Public transport fare elasticities from smartcard data: A natural experiment in Stockholm

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Research goals

Fare policy is an essential component of any public transport system. Changes in the fare structure will cause 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). Traditionally, travellers' sensitivity to supply changes is estimated based on aggregated cross-sectional and time series analysis, or disaggregate stated preference surveys. The latter collect 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 alternative choices, which adds bias to the analysis (Linsalata and Pham, 1991). Disaggregated revealed-preference studies have until recently been rare and based on limited data samples (Wardman and Shires, 2003).

The emergence of automated fare collection (AFC) technologies (e.g. smartcards) brings unprecedented opportunities for collecting disaggregate, full population data about passengers' travel behaviour. The goal of this study is to develop a method for analysing the impacts of policy measures based on smartcard data. This involves a series of analysis and modelling challenges. The study considers a public transport fare policy introduced by the regional administration of Stockholm County (SLL) in January 2017. The study exploits this natural experiment to assess passengers' fare elasticities by comparing trip rates before and after the policy introduction. Recently, Wang et al. (2018) conducted a similar analysis for the Beijing metro system.

The policy focused on changing the fare structure for single-use products, in particular switching from a zonal to a flat-fare scheme. This promoted convenience and transparency, which was perceived as lacking by users according to a preliminary study by SLL (2016). Another direct effect of the removal of fare zones was a price change. Thus, some categories of journeys became cheaper while others increased in price depending on the OD (origin and destination) combination. Generally, the administration formulated three main policy objectives: simplifying the fare system, increasing ridership for multi-zonal journeys and achieving a neutrally balanced economy. Table 1 shows the single trip fares in 2016 and 2017 (10 SEK are approximately 1 EUR). The fare zones before 2017 are shown in Figure 1.

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

There is a substantial body of literature available on travellers' response to public transport fare changes, analysed from various perspectives, considering short-term and long-term effects, different geographic scale, types of users and journeys (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 income, disabilities, young and old age, no access to private car, occupation (unemployed, 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 a higher tolerance to price increases (Balcombe et al., 2004; Litman, 2004).

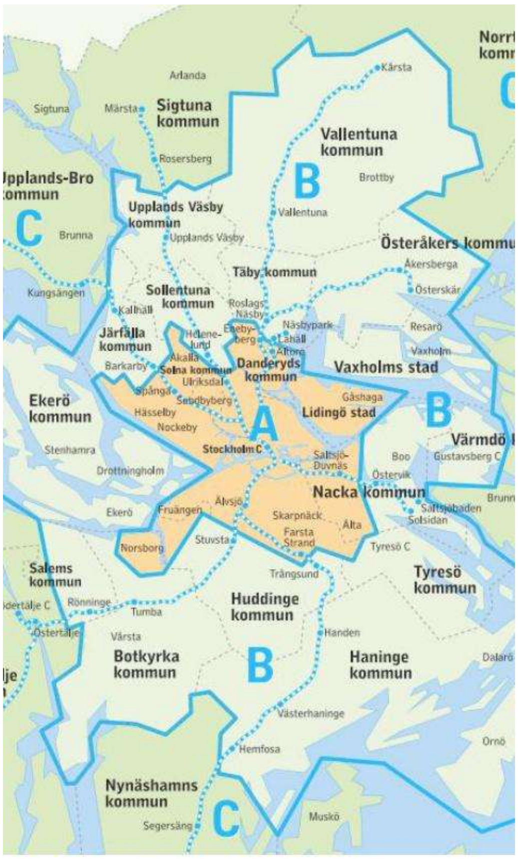

Figure 1. Map of Stockholm public transport fare zones (before 2017). The distance between the northern and southern borders of zone B is ca. 80 km.

Commuter journeys tend to be less sensitive to the fare than leisure journeys (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).

Methodology

The study aims to 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, and associating each card with zonal socio-demograhic information. A methodology is developed to process the smartcard data into traveller journeys. The complete processing framework 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.

Figure 2 visually summarizes the framework workflow.

