FairAccess

How fair is the fare?

Estimating travel patterns and the impacts of fare schemes for different user groups in Stockholm based on smartcard data

Final report for Trafik och Region 2018
SLL-KTH research project

November 2019

Research team: Oded Cats*
Isak Jarlebring Rubensson
Matej Cebecauer
Yaroslav Kholodov
Alex Vermeulen
Erik Jenelius
Yusak Susilo

* Principal Investigator, cats@kth.se / o.cats@tudelft.nl

SUMMARY

There is a rapid increase in the deployment, acquisition and analysis of automated fare collection (AFC) systems, enabling a profound change in the ability to analyze high-volume data that relate to observed passenger travel behavior and recurrent patterns. The analysis of such passively collected data offers direct access to a continuous flow of observed passenger behavior at a large scale, saving expensive data collection efforts. For a review of the spectrum of applications – from strategic demand estimation to operational service performance measurements.

The FairAccess project leverages on the availability of Access-kort data for the vast majority of trips performed in Stockholm County. The overarching goal of this project is to develop means to analyse empirically the impacts of policy/planning measures based on disaggregate passively collected smart card data. This involves a series of analysis and modelling challenges. We develop and apply a series algorithms to infer of tap-out locations, infer vehicles and travel times, and infer transfers to that journeys can be composed. Tap-in records have been matched with corresponding inferred tap-out locations and time stamps for about 80% of all records. Thereafter, we construct time-dependent origin-destination matrices for which segmentations can be performed with respect to geographical and user product features.

We demonstrate the approach and algorithms developed by performing a before-after analysis of the fare scheme change from zone-based to flat fares. We analyse changes in travel patterns and derive price elasticities for distinctive market segments. The introduced fare policy delivered the desirable result of an increased ridership through improved convenience of the single-use products. Nevertheless, the significance of the service convenience component was underestimated, which resulted in the price adjustments being not in line with the mobility effects.

The planning and development of the Stockholm public transport system must rely on the best empirical foundations available to support evidence-based decision-making and make the right priorities. To this end, the development and analysis performed in the FairAccess project lay a necessary foundation for further methodological developments and analyses such as on-board crowding evaluation, demand forecasting and identifying user groups.

TABLE OF CONTENTS

1 INTRODUCTION

1.1 BACKGROUND

Three important developments and related lacks of knowledge set the stage for this project:

- *Availability of large-scale passively collected passenger data, which are greatly underutilized.* Smart card validation records offer a potentially very rich dataset that enables a profound change in the ability to analyze observed passenger travel behavior and recurrent patterns. None of the existing offline functionalities at Trafikförvaltningen (TF) is coupled in a systematic way to long-term planning applications such as demand forecasting and project appraisal. There is a lot of potential in going beyond generating reports upon request for individual stations and gaining knowledge into travel patterns exhibited by different user groups and the corresponding impacts of planning interventions. To uncover the potential of this data, a series of algorithmic developments and data management and fusion capabilities are needed.
- *Greater focus on 'inclusive transport service for all' as a prime policy and planning goal yet no quantification of the distributional effects of interventions.* Very little is known about the patterns that characterize the travel behavior of different users and socio-demographic groups. This lack of knowledge prevents planners from assessing the impacts of alternative investments/policy measures on different groups and as a result undermining its incorporation in the decision making process.
- *Changed from zone-based to flat fare while there is lack of knowledge on the impact of fare scheme changes*. Little empirical knowledge on how fare schemes influence the decisions of different travelers' groups. While changes in fare levels have often been investigated, very little is known on the impacts of fare structure such as differential vs. uniform fees on travel patterns.

The combination of these developments, trends and opportunities paved the way and provide the context for the FairAccess project.

1.2 AIM

The overarching goal of this project is to develop means to analyse empirically the impacts of policy/planning measures based on disaggregate passively collected smart card data. This involves a series of analysis and modelling challenges. The application selected for this study is the Stockholm region's fare scheme change from zone-based to flat-fare. Focus is on the distributional impacts of such a policy since smart card data can potentially reveal more information on travel patterns among different user groups.

To achieve this overall aim, the specific objectives of this project are as follows:

(i) Infer the tap-out location and time for tap-in records
(ii) Construct passenger station-to-station journey records
(iii) Identify travel patterns for different user groups
(iv) Develop metrics to quantify the distributional aspects of accessibility and fare schemes
(v) Perform an empirical evaluation of the fare policy change and its distributional impacts

1.3 Approach and work process

To realize the objectives stated above, the project constitutes of a series of algorithmic, theoretical and empirical research steps. The overall workflow is structured into four work packages (WP):

- WP1: From smartcard data to individual (public transport) diaries
- WP2: From disaggregate diaries to user-group travel patterns
- WP3: Quantifying accessibility and equity effects
- WP4: Before-after analysis of changes in fare scheme

The WPs and their relations are depicted in Figure 1.1.

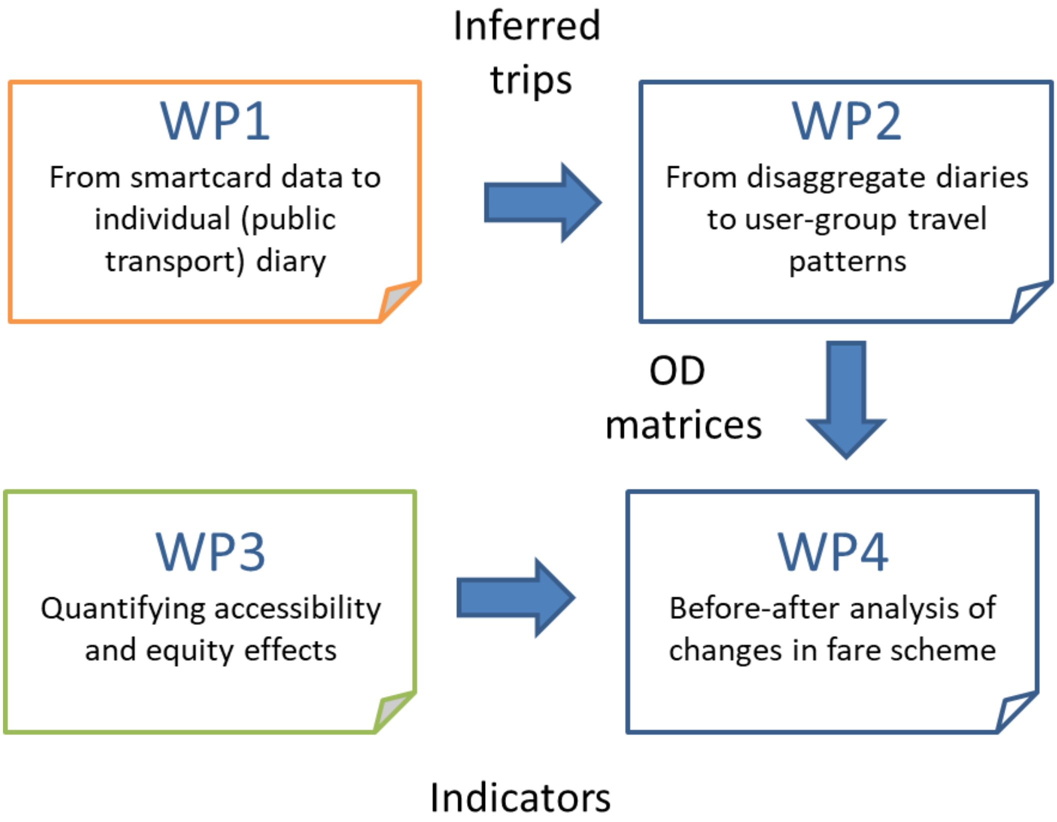


Figure 1.1: FairAccess project workflow

WP1 involves the processing of large amounts of raw disaggregate smart card data and therefore required the development of software solutions to efficiently perform data analytics operations. A series of algorithms were designed and implemented to infer the most likely tap-out location for each tap-in record and the respective time stamp by fusing Automated Fare Collection (AFC) and Automated Vehicle Location (AVL) data and obtaining information over a long period of time per card holder. Thereafter, successive trips were combined into journeys if a transfer (as opposed to an activity) was inferred. In the case of gated tap-ins (i.e. metro and commuter train), transfer locations were inferred. The outputs of these research steps became input to the subsequent analysis in WP2.

The individual journey database was aggregated and travel patterns were analyzed in WP2. We analyzed the spatial and temporal characteristics of the travel patterns observed, also as part of model verification. We also examined the travel patterns at the zonal level and OD level as well as its relation with socio-economic variables available per statistical zone. Furthermore, we analyzed travel patterns for different smart card products such as travel frequency and relate them to attributes of user groups to the extent possible. To support the analysis and dissemination, we invest in developing visualization capabilities to illustrate the travel patterns observed such as transfer hotspots, daily evolution patterns etc.

WP1 and WP3 took place in parallel and provided the building blocks for the remaining activities. In WP3 we reviewed the theory on defining and measuring accessibility and equity. We then focused on methods that capture the distributional aspects of public transport service provision and fare schemes. We chose to operationalize those by employing the Gini and Suits metrics. Moreover, we proposed ways to perform a meaningful comparison among user groups since some of the geographical disparities are inherent to the properties of public transport network gravity and ridership. The conclusions of WP3 were used in selecting and applying the proposed indicators in WP4.

In WP4 we investigated the case of the fare scheme change. The algorithmic development and the analysis performed in WP1 and WP2 allow investigating the travel patterns for specific smart card products before and after the policy change, and segmenting them further by the fare zones combination of the journey and the socio-economic attributes of the home-based zone. The latter can be identified thanks to the availability of (anonymous) data per individual card holder over a long period of time. We then applied the indicators proposed in WP3 to systematically evaluate the impacts of the fare change on ridership, trip frequency, origin-destination combinations and fare expenses, and their distributional dimensions.

1.4 PROJECT MANAGEMENT

The project team consists of researchers with diverse training and skills, interests and backgrounds. Moreover, the research team includes researchers at different stages of their research career, affiliated with different groups and based in different countries. To reduce communication overload and barriers three main mechanisms were introduced:

- Regular project conference calls where all project members share updates, discuss issues and selected WP describe progress and outputs in greater detail. Meetings took place on a bi-monthly basis.
- Slack was used as the main communication channel for discussing technical developments and sharing intermediate results along with supporting tools for software development and project management for the core developers in WP1 and WP2.
- Study visits when either intensive interaction is needed within a short time span or a longer stay to allow for regular contact opportunities.

The combination of these work patterns and communication channels proved very effective yet efficient in ensuring the successful completion of this project, including dependencies within and between WPs.

The role played by Isak Rubensson in his dual capacity was very important in guarantying a short line of communication with Region Stockholm, including granting access to data, getting insights on past and present developments within the organisation and potential applications of interest. In addition, Gabriella Nilsson was updated every 6 months or so on project progress.

Two key meetings were organized with a large group of developers and planners at Region Stockholm on May 2, 2019 and November 13, 2019. During the first meeting, the key smart card processing capabilities were presented as well as an array of applications of smart card data analytics from cities worldwide. During the second meeting, the key findings of this project were presented, and possible applications and use of the capabilities developed as part of business operations were discussed.

1.5 PROJECT DISSEMINATION

Parts of the work performed in this project has been presented in the following international peer-reviewed scientific conferences:

- ”Generating Network-wide Travel Diaries using Smart Card Data”. TransitData2019, Paris. July 2019.
- “Equity Impacts of Alternative Fare Schemes: The Case of Stockholm”. The 98th Transportation Research Board Annual Meeting, Washington DC. January 2010.
- “Fair Accessibility – Operationalizing the Distributional Effects of Policy Interventions”. 99th Transportation Research Board Annual Meeting, Washington DC. January 2020.

In addition, three journal submissions based on the work performed in this project are either under preparation or under review: (i) detailing the smart card data analytics algorithms; (ii) proposing new means of analysing accessibility and equity as part of policy evaluation; (iii) reporting the results of the fare scheme change and discussing their implications.

1.6 OUTLINE

The remaining of this report is organized as follows. Chapter 2 reports the process of estimating individual travel records based on the raw smart card data made available for this project. The individual records and then aggregated in Chapter 3 to generate an understanding of global travel patterns as well as segmented to investigate specific user groups. Chapter 4 describes the notions and metrics of accessibility and equity proposed for quantifying the impacts of policy interventions. Chapter 5 presents the results of the fare scheme change empirical evaluation based on the smart card data and the proposed indicators. Chapters 2-5 correspond to a large extent to the work performed in WP 1-4, respectively. Chapter 6 concludes this work and provides suggestions for future research.

2 FROM SMART CARD DATA TO INDIVIDUAL TRAVEL DIARIES

This chapter present the framework and methodology for building the individual travel diaries, which correspond to work package WP1 and opens numerous possibilities for analysing travel patterns at different aggregation levels in WP2 (Chapter 3). The latter involves the inference of home stop locations of card holders and data fusion with socio-economic data to enable that analysis of travellers' socio-economic context. The techniques and analysis reported in this and the following chapters are essential prerequisites that enable the case study fare analysis performed in Chapter 5.

The methodology carried out in this chapter follows a sequence of steps for processing smart card data to individual travel diaries. Two complete years, i.e. 2016 and 2017, are used for analysing the performance of the framework, followed by an analysis for February 2016 and February 2017 only. These months are selected for analysis of fare change later and its impact on different groups of travellers.

The rest of this chapter is organized as follows. First, we briefly introduce the data format and notation used in this report (2.1). Then, the general workflow framework for processing smart card data is presented (2.2). Later we discuss in detail framework's modules in the following order: inferring of tap-out locations (2.3); Inferring vehicles and travel times (2.4); and journey algorithm (2.5). We close with brief information on model implementation (2.6).

2.1 RAW DATA FORMAT AND RELATED NOTATIONS

The complete database AnalysisDM contains more than 5TB data. There are approximately 2 million tap-ins per day. Every blip or tap-in of a smart card registers a record containing several attributes that can be used for constructing the travel diaries per individual cards.

Let us introduce a notation for the description purposes, with the travel diary for card i denoted by C_i which represents the set of timely ordered trips c_{ij} based on the tap-in b_{ij} record at time t_{ij}. Trip c_{ij} is a vector pair of tap-in b_{ij} and the inferred tap-out record $\hat{b}_{ij}$ such that $c_{ij} = (b_{ij}, \hat{b}_{ij})$. Each tapping contains information about vehicle v_{ij}, line l_{ij}, mode m_{ij}, departure u_{ij}, location s_{ij}, product p_{ij}, date d_{ij} and time t_{ij}. Each of these attributes represents the key to the different database tables containing even more information about particular attributes. For instance, the product p_{ij} in smart card data records enables the linkage that is used in chapters 3 and 5 when analysing particular groups of users.

The ticketing system in Stockholm relies on a tap-in only system, and thus the tap-out $\hat{b}_{ij}$ locations $\hat{s}_{ij}$ for all trips should be inferred. By utilizing automatic vehicle location (AVL) data, which are available in the AnalysisDM database, we are able to infer vehicle v_{ij} and travel times $\hat{t}_{ij} - t_{ij}$ for a significant share of all trips performed in Stockholm County. The sequence of analysis steps and related inference algorithms are described in the following sections.

2.2 PROCESSING FRAMEWORK

The complete processing framework consists of four modules:

- Tap-out location inference algorithm (TOLIA)
- Vehicle inference algorithm (VIA)

- Travel time estimation algorithm (TEA)
- Journey Algorithm (JA)

Figure 2.1 visually summarizes the framework workflow. TOLIA - the estimation of tap-out locations $\hat{s}_{ij}$ - constitutes the initial step in constructing travel diaries. If the tap-out location is inferred and vehicle v_{ij} is recorded on tap-in record b_{ij} then the TEA module checks the AVL record for vehicle v_{ij} from tap-in location s_{ij} to tap-out location $\hat{s}_{ij}$ and infer the tap-out time $\hat{t}_{ij}$. If the vehicle v_{ij} is unknown then VIA is activated to infer it from the AVL data and return vehicle v_{ij} to TEA for travel time inference. Once the travel diaries at the level of trips in the set C are completed, the JA module can produce travel diaries at the journey level. The modules can run independently in the following order: TOLIA, VIA, TEA, and JA; or simultaneously for better data loading/storing performance. It can also be easily extended for the real-time processing of data streams. The current implementation focuses on processing historical data. All modules are described in more detail in the sections below.

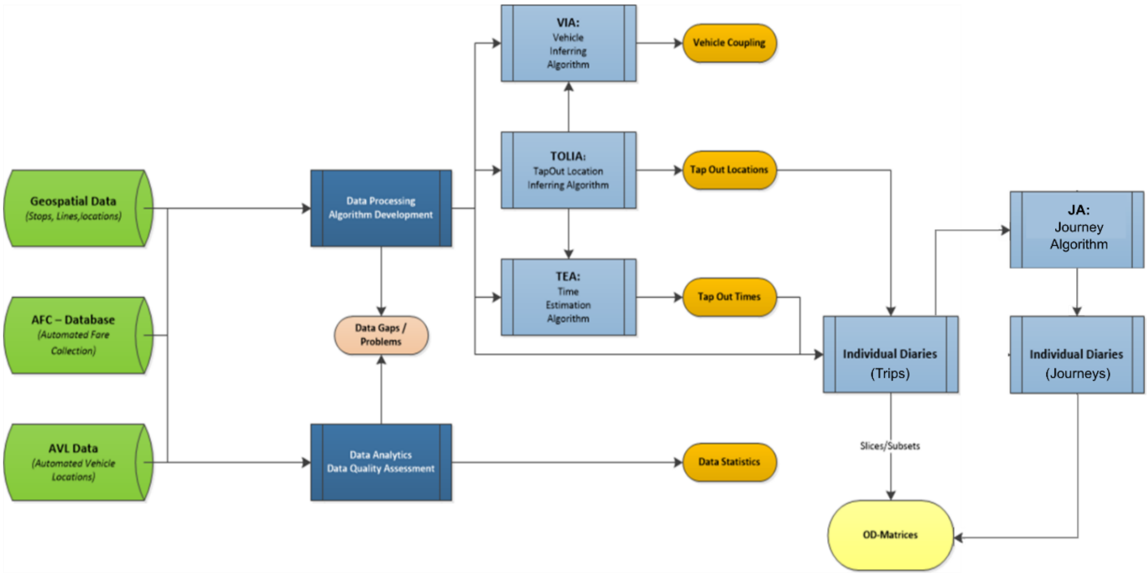


Figure 2.1 Smart card data processing framework

2.3 Inference of tap-out locations

As discussed before, the Stockholm ticketing system is tap-in only, implying that all tap-out locations $\hat{s}_{ij}$ for trips c_{ij} must be inferred. When inferring tap-out locations, all multimodal tap-in data are used. We use a radius r around the next tap-in location $s_{i,j+1}$ to infer the stop location along the same line l_{ij} as the tap-in record b_{ij}. The closest such station is considered as the tap-out location $\hat{s}_{ij}$ for trip c_{ij}. This approach based on radiuses and walking distances is commonly used in the literature (Munizaga and Palma 2016).

