Evaluation of public transport fare policy using smartcard data

Travel patterns change and distributional effects in Stockholm County

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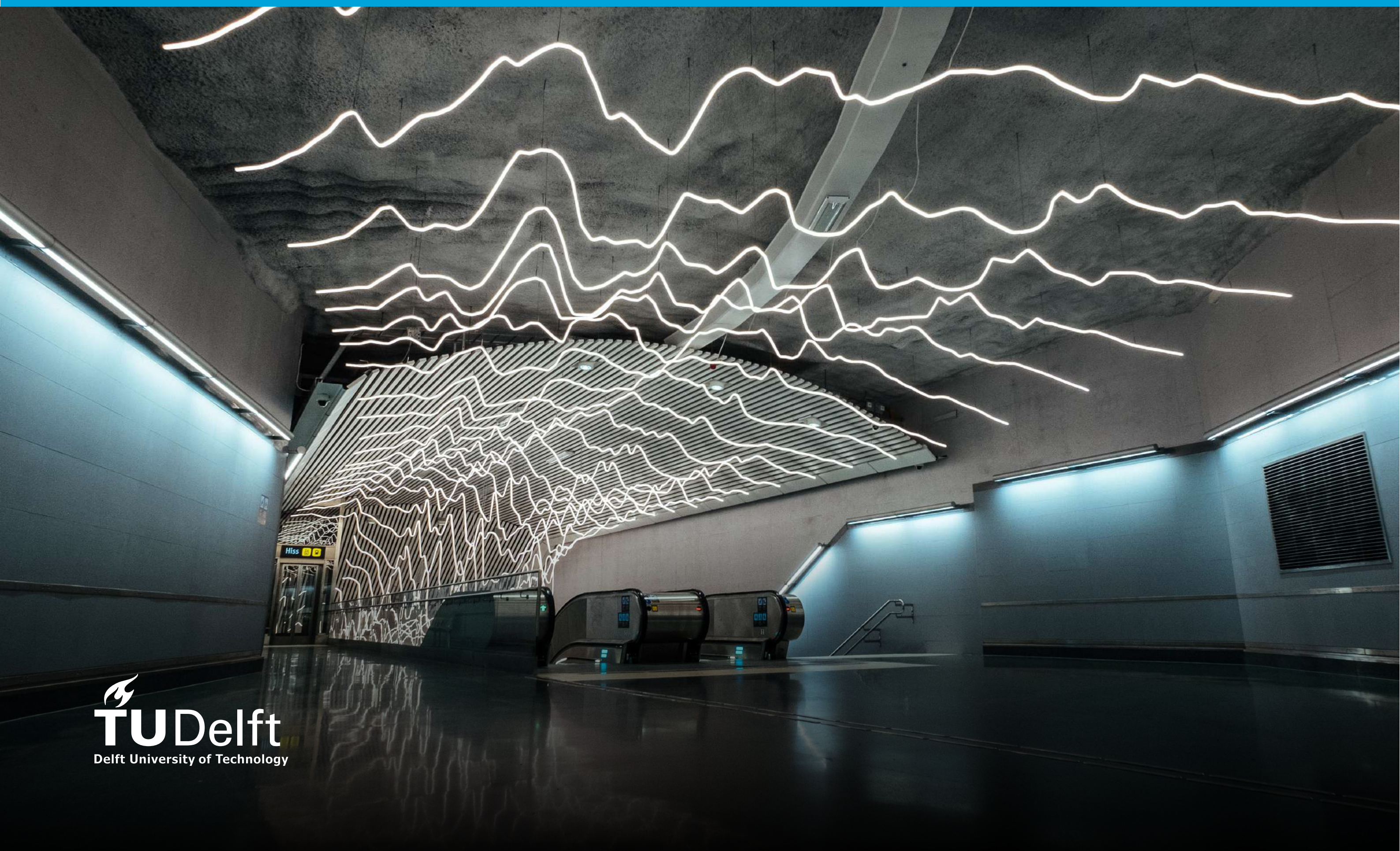

Evaluation of public transport fare policy using smartcard data

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by

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TU Delft

Executive summary

Public transport fare policy is an essential component of any public transport system. It is usually associated with changes in the fare structure that eventually might have substantial impact on a city's (region's) economic, social, and environmental welfare (Liu et al., 2019). For any decision on a fare policy, it is crucial to evaluate the impacts it causes. The evaluation is not a trivial procedure due to the large variety of endogenous and exogenous factors involved, and it requires an individual approach in most of the cases.

In the domain of fare policy evaluation, studies generally look into changes in travel patterns through a set of mobility and accessibility metrics. A few recent works incorporate new trends in the field, for instance, equity analysis and smartcard data (Rubensson et al., 2017; Wang et al., 2018). Equity considers the degree of cost and benefit distribution among various population groups differentiated on a particular basis, for example, geographic or socioeconomic (Litman, 2012). The literature review has led to the identification of opportunities for improvement of the existing practice, which in turn allow to formulate a research gap. It corresponds to a comprehensive ex-post assessment technique utilizing smartcard data, with the main focus on the sensitivity of different user groups to fare change and the distributional effects in the European context.

This research is carried out for the case of a public transport fare policy introduced by the regional administration of Stockholm County (SLL) in January, 2017. The policy focused on changing the fare structure basis for single-use products, in particular switching from a zonal to a flat-fare scheme. This promoted convenience and transparency, lack of which was perceived by users as an important travel impedance, according to a preliminary study by SLL (2016). Another direct effect was a price change due to the removal of fare zones. This means that some categories of journeys became cheaper whilst the others increased in price, based on the O/D combination (origin and destination). Generally, the administration formulated three main policy objectives: simplicity of the fare system, increase in demand for multi-zonal journeys and neutrally-balanced economy. Moreover, the equity aspect of the fare cost drew a lot of attention in the community, even before the policy got implemented.

Stemming from the research background, the predicted policy outcomes are tested as the main hypothesis of this study. The goal is to investigate how the policy affected travelling behavior of different public transport user groups. Furthermore, considering the importance of the social aspect of the policy for Stockholm County, the redistribution of costs and benefits in terms of mobility and fare expenses is assessed through the equity perspective. Essentially, the main research question is formulated:

To what extent did the change from a zonal to a flat fare scheme in Stockholm County affect travel patterns of different public transport user groups, and what were its equity implications?

The core data source of this research project is formed by the previously constructed individual travel diaries within the entire public transport network of Stockholm County for the years 2016 and 2017. The work was done through a collaboration between KTH Royal Institute of Technology, TU Delft and the transport authority SL. The travel diaries are comprised of matched trips, each of them is described by mode, stop (station) and time of boarding and alighting, card identification number and the product used for validation. The second important data source is socioeconomic data collected by Statistics Sweden. The data are stored at the level of 1364 census zones and include names and codes of administrative areas, geospatial data, population split, median income, socioeconomic index, and car ownership.

Figure 1 presents the sequence of steps in data processing, starting with the initial data taken from various sources to the final dataset through intermediate assumptions, cleaning, specified sorting, selection, enrichment and merging. First, a coherent analysis period is chosen accounting for all significant circumstances that might have affected regular operating conditions of the system or demand patterns at that time (e.g. national holidays, public transport upgrades or breakdowns). Consequently, 26 days in February are selected for both years, which deliver consistent and comparable demand profiles.

Second, the trips are combined into journeys with a transfer inference algorithm. The goal of this algorithm is to select the right maximum transfer time threshold that would allow with the best precision possible to identify whether two trips and an activity in between are parts of one complete journey. Afterwards, a sorting and selection process takes place, including journeys with complete and different origin and destination, taken within the analysis period and inside Stockholm County.

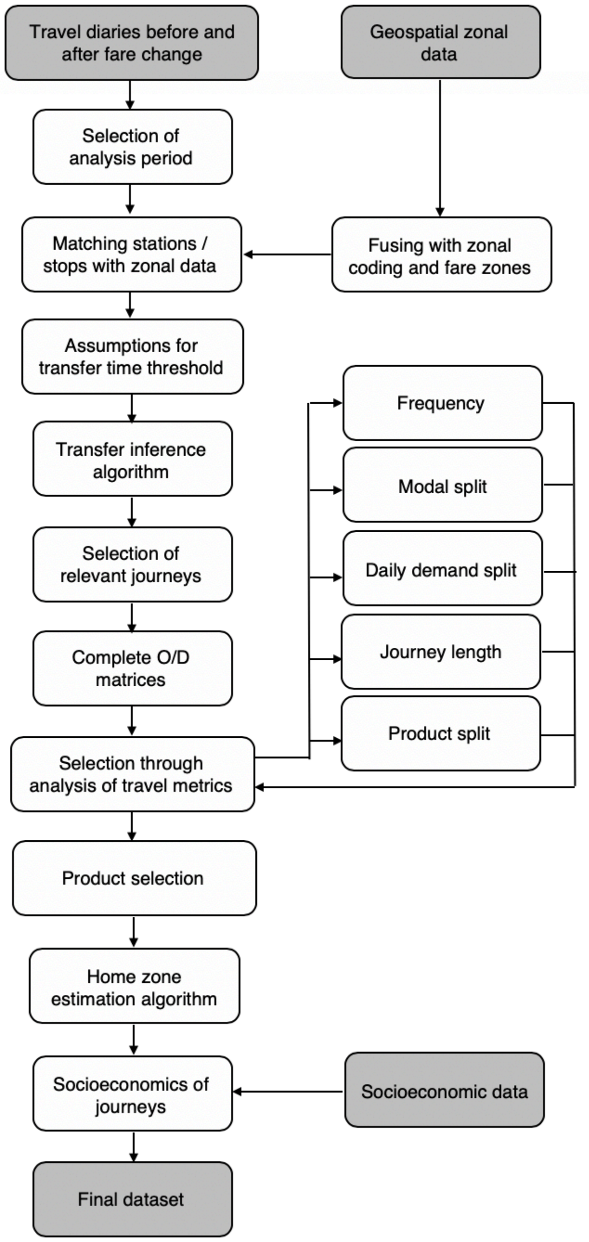

Figure 1: Data processing workflow

Third, several travel metrics are estimated for the two years, including temporal demand split by days and time of the day, spatial demand split by fare zones (A, B, C), journey composition, frequency, journey length, modal and product split. The analysis of the metrics' year-on-year change demonstrates high consistency together with a steady ridership growth (2% for journeys and 3% for cards), and therefore no significant effect of the fare policy on the overall travel patterns. Consequently, journeys with two or fewer transfers, the top-3 most popular modes and the top-14 products are selected for the final dataset. As an extension to the first, a second dataset is created that contains estimated home zone locations for individual cards. To do so, spatial regularity of usage is investigated setting the right threshold that separates sporadic travelers from regular ones. This eventually allows to assign socioeconomic characteristics to public transport users. Altogether, the processing brings a loss of 8% of trips and 11% of cards for the final dataset, and additional 4% of trips and 22% of cards for the dataset with home zones. Despite some distortion in the growth rates, the initial trend line is still maintained.

Analysing the product split in a more elaborate manner reveals the high relevance of the product "travel funds" to the current study. It is one of the five products that form the demand basis, with 40% of cards and 11% of journeys. Travel funds exhibit a significant influx of new users in the system in 2017. Most importantly, it is the only product that demonstrates a non-coherent demand growth among fare zones, reaching a great disparity between the one-zone O/D and the two- or three-zone O/Ds (0-5% against 20-60%). These findings are in line with the expectations on the main fare policy effects and create favourable conditions for the policy evaluation.

