønsberg – Oslo	103	2.05	7.4	134.0	−0.65	−0.13
Fredrikstad – Oslo	103	2.05	7.3	125.8	−0.65	−0.13
Hamar – Oslo	103	2.05	6.2	153.4	−0.65	−0.09
Drammen – Oslo	103	2.05	5.1	69.2	−0.39	−0.10
Tønsberg – Oslo	103	2.05	7.4	134.0	−0.39	−0.08
Fredrikstad – Oslo	103	2.05	7.3	125.8	−0.39	−0.08
Hamar – Oslo	103	2.05	6.2	153.4	−0.39	−0.06

Note: Delay refers to the average total delay per day (morning and return trip) and price refers to the average price per day if the commuter travels every working day (Monday–Friday).

−0.04 and −0.10, depending on the potential bias due to reverse causality. Is this a big or small effect?

Following Wardman and Batley (2014), the *implicit demand elasticity with respect to delays, η_D*, can be calculated as:

$$\eta_D = \frac{VTTS/60 \cdot RR \cdot Delay}{Price} \cdot \eta_P$$

where *VTTS* is the value of travel time savings (in NOK per hour) and *RR* is the 'reliability ratio',[3] the value of a reduction in delays relative to a corresponding reduction in travel time. *Delay* is average delay (in minutes), *Price* is ticket price (in NOK) and η_P is the price elasticity.

Table 4 shows examples of such implicit delay elasticities, based on the SP results from the official Norwegian valuation study (Samstad et al. 2010) for commuting trips of 50 kilometers or more by train. Furthermore, we use price elasticities from two different studies: de Jong et al. (2002) find a price elasticity of −0.65 for commuters using public transport in Norway. The more recent study by Flügel et al. (2015) focuses on urban railway trips in particular but does not distinguish between trip purposes. Their price elasticity of −0.39 could reflect that leisure trips are less price sensitive.

Like Wardman and Batley (2014), we find that the implicit delay elasticities in Table 4 are higher than the ones estimated based on market data in Table 2 (which were between −0.04 and −0.05). However, as argued in the previous question, the estimated elasticities would probably have been between −0.06 and −0.10 in the absence of reverse causality. This is close to the implicit delay elasticities in Table 4 if we assume that the moderate price elasticity (−0.39) is the correct one.

Discussion

Our results show that train delays have a negative effect on the number of commuters choosing the train, consistent with the evidence from stated preferences (SP) on the value of reliability. We also find evidence suggesting that the estimated demand elasticities are biased towards zero because of passenger crowding, which could explain part of the discrepancy between SP and RP results pointed out by Wardman and Batley (2014). However, even if we take this into account, the estimated elasticity is still at the lower bound of the range suggested by SP evidence.

Another explanation for low demand elasticities could be that commuters lack alternatives to their current mode of transport, which means that they cannot make choices based on the level of reliability in real life as much as they can in a hypothetical SP setting. However, the lack of alternatives should also dampen the price elasticities, which are estimated on revealed preference (RP) data. It is therefore not clear that this would affect the estimated elasticities based on ticket data differently than the implicit elasticities based on SP data.

Travelers, and consumers in general, do not always act as rational agents who choose the alternatives that give the highest utility. For instance, evidence from the London Underground shows that travelers can find better ways to travel if they are forced to experiment more (Larcom, Rauch, and Willems 2017). This and other types of limited rationality could also be relevant for the market that we study, although survey evidence suggests that many travelers do switch between travel modes.

Finally, it could be that the value of reliability based on SP data is biased upwards due to the hypothetical nature of SP. One challenge in this field is to present reliability in a format that respondents can understand (Tseng et al. 2009). Another is that survey respondents could answer strategically in an attempt to impact the results (Lu, Fowkes, and Wardman 2008).

For transport authorities and railway operators, our results suggest that improving reliability alone does not lead to massive increases in passenger volumes. However, the effect is not unsubstantial. The most conservative estimate ($\beta = -0.04$) implies that if average delay can be lowered from three minutes (Table 1) to, e.g., two minutes per train, passenger volumes would increase by about 2%.[4] Higher reliability also frees up track capacity, which means that one can increase service frequency and reduce crowding. Aiming for more precision in train operations could, therefore, be a profitable strategy in the long run.

Notes

1. We do not use data on trips starting and ending within the Oslo metropolitan area because they are covered by a zonal ticketing system which does not allow us to measure ticket volumes at a specific station.
2. Trains going outward are less crowded than trains going inward, but most trains go *through* the metropolitan area, with passengers boarding and getting off the train at different stations. Many of the outward commuters will, therefore, be boarding a crowded train, which gets less crowded as it leaves the metropolitan area.
3. This term is also used in some studies to describe the relative valuation of a reduction in the standard deviation of travel time and a reduction in travel time.
4. $0.04 \cdot (\ln(3) - \ln(2)) = 0.04 \cdot 0.41 = 0.016$.

Acknowledgments

We would like to thank Nils Fearnley, Kjell Werner Johansen, Tørris Rasmussen, Andreas Vigren and participants at the 1st Nordic Meeting in Transport Economics for comments on earlier versions of this manuscript. We are also grateful to NSB and The Norwegian National Rail Administration for sharing their data on monthly tickets and train reliability and to Andreas D. Landmark (SINTEF) for assistance in extracting the data. This paper is based on the project PRESIS, which is a cooperation between NNRA, CargoNet, NSB, Flytoget, SINTEF, TØI and NTNU. PRESIS has received support from the Norwegian Research Council, project code 227123.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by Norges Forskningsråd [227123].

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