In describing the TOLIA algorithm in more detail, we refer by L_{ij} to the set of lines operating at stop s_{ij}. In order to infer the tap-out $\hat{b}_{ij}$ for trip c_{ij} the existence of the next tap-in $b_{i,j+1}$ is needed. If $b_{i,j+1}$ exists, the radius r around the location $s_{i,j+1}$ is searched for the candidates for tap-out location $\hat{s}_{ij}$. If the tap-in b_{ij} has line l_{ij} defined, the algorithm selects the closest stop to the $s_{i,j+1}$ in radius r including $s_{i,j+1}$ where the line l_{ij} operates. To describe the case when l_{ij} is unknown, the algorithm looks for the closest stop to $s_{i,j+1}$ which is served by one of the lines in the set L_{ij} serving tap-in stop location s_{ij}. If the tap-location $\hat{s}_{ij}$ is not inferred by considering the direct line connections, the algorithm applies the very same approach as with lines for the transport mode m_{ij}. In most of the cases vehicle v_{ij} or line l_{ij} are known only for tap-ins on buses and for all tap-ins with recorded stop location s_{ij}.

In our setting, we consider a maximum gap of 5 days between tap-in b_{ij} and next tap-in $b_{i,j+1}$ to be used for tap-out location $\hat{s}_{ij}$. In total 99.37% of all records in 2016 and 90.20% in 2017 have card key recorded. The remaining data cannot be used for inferring travel diaries. The reason of higher error in 2017 is that all tap-ins for March 2017 are recorded with an unknown card key. Thus, for an adequate evaluation of success rates of TOLIA algorithm, rates in the tables below are proportional to the yearly tap-ins with identified card keys, i.e. correctly registered raw data. As the maximum search radius r we use 1 kilometre, reflecting a walking distance of 500 meters given that the actual origin might be positioned in the middle of an axis between two stop locations.

Table 2.1 summarizes the overall rates of tap-out estimates for the entire years of 2016 and 2017 as well as for the respective months of February separately, which are higher than 80% in all cases. We provide some analysis for 400 meters and 1 kilometre radiuses for the non-metro trips where tap-out is identified based on the recorded line l_{ij} or lines on the tap-in location $l_{s_{ij}}$. Increasing the radius from 400 to 1000 metres results in an increase of 8-9 % (sum of reference lines 4 and 6 in Table 2.1) in the total number of estimated tap-outs from which about 75% (sum of reference lines (2,3,5) divided by sum (2,3,4,5) in Table 2.1) of tap-out locations are estimated within 400 meters. Many of the trips are made by metro, trains and trams without a line record.

Ref.		**2016**	**2017**	**February 2016**	**February 2017**
1	Rate of inferred tap-outs	83.36%	81.38%	87.88%	86.87%
	From which				
2	$\mathrm{l}_{i,j}$ *and* $\mathrm{l}_{i,j+1}$ *is the same*	9.78%	10.34%		
3	$\mathrm{s}_{i,j+1}$ *in 400 meters radius considering* $\mathrm{l}_{i,j}$	13.72%	14.40%		
4	$\mathrm{s}_{i,j+1}$ *in 400 – 1000 meters radius considering* $\mathrm{l}_{i,j}$	7.22%	7.43%		
5	$\mathrm{s}_{i,j+1}$ *in 400 meters radius considering set of lines* $\mathrm{l}_{\mathrm{s}_{ij}}$	3.11%	2.45%		
6	$\mathrm{s}_{i,j+1}$ *in 400-1000 meters radius considering set of lines* $\mathrm{l}_{\mathrm{s}_{ij}}$	1.40%	1.54%		
7	$\mathrm{m}_{\mathrm{s}_{ij}}$ *and* $\mathrm{m}_{\mathrm{s}_{i,j+1}}$ *are the same,* $\hat{\mathrm{s}}_{ij} = \mathrm{s}_{i,j+1}$	31.38%	30.01%		
8	*Only one location with mode as* $\mathrm{m}_{\mathrm{s}_{ij}}$ *in radius of 1 km*	1.70%	1.44%		
9	*Multiple locations with mode as* $\mathrm{m}_{\mathrm{s}_{ij}}$ *in radius of 1 km*	15.05%	13.77%		

Table 2.1 Rates of tap-out estimates

Inference rates per transport mode are presented in table 2.2. The highest rate is for metro and the lowest for ferries. When it comes to trains and trams, some stations do not have tap-in gates and thus records can be missing. This can be an issue in cases when the next tap-in $b_{i,j+1}$ is at these stations but is not recorded. An opposite case is when the tap-in record b_{ij} is missing and thus the trip c_{ij} as well. The success rate for busses is lower than for metro and commuter train services because we choose to apply a more strict rule for this mode due to its stop density, yielding arguably more reliable estimates. The drop in the rate of tap-out estimates for trains from 2016 to 2017 is because Citybanan was introduced in the second half of 2017. It connects the metro and the commuter trains without requiring tapping-in at two metro stations (T-centralen and Odenplan). In this project we selected February 2016 and 2017 for the fare scheme evaluation purposes and hence it is not necessary to reflect this change, allowing us to consider metro and commuter systems as independent modes. A different logic reflecting the change introduced at these stations can be added for specific dates in future applications of the model to relax the current assumption.

Rates per transport mode	2016	2017
Metro	88.53%	86.21%
Bus	80.27%	79.54%
Train	85.29%	79.49%
Tram	67.64%	64.80%
Ferry	58.98%	51.98%

Table 2.2 Rates of tap-out estimates per transport mode.

Table 2.3 shows the rates for cases when the tap-out location $\hat{s}_{i,j}$ has not been inferred. When there is no location $s_{i,j+1}$ matching the line l_{ij} or any of the lines in L_{ij} for the bus mode, there is no clarity on which location within the allowable radius should be selected as the tap-out location. It is thus assumed that there is a trip missing or an alternative form of transport took place and cannot be directly identified from the smart card data. This is also likely to be the case if the stop locations of tap-in and next tap-in are the same ($s_{i,j+1}= s_{ij}$). This constitutes 9% (sum of ref. lines 1 and 6 in Table 2.3) of all trips, and indicates a potential improvement if machine-learning or pattern recognition would be applied to fill missing gaps based on individual user history. This lies outside the scope of this project and is a computationally and timely demanding task with uncertain reward. In all other cases inference of tap-out is not possible because of lack of information. For example, the rate for the case where there is no next tap-in $b_{i,j+1}$ is about 3.5% (see ref. line 4), but this statistic also includes the natural end of each travel diary as for the last trip in the year.

Ref.	Rates for	2016	2017
1	Tap-in and next tap-in locations are the same $\mathrm{s}_{\mathrm{i,j+1}}= \mathrm{s}_{\mathrm{i,j}}$	3.66%	3.57%
2	Next tap-in location $\mathrm{s}_{\mathrm{i,j+1}}$ is unknown	0.61%	0.61%
3	Tap-in location $\mathrm{s}_{\mathrm{i,j}}$ is unknown	1.00%	0.97%
4	There is no next tap-in $\mathrm{b}_{\mathrm{i,j+1}}$	3.32%	3.66%
5	No station in radius r, other modes as bus	2.79%	3.87%
6	No station in radius r matching lines for bus	5.25%	5.57%
7	Unknown mode	0.01%	0.37%
	In Total	16.64%	18.62%

Table 2.3 Rates for cases without tap-outs inferred

2.4 INFERENCE OF VEHICLES AND TRAVEL TIMES

Next, we infer trip time stamps by fusing the smart card data with the multimodal AVL data. It is important to note that the AVL data made available for this project are unfortunately incomplete, i.e. many departures or entire line operations are missing. In the case of buses, linking the smart card data with AVL data is simple since vehicle v_{ij}, line l_{ij} and departure u_{ij} are registered in most tap-ins records. In case that particular departure u_{ij} of vehicle v_{ij} is known and recorded in the AVL data, a simple search in the AVL data of vehicle v_{ij} is performed until the tap-out location $\hat{s}_{ij}$ is reached, allowing the extraction of the exact tap-out time $\hat{t}_{ij}$ based on the vehicle v_{ij} arrival time to location $\hat{s}_{ij}$.

In case the vehicle v_{ij} and departure u_{ij} are unknown, which is the case for most tap-ins in modes with tap-ins at gates, the first vehicle departing tap-in location s_{ij} after tap-in time time t_{ij} towards tap-out location $\hat{s}_{ij}$ on the same line is considered as inferred vehicle v_{ij}. The maximum accepted waiting time is 35 minutes. For metro trips, we perform a transfer inference if the tap-in and tap-out stop locations are not on the same lines. In the case of a journey involving a transfer, the tap-out time from the first vehicle towards the transfer stop has to be inferred, followed by the inference of vehicle from transfer stop to the tap-out location $\hat{s}_{ij}$. Once the vehicle is inferred, a simple search in the AVL data takes place when vehicle arrival time at tap-out location $\hat{s}_{ij}$ is considered as tap-out time $\hat{t}_{ij}$.

Table 2.4 summarizes the performance of travel time estimates at the level of trips relative to the total number of complete trips with estimated tap-out locations (known $\hat{s}_{ij}$). We are able to estimate tap out times for 66% of the cases in 2016 and 60% in 2017.

Ref.		**2016**	**2017**	**February 2016**	**February 2017**
1	Rate of inferred tap-out times	65.79%	60.34%	70.36%	64.00%
	From which				
2	*Vehicle* v_{ij} *known, TEA only*	25.97%	27.96%		
3	*Vehicle* v_{ij} *unknown, VIA and TEA*	28.67%	23.78%		
4	*Metro transfer with VIA and TEA*	11.15%	8.61%		

Table 2.4 Rates of tap-out time $\hat{t}_{ij}$ estimates

The vehicle v_{ij} has to be inferred by the VIA algorithm in almost 49% (sum of ref. lines 3, 4 in Table 2.4 and 1 – 9 in Table 2.5) of the cases and is successful in 29% of trips in 2016 and 24% in 2017 (ref. line 3 in Table 2.4). In cases when vehicle v_{ij} is recorded or inferred by VIA, TEA is unsuccessful only for about 10% of the trips, mostly because of missing AVL data (see sum of ref. lines 10 – 12 in Table 2.5). When combining rates in Table 2.4 with rates in Table 2.5 (sum or ref. lines 4 in Table 2.4 and ref. lines 6 – 9 in Table 2.5), about 15% of all trips corresponding to metro trips with transfer within the metro system are not inferred.

Table 2.5 shows the rates for the cases when tap-out time $\hat{t}_{ij}$ is not estimated.

	Ref.	**Rates for**	**2016**	**2017**
VIA	*1*	*Tap-in location $s_{i,j}$ vehicle cannot be inferred*	0.52%	0.53%
	2	No AVL data on tap-in s_{ij}	0.31%	1.96%
	3	Vehicle not inferred within 35 minutes from t_{ij}	14.22%	14.75%
	4	Out of the 2 days constraint or over next-tapin day $d_{i+1,j}$ and $t_{i+1,j}$ time	0.72%	0.91%
	5	No AVL data for tap-in d_{ij} and tap-out $\hat{d}_{ij}$ days	1.62%	2.60%
VIA (metro transfer)	6	Vehicle not inferred within 35 minutes from t_{ij}	2.82%	3.88%
	7	Over next-tapin day $d_{i+1,j}$ and $t_{i+1,j}$ time	0.06%	0.06%
VIA *(metro tap-in)*	8	Vehicle not inferred within 35 minutes from t_{ij}	2.61%	3.63%
	9	Over next-tapin day $d_{i+1,j}$ and $t_{i+1,j}$ time	0.10	0.53%
TEA	10	No AVL data on tap-in s_{ij} and tap-out $\hat{s}_{ij}$ location	9.44%	9.44%
	11	Out of the 2 days constraint or over next-tapin day $d_{i+1,j}$ and $t_{i+1,j}$ time	0.60%	0.54%
	12	No AVL data for tap-in d_{ij} and tap-out $\hat{d}_{ij}$ days	1.19%	0.82%
	13	In Total	34.21%	39.66%

Table 2.5 Rates for cases without tap-out times $\hat{t}_{ij}$ inferred

The main shortcoming of the analysis performed is that not all vehicles and departures are covered by the AVL data. This can mean an overestimation of travel times in case of missing AVL data if some departure is missing. GTFS timetables should be considered to identify and fill gaps and provide at least some travel time estimates. The advantage of AVL data is that they represent the real vehicle travel times for a particular day and time.

2.5 JOURNEY ALGORITHM

The Journey algorithm processes individual trips made by card i from the temporally ordered set of trips C_i with the tap-out estimated by TOLIA. A necessary step in constructing journeys from trips is to infer transfers. For the actual compilation of trips into journeys, the approach used by Seaborn et al. (2009) is adopted. It defines a transfer as the interchange between vehicles of the same or different modes. However, throughout this change some activities might be performed, including "incidental" activities or activities that are the purpose of the journey. In the former case, a passenger would perceive two trips and an activity in between as one complete journey, whereas the latter would be considered as two journeys separated by an activity, regardless of its duration. The goal in transfer inference is to select the right time threshold that would allow identifying whether there is only an incidental activity between two trips with the best precision possible. In other words, the time threshold is the maximum transfer time for these two trips to be considered to constitute a single journey.

Transfer inference

As smartcard data do not provide any information on activities, it is recommended to rely on a network-wide analysis of the available time gap distribution. This opens up some insightful relations that lead to a decision on the approximate thresholds for the entire network. Yet they can be applicable to a specific route too, as long as the physical and operational context is similar. Taking into account the system specifics in Stockholm County, in particular the tap-in validation system, the analysis of inferred tap-out/next tap-in gaps like $g_{i,i+1} = t_{i,j+1} - \hat{t}_{ij}$ does not seem sufficient, because tap-out time $\hat{t}_{ij}$ is estimated for only 60% of the trips. In this case, it can be complemented with tap-in/next tap-in gaps $g_{i,i+1} = t_{i,j+1} - t_{ij}$ which apart from the net transfer time and activities, include also the in-vehicle time. In other words, we check not only the transfer time but also the overall journey time.

The logic behind the transfer inference is presented in Figure 2.2. It considers a set of potential time gaps and assigns a transfer status to those which fall short of a certain threshold. The priority is given to the inferred tap-out/next tap-in rule with known $\hat{t}_{ij}$, and only if the tap-out information is not available, then the tap-in/next tap-in condition is checked. It allows to consider a tap-in record where tap-out location $\hat{s}_{ij}$ or time $\hat{t}_{ij}$ is not estimated if it falls within the time gap $g_{i,i+1} = t_{i,j+1} - t_{ij}$. A journey is compiled when $g_{i,i+1}$ time gap exceeds the transfer threshold, or there is no next tap-in available.

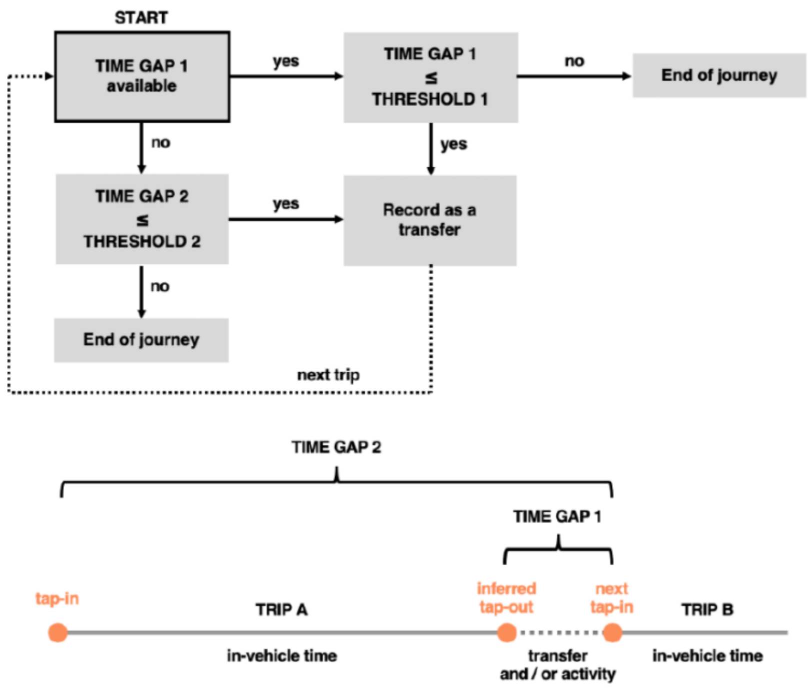


Figure 2.2 Logic of transfer inference algorithm

Figure 2.3 presents the distribution of all available time gaps between successive trips, both for the tap-in/next tap-in and inferred tap-out/next tap-in combinations. There are no substantial differences between 2016 and 2017 data. In the case of tap-in/next tap-in gaps, 93% of them take place within 24 hours, with an average of 9,3 hours (9,2 hours for 2017). People tend to use public transport on a daily basis, where the two peaks around 9 hours and 14 hours most likely correspond to the majority of commuters, who spend this amount of time at work (between morning and afternoon/evening tap-ins on the same day) and home (between afternoon/evening and the following morning), respectively. When it comes to the distribution in minutes of the first hour, tap-in/next tap-in demonstrate an average of 23 minutes (23,2 minutes for 2017) and 80% gaps within 35 minutes. In turn, inferred tap-out/next tap-in have an average of 11,4 minutes (11,1 minutes for 2017) and 80% of the gaps are within 20 minutes. Most of the transfers are done within the first few minutes, whereas the in-vehicle time is more evenly distributed along the hour. It is facilitated by the highly efficient and frequent public transport system.