User sensitivity to the fare change is computed for different factors: socioeconomic characteristics, transport modes, travel time period, travel distance, regularity of usage, fare category and directionality of fare change. To estimate user sensitivity, an indicator fare elasticity is introduced. Fare elasticity is defined as a percentage change in public transport demand caused by a one percent change in the fare price. The aggregated elasticity values determined in this study as well as their fit into the existing research are presented in Figure 2. For most of the factors, the fit of the elasticity values is noted to be satisfactory, as the values either match with the common averages or stay fairly close to them.

The group of regular users is more sensitive to the fare policy (-0,46 compared to -0,29 for occasional), as well as users with the full product (-0,57 versus -0,31 for reduced). Sensitivity of users in time does not have a lot of variation, which can be explained by the product's specific use. User sensitivity grows along with the journey distance and substantially rises after the 10-km mark. Metro users demonstrate the lowest sensitivity, followed by a slightly higher value for bus and by far the most sensitive commuter train riders. Within the socioeconomic factors, the low-factor groups (i.e. low income, socioeconomic index, car ownership rate) are very sensitive to a price increase and do not adjust their behaviour with a price decrease (due to the already high patronage rate), whereas the high-factor groups' sensitivity is the opposite (the cost element becomes less crucial). The directionality of the price change creates a significant asymmetry. The sensitivity to a price increase is -0,51 and -0,11 for the full and reduced fare categories respectively, while in the case of price decrease the values are -1,10 and -1,81. This observation is contrary to the existing practice, in which price increase usually bears a larger value. However, it confirms the hypothesis on the importance of product convenience brought by the fare policy, as convenience got improved for the fare zones B and C, exactly where the price decrease is observed.

The equity analysis focuses on two intertwined aspects, namely the distribution of product usage and travel expenses. Both horizontal and vertical equity are elaborated on. Distribution of expenses for horizontal equity implies that the general population is ordered by the expense magnitude per capita. For vertical equity, it grasps several user groups ordered by socioeconomic factors and distance from home to the city centre, which are supposed to distinguish population cohorts. For each category, the Gini and Suits indices are computed along with plotted Lorenz curves. This allows to identify how evenly expenditures are distributed as well as how the situation changed between the two years. For a more detailed investigation, three indicators are estimated for each user group: journeys/capita, expenses/capita, and the average journey cost.

Looking at the aggregate distribution of travel expenses, no change in the degree of equity is present between the two years. After a more detailed analysis, it can be observed that the expenses grew for every commune, with the rates ranging from 3% to 43%. The policy impacts fall into the horizontal domain, as there is no clear separation of effects between different user groups, but between geographic areas. Car ownership is the only socioeconomic factor that is found to be relevant to changes in equity, yet even in this case the change takes place due to the high correlation between fare zones and the ownership rate. The fare policy induces a higher journey cost in the zone A which directly leads to the lower travel frequency. In the zones B and C, the policy leads to more journeys, however imposes a larger journey cost on some areas with a preference for local traveling (See Figure 3). This nevertheless does not stop customers from using travel funds more often, which proves the prevailing importance of the improved convenience aspect in public transport users' behaviour.

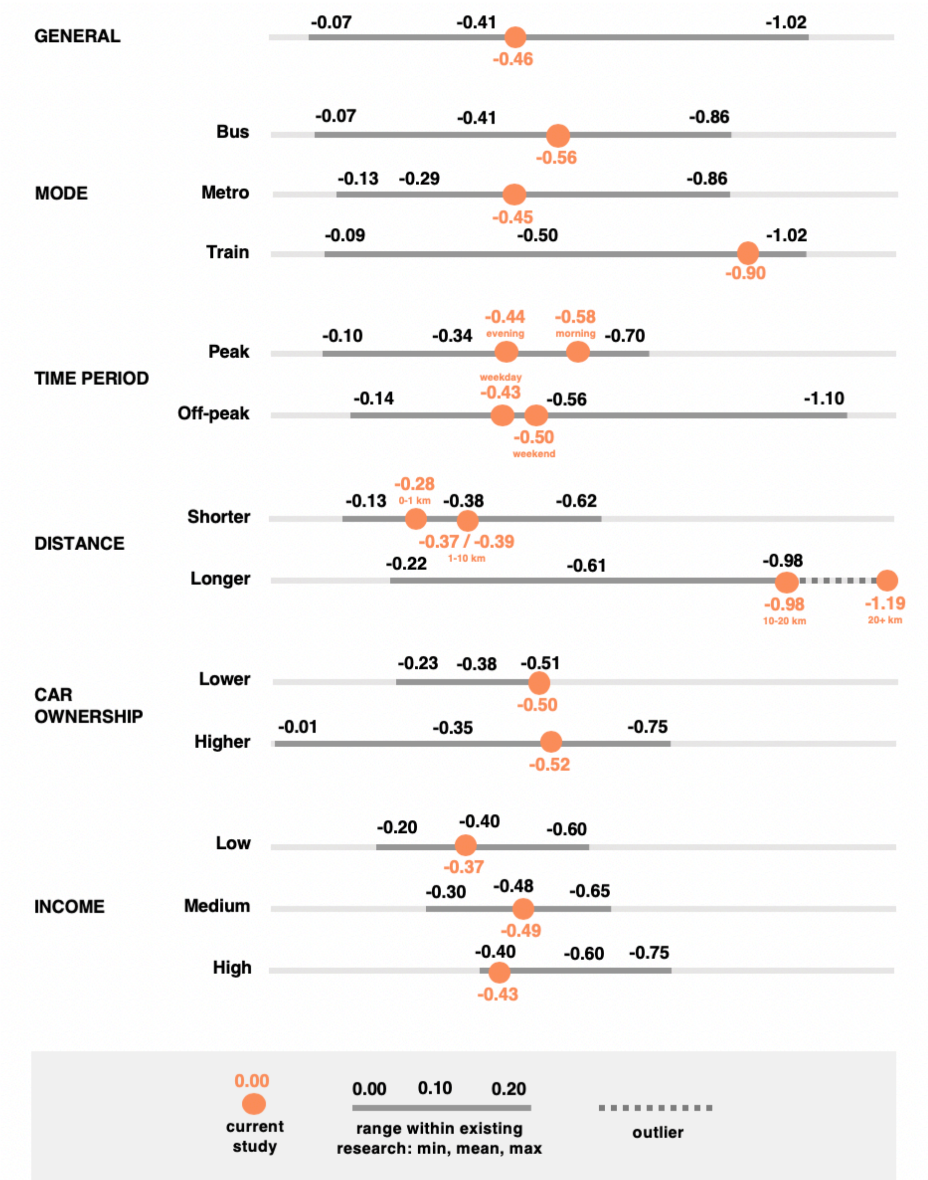

Figure 2: Fit of estimated elasticity values into existing research

The evaluation results are compared to the SLL's policy objectives. With some deviation from the initial prognosis, not all of the three are successfully met. As expected, there is an observable effect of product consistency and user-friendliness on the demand growth for the single-use category. However, the initial ridership increase rates appear to be inaccurate, as the preliminary report used the existing price elasticities for prediction and underestimated the significance of the service component. A much larger growth is obtained for journeys crossing two and three fare zones (20-65% versus 1,4-6,2% predicted). Moreover, a growth takes place within the zones B and C, which were expected to demonstrate a negative change. The inaccurately predicted demand implications led in turn to an imbalanced pricing of the single fare. Therefore, the policy contributes to a reduction of geographical disparity in terms of mobility, yet brings an additional variation when it comes to travel expenses.

The study delivers a certain scientific and practical contribution. It provides an explicit workflow of public transport fare policy evaluation through the analysis of elasticity and distributional effects. The workflow is built on the processing of smartcard records fused with socioeconomic and geospatial data. This in turn allows to improve the level of comprehensiveness and diversity when it comes to the number of travel categories utilised. The estimated elasticity and distribution values might be considered comparable and applicable in Europe and the Nordics for cities of similar scale, structure and function. From the practical perspective, the analysis brings empirical insights on travelling behavior in Stockholm County that might improve the SL's and SLL's evaluation and planning processes. The equity assessment provides a facilitating input to decision-makers striving for accessible and inclusive transport.

Despite the valuable findings of this study, it still has a number of limitations. There are a few indistinguishable types of user sensitivity (fare and service, public transport and product) due to the policy specifics. Aggregation at the census zonal level leads to a homogeneous population within each zone. Because of non-personalised smartcards, one card does not represent one actual user. Initial travel diaries based on tap-in records might bring some incorrectly or inaccurately estimated travel patterns. A one-dimensional transfer inference algorithm could result in an incorrect journey compilation, whereas an ambiguous identification of regular users during the home zone assignment could exclude some representative users from the final dataset. Lastly, the selected elasticity analysis leads to the unseparated fare policy effects from other factors (such as economic and demographic development).

The identified policy outcomes and limitations of this study pave the way for further research in fare policy evaluation with smartcard data as well as future policy-making for public transport fares. A longer time period could be chosen for the analysis under the condition that data for two years are valid and comparable. The transfer inference could incorporate a validation of time thresholds for different time periods and station types. Regarding the home zone identification, the duration of stay in each location could be additionally checked upon. Two other important issues, namely the unseparated types of user sensitivity as well as the effects of fare policy and other factors, could be tackled with the application of a regression analysis. The equity implications outlined throughout the evaluation could be validated and supplemented with an additional study.

In order to further improve the SLL's fare policy, it is suggested to set a focus on the imbalanced pricing strategy. The elasticity values presented in this study could serve as a starting point in the reestimation of the flat fare for each single-use product. The study also reveals a high value of the convenience aspect among public transport users. This could mean a potential to improve the general level of service through the development of travel information, digital services, and so forth. Besides, the study suggests a policy direction for other regions. The implementation of a flat fare scheme might reduce the geographic disparity of public transport travel and attract new users from remote areas who are more prone to be car owners. This policy direction nevertheless highly relies on three interconnected conditions, such as single-core geographic structure, high variability of public transport development in urban and remote areas, and authority's attempt to compensate for the lower transport supply through a fare change.

