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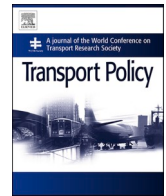
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Public transport fare elasticities from smartcard data: Evidence from a natural experiment

Yaroslav Kholodov [a], Erik Jenelius [b,*], Oded Cats [a], Niels van Oort [a], Niek Mouter [c], Matej Cebecauer [b], Alex Vermeulen [a]

[a] *Department of Transport and Planning, Delft University of Technology, the Netherlands*
[b] *Department of Civil and Architectural Engineering, KTH Royal Institute of Technology, Brinellvägen 23, SE, 100 44, Stockholm, Sweden*
[c] *Department of Engineering Systems and Services, Delft University of Technology, the Netherlands*

A B S T R A C T

This paper develops a method for analysing the elasticity of travel demand to public transport fares. The methodology utilizes public transport smartcard data for collecting disaggregate full population data about passengers' travel behaviour. The study extends previous work by deriving specific fare elasticities for distinct socioeconomic (e.g., car ownership and income) groups and public transport modes (metro, trains and buses), and by considering the directionality of the fare change. The case study involves a public transport fare policy introduced by the regional administration of Stockholm County in January 2017, where the zonal fare system for single-trip tickets was replaced by a flat-fare policy. The overall fare elasticity of travel funds is found to be −0.46. User sensitivity grows along with the journey distance. Metro users demonstrate the lowest sensitivity, followed by bus and commuter train riders. Low socioeconomic groups, in particular with respect to car ownership, tend to be less sensitive than the high-factor groups. In addition to the direct effect of changed fares, simplification and unification of the fare scheme appears to have substantially contributed to its attractiveness. The flat fare may allow the geographic disparity of public transport travel to be reduced and new users to be attracted from remote areas who are more prone to own cars.

1. Introduction

Fare policy is an essential component of any public transport system, not only to manage revenues, but also to steer towards specific policy goals. Changes in the fare structure may lead users to adjust travel habits, which may influence ridership and have substantial impacts on the economic, social, and environmental welfare of the region (Liu et al., 2019). McCollom and Pratt (2004) distinguish four main fare policy objectives: (i) increasing revenues, for instance because of growing operational costs or the need to recover an investment; (ii) maximising ridership in order to stimulate mobility, increase accessibility, contribute to the local economy or affect the modal split, which in turn would relieve congestion and improve the negative impact on the environment; (iii) triggering a ridership shift in time in order to reduce peak variability and utilize the system more efficiently; (iv) improving equity among users, for example with regard to a geographical or socioeconomic perspective, regarding the distribution of expenditures on fares and the level of service received.

To achieve (one of) the goals described above, public transport fare policy can alter the fare structure in the following directions (McCollom and Pratt, 2004): (i) changing the general fare level (the same relative change in all fare categories); (ii) changing fare relationships (deliberately introducing uneven changes in different fare categories); (iii) changing fare categories (introduction or withdrawal of a particular category); (iv) changing the fare structure basis (flat, zonal, distance- or time-based); (v) launching free public transport (eliminating fares completely or for specific periods, zones and services only).

There is a substantial body of literature available on travellers' response to public transport fare changes, analysed from various perspectives, different geographic scales, types of users and journeys and considering short-term and long-term effects (for an overview and references see Kholodov (2019)). Research shows that fare elasticity varies with socio-economic and demographic characteristics. Travellers dependent on public transport tend to be less sensitive to changes in fares compared to those with other travel options (Litman, 2019). Important indicators of public transport dependency include low

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* Corresponding author.
E-mail address: erik.jenelius@abe.kth.se (E. Jenelius).

income, disabilities, young and old age, no access to a private car, un-employment and/or high school and university students. However, income has two potentially counter-acting effects: high-income users tend to have higher car ownership rates, but also tend to have a higher tolerance to price increases (Balcombe et al., 2004; Litman, 2004).

Commuters tend to be less sensitive to the fare than travellers making a leisure journey (Cervero, 1990; McCollom and Pratt, 2004). Fare elasticities are higher for longer journeys (Balcombe et al., 2004) and during off-peak hours (Wang et al., 2015). Elasticities also vary across public transport modes and routes. For example, fare elasticities tend to be lower on routes served by a single mode and higher where people are provided with several alternative modes (Litman, 2019).

Despite the wide use of symmetric elasticities, some studies show that an increase in fare level induces a larger demand change compared to a fare reduction of the same magnitude. Existing travellers will look for alternatives sooner if transport becomes more expensive, whereas it is less likely that someone would change their behaviour immediately due to a price reduction (Litman, 2019).

Traditionally, travellers' sensitivity to supply changes is estimated based on aggregated cross-sectional and time series analysis, or disaggregate stated preference surveys. The latter collects users' direct responses on how they would change travel behaviour (e.g. by mode, frequency or time of day) due to a particular change (e.g., Whelan et al., 2008). However, passengers tend to overestimate their reaction to the policy and underestimate the cost of switching to alternatives, which adds bias to the analysis (Linsalata and Pham, 1991). Disaggregated revealed-preference studies have been rare until recently and were based mainly on limited data samples (Wardman and Shires, 2003). However, the emergence of automated fare collection (AFC) technologies (e.g. smartcards, see Pelletier et al., 2011) brings unprecedented opportunities for collecting disaggregate full population data about passengers' travel behaviour. Wang et al. (2018) utilize smartcard data to evaluate the demand impacts of a change from flat fares to distance-based fares and overall fare increase for the Beijing Metro in 2014. Data from one week before and one week after the policy change are used to assess the change in daily demand, split into weekdays and weekends, peak hours and off-peak hours, and different trip distances. The study finds an average fare elasticity of −0.316, higher on weekends than weekdays, and lower for longer trip distances.