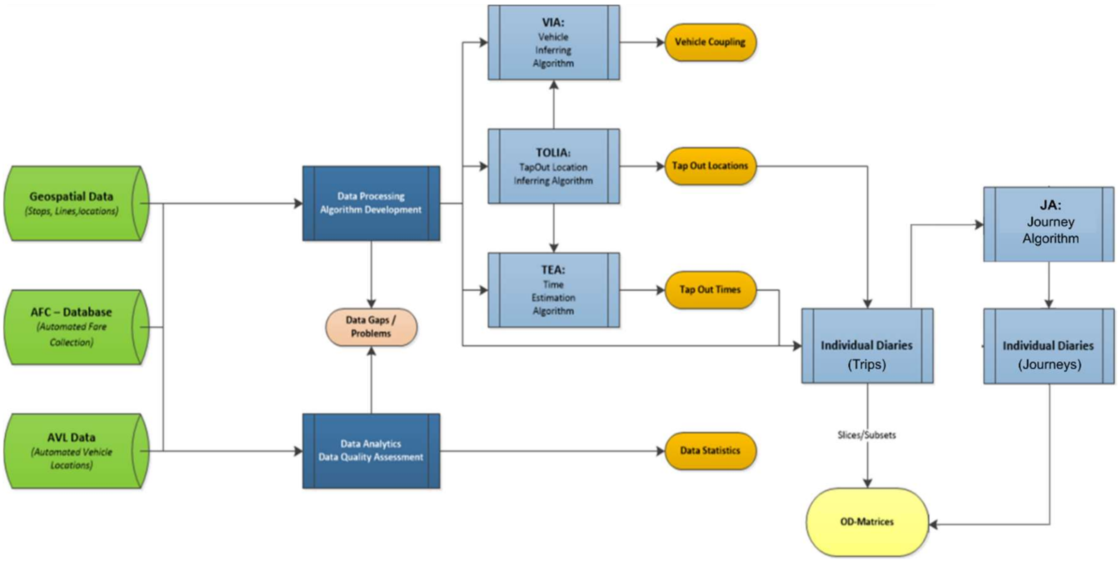

Figure 2. Smartcard processing framework

To assign socioeconomic characteristics to each smartcard, its home location is identified at the census zone level. The algorithm applied in this study partly utilises the methodology from Aslam et al. (2018), adapted to the conditions of the tap-in validation system. Spatial and temporal regularity of usage is investigated and a suitable threshold is specified to separate sporadic travellers from regular ones.

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. Another important data source is socioeconomic data collected by Statistics Sweden (SCB, 2019). The data are stored at the level of 1,364 census zones and include names and codes of administrative areas, geospatial data, population split, median income, socioeconomic index, and car ownership.

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 in these months operating conditions of the system and demand patterns 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%). The analysis is limited to the "travel funds" product group, which makes up 40% of all cards and 11% of all journeys. Travel funds are the only product group whose price scheme was substantially affected by the fare policy.

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, e.g. 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 is here calculated with the mid-arc formula

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

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.

Results

Tap-in records have been matched with corresponding inferred tap-out locations and time stamps for about 80% of all records. Fare elasticities are calculated along multiple dimensions, such as socioeconomic characteristics, transport modes, travel time period, travel distance, regularity of usage, fare category and directionality of fare change. Within the elasticity of every 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 and summarized afterwards.

Compared to prior predictions, a much larger growth is obtained for journeys crossing two and three fare zones. In addition to this, a growth took place within zones B and C, which were expected to demonstrate a negative change: -0.2% versus 5% and -0.3% versus 2.5% respectively.

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 demonstrate a sensitivity that is half as large compared to full fares (-0.31 versus -0.57), reflecting that travellers have reduced mobility or lower access to private transport. 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.

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, 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 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).

The elasticity results for the different socio-economic factors, including income, socio-economic index and car ownership, are in line with each other. Reduced fare users are less sensitive in general. At a disaggregate level, higher socio-economic groups are associated with lower one-zone elasticity (price increase) and higher two- and three-zone elasticity (price decrease). Altogether, this reflects the level of public transport captivity and the importance of fares in different user groups. Lower socio-economic groups assign more weight to the fare and at the same time rely more on public transport. Therefore, a price increase significantly affects their choices, while a price decrease attracts few new users. Higher socio-economic groups, meanwhile, are more prone to joining the system and less prone to leaving it. This is because the cost element becomes less crucial along with a wider range of travel alternatives.