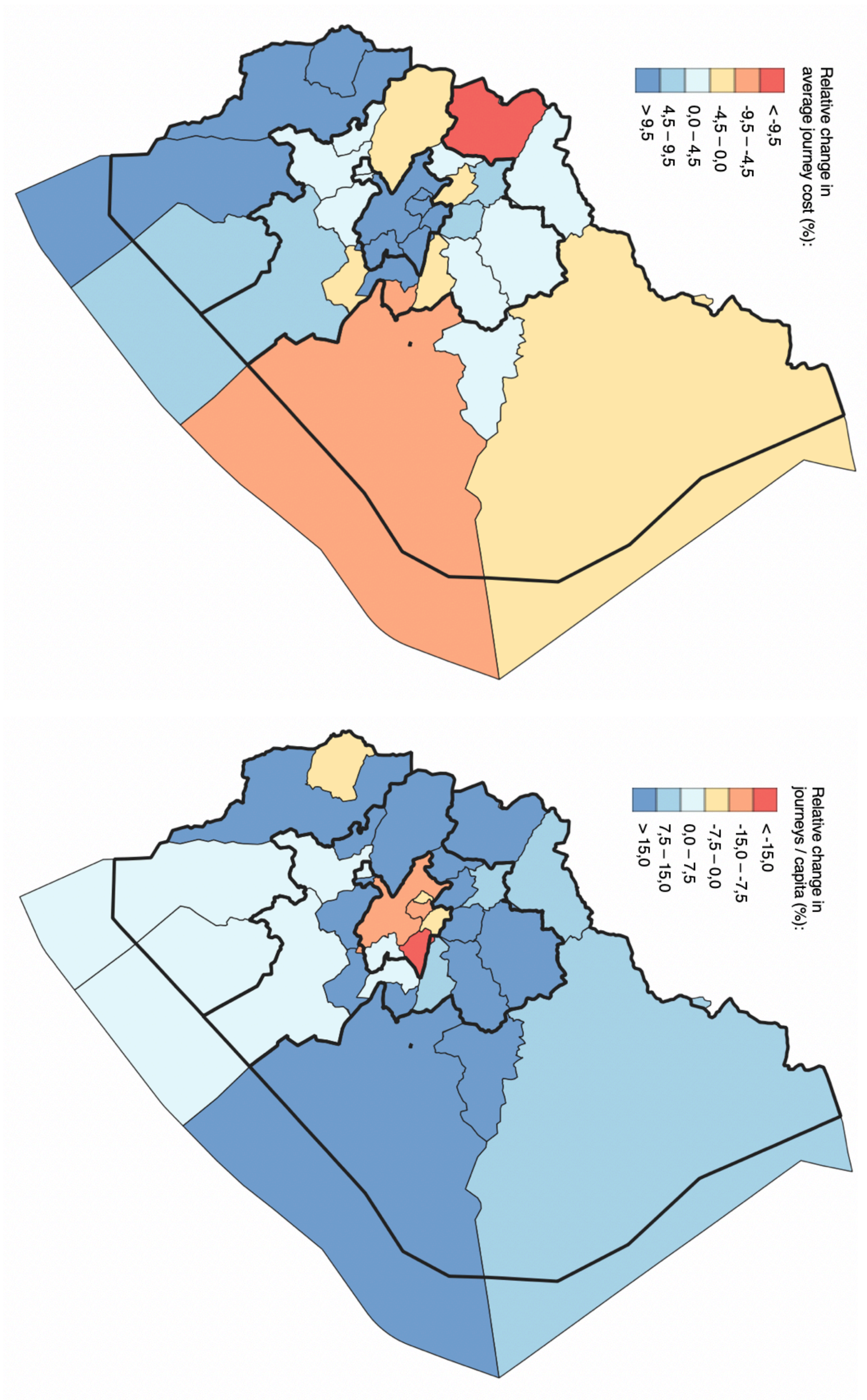

Figure 3: Year-on-year (2016 vs 2017) change of expenses (left) and mobility (right) at the communal level (fare zones highlighted in bold)

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1 Introduction

This chapter aims to get the reader acquainted with all significant aspects of the thesis. First, the field of public transport fare policy is briefly explained, including its role, structure and evaluation procedure. Next, the study case is introduced that explains the research background and delivers a sense of its purpose. This is followed by the definition of the study's scope and goal, research questions and a summary of the research approach containing major workflow steps.

1.1. Role of public transport fare policy and its evaluation

Public transport fare policy is an essential component of any public transport system. It is usually associated with changes in the fare structure that eventually might have substantial impact on a city's economic, social, political and environmental welfare (Liu et al., 2019). It is commonly observed in practice that a fare policy is introduced in an embedded form together with a transit agency's strategic plan or other formal policy. Moreover, fare policies can be seen as a response to system's changes or revealed problems (Fleishman et al., 1996). The studies on public transport fare policy have concluded that policy objectives are usually conflicting due to a large variety of stakeholders with diverse and competing interests, such as politicians, general public, public transport users, operators, investors (Yoh et al., 2012). This has a direct effect on the policy decision process, making it much more complex and challenging.

McCollom & Pratt (2004) distinguish four main fare policy objectives:

- The most widely realised objective is to increase revenues because of growing operational costs or the need to recover the investment. This usually entails a fare increase for most of the users. As an addition, the same objective might focus on minimizing the ridership loss due to higher fares.

- The opposite objective focuses on maximising the ridership. The motivation behind that can be rooted to various reasons. As an example, making public transport more attractive through the fare change might stimulate mobility, increase accessibility, contribute to the local economy or affect the modal split, which in turn would relieve congestion and improve the negative impact on the environment. Such a policy provides discounts to regular users or for certain types of journeys.

- The third objective is to trigger a ridership shift in time, which reduces peak variability and helps to utilise the system more efficiently. In this case, time-specific reductions or extra charges are introduced.

- The last objective attempts to improve equity among users. It is less commonly pursued and sometimes overlooked by authorities during the planning phase. Equity considers both the cost and benefit components for various population groups differentiated on a particular basis (for example, geographical or socioeconomic). From the user perspective, costs account for actual expenditures on fares, whereas benefits represent the level of service received.

For a modern public transport system, it is not unusual to have a broad range of fare categories which are built on the combination of a few properties (McCollom & Pratt , 2004). First, it is the purchase method which defines how a public transport user can pay for a journey: individual tickets (a single fare is charged every time a journey is made); multiple-ride tickets (sold for a certain number of journeys with a discounted price); unlimited-ride passes (allows to get an unlimited access to the system for a limited time period). Second, journey specification matters as well: distance, duration, time of the day and quality of service. Third, rider characteristics that affect the fare composition are: demographics, socioeconomic indicators, occupation and mobility constraints. Considering all these elements together, there is an opportunity to create up to several dozens of different fare categories.

The term fare structure used above is complex and includes three general aspects (McCollom & Pratt, 2004), namely fare categories offered, relationships between the prices charged for each fare category, and the basis on which fares are estimated. In this sense, public transport fare policy can alter the fare structure in the following directions (McCollom & Pratt, 2004):

- by changing the general fare level (the same percent of the change in all fare categories);
- by changing fare relationships (deliberately introducing uneven changes in different fare categories);
- by changing fare categories (introduction or withdrawal of a particular category);
- by changing the fare structure basis (flat, zonal, distance- or time-based);
- by launching free public transport (eliminating fares completely or for specific periods, zones and services only).

For any decision on a certain fare policy, it is crucial to evaluate the impacts it causes. The evaluation can be performed as an ex-ante or ex-post analysis. The former implies prediction techniques and modelling of a future scenario, while the latter operates in retrospective with two factual datasets from the “before” and “after” periods. This evaluation allows to identify and measure the actual outcomes of the policy, define the degree of its success by comparing determined impacts with the initial objectives, and even find some unexpected side-effects of high importance. Nevertheless, public transport fare policy assessment is not a trivial procedure and it requires an individual approach in most of the cases. Due to the large variety of endogenous and exogenous factors involved in the analysis, the existing research does not provide a uniform framework (Liu et al., 2019). Instead, one can find numerous approaches utilising different perspectives and instruments at a different level of depth, which are addressed in detail in Section 2.3. Despite this diversity, the studies generally look into changes in travel patterns through a set of mobility and accessibility metrics, as well as through the sensitivity of particular users to the changes under certain conditions (e.g. in space and time). A few recent studies are incorporating new trends in the field of policy evaluation, such as equity analysis and smartcard data as the main data source (Rubensson et al., 2017; Wang et al., 2018).

1.2. Research background

This research is carried out for the case of the public transport fare policy introduced by the regional administration of Stockholm County (SLL) in January, 2017. The introduction of the new policy focused on changing the fare structure basis, in particular switching from a zonal to a flat-fare scheme (see Section 3.3).

According to a preliminary study by SLL (2016), the policy aimed to resolve the issue of inconsistency within the fare system, which was perceived by travelers as one of the most difficult. Along with zone-free subscriptions in 2016, there were single-ride products that incorporated zonal fares. Public transport users were responsible for choosing the correct product according to the number of zones they wanted to cross. As a result, the system conditions were not followed, as every second multi-zonal journey was taken with a wrong product and underpaid. This led to a significant loss in revenues as well as a low level of customer satisfaction, which was revealed by a travel survey in late 2015: 37% of users found it difficult to navigate between the zones, and 43% confirmed that it was hard to estimate the exact journey cost (SLL, 2016).

In order to avoid the risk of decreasing ridership and negative environmental impacts (in case of public transport users shifting to car), the fare policy was introduced promoting convenience and transparency of the single-use products. Another important direct effect of the policy is the price change. Certain categories of journeys became cheaper whilst the others increased in price, based on the combination of origin and destination (see Section 3.3). Generally, the administration formulated three main policy objectives: simplicity of the fare system, increase in demand on longer distances as given in Table 1.1 and a neutrally-balanced economy (which justified the exact price level).

Before the fair policy got implemented, a customer survey was organised to identify the level of its acceptance (SLL, 2016). Despite the fact that 80% of the passengers interviewed traveled within one zone, thus were about to experience the price growth, they supported the proposed policy draft. This proves the aforementioned importance of the fare system being user-friendly and consistent.

Table 1.1: Predicted relative growth in demand for travel funds product after policy implementation (SLL, 2016)

O/D group	Relative growth in demand, %
Within zone A	-0,4%
Within zone B	-0,2%
Within zone C	-0,3%
Between zones A and B	1,4%
Between zones B and C	2,0%
Between zones A and C	6,2%
Total	0,2%

Respondents also had to decide whether the proposed policy was fair (SLL, 2016). Reflecting on the equity aspect, customers demonstrated less accordance and can be split into two opposite groups of a relatively equal size. This can be explained by two perspectives on the price change that the policy entails. On the one hand, it can be considered fair to pay more for longer journeys, and on the other hand, the price can be adjusted according to the level of public transport service provided in a particular zone.

Regarding the latter, the majority of users travel solely within zone A, where the network density and diversity is significantly higher compared to zones B and C. At the same time, users from zones B and C tend to take multi-zonal journeys more often, hence travel on longer distances. This creates a correlation between long journeys and lower transport supply. Following this logic, the administration of Stockholm County considered it equitable to apply the flat fare, because it would compensate for the unequal ticket “value”.

As the research background is presented, it becomes clear that the introduction of the policy provides a great opportunity to study the impacts of the fare change in a real case.

1.3. Research scope and goal

Building on the research background in Section 1.2, the predicted policy outcomes are tested as the main hypothesis of this study. In particular, it is expected that the introduced fare policy would improve simplicity and convenience of single-use products. Together with readjusted prices, it would stimulate demand growth for multi-zonal journeys, which consequently would support travelers of zones B and C.

Therefore, the goal of this thesis is to investigate how the policy affected traveling behavior of different public transport user groups. Moreover, considering the importance of the social aspect of policies for Region Stockholm (see Section 3.2), the redistribution of benefits and costs in terms of mobility and fare expenses is assessed through the equity perspective. The availability of smartcard data granted by Stockholm Public Transport, together with socioeconomic data (see Section 4.1), substantially contributes to the overall quality of the policy evaluation.

With respect to the scope, the research looks into traveling patterns of Stockholm County's population. The set of transport modes includes commuter train, metro, and bus which together comprise about 98% of all trips made by public transport. Based on data availability, public transport users are grouped under consideration of their place of residence, fare categories and socioeconomic characteristics. Two time periods are utilised in the evaluation procedure, specifically before and after the fare policy was introduced (years of 2016 and 2017). Mobility indicators are estimated at the individual level with further aggregation for user groups and statistical zones. The setup of the research workflow is elaborated in Section 4.2.

1.4. Research questions

According to the research gap outlined in the literature review (Section 2.4) as well as the identified goal and scope, the main research question of this thesis is the following:

To what extent did the change from a zonal to a flat fare scheme in Stockholm County affect travel patterns of different public transport user groups, and what were its equity implications?

This entails a series of sub-questions that aim to split the research process into a few more tangible blocks:

1. What were the main public transport user groups in Stockholm County to be distinguished, based on travel, geographic and socioeconomic data?
2. What were the travel patterns of the user groups expressed through metrics in the spatial and temporal dimensions, before and after the fare scheme change?
3. What was the degree of the fare policy impact on the change in travel patterns for each user group?
4. What equity effects did the fare policy bring to the public transport user groups?