The goal of this study is to add new evidence to the limited literature on revealed-preference fare elasticity from disaggregate data. The use of smart card data and the features of the natural experiment in Stockholm allows obtaining elasticities for different user groups as well as analysing directionality effects. To this end, we further develop the methodology for analysing the elasticity of demand to fare policy changes using smartcard data. The study considers a public transport fare policy introduced by the regional administration of Stockholm County (SLL) in January 2017, where the zonal fare system for single-trip tickets was replaced by a flat-fare policy. Our study assesses passengers' fare elasticities by comparing trip rates before and after the policy introduction. The paper extends the analysis of Wang et al. (2018) in several important dimensions. First, it complements smartcard data with socioeconomic data at the zone level based on an inferred home zone location for each cardholder. This allows for the derivation of specific demand elasticities for categories of income, car ownership, etc. Second, it broadens the scope of the analysis to all modes of public transport in the region, including buses and commuter trains. Third, the case study involves a fare change policy that involved fare increases for some travellers and reductions for others, which allows us to consider the directionality of the fare change on the demand response.

The outline of this paper is as follows: Section 2 gives a detailed description of the methodology and Section 3 describes the case study including the implemented policy change. Results are presented in Section 4, and a discussion of both the case-specific and general conclusions is provided in Section 5.

2. Methodology

Fare elasticity is defined as the percentage change in public transport demand after a one percent change in the fare, under the assumption that all other factors are kept constant. The elasticity sign defines the direction of this change: a positive value indicates growth in ridership, whereas a negative value indicates a decrease. Elasticity values below 1.0 (above −1.0) are referred to as inelastic, which means that the fare change brings relatively little effect on ridership. In contrast, values above 1.0 (below −1.0) are classified as elastic, which implies that a fare change causes relatively large shifts in public transport demand (Cervero, 1990). Elasticity η is here calculated with the mid-arc formula

$$\eta = \frac{(Q_2 - Q_1)(P_1 + P_2)}{(P_2 - P_1)(Q_1 + Q_2)} \tag{1}$$

where P_1, Q_1 and P_2, Q_2 are the prices and the number of trips before and after the policy change, respectively.

We extract direct fare elasticities from disaggregate smartcard data. The process consists of two main steps: extracting a travel diary of journeys for each individual card (the card id is persistent in the dataset throughout the analysis period) and associating each card with sociodemographic information collected for small census zones. The complete framework for processing the smartcard data into traveller journeys consists of four modules:

1. Tap-out location inference algorithm (TOLIA), which infers the stops and stations where the passengers exit or alight (adapted from Munizaga and Palma, 2016),
2. Vehicle inference algorithm (VIA), which infers the specific vehicles boarded in cases tap-in occurs at the station,
3. Travel time estimation algorithm (TEA), which infers the exit and alighting times, transfer times and in-vehicle travel times, and
4. Journey algorithm (JA), which concatenates trip legs into passenger journeys.

Fig. 1 visually summarizes the framework workflow. For a detailed description of the process the reader is referred to Cats et al. (2019), who describe algorithms for inference of tap-out locations, boarded vehicles, travel times, journeys, and home location. Here we give a brief description of the algorithms.

Stockholm County public transport is a tap-in only system. This means that for each individual trip $t_{c,i}$ made by the card c, the tap-out or alighting location is unknown. This location can be inferred based on the assumption used, also in Munizaga and Palma (2012), that the next trip in time order starts close to the tap-out location of the previous trip. The tap-out location of trip $t_{c,i}$ is inferred by searching for the tap-out location in close surrounding radius around the tap-in location of next trip $t_{c,i+1}$ (1 km in our case). The selected tap-out location has to be served by at least one line that serves up-stream the tap-in location of trip $t_{c,i}$.

In this study we fully rely on historical automatic vehicle location data (AVL), and thus the vehicle boarded must be known or inferred by the VIA algorithm for each trip to estimate travel time. For each trip with unknown vehicle, the boarded vehicle is inferred as the earliest vehicle approaching the stop/station from the tap-in time that serves the tap-out stop location downstream of the line. Once the vehicle is known, the trip travel time is inferred by the TEA algorithm as the vehicle travel time from the boarding tap-in location to the alighting tap-out location.

Finally, the JA algorithm aggregates sequential trips made by card c to journeys by using a set of time thresholds (based on mode change) to decide if the time gap is reasonable for transfer or if some activity took place on the location.

The home location, at the level of census zones, is used to link cards to socioeconomic factors related to the home zone. The algorithm applied in this study for identifying the home location partly utilizes the methodology from Aslam et al. (2018), adapted to the conditions of the
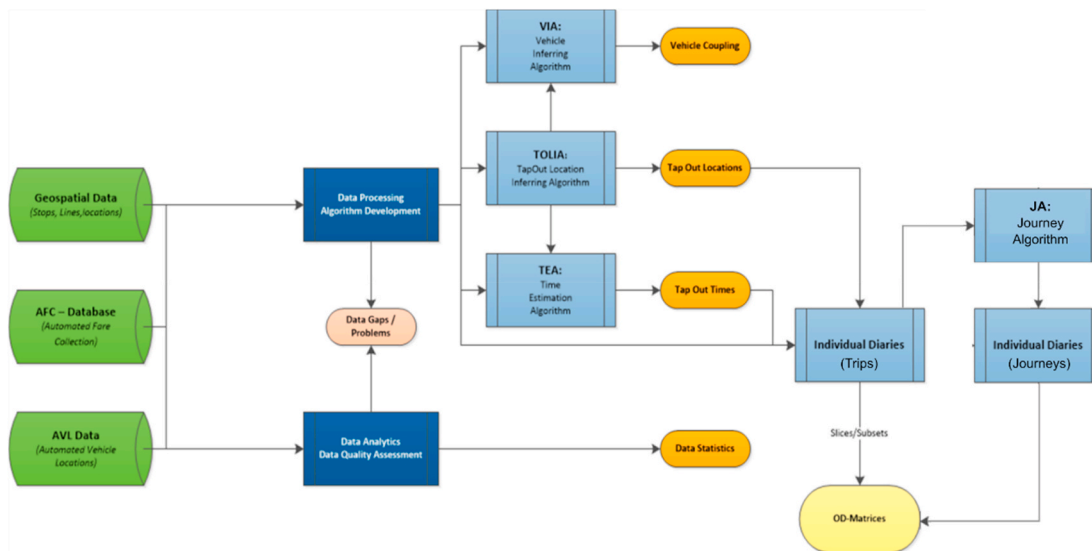
Fig. 1. Smartcard processing framework.

tap-in validation system. For each card, the algorithm records the frequency of days when the first trip of the day takes place from a particular zone. A suitable trip frequency threshold is specified to separate regular travellers, for which the home zone is inferred, from occasional travellers (see Section 3.3 for details on the case study application). For each regular traveller the area with the highest count is classified as home zone.