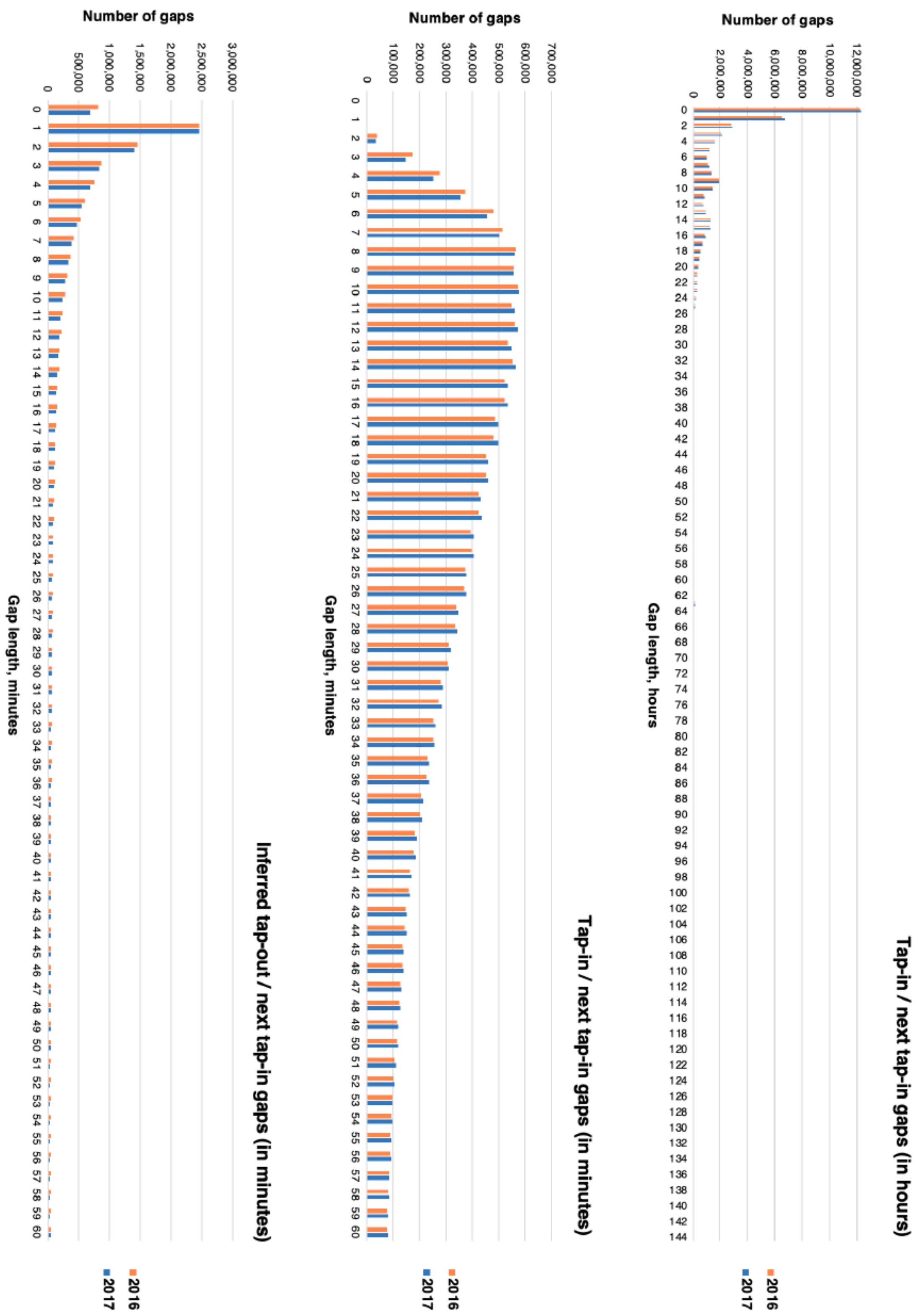


Figure 2.3 Distribution of available time gaps between trips

Due to the high consistency between the two years, it is decided to continue the time gap analysis with the year 2016. To identify a set of thresholds, a cumulative distribution graph of available time gaps is plotted, based on a certain parameter (Seaborn et al., 2008). With the inferred tap-out/next tap-in combination, the most important parameter is likely to be mode combination, as the physical infrastructure connecting two modes as well as their frequencies would determine the total transfer time. Table 2.6 presents top-eight combinations of three modes (metro, bus, commuter train) that yield 95% of all available gaps of the first hour.

Mode transfer down stream		Number of time gaps	Share [%]	Accumulative share [%]
Bus	Metro	3,546,233	20.94	20.94
Metro	Bus	3,224,930	19.04	39.97
Bus	Bus	2,867,267	16.93	56.90
Metro	Metro	1,847,922	10.91	67.81
Bus	Train	1,352,640	7.99	75.80
Train	Bus	1,282,324	7.57	83.37
Train	Metro	954,564	5.64	89.00
Metro	Train	923,858	5.45	94.46
Other		938.956	5.54	100.00

Table 2.6 Split of available time gaps by mode combination (top-eight results)

The cumulative distribution of inferred tap-out/next tap-in time gaps for the aforementioned mode combinations is displayed in Figure 2.4. As explained in Seaborn et al. (2008), vertically oriented lines represent pure transfer (frequently observed), horizontally oriented correspond to gaps separating two journeys (evenly distributed, thus an activity of random duration is involved), while the curve connecting them is a transition phase that includes “incidental” activities. The threshold lies somewhere in the transition range, and choosing the exact value is an ambiguous task. To make sure that most of the potential transfers are covered, the point before linearity is selected. In Figure 2.4, four clusters are distinguished due to their similar distribution: (i) bus-train and bus-metro; (ii) metro-train, train-metro, metro-bus and train-bus; (iii) bus-bus; (iv) metro-metro.

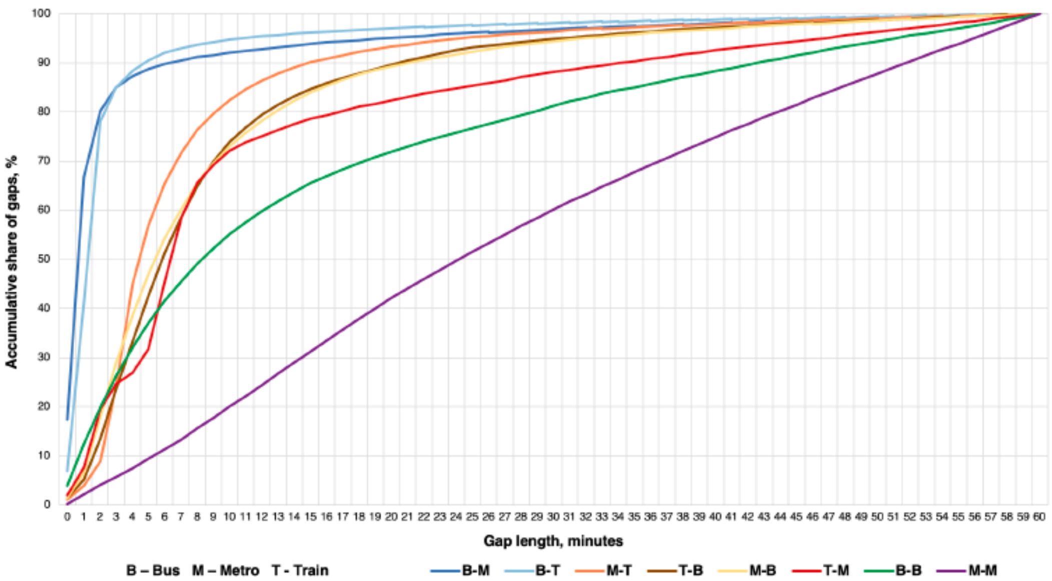


Figure 2.4 Cumulative distribution of available inferred tap-out / next tap-in time gaps based on mode combination

The distribution for metro-metro is fairly even, because a transfer is by default "hidden", hence it only gets registered when the user leaves the system and enters again. In order to account for any unconventional cases, the threshold is set to 5 minutes. The time thresholds for tap-out/next tap-in gap $g_{ij} = t_{i,j+1} - \hat{t}_{ij}$ are summarized in Table 2.7.

Mode/Mode	*Bus*	*Metro*	*Train*	*Other*
Bus	30	10	10	20
Metro	20	5	20	20
Train	20	20	20	20
Other	20	20	20	20

Table 2.7 Gap time thresholds for tap-out → next tap-in

In case that the tap-out time $\hat{t}_{ij}$ is not estimated, the tap-in time t_{ij} and next tap-in time $t_{i,j+1}$ are considered when computing the gap $g_{ij} = t_{i,j+1} - t_{ij}$. The distribution of these gaps is plotted in Figure 2.5. What matters is the duration of in-vehicle time, which is much longer than an average transfer is (refer to Figure 2.3). The Origin-Destination combination affects the length of a trip, therefore the fare zones that existed in 2016 are chosen to be the defining parameter. For every stop the fare zone is defined as f_s. In this way, three clusters are clearly visible, each of them representing trips within one zone, between two or three zones. The Table 2.8 summarizes the time thresholds in this case.

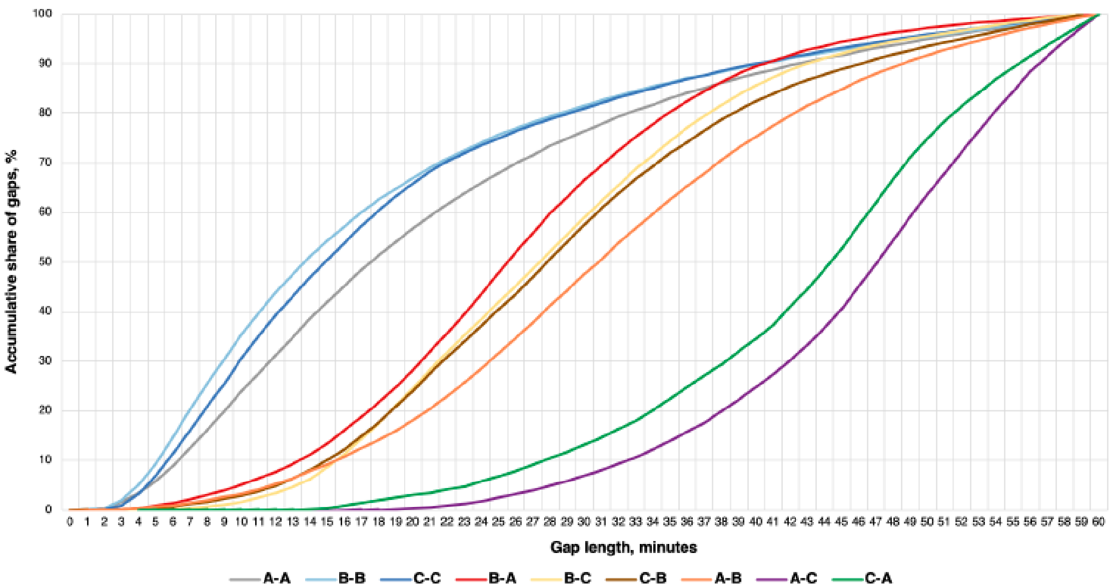


Figure 2.5 Cumulative distribution of available tap-in / next tap-in time gaps based on location located in one of the particular fare zones (A,B and C)

Zone/Zone	*A*	*B*	*C*
A	40	50	60
B	50	40	50
C	60	50	40

Table 2.8 Gap time thresholds for tap-in → next tap-in in minutes.

Figure 2.6 shows the combinations of successive modes for passengers transferring on 1 February 2017.

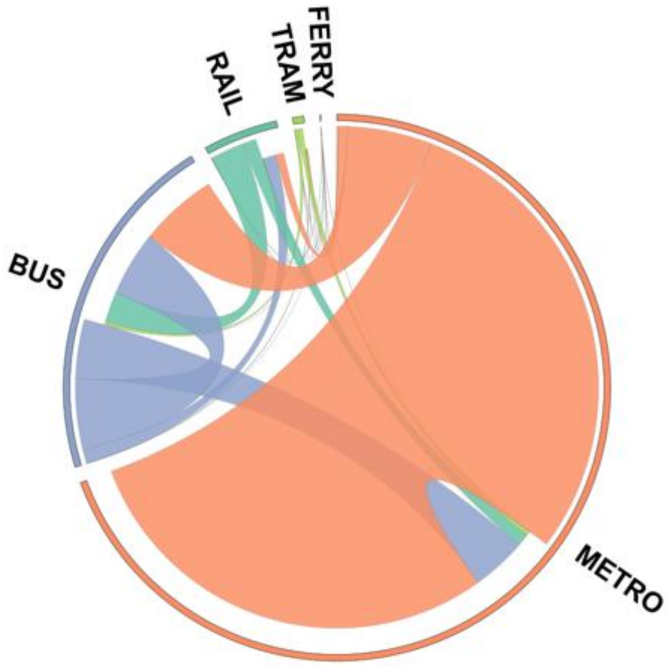


Figure 2.6 Transfer mode migration for 1 February 2017

Given the decision on time thresholds, one can continue with the application of the transfer inference in the journey algorithm.

Journey algorithm

The Journey algorithm goes through the temporally ordered set of trips C_i for every card *i* and follows the rules regarding the time thresholds and transfer inference discussed in detail above. Each pair of successive tap-in records for which the gap $g_{ij}$is larger than the pre-set threshold or there is no next tap-in $b_{i,j+1}$, the current journey ends and new starts. It results in a new set Y_i of temporally ordered journeys made by card *i*. Every journey y_{ij} inherits all the attributes from its first tap-in and last tap-out. The origin location $s^o_{y_{ij}}$ and tap-in time $t^o_{y_{ij}}$ as is inherited from first tap-in in the journey y_{ij}. The destination location $\hat{s}^d_{y_{ij}}$ and last trip tap-out time $\hat{t}^d_{y_{ij}}$ are based on the last tap-out in the journey y_{ij}. Table 2.9 summarizes the distribution of cases when the current journey is terminated and a new journey starts. Trips without tap-out recordings can still be associated with a transfer based on their tap-in information only, which is the case for 46,4% (37,0% plus 9,4%) and 53,5% (42,4% plus 11,1%) of the journeys in 2016 and 2017 respectively.

Transfer inference conditions		***Feb 2016***	***Feb 2017***
Tap-out time $\hat{t}_{ij}$ available	large gap	48,6%	42,5%
	no next tap-in	5,0%	3,9%
Tap-out time $\hat{t}_{ij}$ not available	large gap	37,0%	42,4%
	no next tap-in	9,4%	11,1%

Table 2.9 Rates for cases of terminating journeys in journey algorithm

The inference rates for complete journeys with estimated last tap-out location $\hat{s}_{ij}$ and time $\hat{t}_{ij}$ are summarized in Table 2.10. The success rates of estimating tap-out locations $\hat{s}^d_{y_{ij}}$ are high, about 85%. The journey tap-out time $\hat{t}^d_{y_{ij}}$ is estimated for almost 63% of journeys in 2016 and 55% in 2017.

Rates	**Feb 2016**	**Feb 2017**
Destination tap-out location $\hat{s}^d_{y_{ij}}$ estimated	85.51%	84.03%
Destination tap-out time $\hat{t}^d_{y_{ij}}$ estimated	62.63%	55.42%
Destination tap-out time $\hat{t}^d_{y_{ij}}$ estimated relative to the journeys with $\hat{s}^d_{y_{ij}}$ estimated only	73.24%	65.94%

Table 2.10 Rates for JA algorithm

Figure 2.7 shows the spatio-temporal illustration of origins and destination concentrations during the morning and afternoon peak on 1 February 2017. One can clearly observe in the morning the high concentration of destinations in city centre while origins are more spread around the inner city and corresponds to commuting flows. The exact opposite effect is visible in afternoon when people travel back home.

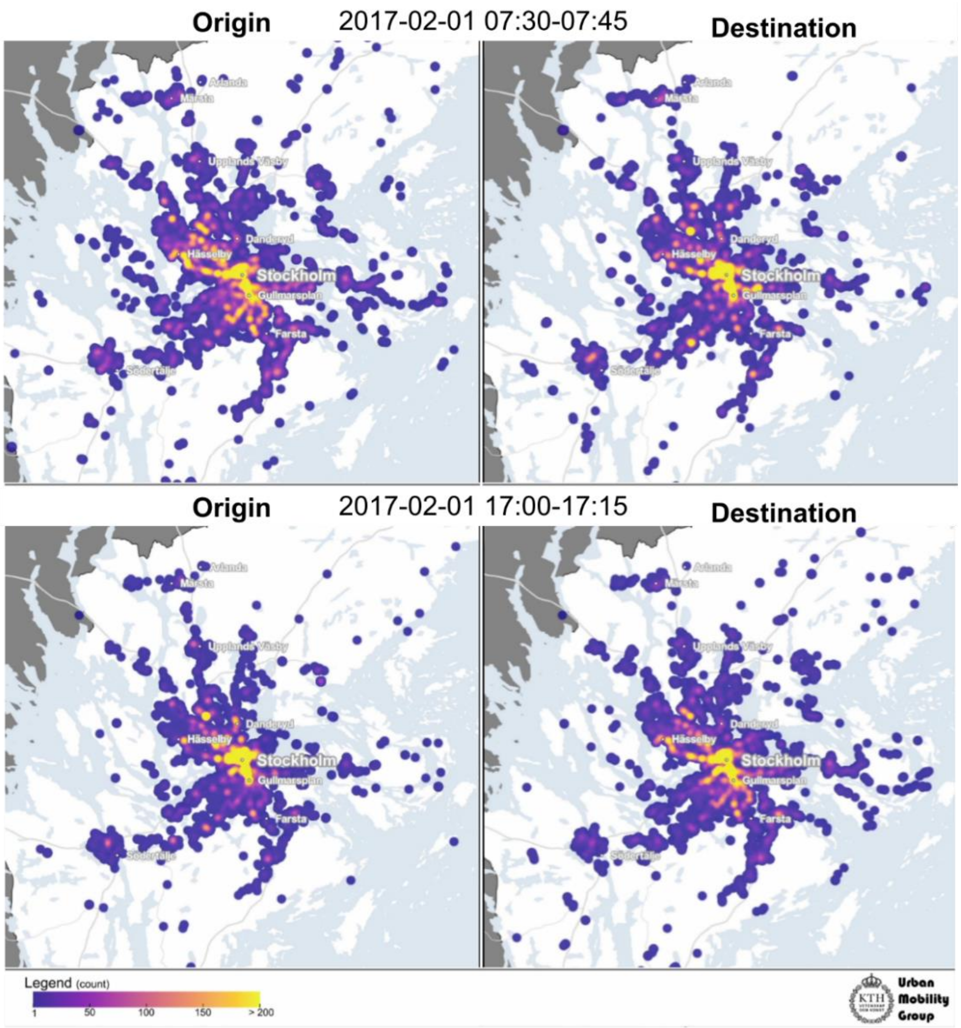


Figure 2.7 Spatio-temporal illustration of origin and destination heat maps for the morning and afternoon peaks on 1 February 2017.

Figure 2.8 present the distribution of journeys with a certain number of trips and Figure 2.9 shows the distribution of journey lengths.