1.5. Research approach

The research work is executed through a sequence of steps, starting from problem definition to the discussion of the results, conclusion and recommendations. Figure 1.1 depicts a visual structure of the research workflow.

First, a brief problem understanding leads to the definition of the scope and the goal of this thesis, which in turn allows to formulate the set of research questions. The initial set of questions and the project's scope get refined through a recurrent process of literature review and context study.

The literature review in Chapter 2 mostly focuses on the existing practice of public transport fare policy evaluation. This enables to distinguish useful instruments and methods, including travel metrics, but also to determine a research gap, covering which would bring considerable scientific and practical contribution. The notions of elasticity and equity within the fare policy domain are given a detailed look as well. By doing so, the study addresses the theoretical sides of the sub-questions 3 and 4. To complement the scientific background, Chapter 3 elaborates on the research context. This includes a brief overview of Stockholm County with its public transport system, followed by a comparison between the two fare structures before and after the policy introduction. Together, the literature review and the context study set up a conceptual framework, including clear research boundaries with corresponding terms, processes and influential factors.

The next stage of the thesis work is presented in Chapter 4, which specifies a method and prepares data for the analysis. Two major data sources are described, i.e. smartcard and socioeconomic data. Stemming from the conceptual framework, the reasoning of the method is stated that is building on feasible assumptions regarding temporal and spatial aspects, transport modes and user groups. The specification of the latter ensures that the sub-question 1 is answered. The method delivers clear requirements for input and output elements in data selection and processing. This is followed by a definition of the data treatment procedure as a step-by-step workflow that allows to create a final working dataset. This treatment implies a large number of operations, most important of which are cleaning, sorting, fusing, enrichment and standardisation. As a next step that builds on filtered and processed data, the computation of travel metrics before and after the fare scheme change takes place. The results of this computation are delivered in a form of descriptive statistics and supported by visual representations. This ensures that the sub-question 2 is addressed.

Chapter 5 is devoted to the fare policy evaluation through elasticity and equity analysis. The analysis of user sensitivity is executed with a high level of detail in order to relate it to certain traveler response factors. By reporting on the outcomes, the study answers the sub-question 3. To resolve the sub-question 4, the distribution of travel expenses and journeys is investigated in a thorough way, taking into account a bifold concept of equity (horizontal and vertical).

Finally, Chapter 6 discusses the findings of this study, answers the research questions, and reflects on the results from a theoretical and practical point of view. The conclusion underlines contribution of the thesis, its limitations and suggested directions for the future work in the field of public transport fare policy evaluation. Recommendations are drawn up for Region Stockholm and other relevant stakeholders on general applicability of the findings and further steps to be considered with a similar practice in fare policy.

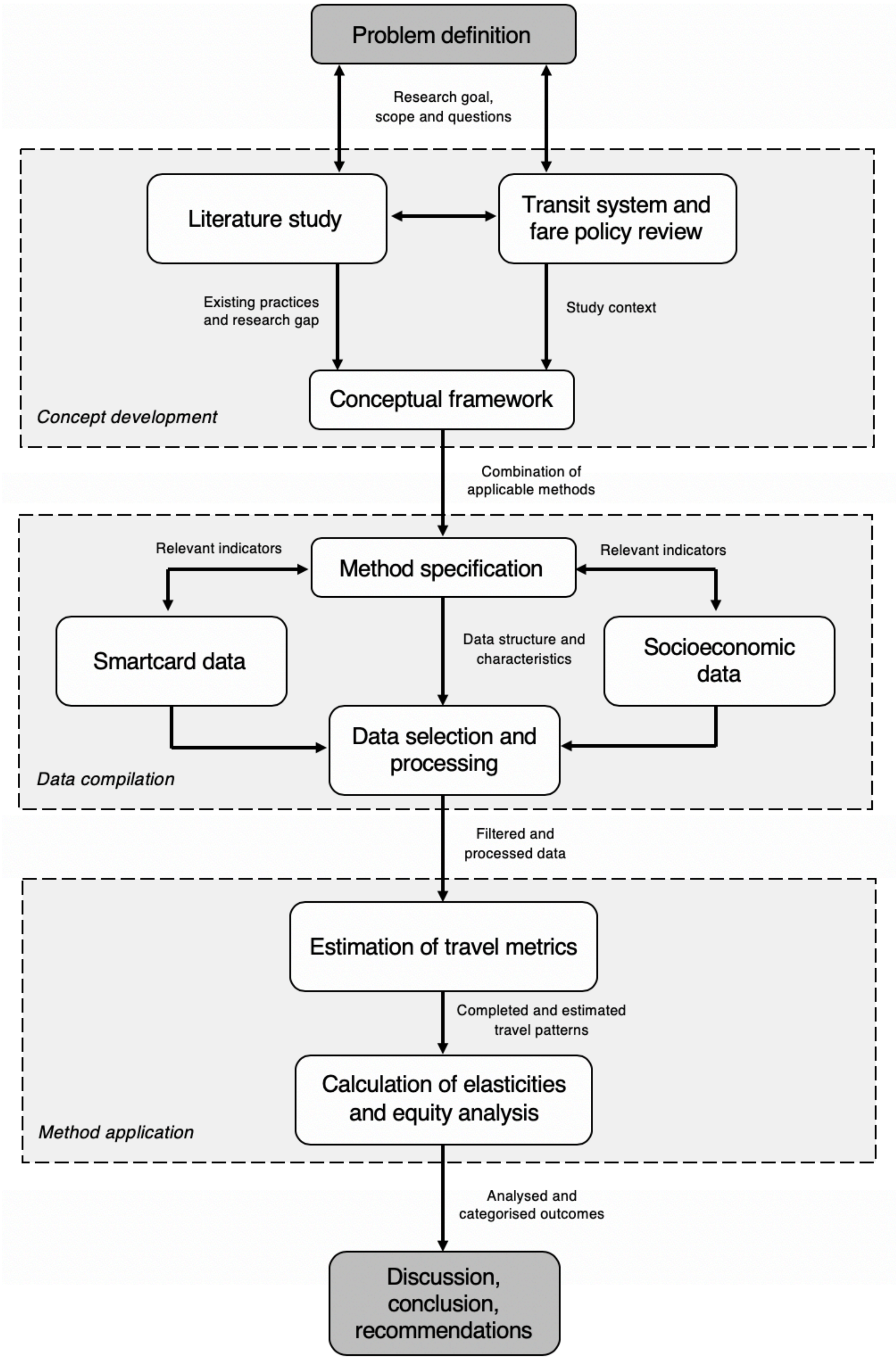


Figure 1.1: Research workflow

2
Literature review

This chapter delivers a summary of the literature review that has been done within the thesis' scope. First, it elaborates on how to quantify the user sensitivity to public transport fare changes through the price elasticity, and recent findings on this topic. Afterwards, the notion of equity and certain equity categories relevant to fare policy are described in detail. The following section focuses on the existing practice in fare policy evaluation and juxtaposes different approaches within this domain. The last section takes the form of a literature review synthesis, where a clear research gap is identified.

2.1. User sensitivity to public transport fare change

Public transport is one of the examples that underlines that the consumption level of any product or service is dependent on its market price (McCollom & Pratt ,2004), as its fare structure has direct effects on the travel demand. However, there is a particularity about travel demand, because the use of public transport is not perceived as a direct good, but as a mean to reach certain activities that would bring an additional benefit to the user, be that work, study, shopping or leisure. Making a choice with regard to traveling, one considers a variety of factors that eventually shape a person's demand pattern. Litman (2019b) presents several factors of influence, splitting them into six general categories: demographics, economic activity, transport options, land use, mobility management (policy) and prices. The price factor combines direct costs (fuel price, parking fees, public transport fares) and indirect costs (travel time, level of comfort, risks). To estimate the extent of change in demand caused by a change in price, a special indicator is introduced called price elasticity. In case of public transport fare policy, fare elasticity attempts to relate changes in ridership to changes in the fare structure.

2.1.1. Fare elasticity and its measurement

Fare elasticity is defined as the percentage change in public transport demand after a one percent change in the fare price, under the assumption that all other factors are kept constant. The elasticity sign defines the direction of this change, e.g. a positive value indicates growth in ridership caused by the new fare structure, whereas a negative value indicates a decrease. In addition to this, the value of elasticity shows how sensitive public transport users are to the fare change. An absolute value with a magnitude of 1.0 is called unit elasticity, as it leads to a proportional change of indicators (a 1% of change in price entails a 1% of change in demand). All the values below 1.0 (above -1.0) are referred to as inelastic, which means that the fare change brings relatively little effect on ridership. In contrast, the values above 1.0 (below -1.0) are classified as elastic, which implies that even a slight fare change causes relatively large shifts in public transport demand (Cervero, 1990).

There are several widely used methods to estimate public transport fare elasticity. As stated by Linsalata & Pham (1991), these are the following:

- Stated preference surveys collect users' direct responses on how they would change their travel behaviour (e.g. by mode, frequency or time of the day) due to a particular fare change. With a sufficient number of responses, it is statistically possible to estimate the sensitivity for various aspects of traveling. However, passengers tend to overestimate their reaction to the fare policy and underestimate the cost of switching to alternative choices, which adds bias to the analysis.
- Shrinkage analysis is based on the monitoring of demand levels before and after the fare change. Fare elasticity is then computed as the ratio of the change in demand to the change in price. Because of its simplicity, this method is the most common in user's sensitivity studies. However, it does not consider any other factors which coincide with the fare policy and might affect the ridership as well. Therefore, in shrinkage analysis one should assume that all the side factors are constant.
- Econometric methods, with regression analysis being the most popular in this group, address the main disadvantage of shrinkage analysis by determining public transport demand according to a set of influential factors. The relationship between these factors and ridership is expressed in a mathematical form, with further isolation of the fare change impact. Therefore, econometrics provides an estimate of unbiased fare elasticity. Despite the method's accuracy, it is very time and resource demanding.

With regard to the mathematical formulation of fare elasticity, the research distinguishes point elasticity and arc elasticity, with mid-point arc elasticity as a variation of the latter (Litman, 2019b). Point elasticity is the simplest approach that considers two data points only, assuming a linear demand relationship between them. The problem with this approach lies in the fact that the demand curve is not linear and asymmetrical for different directions of change (demand is more sensitive to fare increase than decrease). Hence it is accurate only for fairly small changes in fare price (Cervero, 1990).

A more representative approach for fare elasticity estimation is arc elasticity. It establishes an exponential relationship between two points (original and final), and measures demand change incrementally for each percent of the price change (Litman, 2019b),

$$\eta = \frac{\log Q_2 - \log Q_1}{\log P_2 - \log P_1} \tag{2.1}$$

where η is the elasticity value, Q_1 and Q_2 are "before" and "after" public transport demand, and P_1 and P_2 are the "before" and "after" fare prices.

The arc elasticity can be closely approximated by its mid-arc formulation that considers the arithmetic average of the original and final values of fare price and ridership. The accuracy is noted to be very similar except for very large changes in price, which is not the case for the majority of fare policies (Litman, 2019b).

$$\eta = \frac{\Delta Q}{\frac{1}{2}(Q_1 + Q_2)} \div \frac{\Delta P}{\frac{1}{2}(P_1 + P_2)} = \frac{(Q_2 - Q_1)(P_1 + P_2)}{(P_2 - P_1)(Q_1 + Q_2)} \tag{2.2}$$

Apart from changes in the overall level of public transport demand due to changes in fare price, some shifts of users might be observed within the public transport system. This phenomenon is called ridership diversion rate and can be identified through cross-elasticity (Hickey, 2005). Cross-elasticity refers to the percentage change of demand between related groups of travelers due to the rearrangement of prices for these groups (Litman, 2004). As an example, a fare policy change might affect riders to switch from one mode of public transport to another, choose another fare product instead of the previously used, or change their travel behavior in space and time (stop traveling at peak times or to farther zones).