3. Case study

In this section we first provide an overview of Stockholm County and its public transport system, followed by a discussion of public transport fare structures: flat and three-zone structures. Last we present the data and case study settings.

3.1. Stockholm County and its public transport system

Stockholm County is located on the central east coast of Sweden and comprises 26 municipalities, including the City of Stockholm, the country's political, economic and cultural centre. The region was home to 2.3 million residents in 2018 (0.96 million in Stockholm City). The metropolitan region structure is monocentric with a large variability in population densities: from 285 inh./km^2 in rural areas to 4.100 inh./km^2 in Stockholm City.

Stockholm County has an extensive public transport system consisting of metro, commuter trains, light rail transit, trams, buses and ferries. The network has a clear hierarchy, where rail transport (with a total network length of 469 km) serves as a mass transit backbone at the regional level, accompanied by bus services (9079 km) (SLL, 2019). The mass transit network in Stockholm County is presented in Fig. 2 along with important urban areas and transfer points. In terms of access to the public transport system, around 76% of the population live within 1.2 km from the nearest train station (SLL, 2017).

The daily passenger volume is more than 800.000 people, which constitutes 32% of all journeys made in the region. Fig. 3 shows the share of public transport journeys for different geographical segments. Public transport serves 47% of all journeys within one municipality (14% of which are in Stockholm City) and further 26% to connect the central core with other areas, bringing people to and out of Stockholm City. In addition, 25% of the journeys are between municipalities other than Stockholm, including 14% of all journey taking place within either the Northern parts or the Southern parts of the County (without crossing the central parts).

Regarding public transport, the organisation Stockholm Public Transport (Storstockholms Lokaltrafik or SL) as a part of Region Stockholm is responsible for the provision of public transport services through long-term planning, procurement, establishment and control of standards for operation, quality and sustainability.

3.2. Public transport fare structure

The public transport fare structure in Stockholm County is relatively complex as it provides a wide range of travel products that are designed for different areas, periods, modes and user groups. Three product types constitute the majority of the demand: 30-day pass with the full and reduced fare, together accounting for 60% of the journeys and 35% of the cards; single-trip travel funds (full and reduced fare) accounting for 11% of the journeys and 40% of the cards; and general school passes with 9% of the journeys and 7% of the cards. These shares were largely unaffected by the fare policy change in 2017.

In terms of frequency, all product types have the same pattern of regular usage between 32 and 35 times during the analysis period. The school category involves less frequent yet still regular traveling (23 journeys for studying and 17 for leisure based on the time of use). As expected, travel funds are used by users who only travel occasionally with an average usage frequency of five trips within the analysis period.

The fare structure pertaining to travel funds and other single-trip tickets was in 2016 organised on a zonal basis, with three fare zones A, B and C as displayed in Fig. 4. Zone A covered the Stockholm City core and inner suburbs, zone B stretched over outer suburbs, and zone C included remote areas at the county's fringe. No zonal hierarchy was present in terms of pricing; it was only important how many zones a traveller traverses on a given journey. For example, a journey from zone A to zone B would cost the same as a journey from zone B to zone C.

Stockholm County has a tap-in only ticket validation system (including for pass holders), which means that the number of traversed zones on a trip cannot be automatically detected. This was handled by requiring each passenger to define a default number of zones based on which the corresponding fare would be charged for each journey. Any time the passenger would travel a non-default number of zones, this had to be adjusted manually at a ticket machine in advance or by communicating with the bus driver. This process led to some inconvenience for travellers using travel funds. A study by SLL (2016) showed that users found the zone-based system lacking in convenience and transparency.

The policy of January 2017 brought a shift from the zonal to a flat-fare basis. The fare zones were removed, and a single fare was applied
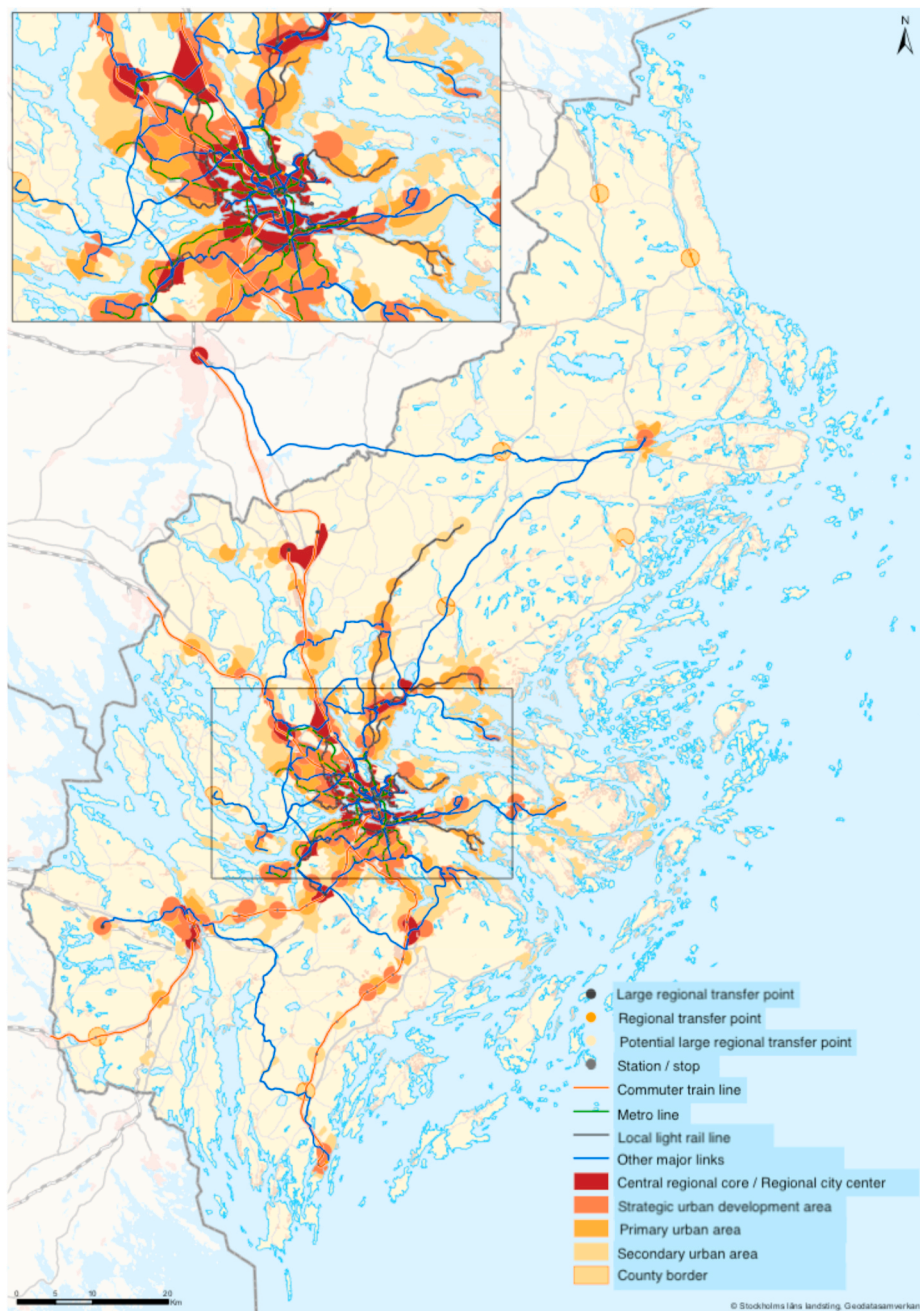
Fig. 2. Geographic location of public transport network (SLL, 2017).