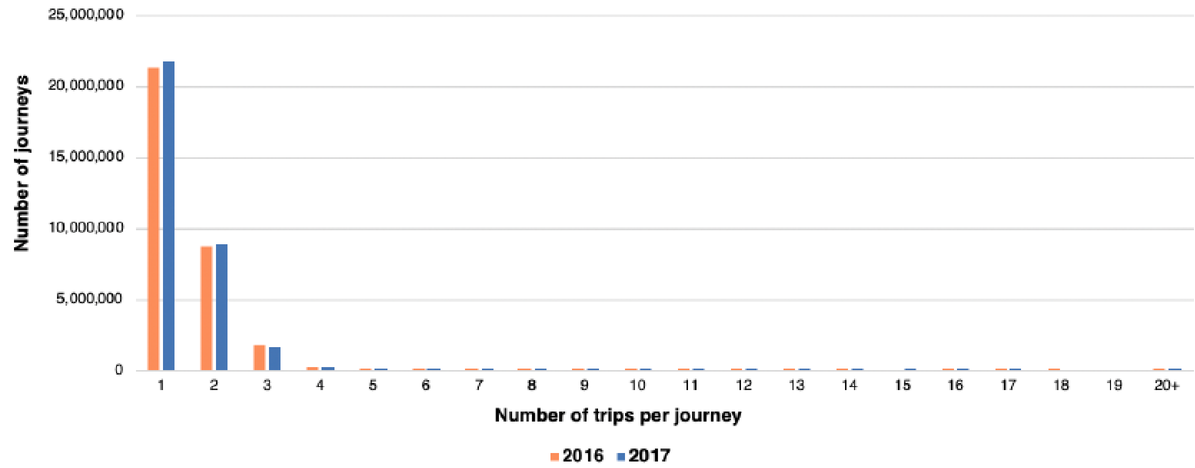


Figure 2.8 Distribution of journeys with a certain number of trips

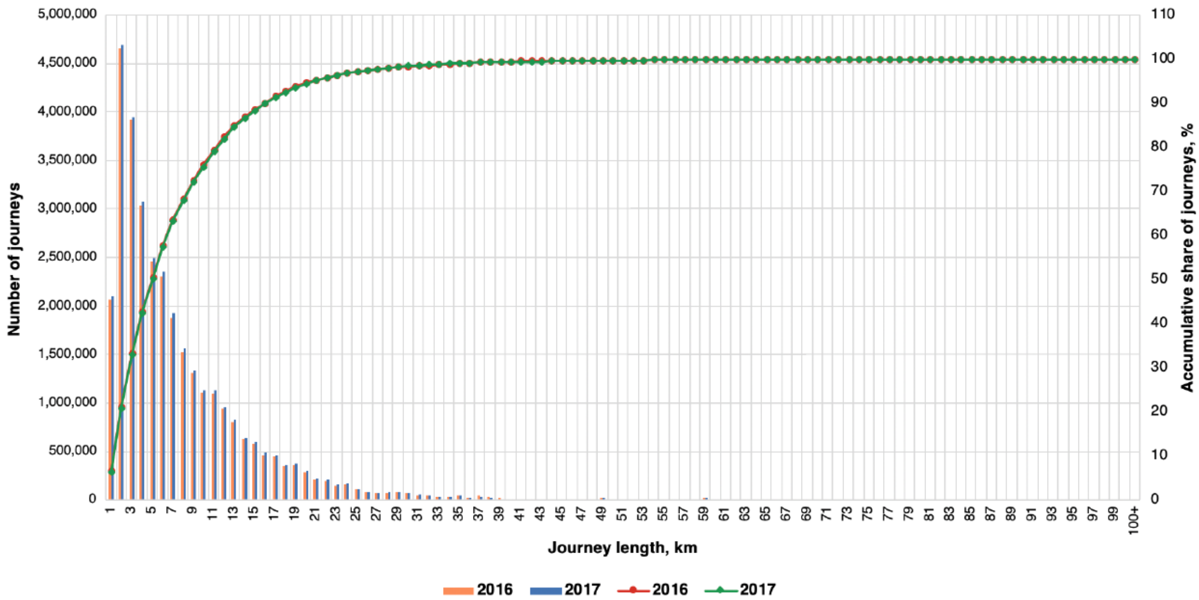


Figure 2.9 Cumulative distribution of journeys by length

2.6 Implementation

For processing the raw smart card data and running the TOLIA, TEA, VIA and JA algorithms, we used Python 3.7 and Ubuntu 14 Operating system. The resulting data are stored in a PostgreSQL database.

3 FROM DISAGGREGATE DIARIES TO USER GROUP TRAVEL PATTERNS

The previous chapter covered the work package WP1 and opened numerous possibilities for analysing travel patterns at different aggregation levels in WP2. This chapter covers WP2 and introduces the process for aggregating the individual travel diaries based on different attributes from smart card data and fusion with socioeconomic data. Socio-economic data enables the analysis of travellers' socio-economic context, and thus the techniques and analysis reported in this chapters are essential prerequisites for the case study fare analysis performed in Chapter 5.

The set of trips C and set of journeys Y, where each journey y_{ij} inherits attributes from the origin and destination, allows for various aggregations of the individual journeys at different levels, such as: origin-destination; spatio-temporal; product; line; vehicle; departure; and stop.

The socio-economic data are defined at the fine level of administrative/statistical census zones as illustrated in Figure 3.1 for the variable car ownership.

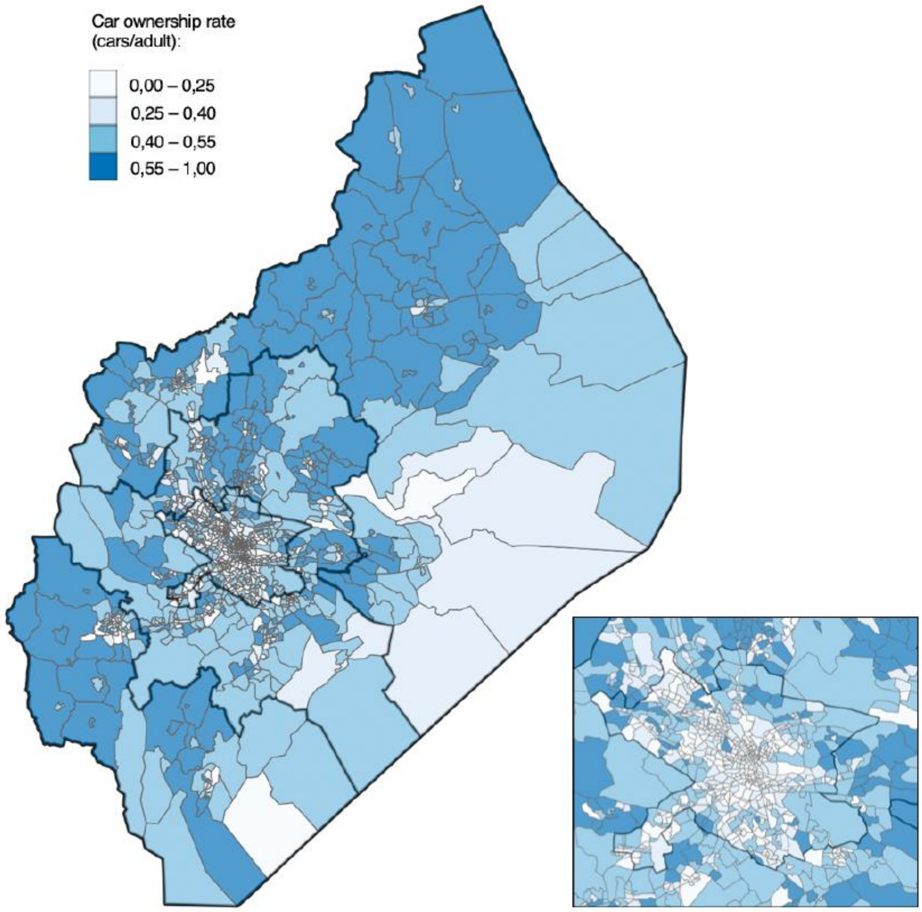


Figure 3.1 Illustration of resolution for socioeconomic data for the Stockholm region, illustrated by the index for car ownership.

As these zones are represented by geographical polygons it is straightforward to add to each location s the attribute that defines the socioeconomic zone e_s. When combining the socio-economic data with smart card data, the most likely home location for every card *i* needs to be identified, based on which the socioeconomic zone e_s can be assigned. We call this analysis procedure "home zone estimation".

Another segmentation of users can be based on product p_{ij} information, which is recorded with all tap-ins, making it very straightforward when aggregating trips, journeys or cards based on the product.

3.1 HOME ZONE ESTIMATION

In order to assign socioeconomic characteristics to each card, its home location should be identified at the socioeconomic 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. Essentially, spatial and temporal regularity of usage is investigated, which helps to set up the right threshold that separates sporadic travellers from regular ones. This creates a meaningful dataset of cards assigned to home zones with a sufficient degree of confidence.

The algorithm is based on the general assumption that the first journey of the day starting from 5 am (tap-in time of the journey $t^o_{y_{ij}} > 5\ am$) always originates from home, thus zone $e_{s^o_{y_{ij}}}$ is considered as candidate for the home zone location in set E_i of unique $e_{s^o_{y_{ij}}}$ observed candidates for home zone with the counts for each one. Journey destinations $s^d_{y_{ij}}$ are not considered to avoid reinforcement of any errors stemming from the travel diary compilation and related inferences. For each card i, a routine analysis is run that counts the number of first journeys of the day taking place from a particular census zone, or visit frequency in other words. If a zone reaches the defined frequency threshold and it is the only zone with the highest count, it is classified as the home location h_i for this card i.

The selection of a threshold stems from the empirical data of four months for each of the analysis years: January, February, April and May. Figure 3.3 displays the relation between the number of cards that have their home location identified and the visit frequency threshold. It can be seen that a value between 8 and 9 provides a transition point, after which the number of cards decreases at a slower and more even rate than for lower values. This distinguishes regular travellers from occasional ones, hence the threshold of visit frequency is set to 9 trips within the four-month period. This is in line with the research by Aslam et al. (2018), who found a threshold of 5 for a two-month period. The threshold is half as high, as is the analysis period (two months instead of four).

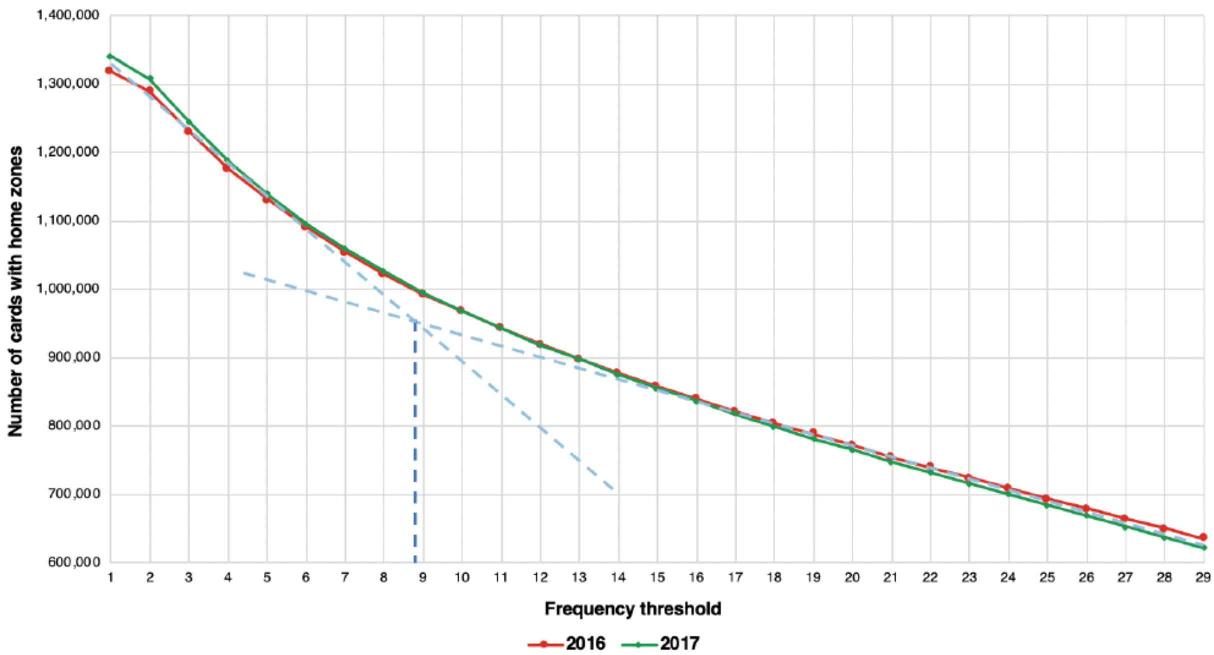


Figure 3.2 Number of cards with identified home zones based on frequency threshold

Subsequently, the home zone estimation is performed under the frequency threshold 9. The location is found for 70% of the cards, which account for 95% of all journeys. Thus, the removal of a significant number of infrequent travellers does not lead to a great reduction in journeys. The cards with assigned home zones are aggregated at the socioeconomic level and juxtaposed to the total population.

Another aspect of visit frequency is the home zone observation rate. It indicates the fraction of the estimated home zone out of the total count of visited zones for each card. With a higher rate, the conclusion on the home location becomes more robust. As can be observed from Figure 3.3, around 75% of all cards have their home location as their journey destination for more than 50% of all their journey (rate higher than 0,5), and 90% of cards more than 40% of all times (rate higher than 0,4).

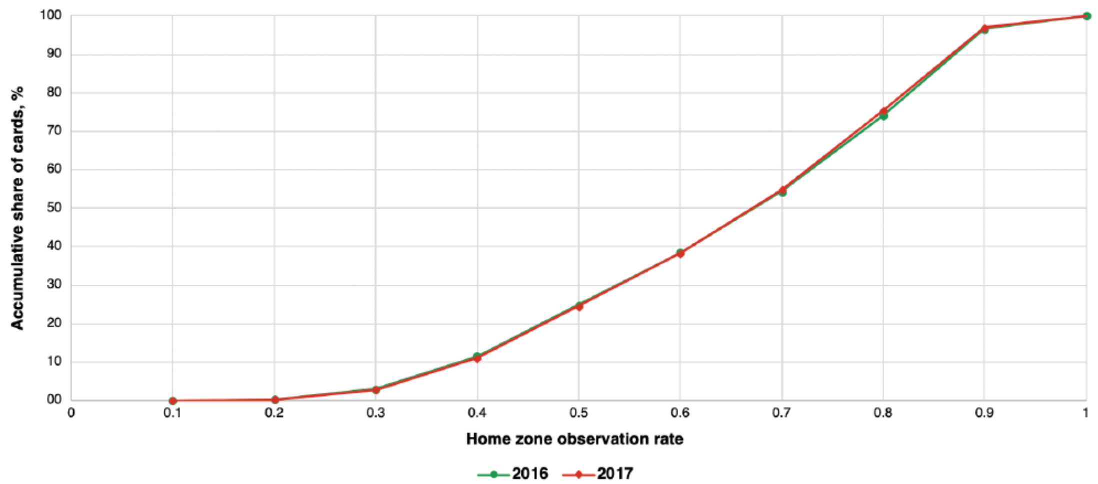


Figure 3.4 Cumulative distribution of cards by home zone observation rate

Figure 3.5 shows the number of cards inferred for each socioeconomic zone. It is noticeable that some zones in the city centre representing big transport hubs are assigned to be the home location for significantly more cards as others (see Figure 3.5(b)). These hubs or important back-bone stations are attracting travellers from neighbouring zones or zones within walking distance. There are two problems that should be addressed. First, the socioeconomic zones are especially granular in the city centre, just a few 100 square meters, so a lot of people can walk to stations in other zones and thus get assigned to a wrong home location and different socioeconomics. Second, when considering trains there are some stations without tap-in required and thus some travellers are assigned to the zone of first tap-in, which is usually one of the main transport hubs with mandatory tap-in on gates. This also does not reflect their true location and socioeconomics attributes.

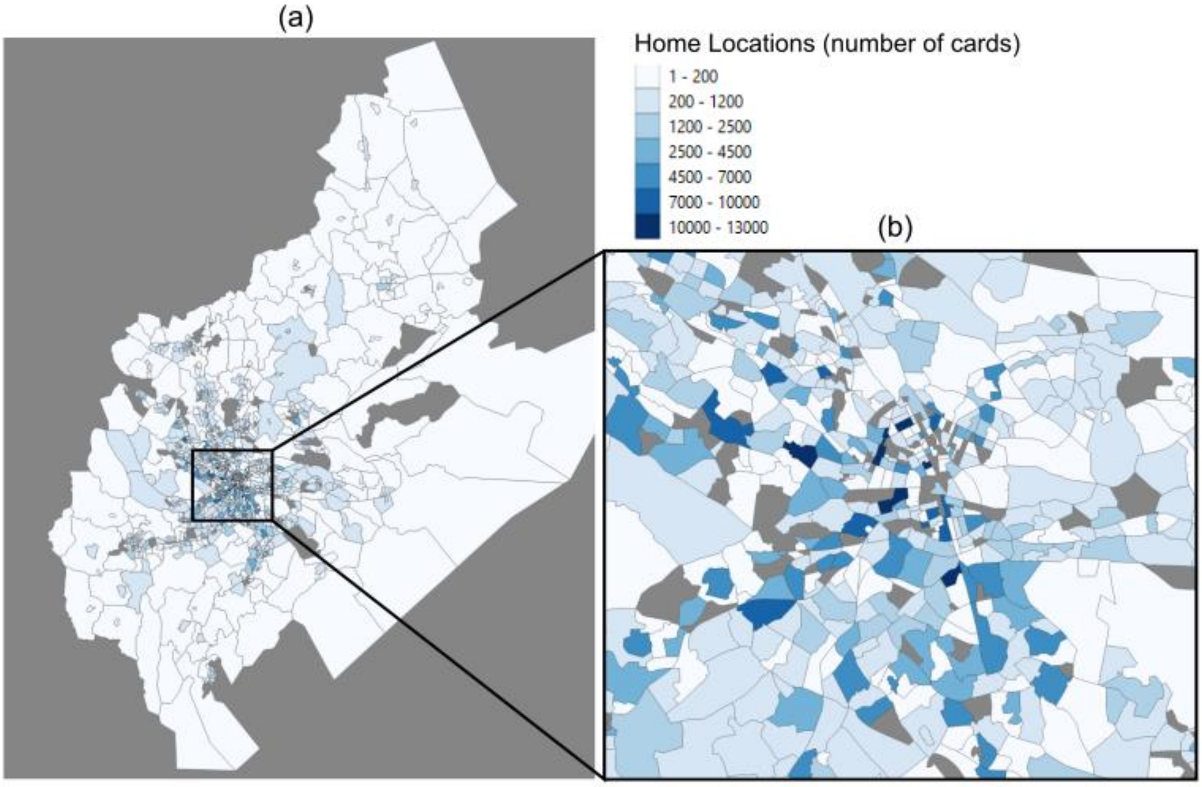


Figure 3.5 Illustration of inferred home locations on the socioeconomic zones. (a) Stockholm county (b) Stockholm City.

Identifying home locations has some important limitations but as there is no connection between card and user and its true home location, the above estimation at the level of the most frequent first morning tap-in location is used. Nevertheless, Figure 3.5 concurs with overall expectations given the spatial distribution of land-uses and activities in Stockholm County.

3.2 AGGREGATION METHODOLOGY

Trips in set C or journeys in set Y can be easily queried and aggregated from the database based on their attributes. In order to extract the group of travellers using a specific product or trips made by this product, trips c_{ij} or journeys y_{ij} can be aggregated based on their products p_{ij} or $p^o_{y_{ij}}$. This also enables origin-destination matrix generation based on origin stops $s^o_{y_{ij}}$ and $s^d_{y_{ij}}$, fare zones $f_{s^o_{y_{ij}}}$ and $f_{s^d_{y_{ij}}}$, socioeconomic zones $e_{s^o_{y_{ij}}}$ and $e_{s^d_{y_{ij}}}$, or just home zone location h_i. The latter allows populating attributes connected to socioeconomic data such as car ownership, income etc. In addition, the combination of several different attributes can be obtained.

4 QUANTIFYING ACCESSIBILITY AND EQUITY EFFECTS

4.1 EQUITY MEASUREMENTS LORENZ, GINI AND SUITS

We investigate distributional effects of policies to assess the horizontal and vertical equity of a policy. Horizontal equity indicates if the policy benefits or harms all approximately equally or if some are receiving higher shares than others are. Vertical equity indicates if unevenly distributed effects harm or benefits specific groups more than others.

In the literature there are a host of different measures and proposed metrics for assessing horizontal equity, se e.g. Banister (2018), p. 33-39 and World Bank Institute (2005), chapter 6 for discussions on alternative measures. The, by far, most used method is the combination of Lorenz-curves and Gini-coefficient with widespread applications regarding assessments of distribution in e.g. transport, income, wealth, and education(Lorenz 1905; Gini 1912).

In studies of vertical equity, there is not such a clear front-runner metric as Gini is for horizontal equity. In this project we have chosen the Suits metric (Suits 1977) due to its neat symmetrical similarity with Gini in computation and interpretation. In this sub-chapter, we first present the Lorenz-curve and its interpretation and then continue with the definitions, computations and interpretations of the Gini and the Suits metrics.