2.1.2. Studies on fare elasticity and its determinants

There is a substantial body of literature available on travelers' response to public transport fare changes, analysed from various perspectives, considering short-term and long-term effects, revealed and stated preferences, different geographic scale, types of users and journeys. It has been revealed that several factors might determine fare elasticity, and each of those has its own impact. Because of the high variability of these factors, elasticity is usually analysed for a particular case. Among other important studies, a few are incorporated in this thesis (Balcombe et al., 2004; Cervero, 1990; Litman, 2004; Litman, 2019b; McCollom & Pratt, 2004; Wang et al., 2015).

Most importantly, fare elasticity relies on the public transport user's type stemming from socioeconomic and demographic characteristics. Altogether, they define whether an individual is public transport dependant or not. The public transport dependant riders tend to be less sensitive to changes in fares, compared to those who have an alternative choice in travelling (Litman, 2019b). Some of the important indicators of public transport dependency include low income, disabilities, young and old age, absence of private transport, occupation (unemployed, high school and university students). However, income has two effects: it is related to the higher car ownership rate for wealthier people (which increases sensitivity), but at the same time high-income users have a higher tolerance to price increase (which decreases their sensitivity). According to a meta-analysis conducted by Balcombe et al. (2004), elasticity differs between -0,23 for public transport users with no car available and up to -0,35 for users with at least one car (-0,10 and -0,41 respectively in Litman (2004)). Regarding the level of household income (Balcombe et al., 2004), the elasticity range varies from -0,40 to -0,60 (from -0,19 to -0,28 in Litman (2004)). In case of age, the fare elasticity goes from -0,32 for riders under 16 years old to -0,16 for riders over 65 years old in McCollom & Pratt (2004) and from -0,32 to -0,14 in Litman (2004).

The next factor of influence is the journey type, which is identified by journey purpose, length and time. Commuter journeys are observed to be less sensitive than leisure ones, as the riders going to work or study locations do not have a high degree of flexibility in their travel choice (Cervero, 1990). McCollom & Pratt (2004) report the elasticity values of -0,11 to -0,19 for commuter journeys and -0,25 to -0,37 for leisure journeys (shopping, recreation, social), whereas Litman (2004) reports -0,10 to -0,19 and -0,32 to -0,49 respectively. The journey length significantly affects the fare elasticity, as the value for short journeys is -0,38, opposed to -0,61 for longer journeys (Balcombe et al. (2004)). Despite the high relevance to the journey purpose, the peak/off-peak time is recognised as a separate factor. According to Wang et al. (2015), the fare elasticity is -0,26 to -0,34 for peak demand and -0,48 to -0,79 for off-peak demand.

Public transport mode and routes bring different elasticity values. Usually bus is considered to be the least comfortable and reliable mode that cannot compete on the same level with automobile transport as rail modes do. Thus bus and rail generally serve slightly different markets (Wang et al., 2015). A study by Balcombe et al. (2004) finds elasticity values of -0,29 for metro, -0,41 for bus and -0,50 for rail riders. Moreover, fare elasticities are noted to be lower on routes with substantial public transport dependency on a single mode and higher where people are provided with a few alternative modes (Litman, 2019b).

Interestingly, the direction of price change also matters. Despite the wide use of symmetric elasticities, a few studies reveal that an increase in fare levels brings higher demand sensitivity compared to the case of fare reduction of the same size. Existing riders will look for alternatives sooner if transport becomes more expensive, whereas it is less likely that someone would change their behaviour immediately due to the price decrease (Litman, 2019b).

Two more factors have an important role in fare elasticity estimation. These are the time passed since the fare change and the city's geography. The former reflects on the delay in users' response to the fare change, which means that it takes a considerable amount of time for some people to adjust their travel patterns (Litman, 2004). This might lead to change of work and residence locations, purchase of a car, etc. Therefore, short-term (1-2 years), mid-term (up to 5 years) and long-term (more than 5 years) elasticities are recognised. The demand sensitivity is usually two to three times higher for longer periods, e.g. -0.34 and -0.66 respectively, according to Wang et al. (2015). Nevertheless, this factor is not considered in the thesis due to the availability of short-term data only. In terms of scale and density of a particular urban area or a city, the fare elasticity has an inverse relationship with these two aspects (Litman, 2019b). This finding can be explained by a better level of service provided in large and dense cities, problems associated with congestion and parking, along with a greater fraction of public transport dependant population.

Apart from getting direct results on public transport users' sensitivity to the fare change under different factors, the outcomes can be investigated together with other data in the form of a case study. Hence, the detailed impacts of a fare policy can be evaluated. As an example, elasticity of individual fare products might vary, as well as relative sensitivity among them. A change in the fare structure matters significantly, which leads to a comparative analysis of policy alternatives for justification of the most optimal choice. By doing so, researchers reach the understanding of travel patterns together with the rider's sensitivity in space, time, by mode, etc. Looking at this from both users' and service provider's perspectives, one can identify who benefits from a particular fare structure change and to what extent, e.g. how a policy contributes to system's revenues, mobility and welfare of the entire population and specific subgroups. Notwithstanding, to this moment research in the domain of detailed and complex fare policy evaluation through quantified passengers' response is scarce (Wang et al., 2018). The existing gap is described in Section 2.4.

2.2. Equity

Nowadays equity is taking a larger role in various spheres, such as project planning and appraisal or policy evaluation. Based on Litman (2012), equity is closely related to the notions of justice and fairness. It implies a distribution of advantages and positive effects along with burdens in the society followed by the question on how adequate this distribution is. If a project or a policy are to be designed equitable, they have to deliver a fair allocation of benefits and costs among the population (Cadena et al., 2016).

In the transportation field, equity is usually considered in conjunction with sustainability (van Oort et al., 2017). In addition to major goals of any transport system, be that an improved economy or quality of life through higher mobility, increased safety, mitigated negative environmental impacts, equity comes into play as another important aspect. It is concerned with inter alia the distribution of accessibility, health impacts, investments, taxes, road tolls and public transport fare pricing (Farber et al., 2014).

Being a vital component of a project or policy assessment, the strive for equity steers the decision-making process, however in a quite inconsistent way (Taylor & Norton, 2009). Based on stakeholders and their goals, transportation equity can be categorized differently with significant variation in what impacts to include, how to estimate them, and most importantly, who are the affected groups. Contradictory points of view and subjective problem framing might lead to a significant misuse of the existing methodology, overlooked specific social needs and unsuccessful attempts to deliver the essential functions of the transport systems. Therefore, an integral approach is required that aims to incorporate alternative theories in an optimal manner. (Nahmias-Biran et al., 2017).

2.2.1. Types of equity

In order to understand how the notion of equity is treated in the transportation field, one should look into more generic concepts first. Taylor & Norton (2009) provide an overview of different philosophical theories on distributive justice where equity is stemming from. Table

2.1 represents different types of equity through the lens of justice in public finance. The authors argue that this set provides a comprehensive picture of competing definitions of equity.

Table 2.1: Types of equity through conceptions of distributive justice (Taylor & Norton, 2009)

Theory of justice	Conception of justice in relation to public finance	Type of equity
Strict egalitarianism	Each individual in society receives the same magnitude of goods and services irrespective of contribution	Outcome equity
Difference principles	Individuals have equality in basic rights and liberties, but society is better off when individual success is cultivated and allowed to benefit individuals directly	Opportunity equity
Resource-based principles	Goods and services are equally distributed to individuals at the outset, but there is little or no societal cross-subsidization from that point forward	Opportunity equity
Desert-based theories	Individuals who increase wealth in society are entitled to benefit directly from that wealth	Market equity
Libertarianism	Consensual transfers of goods and services between individuals within a society are just by definition	Market equity

Distributive justice has the primary goal to reasonably allocate a finite amount of goods and services. The two key components leading to variation are the unit of distribution (geographic areas, groups or individuals) and the logic behind the distribution (need, merit and fortune). Taylor (2004) elaborates more on this framework in the context of equity in transportation finance. He juxtaposes the three units of analysis with the three types of equity seen in Table 2.1. By doing so, he creates an ultimate multi-level matrix specifying how its different combinations evolve into divergent concepts of equity (see Table 2.2). Notwithstanding, when it comes to eventual effects, the idea of opportunity equity has been highly accepted by the experts, yet the outcome equity still rises some questions. The main concern is whether it is sufficient to provide adequate support to certain groups and individuals, or if the society must ensure that those population units actually succeed in their activities due to the transport service provided (Litman, 2019a).

Table 2.2: Concepts of equity in transportation finance (Taylor, 2004)

Unit of analysis	Type of equity		
	Market equity	Opportunity equity	Outcome equity
Geographic: States, counties, legislative districts, etc.	Transportation spending in each jurisdiction matches revenue collections in that jurisdiction	Transportation spending is proportionally equal across jurisdictions	Spending in each jurisdiction produces equal levels of transportation capacity or service
Group: Modal interests, racial/ethnic groups, etc.	Each group receives transportation spending or benefits in proportion to taxes paid	Each group receives a proportionally equal share of transportation resources	Transportation spending produces equal levels of access or mobility across groups
Individual: Residents, voters, travelers, etc.	The prices or taxes paid by individuals for transportation should be proportional to the costs imposed	Transportation spending per person is equal	Transportation spending equalizes individual levels of access or mobility

One of the most common approaches to classify transportation equity includes two categories: horizontal and vertical equity (Caggiani et al., 2017). Horizontal equity deals with fairness and follows the ideas of egalitarianism. It looks into the distribution of costs and benefits between equal units (individuals or groups). Therefore, those who are equal in abilities and needs are supposed to be treated in the same way. The most substantial branch of this study considers spatial distribution of transportation burdens and impacts. Vertical equity in turn is concerned with social justice. The main focus of vertical equity is the distribution between unequal units, i.e. those that differ in their abilities and needs. Disadvantaged individuals or groups are distinguished based on one or several indicators, such as income, social characteristics, degree of mobility, etc. Therefore, a policy or a project, which recognises these groups, can compensate for some inequities, be that accessible modes, special pricing schemes or reduced health risks. In the opposite case, a policy or a project might also bring additional burdens to disadvantaged units.

For transport planning and evaluation, equity objectives are important to consider. The bifold concept of horizontal and vertical equity brings several objectives followed by their indicators (Litman, 2019a):

1. Horizontal equity
   - Everybody is treated equally as long as there is no justified reason for specific exceptions: policies are applied equally to all users, costs and benefits per capita are equal for different population units, modes receive support according to their use.
   - Users carry the costs imposed by their travel.
2. Vertical equity
   - Policy based on income levels: more affordable modes receive additional support, user-tailored price reductions are provided to low-income households, areas with a higher number of users in economic need get a larger share of investment.
   - Policy focusing on people with a lower degree of mobility: development of accessible and multi-functional transport services, transport facilities are implemented through the universal design, or the introduction of special services for users with disabilities.
   - Improvement of basic access: a provided service favors traveling to necessary activities for the broader public (e.g. work and study locations, medical and administrative facilities).

As it was stated above, different stakeholders are usually guided by a one-sided approach, acknowledging a single type of equity along with a separate unit of distribution. For instance, researchers in social science prefer to recognise the individual opportunity equity, operators and activists are concerned with the group market equity, whereas politicians are likely to focus on the geographic outcome or opportunity equity (Taylor & Norton, 2009). In this study, the notion of transportation equity, and equity of public transport fares in particular, is elaborated on in a more comprehensive manner, utilizing the concepts of Taylor (2004), Caggiani et al. (2017) and Litman (2019a). The horizontal and vertical equity are assessed at the geographic and group levels.