to all journeys within the county. Generally, the administration formulated three main policy objectives: simplifying the fare system, increasing ridership for multi-zonal journeys and achieving a neutrally balanced economy. A direct effect of the removal of fare zones was a price change. With the new fare basis, traveling within one fare zone became more expensive while traveling through two and three fare zones became cheaper. Table 1 shows the single trip fares in 2016 and 2017 (10 SEK are approximately one EUR).

Travel funds are the only product group whose price scheme was substantially affected by the fare policy. The fare elasticity analysis in this paper is thus limited to the travel funds product group. It should be noted that there is a potential selection bias as travel funds users likely have different socioeconomic and public transport use characteristics than users of other ticket types (as evidenced by the trip frequency discussed above).

3.3. Data and case study settings

The core data source of this study consists of disaggregate smartcard data within the entire public transport network of Stockholm County for the years 2016 and 2017. Tap-in records have been matched with corresponding inferred tap-out locations and time stamps for about 80% of all records. In this case, each journey must have complete and different origins and destinations and must be taken within Stockholm County. Inbound and outbound journeys are excluded due to different characteristics, such as fares, operators, types of travellers, etc.

While offering a rich passively collected data source, using smartcard data has its limitations. Smart card data may be incomplete due to fare evasion and the co-existence of other ticket types. Fare evasion is prevalent across the world, albeit to varying extents; see Barabino et al. (2020) for a recent review. It is therefore necessary to correct observed
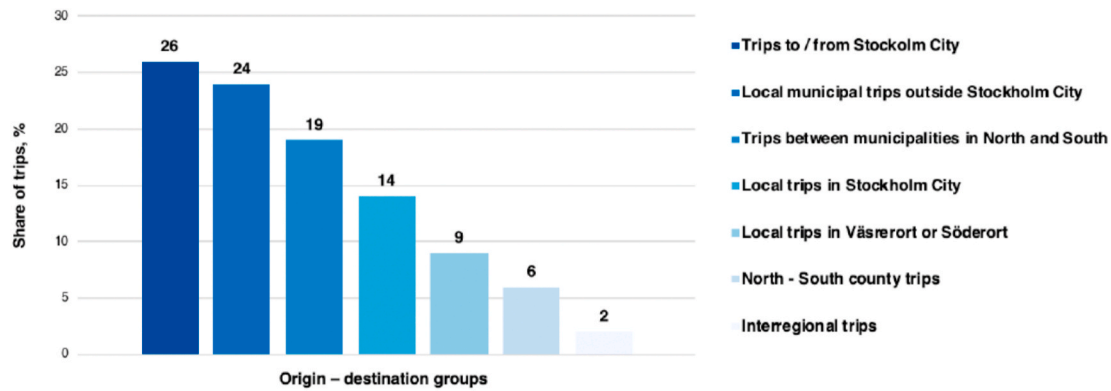
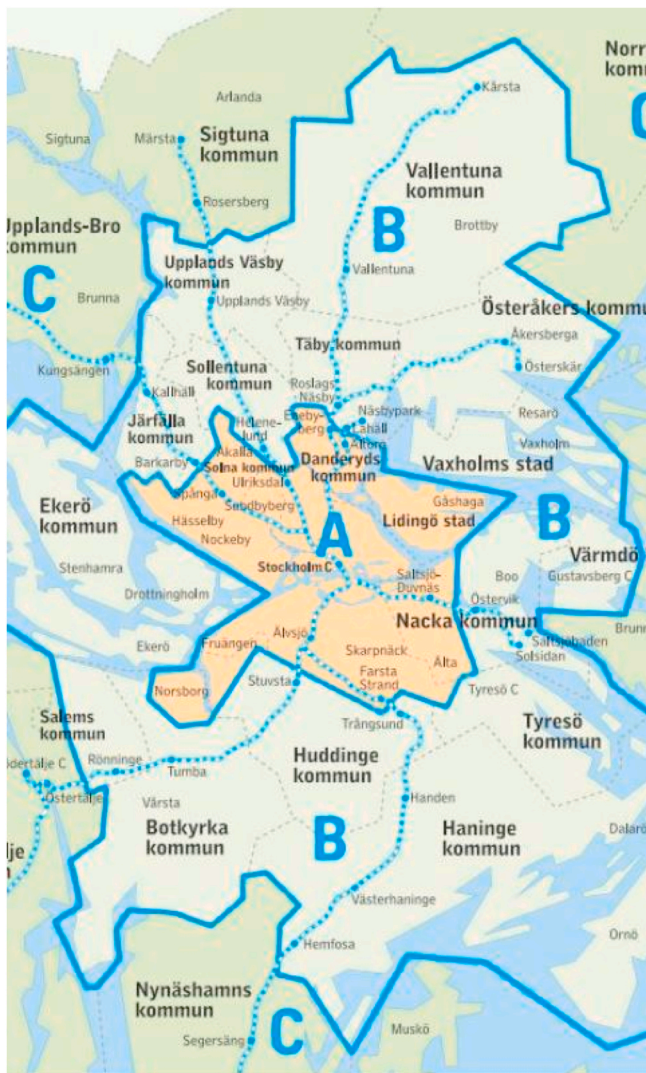**Fig. 3.** Spatial distribution of public transport journeys (SLL, 2019).