Both Suits and Gini use the Lorenz curve (LC) for their computation, but the LC is also in its own right a source of information on the distributional effects studied. To prepare the LC, first chose the policy effect to study. The policy effect, benefit or cost, should be additive. Then, ordering the population by increasing policy effect per capita (in case of Horizontal equity), the LC is plotted as y=f(x), where y is the accumulated share of the total policy effect that is bestowed the x percentage of the population receiving the lowest shares of policy effect per capita. In Figure 1 we see a schematic illustration of the LC.

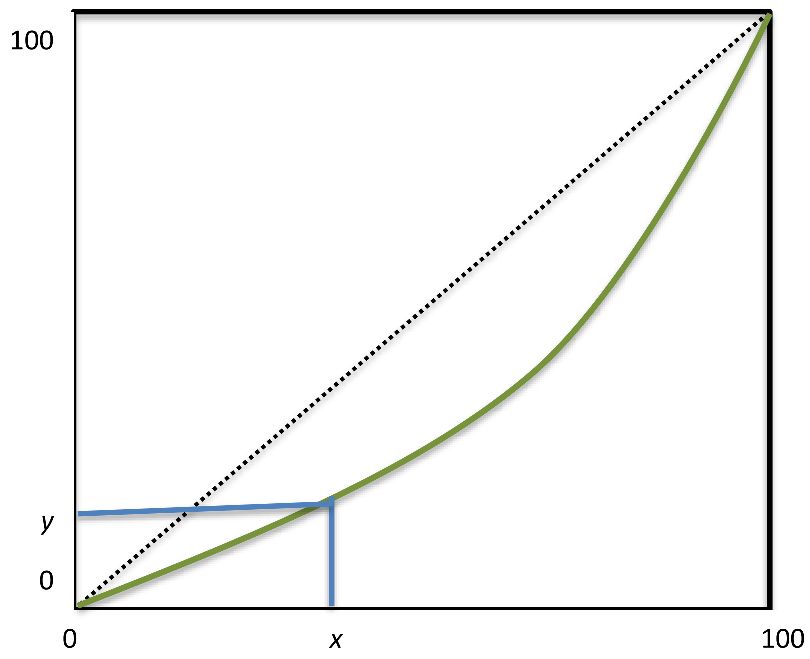


Figure 1 Schematic illustration of the Lorenz curve (green)

The interpretation of a point (x,y) on the Lorenz curve is that the x percent of the population that have the lowest share per capita of the policy effect have y percent of the accumulated effect (income, accessibility, fare expenses). The LC, then, gives the reader the ability to look at the distribution throughout the population. Due to its definition, The LC will always be below or on the dotted diagonal.

To understand how a segment of the population is affected, Figure 2 shows the LC for the population between x_1 and x_2. This group are those that are included in the bottom x_2 percent of the population, in terms of policy effect per capita received, but not the bottom x_1 percent. This group receives the share (y2-y1)/(x2-x1) of the total policy effect per capita. If the slope, α, is 45 degrees, then the segment receives a policy effect in proportion to its size, if α is larger they receive an outsized share and if α is smaller they receive a lower than proportional share. Since the ordering of the population is by increasing share of policy effect per capita, α of the LC will always be equal or increasing with increasing x. If the policy effect is equal for each person in the population, the LC will trace the dotted diagonal.

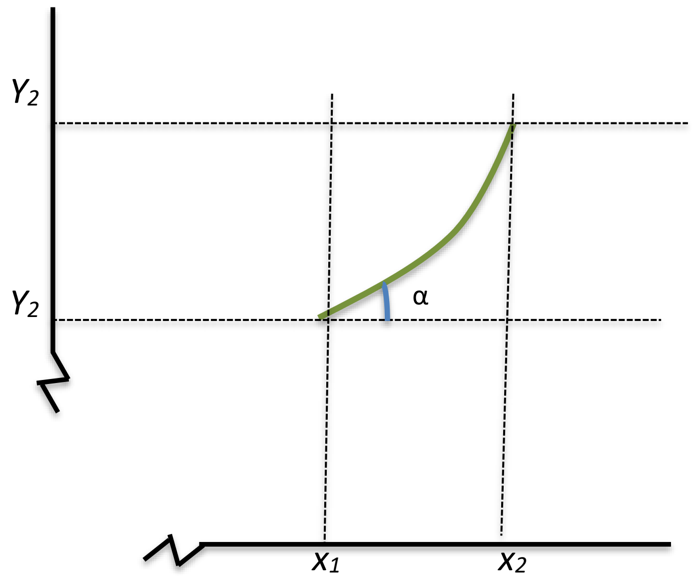


Figure 2 Interpretation of a segment of the Lorenz curve.

The Gini coefficient (G) is a scalar measure of the Lorenz curve. It takes values between 0 (equal) and 1 (unequal) and is defined by the relative size of the areas below the diagonal and the LC. If the area below the diagonal is D and the area below the LC is L, then the Gini coefficient is formulated as:

$$Gini = \frac{(D - L)}{D} = 1 - \frac{L}{D} \quad (1)$$

Figure 3 show three examples of LC with associated G (Table 1 reports their tabulated distributions). One can note that e.g. a G of 0.02 is associated with the bottom half of the population receiving 49 percent of the policy effect (almost entirely proportional), while a G of 0.51 mean that the bottom half only receives 15 percent of the policy effect.

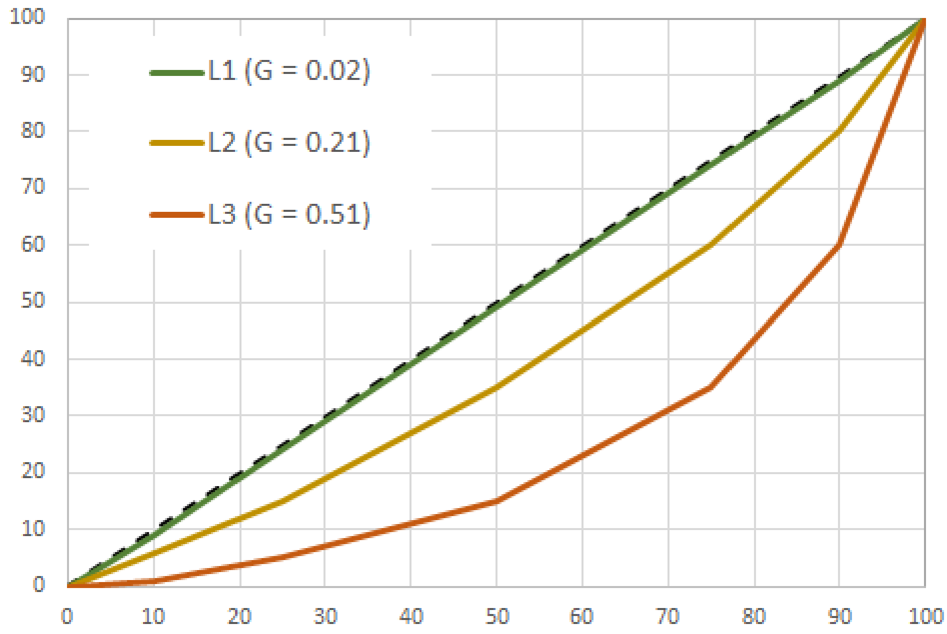


Figure 3 Example of three Lorenz curves with associated Gini coefficients (G).

Table 1 Tabulated accumulated policy effects received in the three example distributions

Accumulated Population (ordered by increasing policy effect/capita)	L1	L2	L3
0	0	0	0
10	9	6	1
25	24	15	5
50	49	35	15
75	74	60	35
90	89	80	60
100	100	100	100

To compute the Suits coefficient (S), there has to be another sorting of the population for the LC. Instead of sorting it by per capita received policy effect, the sorting is by the variable that distinguishes the vertical dimension of the vertical equity. In this project, this dimension is income, so the population is sorted by increased income. This means that the point (x,y) on the LC represents that the x percent of the population with the lowest incomes receive y percent of the total policy effect. The slope for this LC has the same interpretation as the more common LC, but in contrast to the common definition, this LC can be above the diagonal. In fact, if the LC is constantly above the diagonal, then the policy effect is more geared toward low incomes than high incomes. If it is constantly below, the effect falls out towards those with high incomes. With L and D defined as for the Gini coefficient, the equation for Suits is:

$$Suits = \frac{(L - D)}{D} = -1 + \frac{L}{D} \qquad (2)$$

Note that in contrast to Gini, Suits take values between 1 (effects to the poor), through 0 (proportional shares of the effects to all), to -1 (effects to the rich). Table 2 and Figure 4 show three tabulated distributions and their associated Lorenz curves and Suits coefficients. A suits coefficient of -0.21 is associated with the half of the population with the lowest incomes receive 35 percent of the policy effects while a Suits of 0.18 give them 65 percent of the effects.

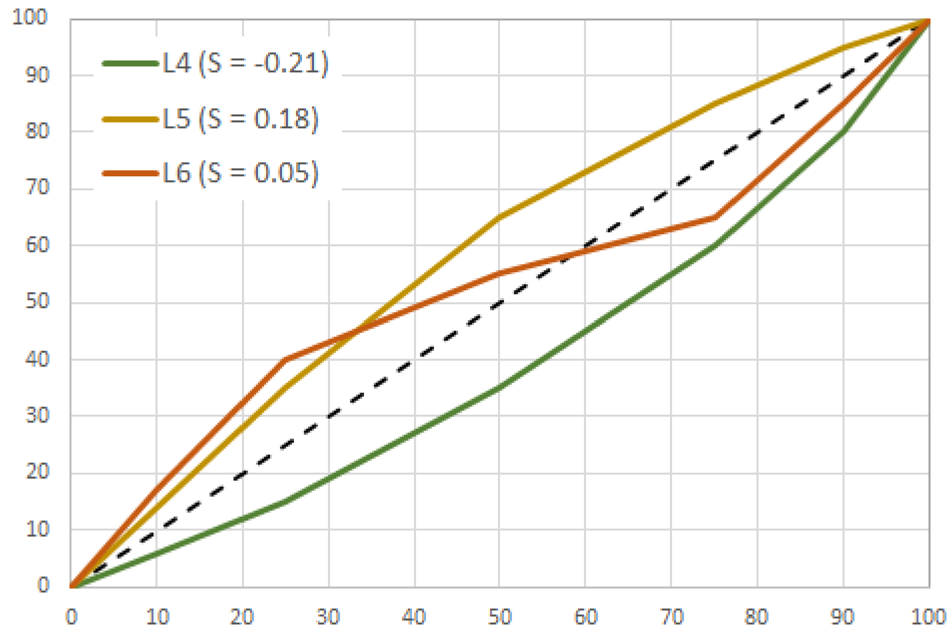


Figure 4 Example of three Lorenz curves with associated Suits coefficients (S)

Table 2 Tabulated accumulated policy effects received in the three example distributions

Accumulated Population (ordered by increasing income)	L4	L5	L5
0	0	0	0
10	6	14	17
25	15	35	40
50	35	65	55
75	60	85	65
90	80	95	85
100	100	100	100

4.2 QUANTIFYING EQUITY EFFECTS OF FARE CHANGE

Quantifying effects of fare changes is straightforward with the use of LC, G and S. The policy effect to be evaluated is the total fares paid. High Gini coefficients will imply that some segments of the population pay much more in fares for their trips than others, positive Suits coefficients will imply that low-income segments pay disproportionally much in fares and high-income segments pay disproportionally less. The converse holds for negative Suits coefficients.

Rubensson et al (2019) computed distributional effects for fare changes using transport model data, without changes in demand with changed fares. Chapter **Error! Reference source not found.** presents a more full-fledged analysis, using travel patterns extracted from smart card data and the natural experiment of the Stockholm fare change of January 2017.

4.3 QUANTIFYING EQUITY EFFECTS OF CHANGES IN ACCESSIBILITY

The primary output of public transport is the accessibility, i.e. what ability the system renders to residents in terms of getting to locations where they can perform sought after activities. Accessibility of public transport is strongly uneven in its distribution, with more accessibility in central and densely populated areas than in remote and sparsely populated areas. It is impractical and hard to justify full equality of accessibility, since it will never be possible to let the rural traveller have the short travel time, frequency of service and breadth of close by attractive destination as the resident in the downtown central business district.

One worthy equity goal, however, could be that residents on the same distance from the city center and living in equally densely populated areas have the same accessibility. Rubensson et al (2020) proposes this equity goal and develops a methodology by which public transport accessibility can be measured and assessed with regard to this goal. The proposed accessibility measure uses model-generated logsums wich encompass generalized travel costs (time and money) as well as destination attractivity. These logsum accessibility measures are then used as dependent variables in a linear regression with two independent variables; distance to city centre and population density in the origin zone. To measure distributional impact, the monetized difference between the logsum and the expected logsum (from the regression) is then used as policy effect in a LC, G and S analysis.

5 BEFORE-AFTER ANALYSIS OF CHANGES IN FARE SCHEME

5.1 PRODUCT SELECTION

Among the entire product range, Figure 1 shows that five products form the demand basis. 30-day passes with the full and reduced fare, together account for 60% of journeys and 35% of cards. Travel funds (full and reduced) have a much lower share of journeys 11%, but the largest share of cards 40%. General school passes comprise 9% of journeys and 7% of cards.

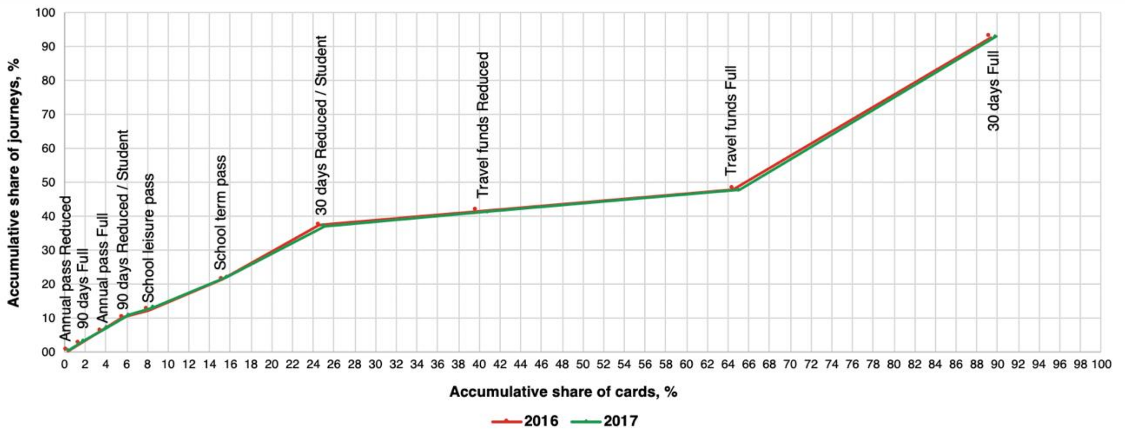


Figure 5.1: Cumulative distribution of cards and journeys by products

In terms of the policy impact, it is important to look at the product split from the O/D perspective, as exhibited in Table 1. All products except for travel funds show a fairly coherent growth among the fare zones. This increases on both the negative and positive side when it comes to remote combinations that include fare zone C, namely A-C (C-A), B-C (C-B), and especially C-C. It is partly explained by lower demand levels for these O/D pairs, so every incremental change is weighted more, however a redistribution of demand undoubtedly takes place. Considering these circumstances, travel funds pose the highest interest for evaluation. It is the only product group which price scheme got greatly affected by the fare policy, which also creates favorable conditions for an elasticity analysis. The effect on demand is evident - the disparity between one-zone O/D and two- or three-zone O/D is substantial (0-5% against 20-60%). This observation falls in line with the expectations on increasing ridership with more affordable fares. Moreover, the market penetration of travel funds is large enough for representative outcomes.

Travel funds reach a disproportionate development of journeys and cards that also reduces the average frequency, especially for reduced fare. To investigate the origins of the card influx, a card migration analysis can be performed. 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 either 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 proven to be quite identical in both directions.

Product ID	Product name	A - A		A - B		A - C		B - A		B - B		B - C		C - A		C - B		C - C	
		Absolute	Relative, %	Absolute	Relative, %	Absolute	Relative, %	Absolute	Relative, %	Absolute	Relative, %	Absolute	Relative, %	Absolute	Relative, %	Absolute	Relative, %	Absolute	Relative, %
1022	30 days Full	8.693	2,2	1.031	2,1	324	4,7	1.262	2,4	818	3,4	33	1,3	350	5,0	76	3,4	2.881	43,4
1024 / 1356	30 days Reduced / Student	-6.835	-4,8	-867	-5,6	-250	-11,6	-832	-5,2	-780	-6,1	-98	-10,4	-170	-7,9	-65	-7,5	435	11,0
1064	90 days Full	6.645	37,0	874	36,7	125	44,2	951	36,9	356	39,1	40	47,6	121	39,7	34	41,5	181	108,4
1065 / 1357	90 days Reduced / Student	-934	-2,5	-24	-0,6	-15	-3,6	4	0,1	-4	-0,2	7	4,9	-15	-3,4	14	11,1	23	5,6
1104 / 1107	Annual pass Full	2.138	6,3	296	6,7	73	12,7	303	6,3	86	4,9	22	13,6	96	15,3	12	7,7	82	21,4
1108	Annual pass Reduced	1.417	26,8	98	19,6	14	25,0	113	21,1	87	23,3	5	21,7	16	26,7	5	23,8	32	42,1
1250 / 1266	School term pass	2.349	3,8	245	2,9	21	2,4	530	5,5	915	4,8	34	3,0	46	4,5	74	7,5	-476	-7,6
1309	School leisure pass	-685	-3,8	-173	-6,9	-42	-15,2	-173	-7,2	-129	-3,7	-27	-15,0	-38	-15,4	-23	-14,6	-107	-16,6
40_1	Travel funds Full	-3.449	-5,1	660	22,8	241	68,3	1.028	22,8	98	4,8	61	49,2	358	56,9	76	56,7	24	2,5
40_2	Travel funds Reduced	89	0,2	549	21,3	161	47,8	760	18,6	188	5,0	57	38,3	228	36,1	59	35,1	-43	-2,9
Total		9.428	1,1	2.689	2,9	652	5,3	3.946	3,9	1.635	2,3	134	2,5	992	7,6	262	5,3	3.032	14,5

5.2 ELASTICITIES

User sensitivity is tested for different factors, 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 O/D fare zones. In the former case, this means that full, reduced and combined fares of travel funds are distinguished. In the latter case, the O/D groups indicate how many fare zones a user crosses. In order to acquire aggregate values, elasticities of each O/D group are weighted based on the corresponding ridership share and summarized afterwards.

The selection of travel metrics as sensitivity factors includes the following. 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. The travel distance groups are 0-1, 1-3, 3-5, 5-10, 10-20 and 20+ km. In order to find a good balance between reliable outcomes and a fine level of disaggregation, three user groups are distinguished within each socioeconomic factor. Consequently, the total population is divided into the lowest 25%, middle 50% and highest 25%, as two extremes and an average majority. The demarcation values of each factor in this distribution are used to separate the groups. As a result, the income levels are 0-220, 220-350 and 350+ thousand SEK, the socioeconomic index ranges are 3-4, 5-11 and 12-15, the car ownership groups are 0-0.25, 0.25-0.55 and 0.55+ cars/adult. Factors such as age and citizenship status do not provide a distinct partition at the census zonal level, and hence are not used in the elasticity analysis.