2.2.2. Assessment methods

Following Farber et al. (2014) and Taylor (2004), transportation equity poses a significant challenge in its assessment due to the wide range of categories, including equity types, social units of analysis, and impacts to consider. In this diversity, one cannot find the only possible and correct approach to measure equity. Moreover, a policy or a project could be equitable being assessed through one method and absolutely inequitable through another. Each case therefore requires the choice of a certain benchmark applicable to a specific context, which would eventually set the desired policy (project) outcomes for the assessment procedure. Lucas et al. (2019) provides a sequence of steps to be taken in a comprehensive equity assessment (see Figure 2.1), stating that there is a long way between the identification of disparity and judgement on the degree of policy (project) fairness.

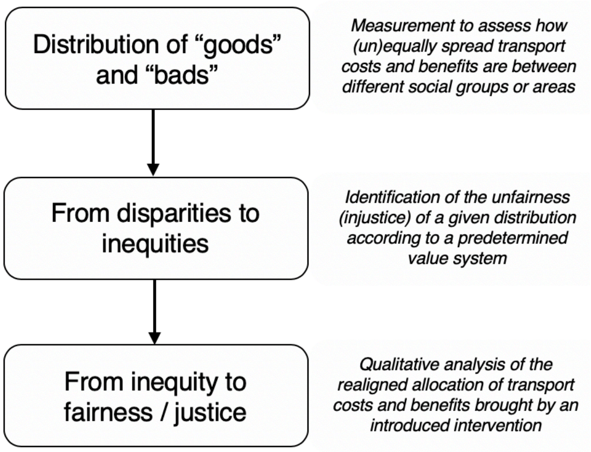


Figure 2.1: Different stages of transport equity assessment and interpretation (Lucas et al., 2019)

The first step in the sequence is to study people's patterns and differences between them from the cost and benefit perspective, which facilitates the measurement of disparities. Most importantly, the disparity should have a descriptive function only, as by itself it does not point at an issue of justice and fairness. As the second step, a transition from the degree of equality to the degree of equity is to be done through the definition of a concrete and explicit value system. A few examples of value systems stemming from the concepts of horizontal and vertical equity are presented above. Based on what distribution of transport impacts is considered to be desirable, one can judge how equitable a certain situation is. The third, and final step, is to relate policy's (project's) implications to change in equity. This implies a qualitative analysis of the introduced interventions through the lens of their equity effects. As this study aims to be impartial and objective at every stage, including equity evaluation, it incorporates only the first step of the sequence. Hence, the descriptive findings can serve as a great basis for further interpretation.

Various indicators can be adopted in equity assessment that would lead to different functionalities and implications. For instance, one might use "per capita" to include the whole population, or "per journey" scaling down to users of the transport system only, whereas "per kilometer" outlines the prevailing importance of distance (Feng & Zhang, 2014). In case of equity in public transport fare policy, the evaluation usually looks into pricing impacts on travel costs, ridership and accessibility for different groups and individuals (see Section 2.3). The most popular way of equity assessment involves the application of formal indicators, such as the Gini and Suits indices accompanied by a visualisation of Lorenz curves (Gini, 1912; Rubensson et al., 2017; Suits, 1977). They aim to measure the gap between the absolute uniformity and the current situation, thus presenting distributional differences of costs and benefits in a simple yet representative and unbiased way.

The goal of the Gini index is to estimate a degree of horizontal equity (Gini, 1912). A good example of its utilization in public transport fare equity assessment is presented in Rubensson et al. (2017). The focus in this work is put on how public transport expenses are distributed among the population with an absolute case of these expenses to be equal for everyone regardless their place of residence. First, the total fare expenses per capita are calculated for each zone. Second, a graph is constructed, where the abscissa contains zones arranged by increasing fare expenses and the ordinate contains accumulated fare expenses related to each zone. This graph is called the Lorenz curve and allows to graphically estimate the Gini index (see Figure 2.2).

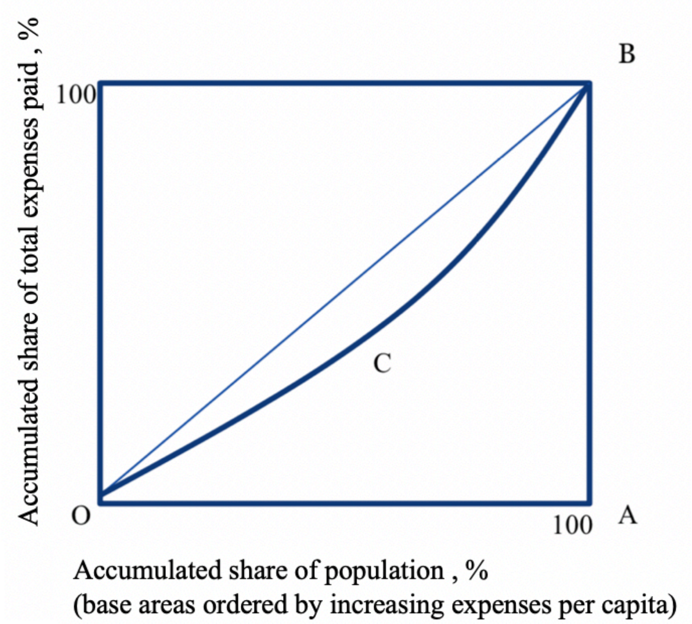


Figure 2.2: Example of Lorenz curve in horizontal equity of public transport fare (Rubensson et al., 2017)

Looking at the graph, the area of the triangle OAB is expressed as K and equals 5000 (100*100/2). The area between OA, AB and OB (Lorenz curve C) is expressed as L. For a certain segment of the population y, the accumulated fare expenses $T(y)$ include both the segment y and the areas with lower expenses per capita than y. The Gini coefficient then equals (Rubensson et al., 2017):

$$Gini = \frac{K-L}{K} = 1 - \frac{L}{K} \tag{2.3}$$

$$L = \int_0^{100} T(y)dy \tag{2.4}$$

$$Gini \approx 1 - \frac{1}{K}\sum_i (\frac{1}{2})[T(y_i) + T(y_{i-1})](y_i - y_{i-1}) \tag{2.5}$$

A value of the Gini index along with a shape of the Lorenz curve reveals a level of horizontal equity which can be found lying between two extremes. Absolute equity, where fare expenses per capita are equal for everyone, is represented by a Gini value of 0 and the curve C matching with the diagonal OB. Absolute inequity, where fare expenses are borne by a single person, is represented by a Gini value of 1 and the curve C taking a shape of the lines OA and AB.

The Suits index in turn is computed in a similar way as the Gini index, however the population on the abscissa of the Lorenz curve is sorted by the size of the income instead of rising public transport fare expenses (Suits, 1977). This change leads to the measurement of vertical equity among different income groups. The ultimate idea is that public transport pricing should be organised in order to support low-income users (Rubensson et al., 2017).

In terms of outcomes, the Suits coefficient might take either positive or negative value, and the Lorenz curve can slice both sides of the diagonal OB (see Figure 2.3). If the Suits value equals 1 and the Lorenz curve C overlaps with the lines OA and AB, the extreme state is reached when all expenses are covered by the richest one. In contrast, the Suits value of

-1 and the Lorenz curve C' taking a right angle shape indicate the state of another extreme, meaning the poorest individual is paying all fares. The absolute equity situation is characterised by the diagonal shape of the Lorenz curve and the Suits index yielding 0. If such happens, all income groups bear equal expenses of public transport fares.

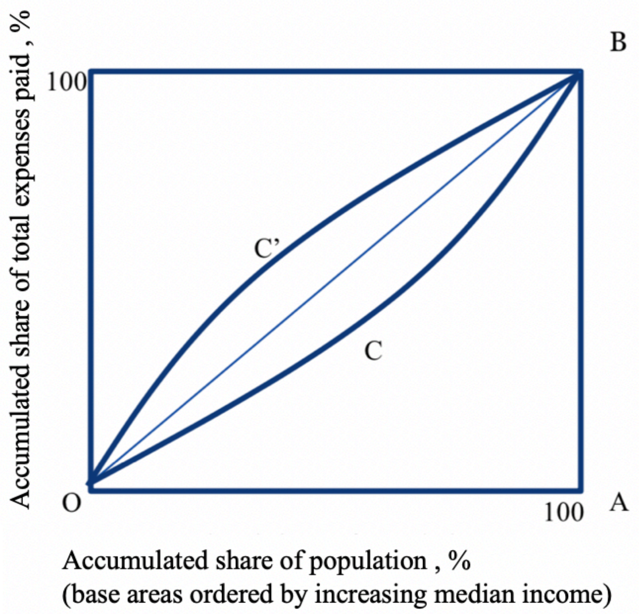


Figure 2.3: Example of Lorenz curve in vertical equity of public transport fare (Rubensson et al., 2017)

It should be noted that the example by Rubensson et al. (2017) does not provide the only possible application of the Gini and Suits indices. However, it is a good reflection on the methodology in general and its specific case of equity in public transport fare policy assessment. Even in this domain there are numerous metrics to be considered. Instead of the fare paid, an affordability component (a fraction of fare expenses in income) or accessibility level might be incorporated. Moreover, the population can be ordered based on other parameters, e.g. car ownership or education level.

2.3. Existing practice on public transport fare policy evaluation

In the domain of fare policy evaluation, an increasing number of recent studies contribute a lot to the establishment of more advanced methodologies and comprehensive frameworks which attempt to utilize the equity component. Table 2.3 contains an overview of studies fully or partly devoted to the assessment of fare policies. There is no goal to make this list complete and all-encompassing, but sufficient to outline the diversity of the existing research, its accomplishments and observable gaps for further improvement. The table clearly indicates the backbone structure of such research including the main aspects which could be found in the majority of cases. The following subsections will describe these aspects in detail and compare for each case how theory and practice merge to achieve sensible results.

2.3.1. Study context

The study context includes a few elements, such as the geographic location, the public transport system with its set of modes, a range of fare scenarios and their types.

To this date, most of the research on fare policy assessment has been performed in the American context (Brown, 2018; Guzman et al., 2018; Hickey et al., 2010; Ma et al., 2017; Nuworsoo et al., 2009). This is due to the national laws and regulations making it obligatory to provide an extensive analysis of discriminatory impacts of state funded policies. However, the topic is emerging in different regions of the world, including Europe (Bureau & Glachant, 2011; Cats et al., 2017; Rubensson et al., 2017), Asia (Wang et al., 2018) and Middle East (Bandegani & Akbarzadeh, 2016; Nahmias-Biran et al., 2014). It is also important to note that the American research usually puts vertical or social equity in the spotlight, whereas European and Eastern scholars try to investigate impacts in a broader way, looking into both horizontal and vertical equity. Studies in Asia are mostly concerned with performance outcomes rather than equity effects.

In terms of transport modes being analysed, there is a great variability, starting from a single mode, with bus being the most observed one (Bandegani & Akbarzadeh, 2016; Guzman et al., 2018; Nahmias-Biran et al., 2014; Nuworsoo et al., 2009), and proceeding to whole multimodal networks, where the bus service is accompanied by metro and rail (Hickey et al., 2010; Rubensson et al., 2017). The presence of a few modes might entail a more complex fare structure with different product types and costs for each mode as well as transfer charges. In addition, it makes evaluation challenging because of differences in specific functional characteristics as well as data collection and processing.