Fig. 4. Map of Stockholm public transport fare zones (before 2017). The distance between the northern and southern borders of zone B is ca. 80 km. Source: SLL, www.sll.se/verksamhet/kollektivtrafik/.

ridership levels based on the fare evasion rate, estimated to be approximately 3% by the Stockholm public transport authority for the analysis period considered in this study. According to the Stockholm public transport authority, other ticket types affected by the fare system change (mobile phone tickets, zonal and machine-purchased tickets) make up

ca. 6% of the ticket revenues in both 2016 and 2017, compared to 22% for travel funds. Since our interest lies in the analysis of ridership changes – before-after fare policy change comparison – we calculate elasticities based on the number of recorded journeys, avoiding having to make assumptions on the spatial distribution of fare evasion and other ticket types.

Another important data source is socioeconomic data collected by Statistics Sweden (SCB, 2019). The data are stored at the level of 1364 census zones and include names and codes of administrative areas, geospatial data, population split, median income, socioeconomic index, and car ownership. We populate for each stop in the public transport system the corresponding census and fare zone attributes based on its geographical coordinates.

For the purpose of the comparison at a general level, both the set of all users and the subset of regular users are used for the elasticity calculation. Only the subset of regular users, for which home zones are inferred, is utilised to compute specific elasticities for modes, periods, trip distance, car ownership and income levels. The selection of a threshold represents a trade-off between more reliable home zone identification and a larger set of travellers for the elasticity analysis. The relation between the number of cards that have their home zone identified and the visit frequency threshold was analysed based on empirical data of four months in 2016 and 2017 respectively (January, February, April and May). It was found that a value between 8 and 9 provides a separation point, after which the number of cards decreases at a slower and more steady rate. Hence, the threshold of visit frequency is set to be 9. The value is in line with the research by Aslam et al. (2018), who found a threshold of 5 trips for a two-month period.

To analyse the impact of the fare change, data from February 2016 and February 2017 are used. We selected February 2016 and February 2017 because operating conditions and demand patterns during these months were relatively unaffected by circumstances such as national holidays, public transport upgrades or breakdowns. The total number of tap-in records is 58.5 million for February 2016 and 59.0 million for February 2017. Most trips use metro (49%), followed by bus (37%), train (12%) and tram (2%). Approximately 65% of all journeys consist of a single trip/vehicle. The analysis is limited to the "travel funds" product group, which is the only product group whose price scheme was substantially affected by the fare policy.

Fare elasticities are calculated along multiple dimensions, such as socioeconomic characteristics, transport modes, travel period, travel distance, regularity of usage, fare category and directionality of fare change. The transport modes are metro, bus and commuter train. The time periods are an average weekday and weekend, with the weekday also split into morning peak, evening peak and off-peak. When it comes to travel distance, the journey accumulative share and features of each range are considered. We use the following distance intervals in our analysis: 0–1 km (walking distance, 6% of all journeys), 1–3 km (short urban journey, 33%), 3–5 km (average distance within a city, 50%),

Table 1
Stockholm public transport single trip fares in 2016 and 2017.

Trip	Fare 2016 (SEK)		Fare 2017 (SEK)		Absolute change (SEK)		Relative change (%)	
	Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced
1 zone	25	15	30	20	5	5	20	33
2 zones	37.5	22.5			−7.5	−2.5	−20	−11
3 zones	50	30			−20	−10	−40	−33

5–10 km (long urban journey, 75%), 10–20 km (inter-zonal distance for two zones, 95%), 20+ km (inter-zonal distance for three zones).

Three user groups are distinguished with respect to income and car ownership: the lowest 25%, middle 50% and highest 25% group. As a result, the income levels are 0–220, 220–350 and 350+ thousand SEK, and the car ownership groups are 0–0.25, 0.25–0.55 and > 0.55 cars/adult.

Within the elasticity of each factor, a split is made between fare categories and OD fare zones. In the former case, this means that full, reduced and combined fares of travel funds are distinguished. In the latter case, the OD groups indicate how many fare zones a user crosses. In order to acquire aggregate values, elasticities of each OD group are weighted based on the corresponding ridership share,

$$TE = \sum_{i=1}^{3} \eta_i * \frac{D_i}{TD} \qquad (2)$$

where TD and TE are the total demand and elasticity respectively, D_i and η_i are the corresponding demand and unweighted elasticity values for each fare zone OD group (1, 2 or 3 fare zones).

4. Results

This section presents the demand impacts of the fare system change. The overall zonal demand patterns and ticket product selection are analysed first, followed by the derived fare elasticities.

4.1. Travel demand

Table 2 presents the general demand split between fare zones for each OD pair. The passenger flow for the OD pair A-A is by far the highest, contributing 72% of the total ridership. The second most popular connection is A-B in both directions with around 8%–9% each. The internal ridership within zone B is also substantial with its share of 6%, whereas other combinations vary within the range of 0.5%–2%. A significant growth in absolute terms is noted for the OD pairs A-A, C-C and A-B (B-A), and in relative terms for the OD pair A-C (C-A) which is higher than the total average. This shows that travel patterns in Stockholm County are very core-oriented.