All elasticity values estimated in this study are shown in the tables below. 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. Further on, each factor is examined closely with the main observations highlighted and interpreted.

O/D group	General					
	Frequency threshold 2			Frequency threshold 9		
	Combined fare	Full fare	Reduced fare	Combined fare	Full fare	Reduced fare
1 zone	-0,14	-0,24	0,02	-0,32	-0,47	-0,10
2 zones	-0,14	-0,09	-0,21	-0,13	-0,09	-0,20
3 zones	-0,01	-0,01	-0,02	-0,01	-0,01	-0,01
All	-0,29	-0,34	-0,21	-0,46	-0,57	-0,31

O/D group	Transport mode								
	Combined fare			Full fare			Reduced fare		
	Metro	Bus	Train	Metro	Bus	Train	Metro	Bus	Train
1 zone	-0,35	-0,35	0,06	-0,50	-0,56	0,04	-0,10	-0,14	0,10
2 zones	-0,09	-0,19	-0,89	-0,05	-0,14	-0,58	-0,16	-0,25	-1,33
3 zones	-0,01	-0,01	-0,08	0,00	-0,01	-0,07	-0,01	-0,01	-0,10
All	-0,45	-0,56	-0,90	-0,56	-0,71	-0,61	-0,26	-0,40	-1,32

O/D group	Time of the day														
	Combined fare					Full fare					Reduced fare				
	Weekend	Weekday	Morning peak	Evening peak	Off-peak	Weekend	Weekday	Morning peak	Evening peak	Off-peak	Weekend	Weekday	Morning peak	Evening peak	Off-peak
1 zone	-0,37	-0,30	-0,42	-0,29	-0,28	-0,58	-0,45	-0,51	-0,43	-0,43	-0,10	-0,10	-0,05	-0,08	-0,11
2 zones	-0,12	-0,14	-0,16	-0,14	-0,13	-0,06	-0,09	-0,12	-0,10	-0,08	-0,19	-0,21	-0,31	-0,20	-0,20
3 zones	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01	-0,01
All	-0,50	-0,45	-0,58	-0,44	-0,43	-0,65	-0,55	-0,64	-0,53	-0,52	-0,31	-0,31	-0,38	-0,29	-0,31

O/D group	Journey distance, km																	
	Combined fare						Full fare						Reduced fare					
	0-1	1-3	3-5	5-10	10-20	20+	0-1	1-3	3-5	5-10	10-20	20+	0-1	1-3	3-5	5-10	10-20	20+
1 zone	-0,28	-0,37	-0,37	-0,31	-0,19	0,03	-0,42	-0,55	-0,56	-0,42	-0,31	0,03	-0,13	-0,12	-0,07	-0,12	-0,04	0,03
2 zones	0,00	0,00	-0,01	-0,06	-0,79	-0,83	0,00	0,00	0,00	-0,04	-0,56	-0,63	-0,01	-0,01	-0,02	-0,11	-1,06	-1,02
3 zones	0,00	0,00	0,00	0,00	0,00	-0,39	0,00	0,00	0,00	0,00	0,00	-0,40	0,00	0,00	0,00	0,00	0,00	-0,38
All	-0,28	-0,37	-0,39	-0,37	-0,98	-1,19	-0,42	-0,55	-0,56	-0,46	-0,87	-1,00	-0,14	-0,13	-0,09	-0,23	-1,11	-1,37

O/D group	Income level, thousand SEK								
	Combined fare			Full fare			Reduced fare		
	0-220	220-350	350+	0-220	220-350	350+	0-220	220-350	350+
1 zone	-0,28	-0,33	-0,30	-0,43	-0,48	-0,47	-0,10	-0,11	-0,02
2 zones	-0,08	-0,15	-0,12	-0,04	-0,09	-0,08	-0,12	-0,22	-0,19
3 zones	-0,02	-0,01	-0,01	-0,02	-0,01	-0,01	-0,02	-0,01	-0,01
All	-0,37	-0,49	-0,43	-0,48	-0,58	-0,56	-0,24	-0,35	-0,22

O/D group	Socioeconomic index								
	Combined fare			Full fare			Reduced fare		
	3-4	5-11	12-15	3-4	5-11	12-15	3-4	5-11	12-15
1 zone	-0,34	-0,31	-0,26	-0,49	-0,45	-0,42	-0,18	-0,12	0,02
2 zones	-0,09	-0,14	-0,16	-0,05	-0,09	-0,11	-0,14	-0,21	-0,25
3 zones	-0,03	-0,01	-0,01	-0,03	-0,01	0,00	-0,03	-0,01	-0,01
All	-0,46	-0,47	-0,43	-0,56	-0,56	-0,53	-0,36	-0,34	-0,24

O/D group	Car ownership rate, cars/adult								
	Combined fare			Full fare			Reduced fare		
	0-0,25	0,25-0,55	0,55+	0-0,25	0,25-0,55	0,55+	0-0,25	0,25-0,55	0,55+
1 zone	-0,46	-0,19	-0,11	-0,63	-0,29	-0,19	-0,13	-0,08	-0,06
2 zones	-0,04	-0,22	-0,38	-0,02	-0,15	-0,38	-0,07	-0,29	-0,38
3 zones	0,00	-0,02	-0,02	0,00	-0,01	-0,03	0,00	-0,02	-0,02
All	-0,50	-0,42	-0,52	-0,65	-0,46	-0,59	-0,21	-0,39	-0,46

Looking at the general elasticity, it becomes evident that the group of regular users is more sensitive to the fare policy (-0,46 versus -0,29 for both regular and sporadic). Such travelers have a higher degree of involvement or dependency on public transport and are thus 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 the case of full fares (-0,31 versus -0,57) due to the fact that they are mostly used by specific travelers with reduced mobility or no opportunity for private transport. This makes them captive riders who usually have to comply with any fare updates. The directionality of the fare change is also relevant. Full fare users, especially the regular ones, are more sensitive to price increase, while reduced fare users are the opposite, yet with a subtle margin.

Sensitivity by transport modes for the combined fare presents a distinct hierarchy. 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. The same trend is maintained among fare groups, however the elasticity of train for the full fare users is notably lower and approaches metro (-0,61 and -0,56 respectively). These findings reflect on the general features of each mode. For instance, the importance and advantage of the metro system is that it outperforms any other mode in terms of speed and frequency. Bus in turn provides a better connectivity and directness, however it lacks comfort and relies on traffic conditions, hence is less retaining. Train plays an almost as crucial role for commuters as metro. The directionality with transport modes might be biased, as metro and bus are mostly present in urban areas and used for shorter journeys, while commuter train undoubtedly dominates in the interzonal travel.

In terms of the journey distance factor, the results are fairly consistent among user groups as well as fare categories. Elasticity gradually increases with distance (from -0,28 to -1,19 for combined fare) and substantially jumps at the 10 km mark (from -0,37 to -0,98 for combined fare), yet a minor drop is observed at medium distances (around 5 km). Higher elasticity for short journeys reflects the fact 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 travelers, especially commuters, to consider other available options, for instance private transport. This reasoning is underlined by Figure 1 that evidently displays areas with higher rate of car ownership located primarily in fare zones B and C. Asymmetry in values should not be considered due to the same bias as in the case of transport modes. The average length of travel through two and three fare zones exceeds 10 km, that is why elasticity for these O/D groups appears at longer distances only.

Sensitivity of users in time does not have a lot of variation. The elasticity values of each period are relatively consistent within the fare categories. The periods with coefficients higher than average 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). Evening peaks do not have the same value as morning peaks due to the fact that the former are more spread over the time, thus do not represent the commuter group that distinctly.

Socioeconomic factors, including income, socioeconomic index and car ownership, can be investigated simultaneously. This is based on the high correlation between the factors. The Pearson coefficients for each combination are: 0,976 for income - car ownership, 0,944 for socioeconomic index - car ownership and 0,915 for income - socioeconomic index. All the values are close to the maximum 1,0, which indicates a very strong positive correlation.

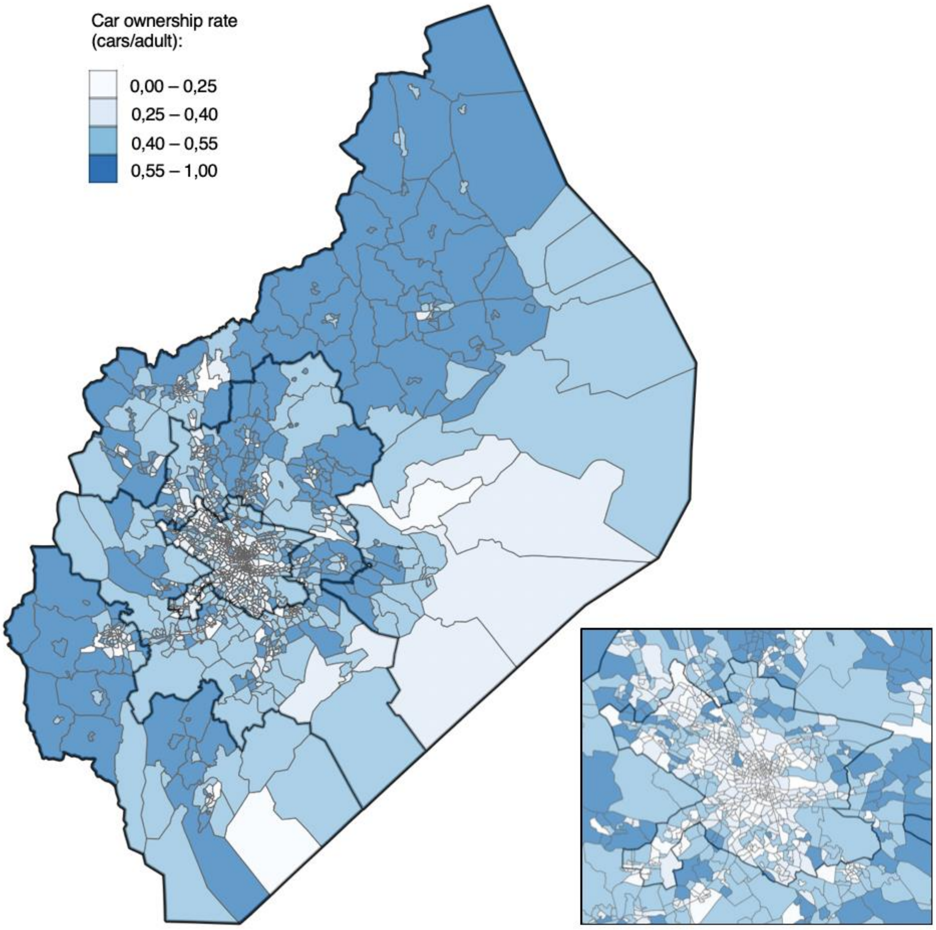
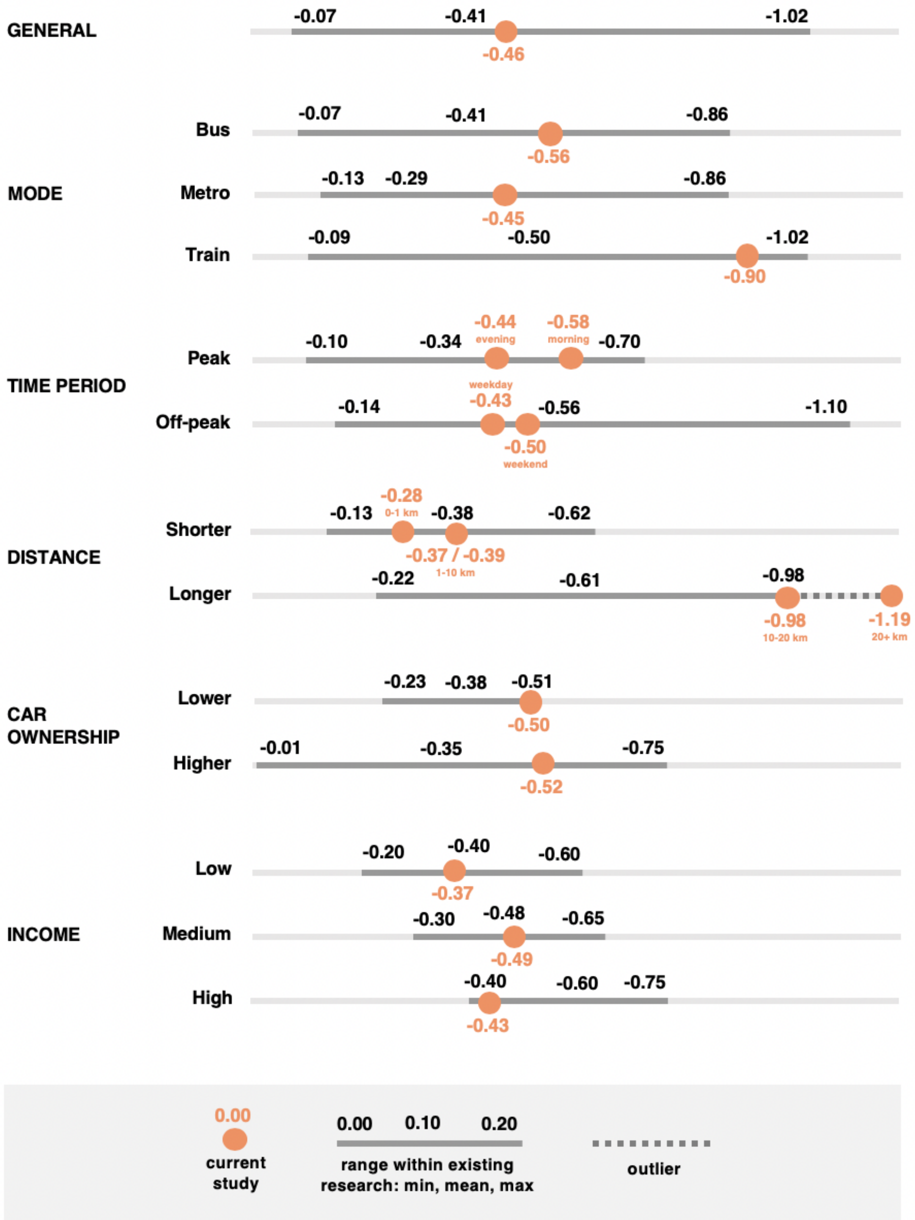


Figure 5.2: Spatial distribution of car ownership in Stockholm County

As expected, the elasticity results for all the factors are very much in line with each other. At the aggregated O/D level, it is difficult to draw particular conclusions, apart from the common fact that the reduced fare users are less sensitive in general. Nevertheless, the situation changes when one looks into disaggregated numbers. In both fare categories, the factor growth induces a reduction in the one-zone elasticity (price increase) and a rise in the two- and three-zone elasticity (price decrease). Altogether, this reflects on two aspects, namely how captive on public transport a user group is and how much importance fare costs bear for the group. The low-factor groups assign more weight to the price aspect and at the same time rely more on public transport. Therefore, a price increase significantly affects their choice, while a price decrease does almost not attract new users, as it is likely that the patronage rate has already reached its higher boundary. The high-factor groups in turn 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 alternatives to travel. Consequently, the users' choice is slightly influenced by a price increase, whereas a price decrease draws more attention to the travel funds product. The explained tendency becomes even more prevalent with the reduced fare and the car ownership factor. Car ownership is the most representative case among the three which is logical due to its direct relevance to the research topic.

On top of the detailed analysis of the determined elasticity values, it is as important to look at them also from a broader perspective, which means how they fit into the existing research. Figure 2 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.



Lastly, directionality, which is mentioned numerous times and outlined as the key element, requires further inspection. So far in this section, elasticity values have always been weighted by ridership share, which did not allow to fully understand the scale of asymmetry within one user group. Table 1 delivers unweighted elasticity for the dataset of regular users. Directionality creates a great contrast, where a price decrease has a two-times respectively up to sixteen-times larger effect on the full and reduced groups. This observation is contrary to the existing research. Nevertheless, the current study fare sensitivity is also combined with service sensitivity. After the fare zones got removed, along with the price change came transparency and convenience associated with the use of travel funds. This aspect is most likely to be the main driving force in the changing travel behavior, especially in the case of the reduced fare users. With the current study's scope and input, it is not possible to fully distinguish impacts of the two sensitivities.

Table 1: Unweighted general elasticity for regular users

O/D group	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 (great decrease in price, improved convenience)	-1,13	-1,03

5.3 DISTRIBUTIONAL EFFECTS

As the policy introduced in 2017 affected the price of the travel funds product and consequently led to changes in ridership, this analysis looks into two intertwined aspects, namely the distribution of mobility and travel expenses. The former represents how product usage is allocated among various population groups, while the latter covers the distribution of expenditures on this product.

First, within each factor, user groups are determined, this time with a higher level of detail than in the case of the elasticity analysis. The general population is split into 26 communes. Income levels progress with a step of 25.000 SEK, the socioeconomic index with 2 scores, the car ownership rate with 0.1 cars/adult, and the distance from the city center with a step of 5 km. Second, for travel funds and all products data is extracted representing the population, journeys and expenses in the years 2016 and 2017. Third, Gini (Suits) indices are computed for two product categories and every user group (see Table 2). The last task is to estimate the following indicators for travel funds: journeys/capita, expenses/capita, average journey cost, and their growth rates (see Table 3). Altogether, this information can serve as an input for the analysis of distributional effects.

Table 2: Overview of equity indices

Distribution type	Travel funds		All products	
	2016	2017	2016	2017
Horizontal (Gini index)	0,249	0,242	0,180	0,174
Vertical (Suits index)				
• income	0,050	0,050	-0,067	-0,075
• socioeconomic index	0,140	0,144	0,063	0,066
• car ownership	-0,581	-0,557	-0,430	-0,426
• distance from the city center	-0,561	-0,562	-0,217	-0,208

Looking at the horizontal distribution (Table 2 and Figure 3), there is a disparity within the general population in terms of travel expenses, which grows significantly for travel funds. In every community diverse groups are present, including captive riders and car advocates, frequent commuters and occasional travelers. Eventually, it results in an uneven distribution of the money spent on public transport. Nevertheless, the degree of unevenness is relatively low, with the Gini coefficient being 0,180 for all products which is close to the state of perfect uniformity. This is a sign of a substantial public transport penetration rate in Stockholm County. Travel funds in particular is a more specific product. Despite the largest number of cards in the system, a smaller group of people actually uses it often enough to lead to large expenses. Between the two periods, there is no significant change, meaning that the transport system as a whole did not get affected by the fare policy.

Through a more detailed analysis of travel funds, it can be seen that travel expenses grew for every commune, with a rate ranging from 3% to 43%. This is related to the increasing frequency and decreasing costs for some groups and the opposite situation for others. Figure 4 is provided to explain these relations. Most of the communes in the fare zone A experience an increase in journey costs along with a declining frequency (fewer journeys are made for higher cost). Within the zone B, all areas experience a growth in frequency, especially the ones that are closer to the city core. However, not all of them have a consistent reduction in journey costs, which could be an indicator for a larger share of one-zone journeys in 2017. Very similar trends can be observed in zone C, where traveling in the southern part seems to be more locally oriented, while interzonal journeys prevail in the northern part (growing frequency with lower expenses). To sum up, in all communes the price decrease resulted in a higher frequency, yet the opposite conclusion cannot be drawn. It is fully valid for the zone A only, while in some cases in the zones B and C the ridership was not only promoted by the price change, but most likely by the improved convenience of the product.