Fare scenarios can be defined by hypothetical cases, where effects of possible future changes on the existing system are investigated (Brown, 2018; Nuworsoo et al., 2009; Rubensson et al., 2017). This implies an ex-ante evaluation attempting to predict and assess potential impacts under realistic inputs. Another reason for policy appraisal is a real transition from an old to a new fare system (Cats et al., 2017; Nahmias-Biran et al., 2014), where impacts are notable. This means an ex-post evaluation dealing with relation of factual changes to certain factors of influence. The fare types mentioned in the research take numerous forms. To give a few examples, a fare might be flat, zone-, distance- or time- based. Moreover, a fare might undergo some hikes or reductions for different user groups.

2.3.2. Data sources

The key element in policy evaluation is to acquire a reliable and sufficient dataset. Data collection always affects research, bringing certain limitations or additional conditions to follow. Having an important case to investigate, one should start selecting a methodology according to the potential amount and type of data that can be obtained. The diversity of the existing research is partly attributable to various data sources.

The two most common data sources for policy evaluation are on-board and household travel surveys. Being similar in their structure and content, they provide outcomes of significantly different quality. On-board surveys (Nahmias-Biran et al., 2014; Nuworsoo et al., 2009) allow to collect information on individual traveling behavior, fare products and socioeconomic characteristics of users. Therefore, by extrapolating the acquired sample on the total population, one can study impacts through the comparison of travel costs for different user groups under a certain fare policy. However, this method is very challenging in terms of getting an unbiased and representative sampling. It considers only certain routes and vehicles based on the survey design, certain users due to generally low response rates and certain single trips recorded on-board and not integrated into a broader traveling diary (Brown, 2018).

Household survey (Ma et al., 2017) collects similar information, but on the higher level of detail and over the wider population. It records a complete day or a week of travel activities, thus better reflecting on public transport user behaviour. Eventually, this contributes to a more representative and comprehensive sampling. Both surveys are suitable for evaluation of either horizontal or vertical equity. Notwithstanding, they utilize elements of stated preference which might bring a certain degree of inaccuracy. Lastly, both surveys are very resource-demanding in performance and processing of the results.

An alternative method in data acquisition is brought by the large-scale deployment of automated fare collection (AFC) systems. Valuable data on traveling behaviour can thus be collected at a disaggregated level and at a large scale. It includes location, time-of-day, fare product and demand. Two major data sources can be distinguished, namely ticket validation (Guzman et al., 2018) and smartcard use (Wang et al., 2018). The sources are analogous, yet the latter provides an opportunity to infer indirect metrics, such as journey length, frequency and even origin-destination matrices (OD-matrices) clustering passengers by travel behaviour and recurrent patterns (Alsger et al., 2016). Another advantage of these sources is the direct access to rich and continuous data flows. Therefore, this passive collection technique brings substantial savings. While it is very detailed in terms of public transport use, the AFC data lack socioeconomic characteristics, thus need to be supplemented with additional datasets to study policy impacts on different user groups and vertical equity (Pelletier et al., 2011).

The most common way to supplement AFC data is to use socioeconomic indicators from the official national statistics (Hickey et al., 2010; Rubensson et al., 2017). Aggregated at the census zonal level, the database contains information on numerous population characteristics. As an example, it might represent demographics, median income, number of workplaces, level of education, occupation, or car ownership. Using a set of assumptions, each smartcard or ticket can be assigned to a particular zone, thus getting enriched with the aspects of this zone. Nevertheless, the individual level of detail will never be reached as in the case of surveys.

To elaborate the outcomes of traveling metrics, geospatial data can be utilized (Ma et al., 2017; Wang et al., 2018). It allows to extract the actual layout of the public transport network with its lines, stops and stations as well as the zonal structure of the area and fuse it with some estimates, i.e. demand and location of journeys. By doing so, an integral system gets established, connecting geographical zones, traveling data and socioeconomic characteristics. This facilitates an estimation of journey duration and length, assignment of stops and stations to zones, construction of OD-matrices, etc. The joint use of geospatial data, AFC and national statistics as data sources provides a powerful tool for public transport fare policy evaluation.

2.3.3. User groups

The main idea of distinguishing public transport user groups lies in the fact that different members of society have unequal opportunities and needs, thus might be affected by new policies in public transport differently (El-Geneidy et al., 2016). This variability of impacts requires to perform a thorough analysis for each group separately. There are two general perspectives on how to define user groups; one incorporates fare products while another focuses on socioeconomic characteristics.

Considering the fare structure of any public transport system, one could always find numbers of products offered to users. This might be some general-use fares, such as single ticket, monthly or annual pass, and also fares designed for certain population categories only, be that the youth, students, seniors or disabled (Hickey et al., 2010; Nuworsoo et al., 2009). Each fare product has its own attributes, including total price, cost of a single journey, validity period, eligibility to obtain and some specific conditions of use. It is observed that users demonstrating particular traveling behaviour opt for corresponding fare types (Hickey et al., 2010). For instance, commuters tend to use public transport systems during peak hours and buy monthly or annual passes. The affordability of fare products matters as well. It is not rare that low-income groups are not able to pay a lump sum for long-term passes to get access to cheaper journeys and therefore end up using costly single rides.

The essential part of equity evaluation is socioeconomic data. The population can be analysed through the lens of wealth (income), degree of mobility (age, car ownership and driver's license availability), traveling needs (occupation), minority status (race, registered residency). Furthermore, an overarching socioeconomic index can be estimated at the zonal level. Based on the research scope and goals, one or a few groups can be included for a separate or combined assessment (Nahmias-Biran et al., 2014; Nuworsoo et al., 2009). In the existing research, the income range appears to be the most prevalent indicator (Brown, 2018; Guzman et al., 2018; Rubensson et al., 2017).

2.3.4. Spatial and temporal distribution

Another important aspect in public transport fare policy evaluation is the spatial and temporal distribution of journeys. As it was outlined above, a policy might imply distance-based or time-based fares offered to different user groups allocated across the study area, having their own abilities and needs. Hence, if one wants to study accessibility and equity in detail, it is inevitable to consider traveling behaviour among different locations and at different times. There are certain scales of distribution relevant for this research.

Spatial distribution is especially important in the case of zone- or distance-based fares as well as in the horizontal equity analysis. Generally, the research scope accompanied by data availability defines how small the units of the distribution should be. Looking at the existing practice, the units are either large districts (Cats et al., 2017; Nahmias-Biran et al., 2014), traffic analysis zones (TAZ) (Ma et al., 2017) or statistical zones (Rubensson et al., 2017). Sometimes it is also useful to account for a distance from the city center (Bureau & Glachant, 2011) or individual stops and stations. The latter has become possible after the introduction of the AFC data (Guzman et al., 2018; Wang et al., 2018).

Temporal distribution plays an important role if the research focuses on time-based fares and vertical equity or simply aims to look deeper into mobility patterns. The most common approach distinguishes peak and off-peak hours (Brown, 2018; Hickey et al., 2010), and it seems very logical due to several reasons. During the peak time, substantial differences are observed in user groups, types of journeys and demand volumes. From the financial perspective, this entails additional operational costs and sometimes higher fares which in turn affect the affordability of public transport. Some alternative temporal scales involve days of the week (weekdays and weekends), months of the year (special events, holidays, seasons) and even years (for long-term impacts of a policy), generally due to the same reasons as for the peak times (Guzman et al., 2018; Wang et al., 2018).

2.3.5. Travel metrics

The most common approach in studying impacts of fare change lies in the determination of traveling behavior before and after a new policy was introduced. This entails a broad range of mobility metrics that can be computed at different temporal and spatial scales, for different transport modes and user groups. The exact procedure is based on the research goals as well as on data availability. Some studies try to predict effects at the global network level (Nuworsoo et al., 2009) or more individual scale (Brown, 2018), whereas the other ones, utilising AFC data, operate with revealed choices at all levels simultaneously (Guzman et al., 2018; Wang et al., 2018).

Regarding the mobility metrics themselves, the widely used are total demand, which is equal to public transport ridership (Guzman et al., 2018), average number of journeys per person (Rubensson et al., 2017), frequency of journeys (Bandegani & Akbarzadeh, 2016), average journey length (Brown, 2018), modal share (Cats et al., 2017), popular origins and destinations (Wang et al., 2018). These metrics are straightforward in estimation and suitable for comparison which makes them very useful from the research standpoint. The associated analysis usually involves a descriptive part, visual representation (graphs, maps, tables), simple statistical instruments, with further relation of the results to the study context and its factors of influence. However, these mobility metrics only focus on the direct effects on traveling patters, which might not be suitable as a basis for qualitative evaluation. Also, they create obstacles in the separation of the impact of fare change from other joint factors.

More sophisticated methods look in-depth on effects related to the fare change, bringing more sensible outcomes of policy assessment. To understand the sensitivity of demand for different user groups, price elasticity is estimated (Bandegani & Akbarzadeh, 2016; Wang et al., 2018), which is also applicable for further equity analysis or revenue calculations. To follow the impact of a fare change as a stand-alone factor as well as in a combination with different influential aspects, a regression model can be used (Bocarejo & Oviedo, 2012; Guzman et al., 2018), providing clear picture of significant interrelations in traveling behaviour.

A few attempts of accessibility estimation have been undertaken (Bocarejo & Oviedo, 2012; El-Geneidy et al., 2016; Ma et al., 2017), that do not only reflect on shifting traveling patterns, but also reveal how these changes contribute to the quality of journeys and users' welfare. The potential job accessibility, representing the number of employment positions that might be reached within a certain time threshold, is chosen in all of the selected cases.

2.3.6. Equity assessment

The majority of the research on fare policy evaluation is not limited to the estimation and description of travel metrics, but proceeds with an equity assessment. Some studies see the equity component as the main point of interest, potentially entirely omitting the mobility part (Hickey et al., 2010; Nahmias-Biran et al., 2014). The concept of horizontal and vertical equity is prevalent regardless the inputs and objectives of the research in this field, even though the methodology takes significantly different forms.

Some studies examine how various social groups with unequal abilities change their behaviour due to the policy introduction, which means that their mobility characteristics are analysed through specification and juxtaposition (Cats et al., 2017; Guzman et al., 2018). It is a simple and direct method that allows to distinguish changes and compare them among user groups, yet it does not yield the cause-effect relationship and does not reflect on qualitative changes.

It is more common to establish the assessment of the fare equity, which helps to understand how fare expenses are distributed in the society. This approach generally does not require substantial datasets or complex calculation techniques to execute the analysis. As an example, such a study on fare equity might explore fare costs for different zones or areas, thus horizontal equity (Bureau & Glachant, 2011; Nahmias-Biran et al., 2014), or for different social groups ranked by the level of a certain characteristic, thus vertical equity (Nuworsoo et al., 2009; Rubensson et al., 2017). A temporal component can be introduced as an additional element in both studies. Eventually, the comparison is done by estimating either relative values of fare expenses in a table format or the Gini or Suits indices together with the Lorenz curves.

As an alternative to the fare equity, the existing research sometimes operates with the accessibility equity (Bocarejo & Oviedo, 2012; El-Geneidy et al., 2016). Nevertheless, it is very rare when accessibility is introduced in the field of fare policy evaluation. What has been observed so far is the estimation of changes in the potential job accessibility due to the new fare scheme. The equity assessment considers levels of accessibility among different geographic zones (horizontal equity), as well as user groups ranked by their median income or the degree of social vulnerability (vertical equity). The computed values are collected in a table followed by the discussion on the qualitative outcomes.