4.2. Product selection

An important assumption in using the before-after analysis of the

natural experiment is that of a static environment. Looking at statistical data of the region between years 2009 and, the annual growth of the population and Gross Regional Product demonstrates steady rates of 1.7% and 3.2%, respectively. This in turn results in a steady increase in public transport ridership of 1.5%–2.5% per year. The statistical data is in line with the findings of the current study, which confirms the existence of the natural demand growth. Despite the general factors, the policy still brings a significant and observable effect that becomes evident for the travel funds category. This effect dominates over the overall trends due to the great disparity between fare zones (year-on-year change ranging from −5% up to 70% growth).

Besides changing trip frequency with a specific ticket type, travellers may also respond to fare changes by switching between ticket types. Thus, before focusing on the travel funds category, a card migration analysis for travel funds is presented in Fig. 5. The card flows from and into the travel funds category is very symmetrical between the years, for both full and reduced fares. The former has a slightly lower migration rate of around 38%, while the latter reaches the share of 44%. Forming the largest proportion of migrated cards, the same product contributes up to 85% of the overall migration, followed by another product in the travel funds range, a 30-day pass, or a combination of both. The reduced fare is more self-contained, whereas the full fare is tightly connected to the 30-day pass, having a card exchange rate of around 22%. Ultimately, the influx is mainly caused by newly introduced cards, as the migration is very similar in both directions. In conclusion, we do not see any evidence of a significant shift in ticket products that could bias the fare elasticity calculations for the travel funds category.

The product split by fare zone combination is shown in Table 3. All products except for travel funds show a fairly coherent growth among the fare zones. The changes are larger in absolute values when it comes to remote combinations that include fare zone C, namely A-C (C-A), B-C (C-B), and especially C-C. This is partly explained by lower demand levels for these OD pairs, i.e. every incremental change is weighted more; however, a redistribution of demand undoubtedly takes place. The effect on demand is evident – the disparity between one-zone OD and two- or three-zone OD is substantial (0–5% against 20%–60%). This observation is in line with the expectations of increased ridership with more affordable fares. Moreover, the market penetration of travel funds is large enough for representative outcomes.

4.3. Fare elasticities

A much larger growth is obtained for journeys crossing two and three

Table 2
Demand split between fare zones.

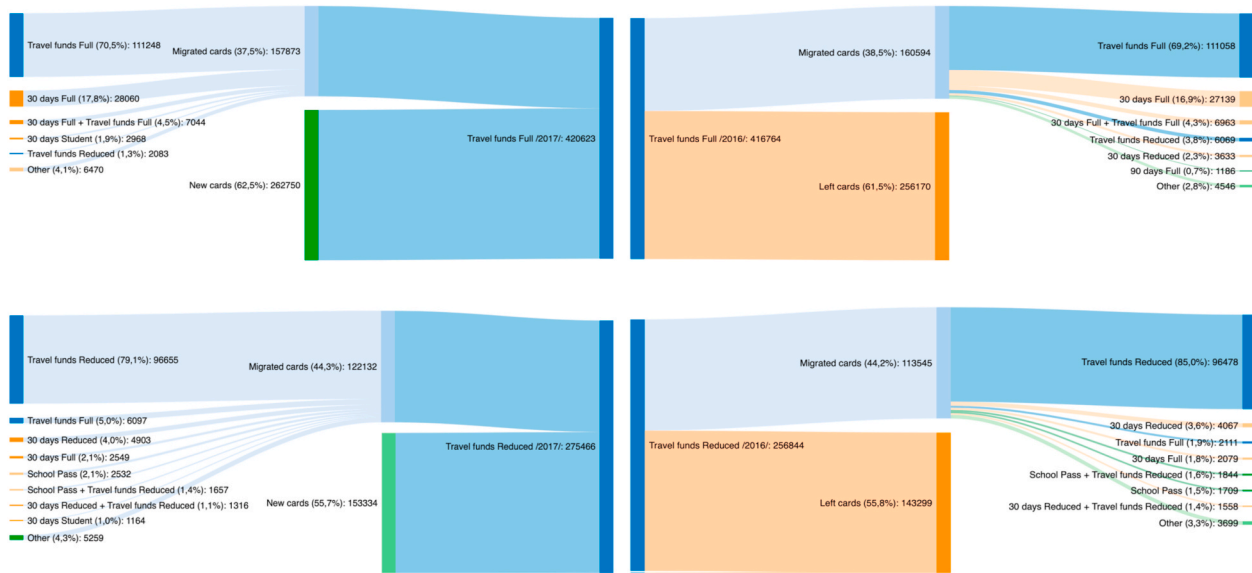| Origin	Destination	2016		2017		Change	
		Number of recorded journeys	Share, %	Number of recorded journeys	Share, %	Abs.	Rel., %
A	A	21,349,146	71.8	21,594,290	71.2	245.144	1.1
A	B	2,414,181	8.1	2,484,079	8.2	69,898	2.9
A	C	319,622	1.1	336,560	1.1	16,938	5.3
B	A	2,643,079	8.9	2,745,688	9.1	102,609	3.9
B	B	1,836,971	6.2	1,879,501	6.2	42,530	2.3
B	C	140,137	0.5	143,663	0.5	3526	2.5
C	A	340,081	1.1	365,910	1.2	25,829	7.6
C	B	128,264	0.4	135,023	0.4	6759	5.3
C	C	545,176	1.8	623,950	2.1	78,774	14.4

Fig. 5. Migration flow of travel funds cards between 2016 and 2017. Top: full fare product. Bottom: Reduced fare products. Left: Migration to travel funds. Right: Migration from travel funds.

Table 3
Change in number of cards for travel funds and in total for all products split by fare zones.