In terms of income category (Figure 5), no substantial distinction can be made neither between user groups nor time periods. Expenses on all products slightly shift towards the lower income travelers, whereas travel funds alone involve a slightly higher expenditure for the wealthier groups. These findings are supported by the detailed results that can be seen in Table 3, where all the three indicators are fairly consistent among the groups. Expenses grow by a rate of 9% to 16%, together with moderate decline in frequency by 1% to 8%, which leads to higher journey costs (from 12% to 18%). Only users with the highest income demonstrate a distinct behavior, with a more intense growth in journey costs (almost 21%) and reduction in frequency by 13%. Notwithstanding, having one group with slightly higher values is not sufficient to establish some relevance of the fare policy to vertical distribution improvements.

User group	Journeys/capita				Expenses/capita				Average journey cost			
	2016	2017	Absolute growth	Relative growth, %	2016	2017	Absolute growth	Relative growth, %	2016	2017	Absolute growth	Relative growth, %
General population (split by commune)												
Upplands Väsby	0,32	0,35	0,04	11,3	7,2	8,5	1,2	17,2	23,0	24,2	1,2	5,3
Vallentuna	0,23	0,31	0,08	35,8	5,5	7,5	2,0	36,5	24,1	24,2	0,1	0,5
Österåker	0,32	0,39	0,07	21,1	7,7	9,7	2,0	25,2	23,9	24,7	0,8	3,4
Värmdö	0,30	0,40	0,10	34,2	7,9	9,9	1,9	24,5	26,4	24,5	-1,9	-7,2
Järfälla	0,39	0,47	0,08	20,9	9,5	11,5	2,0	21,3	24,4	24,5	0,1	0,3
Ekerö	0,38	0,47	0,09	24,4	9,2	11,4	2,2	23,4	24,3	24,1	-0,2	-0,8
Huddinge	0,43	0,50	0,07	16,5	10,7	12,6	1,9	17,8	24,7	25,0	0,3	1,1
Botkyrka	0,44	0,45	0,01	2,4	10,8	11,2	0,3	3,1	24,7	24,9	0,2	0,8
Salem	0,36	0,46	0,10	26,1	8,7	11,2	2,5	28,6	23,9	24,4	0,5	2,0
Haninge	0,36	0,38	0,02	7,0	8,2	9,3	1,1	13,8	22,8	24,3	1,5	6,4
Tyresö	0,41	0,51	0,10	25,0	9,8	12,3	2,4	24,9	24,0	24,0	0,0	-0,1
Upplands-Bro	0,22	0,36	0,14	66,2	6,1	8,8	2,7	43,1	28,4	24,4	-3,9	-13,9
Nykvarn	0,13	0,13	0,00	-1,2	2,5	3,1	0,6	23,6	19,5	24,4	4,9	25,2
Täby	0,27	0,32	0,04	16,3	6,2	7,5	1,4	21,9	22,7	23,8	1,1	4,8
Danderyd	1,38	1,31	-0,07	-5,1	29,3	33,7	4,3	14,7	21,2	25,6	4,4	20,8
Sollentuna	0,52	0,62	0,10	18,5	13,2	15,3	2,1	15,7	25,2	24,6	-0,6	-2,3
Stockholm	1,71	1,57	-0,15	-8,7	37,2	40,9	3,8	10,1	21,7	26,1	4,5	20,5
Södertälje	0,25	0,32	0,06	24,7	5,6	7,8	2,1	37,4	22,2	24,4	2,3	10,2

Nacka	0,74	0,77	0,04	4,7	16,5	19,6	3,1	19,1	22,3	25,3	3,1	13,7
Sundbyberg	1,18	1,12	-0,06	-4,8	25,8	29,5	3,7	14,5	21,9	26,4	4,4	20,2
Solna	1,48	1,33	-0,15	-10,0	31,3	34,2	2,9	9,2	21,2	25,8	4,5	21,4
Lidingö	1,18	0,91	-0,27	-22,7	23,3	22,3	-1,0	-4,2	19,7	24,4	4,7	23,9
Vaxholm	0,45	0,52	0,07	14,7	11,0	12,5	1,5	13,4	24,4	24,1	-0,3	-1,2
Norrtälje	0,23	0,26	0,03	12,5	5,7	6,3	0,6	10,0	24,5	23,9	-0,5	-2,2
Sigtuna	0,30	0,34	0,04	12,2	7,3	8,4	1,1	15,3	24,1	24,7	0,7	2,8
Nynäshamn	0,23	0,23	0,00	0,9	5,1	5,6	0,5	10,4	22,0	24,1	2,1	9,4
Total	1,02	0,97	-0,05	-4,6	22,4	25,0	2,6	11,6	22,0	25,7	3,7	17,0
Population split by income, thousand SEK												
0-225	0,87	0,84	-0,04	-4,2	19,2	21,3	2,0	10,5	22,1	25,5	3,4	15,3
225-250	0,61	0,63	0,02	4,1	13,6	15,8	2,2	16,6	22,3	25,0	2,7	12,0
250-275	1,13	1,11	-0,02	-2,0	25,1	28,2	3,1	12,5	22,1	25,4	3,3	14,8
275-300	0,96	0,91	-0,06	-6,0	20,9	23,3	2,3	11,1	21,8	25,7	4,0	18,2
300-325	1,30	1,20	-0,10	-7,8	28,4	31,1	2,7	9,4	21,9	25,9	4,1	18,6
325-350	1,21	1,15	-0,06	-5,0	26,6	29,9	3,2	12,2	22,0	26,0	4,0	18,1
350-375	0,82	0,82	0,00	-0,5	18,0	21,0	3,0	16,5	21,9	25,6	3,7	17,0
375-400	1,13	1,08	-0,05	-4,6	25,5	28,7	3,3	12,9	22,5	26,7	4,1	18,3
400+	0,90	0,78	-0,12	-13,1	19,6	20,6	1,0	4,9	21,8	26,3	4,5	20,8
Total	1,02	0,97	-0,05	-4,6	22,4	25,0	2,6	11,6	22,0	25,7	3,7	17,0
Population split by car ownership rate												
0-0,2	2,87	2,66	-0,21	-7,3	63,5	70,4	6,8	10,8	22,1	26,4	4,3	19,4
0,2-0,3	1,41	1,30	-0,11	-8,1	30,7	33,7	3,0	9,7	21,7	26,0	4,2	19,4
0,3-0,4	0,75	0,75	0,01	0,8	16,5	18,9	2,4	14,5	22,1	25,1	3,0	13,6
0,4-0,5	0,65	0,67	0,02	2,9	14,5	16,6	2,2	14,9	22,3	24,9	2,6	11,6
0,5-0,6	0,41	0,42	0,01	2,9	9,2	10,5	1,3	14,1	22,3	24,7	2,4	10,8
0,6+	0,17	0,20	0,03	17,5	3,7	4,8	1,1	29,2	22,1	24,3	2,2	10,0
Total	1,00	0,95	-0,05	-4,7	21,9	24,5	2,5	11,5	22,0	25,7	3,8	17,1
Population split by socioeconomic index												
3-4	0,56	0,54	-0,03	-4,6	12,3	13,5	1,2	9,5	21,8	25,0	3,2	14,8
5-6	0,63	0,64	0,01	1,7	13,9	16,0	2,1	14,9	22,0	24,8	2,8	12,9
7-8	1,00	0,95	-0,04	-4,5	22,3	24,5	2,1	9,5	22,4	25,7	3,3	14,7
9-10	0,74	0,73	-0,01	-1,0	16,5	18,6	2,1	12,9	22,4	25,6	3,2	14,1
11-12	1,68	1,57	-0,11	-6,7	36,9	41,0	4,1	11,1	21,9	26,1	4,2	19,0
13-15	0,93	0,92	0,00	-0,3	20,5	23,8	3,3	16,2	22,2	25,8	3,7	16,6
Total	1,00	0,96	-0,04	-4,1	22,0	24,6	2,6	11,8	22,1	25,7	3,7	16,7
Population split by distance from the city center, km												
0-5	2,41	2,18	-0,23	-9,5	51,7	56,2	4,6	8,9	21,5	25,8	4,4	20,3
5-10	1,20	1,11	-0,09	-7,8	25,6	28,7	3,1	12,1	21,2	25,8	4,6	21,6
10-15	0,74	0,68	-0,06	-8,1	15,6	16,5	0,9	5,5	21,3	24,4	3,2	14,8
15-20	0,80	0,76	-0,04	-4,6	14,9	15,5	0,7	4,4	18,6	20,4	1,7	9,4
20-25	0,46	0,59	0,13	28,2	8,9	11,5	2,6	29,3	19,4	19,5	0,2	0,9
25-30	0,35	0,46	0,11	30,7	7,2	10,2	3,0	40,9	20,4	22,0	1,6	7,8
30-35	0,23	0,27	0,04	19,0	6,0	7,2	1,3	21,0	26,1	26,5	0,4	1,7

35-45	0,31	0,24	-0,07	-23,9	6,7	5,6	-1,0	-15,7	21,3	23,5	2,3	10,8
45-60	0,46	0,45	-0,01	-1,9	7,7	8,0	0,2	3,2	16,7	17,6	0,9	5,1
60+	0,49	0,40	-0,09	-18,3	12,6	11,5	-1,1	-8,8	25,5	28,5	2,9	11,5
Total	1,23	1,12	-0,11	-8,6	26,0	28,0	2,0	7,8	21,2	25,0	3,8	18,0

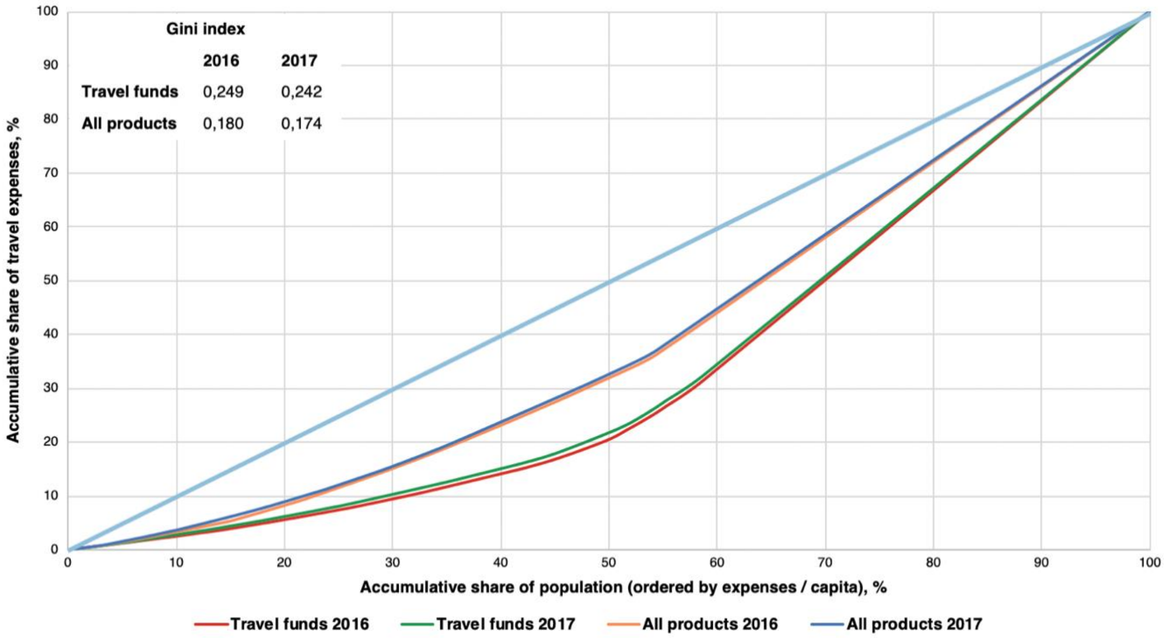
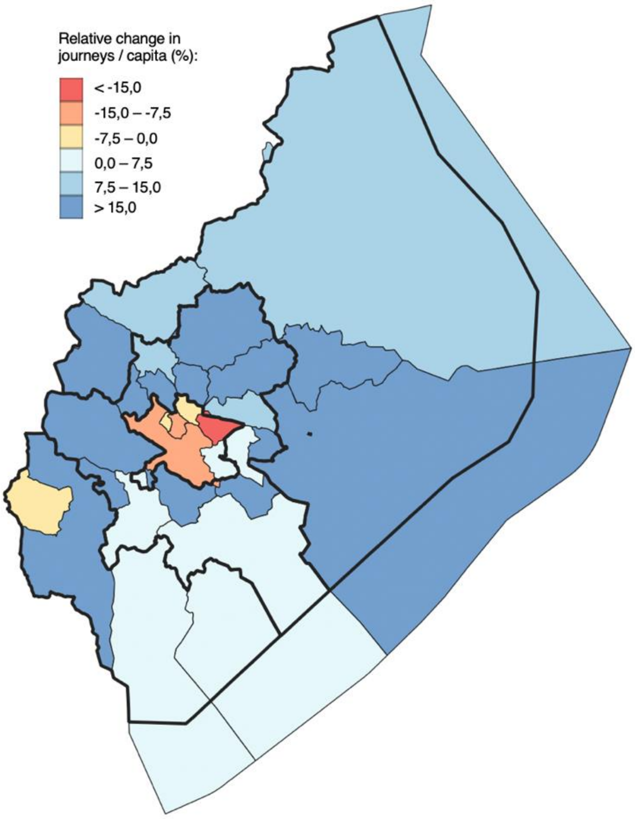


Figure 5.3: Lorenz curves for horizontal equity



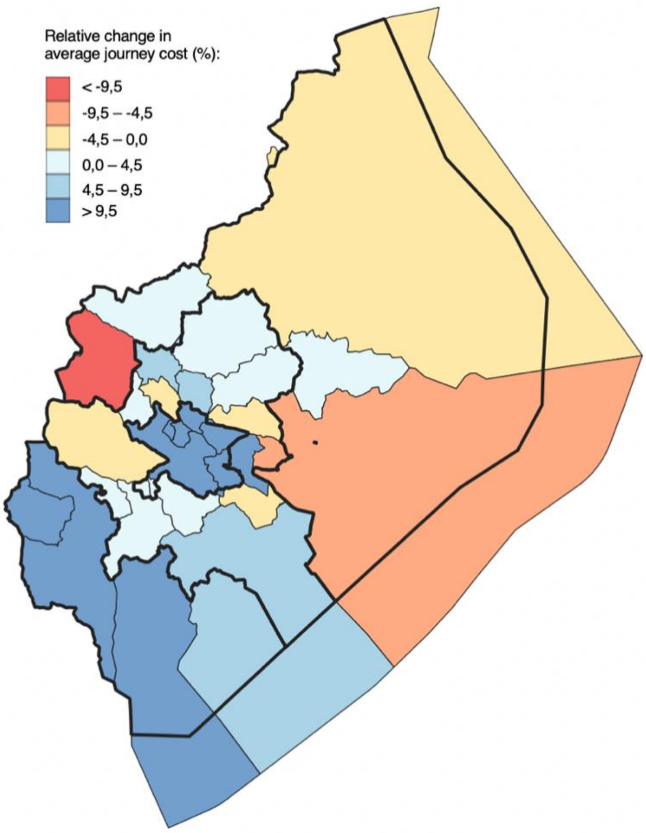


Figure 5.4: Year-on-year (2016 vs 2017) change of expenses (left) and mobility (right) at the communal level (fare zones highlighted in bold)

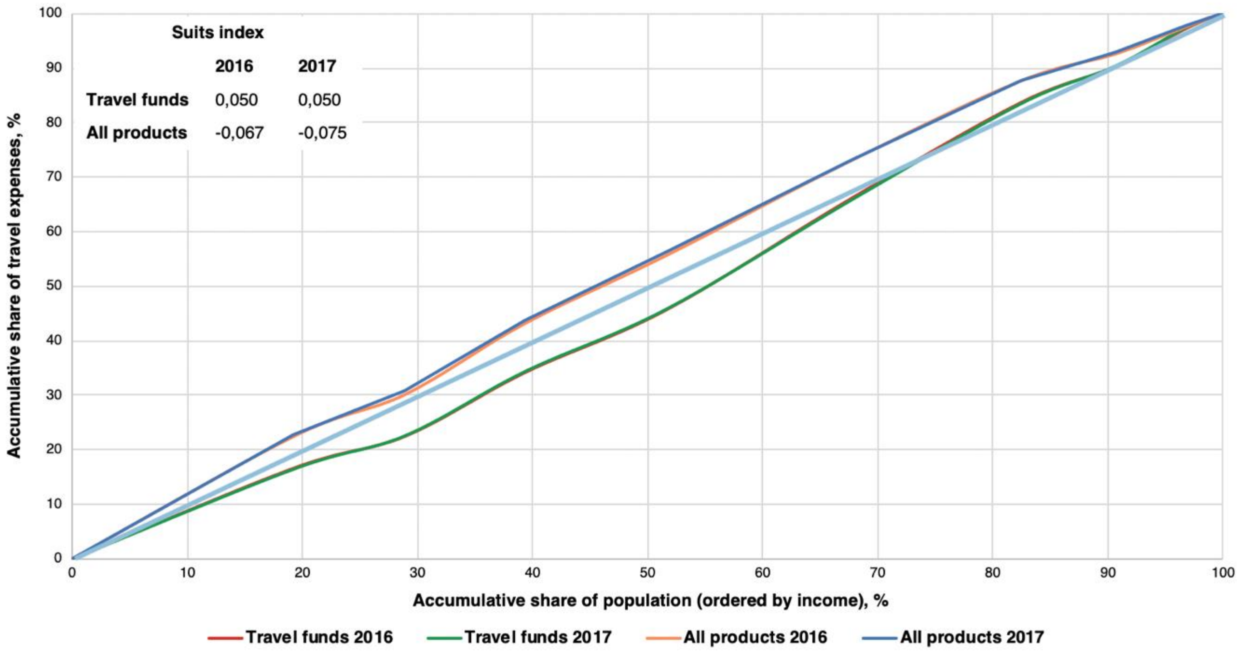


Figure 5.5: Lorenz curves for vertical equity by income

The socioeconomic index as a factor resembles the income results in its structure and trends. The only major difference is that both travel funds and all products have a lower fraction of expenses from the low-factor groups, with a larger shift to the high-factor users for travel funds. This is caused by the higher frequency of traveling, as the average journey cost is very similar among the groups. In terms of year-on-year growth, no change is noted for the overall distribution (see Figure 6). The indicators in Table 3 display exactly the same rates as in the income category: an increase of 9% to 16% in expenses, an increase of 12% to 19% in journey costs and a decline in frequency by 1% to 8%. Therefore, no strong relevance to effects on vertical distribution can be established for socioeconomic index either.