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 existing research. However, in the current study fare sensitivity is combined with service sensitivity. The removal of fare zones induced 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 possible to fully distinguish the individual impacts of the two effects.

Figure 3 presents the elasticity ranges found in the literature as well as the aggregated values (for the combined fare category and all O/D groups) from the current study. For most of the factors, the fit is noted to be satisfactory, as the values either match with the common averages or stay fairly close to them. In total, there are only one outlier and three extreme values, two of which are in the longer distance group. More details and discussion are proved by Kholodov (2019).

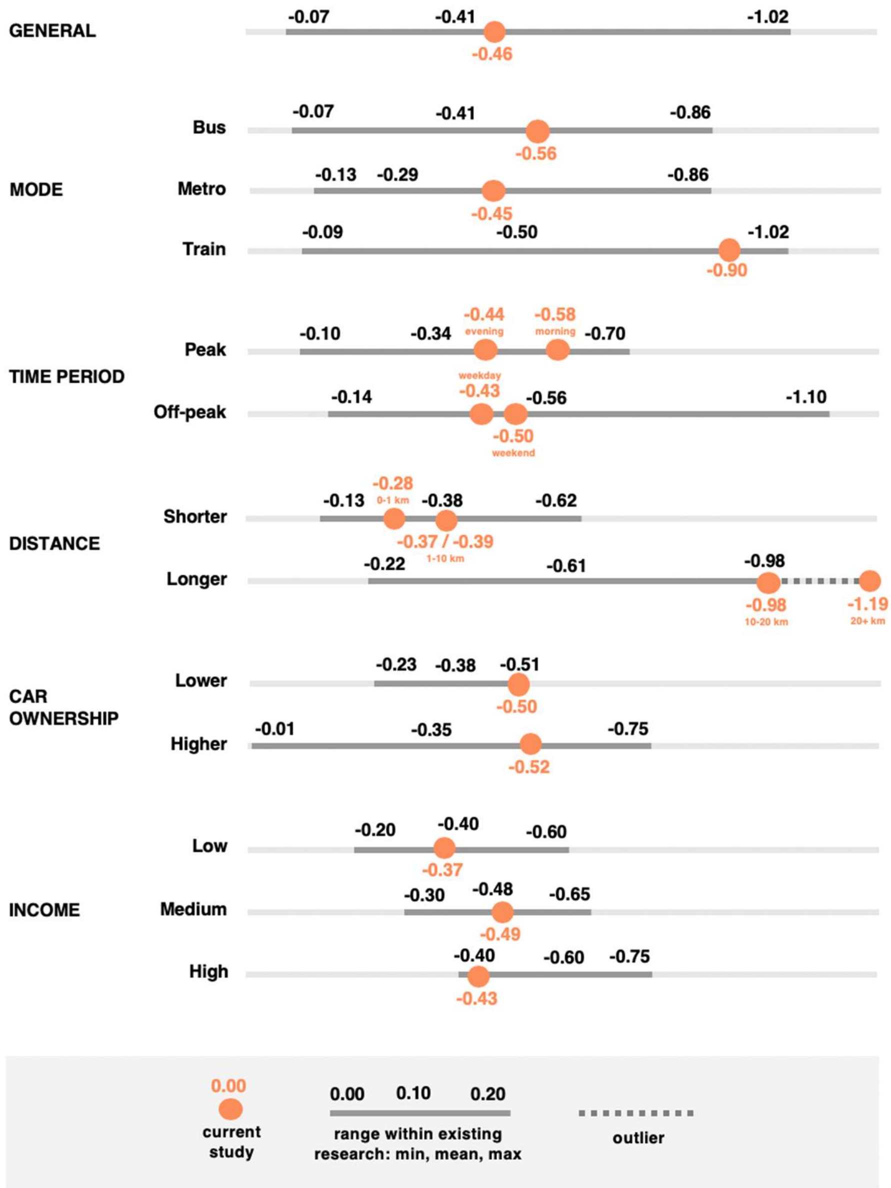

Figure 3. Fare elasticity values

Discussion and Conclusion

The study has presented a method for calculating fare elasticities from smart card validation records. Through a sequence of inferences, public transport smartcard data have been processed to derive time-dependent origin-destination matrices for the Stockholm region. We use the outputs of this process to evaluate the impacts of Stockholm's fare scheme change in 2017 (i.e. from zone-based to flat fare) on different user groups. The study adds new evidence to the limited literature on revealed-preference fare elasticity from disaggregate smartcard data.

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 great demand increase despite the higher journey costs, for intra-zonal journeys in B and C.

An important caveat in using the before-after analysis of the natural experiment is the assumption of a static environment. This means that any changes in travel patterns and user behaviour take place due to the introduced policy. This cannot be fully guaranteed, however, since there is an ever-present change in economic and demographic circumstances even with the carefully chosen analysis period that minimizes the effect of the transport service updates. Looking at the mid-term 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 by 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).

References

Aslam, N.S., Cheng, T., Cheshire, J. (2018). A high-precision heuristic model to detect home and work locations from smart card data. *Geo-spatial Information Science* 22(1), 1-11