Origin	Destination	Number of cards change	Travel funds full	Travel funds red.	All
A	A	Abs	−3449	89	9428
		Rel %	−5.1	0.2	1.1
A	B	Abs	660	549	2689
		Rel %	22.8	21.3	2.9
A	C	Abs	241	161	652
		Rel %	68.3	47.8	5.3
B	A	Abs	1028	760	3946
		Rel %	22.8	18.6	3.9
B	B	Abs	98	188	1635
		Rel %	4.8	5	2.3
B	C	Abs	61	57	134
		Rel %	49.2	38.3	2.5
C	A	Abs	358	228	992
		Rel %	56.9	36.1	7.6
C	B	Abs	76	59	262
		Rel %	56.7	35.1	5.3
C	C	Abs	24	−43	3032
		Rel %	2.5	−2.9	14.5

fare zones than for intra-zonal journeys. In addition to this, a growth took place within zones B and C, which were expected to demonstrate a negative change. The overall fare elasticity of travel funds is found to be −0.46, which means that a 1% price increase entails a 0.46% decrease in demand, and vice versa for the opposite signs. Regular users are more sensitive than sporadic users to the fare policy (elasticity −0.46 versus −0.29). Frequent travellers are expected to be aware about newly introduced changes and consider price of a single journey as an important aspect. Reduced fares are associated with a sensitivity that is half as large compared to full fares (−0.31 versus −0.57), reflecting that travellers have fewer or less competitive alternatives. The directionality of the fare change is also relevant. Full fare users, especially regular travellers, are more sensitive to price increase, while the opposite holds for reduced fare users.

Mode-specific elasticities are calculated at the trip level (i.e., between transfers) rather than the journey level. Among transport modes, metro has the lowest elasticity of −0.45. Bus has a slightly higher elasticity of −0.56 whilst commuter train exhibits by far the largest coefficient of −0.90. These findings reflect the general features of each

mode. For instance, the advantage of the metro system is its speed and frequency. Bus provides better connectivity and directness (i.e. fewer transfers), but lacks comfort and reliability. Bus and metro are mostly used for single-zone journeys, while commuter train has the largest mode share for inter-zonal travel.

Elasticity overall gradually increases with distance (from −0.28 to −1.19 across full and reduced fares) and substantially jumps at the 10 km mark (from −0.37 to −0.98), yet a minor drop is observed at medium distances (around 5 km). Higher elasticity for short journeys reflects that they can be taken with the use of active modes as well. In the case of long journeys, the level of public transport service declines in more remote areas. This incentivizes travellers, especially commuters, to consider other available options, for instance private transport. Sensitivity does not vary substantially for different time periods. Periods with higher than average elasticities are morning peaks and weekends for the full fare (−0.64 and −0.65 respectively versus −0.44 for the rest) and morning peaks for the reduced fare (−0.38 versus −0.30 for the rest).

Table 4 shows elasticities for users who travel 1, 2 and 3 zones with full and reduced fare, respectively. With the flat fare, 1-zone trips became more expensive, 2-zone trips slightly cheaper and 3-zone trips substantially cheaper (see Table 1). It is clear that directionality has a strong influence, where a price decrease has an effect between two and sixteen times larger than a price increase on the full and reduced groups, respectively. This observation is contrary to past research (Balcombe et al., 2004). However, in the current study fare sensitivity is combined with service sensitivity. The removal of fare zones did not only induce a price change, but also an increase in transparency and convenience associated with the use of travel funds. This aspect is likely to be the main driving force in the changing travel behaviour, especially in the case of the reduced fare users. With the current study's scope and input, it is not fully possible to disentangle the individual impacts of the two effects.

The elasticity results for the different socio-economic factors,

Table 4
Fare elasticity values for trips across different numbers of zones.

Number of zones	Full fare	Reduced fare
1 zone (increase in price, no effect on convenience)	−0.51	−0.11
2 zones (slight decrease in price, improved convenience)	−1.09	−1.81
3 zones (large decrease in price, improved convenience)	−1.13	−1.03

including income, socio-economic index and car ownership, are in line with each other. Altogether, they reflect the level of public transport captivity and the importance of fares for different user groups. Reduced fare users are less sensitive in general. Fig. 6 presents the elasticity ranges found in the literature as well as the aggregated values (for the combined fare category and all OD groups) that we obtain in this study. For most of the factors, the values obtained are in line with past findings, with no or minor discrepancies, with the exception of one outlier and three extreme values, two of which are in the longer distance group.

5. Discussion and conclusion

We proposed a method for calculating fare elasticities from smart card validation records, using Stockholm County, where the zonal fare system was replaced by a flat-fare policy, as a case study. Through a sequence of inferences, public transport smartcard data have been processed to derive time-dependent origin-destination matrices

connected to zonal sociodemographic data. We use the outputs of this process to evaluate the impacts of Stockholm's fare scheme change in 2017 on different user groups. The study adds new evidence to the limited literature on revealed-preference fare elasticity from disaggregate data. In particular, we derive fare elasticities for distinct socio-economic groups based on, e.g., car ownership and income, as well as different public transport modes (metro, trains and buses). We also consider the directionality of the fare change impact. While not valid in the context of our case study, the analysis of smart card data may, depending on the local circumstances, be subject to drawbacks such as different lifting validation requirements for pass holders or prohibitive restrictions imposed by privacy regulations. Such limitations may hinder the applicability of the proposed method to other public transport systems, but does not hinder the transferability of our findings to other contexts.