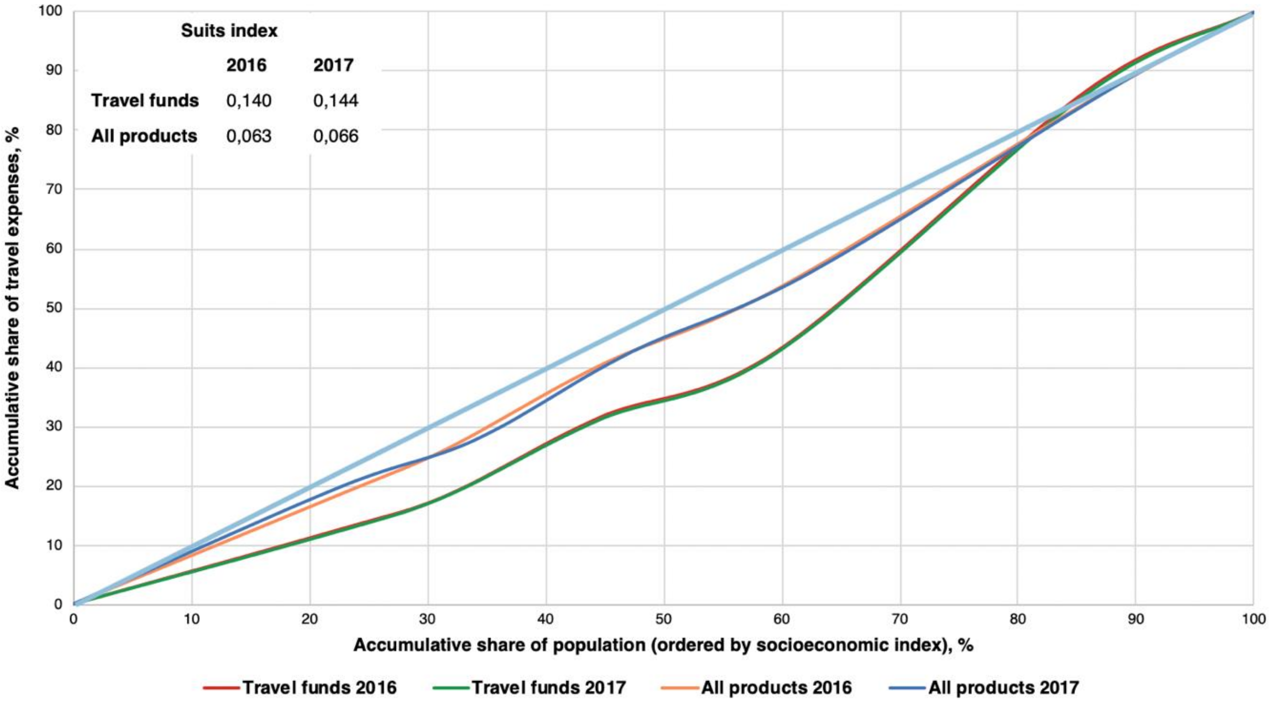


Figure 5.6: Lorenz curves for vertical equity by socioeconomic index

The two other factors, namely car ownership rate and distance from the city center, pose more interest due to their diversity between user groups and temporal development. Figure 7 clearly distinguishes users with lower car ownership rate and the according expenses which are significantly higher. In this domain, travelers from all products and travel funds categories tend to spend very similar amounts on public transport. With the new fare policy introduced in 2017, travel funds slightly moved towards perfect uniformity, which is also pointed out by the change in the Suits coefficient from -0,581 to -0,557.

Table 3 allows to verify these observations. Expenses/capita vary widely between the groups, where the value for the lowest group is 17 times higher than for the highest one. Despite the larger relative growth for the high-rate users, the absolute values for the low-rate stand out more (6,8 SEK against 1,1 SEK). This is accompanied by the expanding disparity in the average journey costs. Being almost equal in 2016 (21,7 to 22,3 SEK/journey), the indicator drastically changed in 2017, rising up to 26,4 SEK/journey (19,4%) for the low-rate users and to only 24,3 SEK/journey (10,0%) for the high-rate. Even with higher expenses, the low-rate groups (rate 0-0,3 cars/adult) reduced their frequency, whereas users on the opposite side started to travel slightly more often. This analysis demonstrates that the fare policy mainly affected the low-rate users, imposing higher prices on them, which consequently led to a decline in ridership and yet still higher expenses. The high-rate users started to spend a little more due to the moderate improvement in their public transport use.

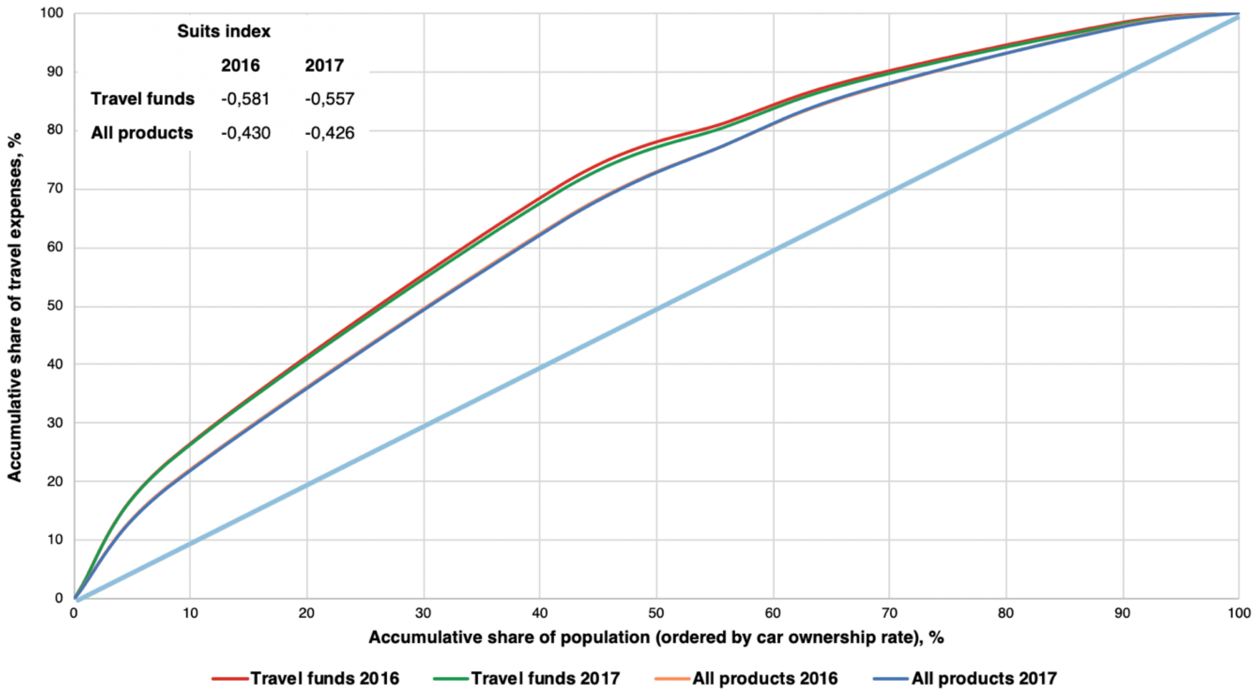


Figure 5.7: Lorenz curves for vertical equity by car ownership rate

The last factor in the equity evaluation procedure is distance from the city center. It has a very distinct Lorenz curve (see Figure 8), with a great proportion of expenses being on the side of centrally allocated users. Travel funds are twice as imbalanced in this distribution than all products. Temporally, the distribution seems to be very stable at the aggregate level, with absolutely equal Suits indices for both years. Nevertheless, Table e reveals some important details. People in general tend to travel much more frequently when they are based closer to the city, having more than 2 journeys/capita within the first 5 km, opposed to 0,2- 0,5 journeys/capita after the 20 km mark.

This leads to unevenness in public transport expenditures. With regard to changes brought by the fare policy, three main groups can be identified. Between 0 and 20 km, travelers experience the highest growth of journey costs and try to compensate for this by reducing travel frequency, which still results in a moderate increase of expenses. This happens due to the fact that the 20 km radius outlines the fare zone A, with the increased price of dominating A-A journeys. Between 20 and 35 km, the average journey cost does not change much. This in turn stimulates an intense increase of ridership and travel expenses. Beyond 35 km, journey costs grow again, and the lowered frequency helps to balance out and reduce expenses. Ultimately, the fare policy supports the mid-distance users that are mostly located in the fare zone B. Making intrazonal journeys cheaper, it incentivizes traveling on the route A-B (B-A), which is prevalent for the mid-distance users. The fare zone C, located further away, is imposed with a larger burden because of the higher share of local journeys made with travel funds. These findings are mostly in line with Figure 4, but also exhibit some differences due to the various ways of aggregation, namely zonal and radial.

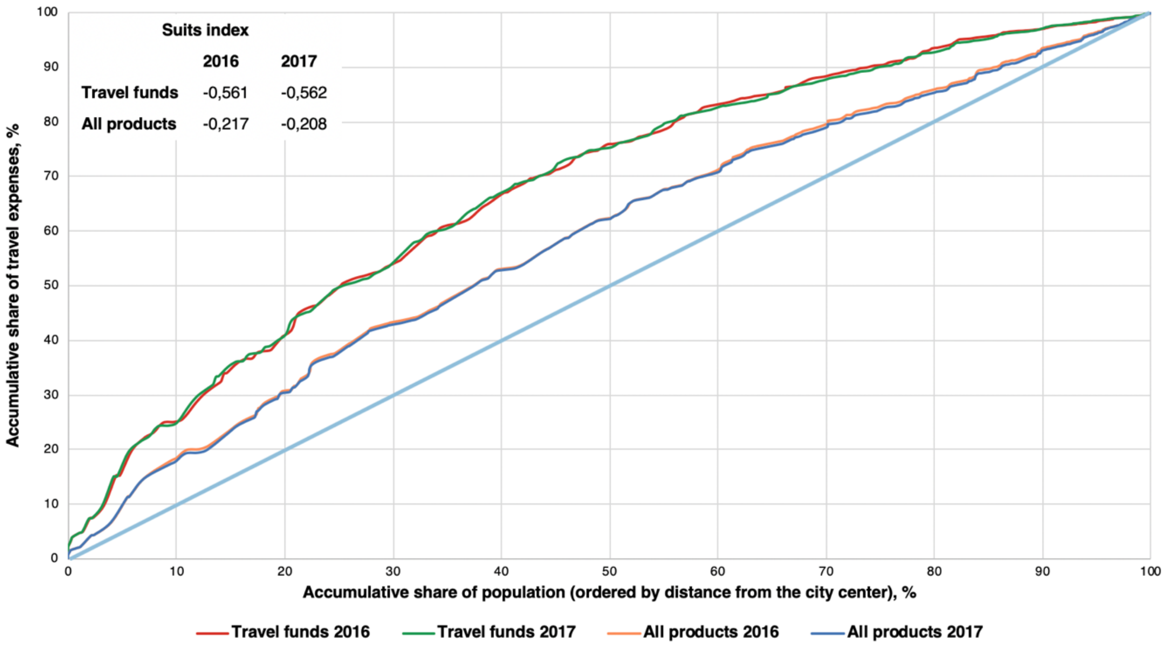


Figure 5.8: Lorenz curves for vertical equity by distance from the city centre

6 CONCLUSIONS AND FUTURE WORK

As stated in Section 1, this project has had three main motivations. First, the availability of large-scale passively collected passenger data, which until now have been greatly underutilized. Second, the increased focus on inclusive transport service for all as a prime policy and planning goal, which requires a way to quantify the distributional effects of policy measures. Third, the lack of knowledge regarding the impacts of the change from zone-based to flat fares in Stockholm. This section summarizes our conclusions from the project with respect to each of the three themes.

6.1 THE POTENTIAL OF SMART CARD DATA

In this project, we have processed Access card data and performed a sequence of inferences to derive time-dependent origin-destination matrices for the entire Region Stockholm system. Tap-in records have been matched with corresponding inferred tap-out locations and time stamps for about 80% of all records. Moreover, we have implemented an algorithm to generate a journey database based on our transfer inference method. 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 profiles. Access card products and zonal attributes have been used for analyzing policy impacts on different market segments.

Through the practical development work, the project has demonstrated the feasibility of extracting valuable information about travel patterns from smart card validation records. The rates with which journey destinations and transfer locations can be inferred are on par with reported results from similar systems internationally. The developed algorithms are readily implemented at Trafikförvaltningen. They also lay a necessary foundation for further methodological developments and analyses such as on-board crowding evaluation, demand forecasting and identifying user groups.

6.2 QUANTIFYING DISTRIBUTIONAL POLICY EFFECTS

There are many proposed metrics for assessing horizontal equity in the literature, but the most used method is the combination of Lorenz-curves and Gini-coefficient. In studies of vertical equity, there is not such a clear front-runner metric as Gini is for horizontal equity. In this project we have chosen the Suits metric due to its neat symmetrical similarity with Gini in computation and interpretation. Both Suits and Gini use the Lorenz curve for their computation, but the curve is also in its own right a source of information on the distributional effects studied.

The proposed equity metrics were first used to compute distributional effects for fare changes using transport model data. The same metrics were the applied to travel patterns extracted from smart card data and the natural experiment of the Stockholm fare change of January 2017. The project has demonstrated that the equity metrics are applicable in both model-based and empirical smart card-based analyses.

6.3 IMPACT OF FARE CHANGE

The results from the evaluation of the fare change can be compared to the initial policy objectives of SLL. First and foremost, there is an observable effect of product consistency and user-friendliness on the demand growth for the single-use category. As expected, simplification and unification of the fare scheme substantially contributed to its attractiveness, especially for new users. However, the initial ridership increase rates appear to be quite inaccurate compared to the actual rates found empirically. A much larger growth is obtained for journeys crossing two and three fare zones: 1.4% versus 18-22%, 2.0% versus 35-55% and 6.2% versus 35-65% for the fare zone O/D pairs A-B, B-C and A-C respectively. 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 preliminary report used the existing price elasticities to predict the effects that the policy would entail, yet it underestimated the significance of the policy's service component. The latter eventually becomes the main driver of the great demand increase despite the higher journey costs, as in the case with intra-zonal journeys in B and C.

The inaccurately predicted demand implications led in turn to the imbalanced pricing of the single fare. Even though the objective was to achieve a neutral economy, it consequently reaches a positive balance, as the ticket revenues within the analysis period grow by almost 7 million SEK, or 13.5%. The distribution of travel expenses highlights the points of attention. The highest increase in the average journey cost is observed for fare zone A, where users mostly travel within one zone and hence try to compensate for the price increase by reducing the frequency of their product use. For zones B and C, travelers use the product more often, being stimulated by its improved convenience, but end up paying a higher price in some areas where local journeys still prevail. Therefore, the policy contributes to the reduction of geographical disparity in terms of mobility, yet brings an additional inconsistency when it comes to travel expenses.

To conclude, the introduced fare policy delivered the desirable result of an increased ridership through improved convenience of the single-use products. Nevertheless, the significance of the service convenience component was underestimated, which resulted in the price adjustments being not in line with the mobility effects.

6.4 FURTHER WORK

The planning and development of the Stockholm public transport system must rely on the best empirical foundations available to support evidence-based decision-making and make the right priorities. It is therefore essential to unravel the demand patterns by utilizing the Access card data and the data processing and inference techniques that have already been developed for generating the passenger journey database. An important direction for further work is to advance the analysis capabilities by discovering to provide a more nuanced understanding of the impacts of a particular infrastructural investment the prevailing demand patterns and identify distinctive user profiles from the data. These may then be used, (e.g., the opening of the Citybanan commuter train railway), on how different user groups travel.

As part of this research direction, several useful algorithmic developments can be identified. First, a data-driven zonal definition that reflects observed demand patterns rather than administrative regions would increase the meaningfulness and explanatory power of the subsequent travel pattern analysis. Following this, origin-destination matrices based on the zones obtained can be derived. Third, a detailed description of user profiles based on the market segmentation analysis can be performed, which allows a better characterisation of distinct user groups in the public transport system.

With the advent of smart card travel patterns, accessibility could be assessed by revealed preference modelling. Adapting a simple utility function with only travel time, travel cost and destination attractiveness, these attractiveness measures could be estimated together with time and cost parameters and then Logsums could be calculated for all origins. This would have the added bonus of also be able to capture improvements in destination quality over time. Such a smart card based accessibility study is a strong recommendation should this project continue in a second phase.

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

Banister, D. (2018). Inequality in transport, Alexandrine Press.

Gini, C. (1912). Variabilità e mutabilità: contributo allo studio delle distribuzioni e delle relazioni statistiche. Tipogr. di P. Cuppini.

Lorenz, M. O. (1905). "Methods of measuring the concentration of wealth." Publications of the American statistical association 9(70): 209-219.

Munizaga M. A., and 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

Rubensson, I. Susilo, Y. Cat,. O. (2019). Equity Impacts of Alternative Fare Schemes: The Case of Stockholm. *The 98th Transportation Research Board Annual Meeting*, Washington DC. January 2019.

Rubensson, I. Susilo, Y. Cat,. O. (2020). Fair Accessibility –Operationalizing the Distributional Effects of Policy Interventions. *The 99thTransportation Research Board Annual Meeting, Washington DC.* January 2020.

Seaborn, C., Attanucci, J. and Wilson, N.H. (2009) Analyzing multimodal public transport journeys in London with smart card fare payment data. *Transportation Research Record*, 2121(1), pp.55-62.

Suits, D. B. (1977). Measurement of tax progressivity. *The American Economic Review* 67(4), 747-752.

World Bank Institute (2005). Introduction to poverty analysis, World Bank Institute: 2018.

APPENDIX: NOTE ON DATA HANDLING AND SECURITY

All people accessing smart card data had to sign "SEKRETESSFÖRBINDELSE M.M. KONSULTER (Non-disclosure agreement)" and be approved by TF to access data. For approved people, access card data has been made available to us via a log-in procedure to the AnalysisDM-database hosted by TF/Soprasteria. Project team members that were granted by TF access are Matej Cebecauer, Alex Vermeulen and Yaroslav Kholodov. No other person was granted access in this project.

The output data of the project, anonymized individual travel diaries and aggregated origin-destination matrices *without any connection to the original card number or holder* are stored at KTH iMobility lab server. The server has limited access with three security layers for securing the access to data. First layer: any computer trying to access the server have to be on KTH-VPN subnetwork, credentials are issued only by KTH to students, employees or after ordering credentials by employees for not affiliated person with KTH. All these credentials are for limited time period and the KTH (Royal Institute of Technology) Rules for computer, network and system facilities" document has to be sign.

The server is accepting communication only on two ports for ssh and PostgreSQL port with ssh-tunnel only. All other ports are closed. KTH-IRT division is permanently scanning computers and servers at KTH for potential vulnerabilities. KTH iMobility lab server is considered by KTH IT as secured and close for KTH-VPN only.

The access to any data or scripts on the server is strictly limited to the member of a defined group working on access card data project and approved by TF. In order to connect to the server, user have to connect to KTH-VPN with issued credentials, use ssh tunnel with ssh-rsa private key. A user has to generate two ssh-rsa keys private and public. The used keys are 2048 bits long. The public key is sent and placed on the server. The private key should be never sent and located on the server for security reasons and user that generate public key should be the only one with a particular private key. User has to provide private key and password defined by user during generation of keys. Private key is not located on the server and only user that generate the both keys has it. This increase the security of login process. Authentication is as follows: user have to provide private key ssh-rsa key and after that provide the password defined by user. Login to Database requires different credentials.

In summary, a user needs KTH-VPN credentials, ssh-rsa keys, and database credentials. Credentials to connecting to the server and database are sent by combination of different channels SMS, in person and e-mail and, never by only one channel in once.