Balcombe, R., Mackett, R., Paulley, N., Preston, J., Shires, J., Titheridge, H., Wardman, M., White, P. (2004). *The demand for public transport: a practical guide*. Report TRL 593. Crowthorne, England: TRL Limited.

Cervero, R. (1990). Transit pricing research. A review and synthesis. *Transportation*, 17(2), 117-139.

Kholodov, Y. (2019) *Evaluation of Public Transport Fare Policy Using Smartcard Data*. MSc Thesis, Delft University of Technology. Available at: https://repository.tudelft.nl/islandora/object/uuid%3A10f4e699-f44e-4f5b-b9c3-0d910966f7a5?collection=education

McCollom, B.E., Pratt, R.H. (2004). *Transportation Research Board. TCRP Report 95: Traveler Response to Transportation System Changes. Chapter 12 - Transit Pricing and Fares*. Washington, D.C.: Transportation Research Board.

Munizaga M. A., Palma C. (2012) Estimation of a disaggregate multimodal public transport Origin-Destination matrix from passive smartcard data from Santiago, Chile. *Transportation Research Part C: Emerging Technologies* 24, 9–18.

Linsalata, J., Pham, L. (1991). *Fare Elasticity and Its Application to Forecasting Transit Demand*. Washington, D.C.: American Public Transportation Association.

Litman, T. (2004). Transit price elasticities and cross-elasticities. *Journal of Public Transportation*, 7(2), 37-58.

Litman, T. (2019). Understanding Transport Demands and Elasticities. How Prices and Other Factors Affect Travel Behavior. Victoria Transport Policy Institute. Retrieved from http://www.vtpi.org/elasticities.pdf

Liu, Y., Wang, S., Xie, B. (2019). Evaluating the effects of public transport fare policy change together with built and non-built environment features on ridership: The case in South East Queensland, Australia. *Transport Policy*, 76, 78-89.

SCB (2019). SCB:s statistikpaket. Statistics Sweden. Retrieved from https://www.h6.scb.se/osdb2015/default.aspx.

Wang, Z.J., Li, X.H., Chen, F. (2015). Impact evaluation of a mass transit fare change on demand and revenue utilizing smart card data. *Transportation Research Part A*, 77, 213-224.

Wang, Z.J., Chen, F., Wang, B., Huang, J.-L. (2018) Passengers' response to transit fare change: an ex post appraisal using smart card data. *Transportation* 45, 1559-1578.

Wardman, M., Shires, J. D. (2003) Review of fares elasticities in Great Britain. Working Paper. Institute of Transport Studies, University of Leeds, Leeds, UK.
Whelan, G., Batley, R., Shires, J., Wardman, M. (2008) Optimal fares regulation for Britain's railways. *Transportation Research Part E* 44(5), 807-815.