The overall fare elasticity of travel funds is found to be −0.46. Regular users are more sensitive than sporadic users to the fare policy
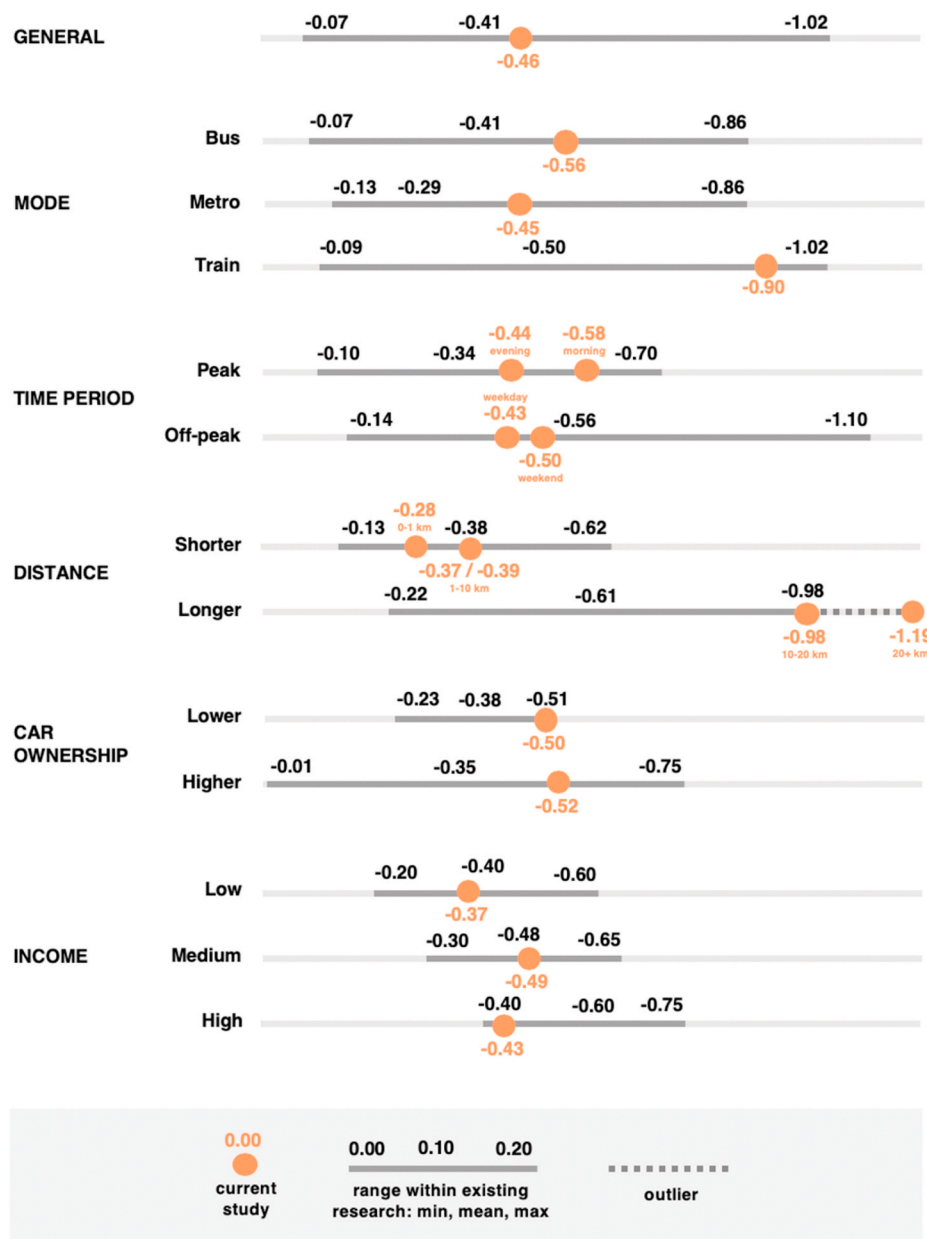

Fig. 6. Fare elasticity values. For car ownership, lower means < 0.25 cars/adult and higher means > 0.55 cars/adult. Values from existing research are taken from Balcombe et al. (2004), Cervero (1990), Litman (2004), Litman (2019), McCollom and Pratt (2004) and Wang et al. (2015).

(elasticity −0.46 versus −0.29). User sensitivity grows with the journey distance and substantially rises after the 10-km mark. Metro users demonstrate the lowest sensitivity, followed by a slightly higher value for bus and by far the most sensitive commuter train riders. Within the socioeconomic factors, the low-factor groups (i.e. low income, socio-economic index, car ownership rate) tend to be less sensitive than the high-factor groups. The directionality of the price change creates a significant asymmetry where the elasticity is higher for fare decreases than increases.

The found elasticity values are generally similar to previously reported values. However, in addition to the direct effect of changed fares, simplification and unification of the fare scheme appears to have substantially contributed to its attractiveness. The latter appears to be the main driver of the demand increase for intra-zonal journeys in zones B and C (outside the city centre) despite the higher journey costs. The elasticities estimated in this study reflect short-run behavioural changes since they were measured two months after the fare scheme change was introduced. Based on results from past research which has compared short-term and long-term elasticities (Holmgren 2007; Cats et al., 2017), we expect long-run fare elasticities to be higher than those estimated and reported here.

The natural fare change experiment analysed here only affected travel funds users, which constitute 11% of the journeys and 40% of the travel cards. Travel funds display lower trip frequencies than longer subscription cards (e.g., 30-day or yearly cards), which suggests a higher share of occasional users with lower mobility or preferences for personal transport. We expect that elasticities for users with longer subscriptions, who have a stronger commitment to public transport use, are lower than for travel funds users.

Understanding the importance of the product's service component and its direct demand effects, it is possible to adjust the level of the flat fare for each single-use product. The elasticity values presented in this study could serve as a starting point in the new fare scheme. However, for more precise results the price and service aspects of user sensitivity should first be separated. The adjusted pricing scheme would increase the product usage even more and improve the spatial uniformity of travel expenses, while staying at the level of neutrally balanced economy.

The study revealed a high valuation of user friendliness and convenience among the users. Looking from a broader perspective, this could indicate a potential to improve the general level of service without large investments in the physical infrastructure. Therefore, it is recommended to consider additional opportunities in the development of high-quality travel information, advanced means of payment, personalised digital services, and so forth.

Elaborating further on the Stockholm County's experience with the flat fare introduction, it suggests a policy direction for other regions. The flat fare may allow the geographic disparity of public transport travel to be reduced and new users to be attracted from remote areas who are more prone to own cars. This policy direction nevertheless highly relies on three interconnected factors: the region's geography, level of public transport service and authorities' political vision. The Stockholm region is characterised by a clear single-core geographic structure that defines the major travel patterns, high variability of population density in urban and remote areas and thus the level of public transport development. This justifies the reasoning behind the fare policy, which attempts to compensate for the lower transport supply through the flat fare, rather than to relate the fare to the level of service consumption. Hence, a region with analogous characteristics can consider the implementation of a flat fare scheme.

CRediT authorship contribution statement

Yaroslav Kholodov: Conceptualization, Methodology, Software,

Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Erik Jenelius:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Oded Cats:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Niels van Oort:** Conceptualization, Writing – review & editing, Supervision. **Niek Mouter:** Conceptualization, Writing – review & editing, Supervision. **Matej Cebecauer:** Software, Resources, Data curation, Writing – review & editing, Visualization. **Alex Vermeulen:** Software, Writing – review & editing, Visualization.

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