Table 2.3: Current study in the field of research on public transport fare policy evaluation

Study	Fare scenarios	Fare type	Set of modes	Data sources	User groups	Spatial distribution	Temporal distribution	Travel metrics	Equity assessment	Equity indicators
Nuworsoo et al., 2009 (California, USA)	Existing vs 5 hypothetical	Complex flat fare based system vs proposals combining fare hikes and reductions, eliminations of free transfers, and discontinuation of passes	Bus	On-board survey	Income, fare category, payment type, race, usage frequency	-	-	Total ridership per year	Vertical equity	Fare change (user split)
Hickey et al., 2010 (New York City, USA)	Existing vs 6 hypothetical	Complex flat fare based system vs fare price restructuring scenarios	Local bus, express bus, metro	Census data, farecard consumption data, daily first swipe database	Income, fare category, minority	-	Peak / off-peak	-	Vertical equity	Fare change (time and user split)
Bureau & Glachant, 2011 (Paris, France)	Existing vs 1 hypothetical	Existing system vs fare reduction by 10%	Suburban rail, metro, suburban bus, city bus	Global transport survey	Income	Distance from city center (3)	-	-	Vertical / horizontal equity	Savings per year on fares (user and location split)
Bocarejo & Oviedo, 2012 (Bogota, Colombia)	Existing vs 1 hypothetical	Complex flat fare based system vs fare price restructuring scenario	BRT	Census data, household travel survey	Income	Planning zones (117)	-	Accessibility per inhabitant (number of employment positions), average travel time	Vertical equity	Accessibility for each zone ranked by income level, percentage of income used on transport
Nahmias-Biran et al., 2014 (Haifa, Israel)	Old vs new	Complex mixed fare system (flat for city and distance-based for intercity journeys) vs zone-based time-based regional fare	Bus	Fare-box revenue data, on-board survey	Car ownership, education, employment status, journey purpose, CBS socioeconomic index	Districts (18)	-	-	Vertical / horizontal equity	Fare change (user and location split), Lorenz curve + Gini index (fare change vs population)
Bandegani & Akbarzadeh, 2016 (Isfahan, Iran)	Existing vs 1 hypothetical	Flat fare vs distance-based fare	Bus	On-board survey	Income, age, gender, journey distance, usage frequency and available alternative mode	-	-	Frequency of journey lengths, price elasticity of demand (user split)	Horizontal equity	Revenue / Cost per mile distribution among passengers with different journey lengths, Lorenz curve + Gini index (Revenue / Cost per mile vs population)
El-Geneidy et al., 2016 (Montreal, Canada)	Existing vs 1 hypothetical	Complex mixed fare system vs variation in fare price	Metro, bus, commuter train	Census data, household travel survey, geospatial network data	Social vulnerability indicator (income, immigrant status, unemployed, education level)	Statistical base areas (921)	-	Accessibility per zone (number of employment positions within a certain threshold)	Vertical / horizontal equity	Standardized accessibility measure on the social deprivation scale
Cats et al., 2017 (Tallinn, Estonia)	Old vs new	Existing system vs free public transport	Tram, trolley bus, bus	Annual municipal survey	Income, gender, age, occupation, car availability and registered residency	Districts (8)	-	Average number of journeys per person, modal share, relation of fare costs to employment opportunities, shopping and leisure destination choice	Vertical equity	Average number of journeys per person and modal share (user split)
Ma et al., 2017 (Kelowna, Canada)	Old vs new	Flat fare vs fare price increase	Bus	Census data, household travel survey, geospatial network data	Income, fare category, age, employment, driver's license and available alternative mode	Traffic analysis zones (184)	-	Job accessibility within 30 min, 45 min and 60 min thresholds	-	-
Rubensson et al., 2017 (Stockholm, Sweden)	Old vs new vs 1 hypothetical	Zonal fare vs flat and distance-based fare	Metro, bus, commuter train, light rail	Census data, national four-step model Sampers, assignment software PTV Visum	Income	Statistical base areas (1300)	-	Morning peak demand per capita (distance split in km or zones, user split)	Vertical / horizontal equity	Weighted average fare (location split), Lorenz curve + Gini index (Fare expenses vs population) + Suits index (Fare expenses vs population by income), fare expenditure per capita (location split)
Brown, 2018 (Los Angeles, USA)	Existing vs 6 hypothetical	Flat fare vs distance-based, time-of-day, mode-based fares and user group discounts	Local bus, express bus, rail	Household travel survey	Income	-	Peak / off-peak	User split: number of journeys (time split), length of journeys (time split), mode share (distance split), fare class share	Benefits received, cost and ability-to-pay	Fare per mile paid (user split)
Wang et al., 2018 (Beijing, China)	Old vs new	Flat fare vs distance-based fare	Metro	Smartcard data (tap-in / tap-out), geospatial network data	-	Network / station level	Peak / off-peak, weekday / weekend	Peak hour / daily demand and journey distance on weekdays / weekends at network and station level, elasticity of demand (time and distance split)	-	-
Guzman et al., 2018 (Bogota, Colombia)	Old vs new	Flat fare vs time-of-day fare	BRT	Ticket validation database, mobility survey	Income	Network / stop level	Peak / off-peak, month, year	Peak / off-peak demand ratio (time split) at network and stop level, regression analysis of fare change impact on the ratio	Vertical equity	Peak / off-peak demand ratio (time and user split), regression analysis of the fare change impact on the ratio (user split)
This study (Stockholm, Sweden)	**Old vs new**	**Zonal fare vs flat fare**	**Bus, metro, commuter train, light rail**	**Smartcard data (tap-in), census data, geospatial network data**	**Fare category, income, car ownership, social vulnerability index**	**Statistical base areas (1364)**	**Peak / off-peak, weekday / weekend, month, year**	**User split: number of journeys (time split), length of journeys, frequency of journeys; mode share; elasticity of demand (time, distance and user split)**	**Vertical / horizontal equity**	**Average journey cost, expenses/capita and journeys/capita (user and location split), Lorenz curve + Gini index (Fare expenses vs population) + Suits index (Fare expenses vs population by various factors)**

2.4. Research gap

The literature analysis on public transport fare policy evaluation has led to the identification of a few opportunities to improve the existing practice. Some of the commonly observed aspects are as following:

- The process of policy evaluation requires an unbiased and detailed approach, thus the level of comprehensiveness becomes important, especially for further consideration of decision makers. Nevertheless, it has been observed that the majority of studies on fare policy assessment touches upon one or a few aspects while omitting the rest of the framework. This can be explained by the limited scope, resources or available data. The missing parts might be as explanatory and revealing, and potentially can change the understanding of the policy impact. First, it is therefore desirable to incorporate both horizontal and vertical equity, as their results can be quite contradictory. By doing so, they would complement each other and diversify the perspective. Second, spatial and temporal distribution of journeys should be introduced in conjunction due to the fact that traveling behaviour differs substantially within an area and at various time periods. Third, user characteristics appear to be a key to establishing a cause-effect relationship. This do not only entail socioeconomic indicators, but also the correlation of travelling abilities and needs. As an example, they include the division of journeys by purpose.
- Despite the growing body of literature on public transport mobility, equity and fare change impacts, very few studies attempted to incorporate all three notions at once. This means that equity assessment is usually performed on the fare itself, which elaborates on the cost side for the population. However, it lacks travelers' response represented by ridership gain or loss. Being the main performance outcome of any public transport system, the demand level is considered to be vital in the fare policy domain. The degree of demand change due to the introduction of a new fair policy should be thoroughly investigated through the lens of fair and just distribution in the society (Bocarejo & Oviedo, 2012; van Wee, 2016).
- For any research it is always challenging to obtain a representative dataset which has a satisfactory size, great level of detail and reliability. Studies on public transport fare policy usually operate with surveys as their primary data source, be that household travel survey or on-board survey. Collecting a large variety of users' individual characteristics, surveys can not provide precise data on traveling patterns nor data for longer time periods because of significant execution costs involved. The introduction of AFC data allows to perform an ex-post evaluation by looking into factual traveling behaviour before and after the fare change. A combination of AFC, geospatial and socioeconomic data could thus lead to a more precise research outcome. However, AFC data have so far been used in fare policy evaluation either to estimate demand levels of different user groups without any analysis of origin-destination patterns (Guzman et al., 2018; Hickey et al., 2010), or to study mobility patterns in detail, yet with no socioeconomic element (Wang et al., 2018). Therefore, an overarching approach is currently lacking.
- As it was outlined in Subsection 2.3.1, the major part of the research on public transport fare policy implications is done in the American context. The observations and conclusions derived from this research cannot be directly related to the European cases due to the significant differences in urban and social structures. Even among the cities in Europe the variability of land use, public transport systems and users' preferences might lead to incompatible factors of influence and fundamental interrelations. Hence, there is a need for more individual studies that could be eventually accumulated into a general framework categorising similarities in structures and distributions.

In respect of the highlighted aspects, the existing research gap in public transport fare policy evaluation corresponds to a comprehensive ex-post assessment technique utilizing smartcard data, with the main focus on the sensitivity of different user groups to fare change and the distributional effects in the European context.

As the research gap has been identified, this study attempts to address it to the largest extent possible. This is done by combining several data sources, explicitly looking into different user groups with their individual characteristics and travelling behaviour, elaborating on fare elasticity and equity. Table 2.3 demonstrates how the study fits into the existing scientific context.

3
Research context

The following chapter provides an overview of the research context from the geographic, socioeconomic and operational perspectives. The region of Stockholm County is presented first including its general characteristics, municipal structure, development trends and ongoing policy programs. Afterwards, the focus is set on the public transport system of the region, describing the mode composition, network layout, major performance indicators and transport authorities. The last section provides a detailed comparison of the fare structure before and after the policy introduction. This involves a specification of the policy itself and all changes it brought to the fare basis, fare categories and fare price levels.

3.1. Overview of Stockholm County

Stockholm County is located on the central east coast of Sweden and comprises 26 municipalities, including the City of Stockholm, the country's political, economic and cultural center. Figure 3.1 displays the municipal structure of Stockholm County. The region was home to 2,3 million residents in 2018 (0.96 million in Stockholm City), which accounts for 23% of Sweden's total population (SCB, 2018). By 2030, this number is expected to grow up to 2,85 million residents. Occupying only 1% of the country's area, Stockholm County is the most populous region in the Nordics. However, the land structure is monocentric with a large variability in population densities: from 285 inh./km^2 in rural areas to 4.100 inh./km^2 in Stockholm City (SLL, 2018).

The regional development plan (SLL, 2017) of Stockholm County reports that the region has experienced high employment rates and robust economic growth throughout the last 18 years. It is responsible for over 32% of Swedish Gross Regional Product with an average increase rate of 3,2% annually. The share of the college educated citizens aged between 25 and 64 years accounts for 34% of the total population. The level of unemployment is lower than the national average, reaching 6,3% compared to 6,7% respectively. Stockholm County relies mostly on the service industry that contributes 85% of the region's economy (SLL, 2018). To underline, 51% of all global companies operating in the Nordics are based in the Stockholm region.

Such an intensive and steady development of Stockholm County is supported by a number of policies, focusing on globalisation, urbanisation, digitalisation and migration (SLL, 2017). The region is shifting towards a green economy, aiming for lower climate and environmental impacts and high-quality living conditions for its residents. The current direction of major investments includes sustainable technologies, healthcare and public transport (SLL, 2018). Moreover, social responsibility is defined by the regional administration as one of the fundamental elements. This implies the consideration of every individual's abilities and needs in order to eliminate any discrimination, promoting equal rights for both genders, children, disabled people and minorities.

Considering all the aspects outlined above, such as the actively growing demographics and urbanisation of Stockholm County, its substantial development, the strive for highest living standards, focus on the social side of the policy, the importance of public transport becomes evident. The trends and goals within the region set up a framework for making public transport more efficient and accessible.

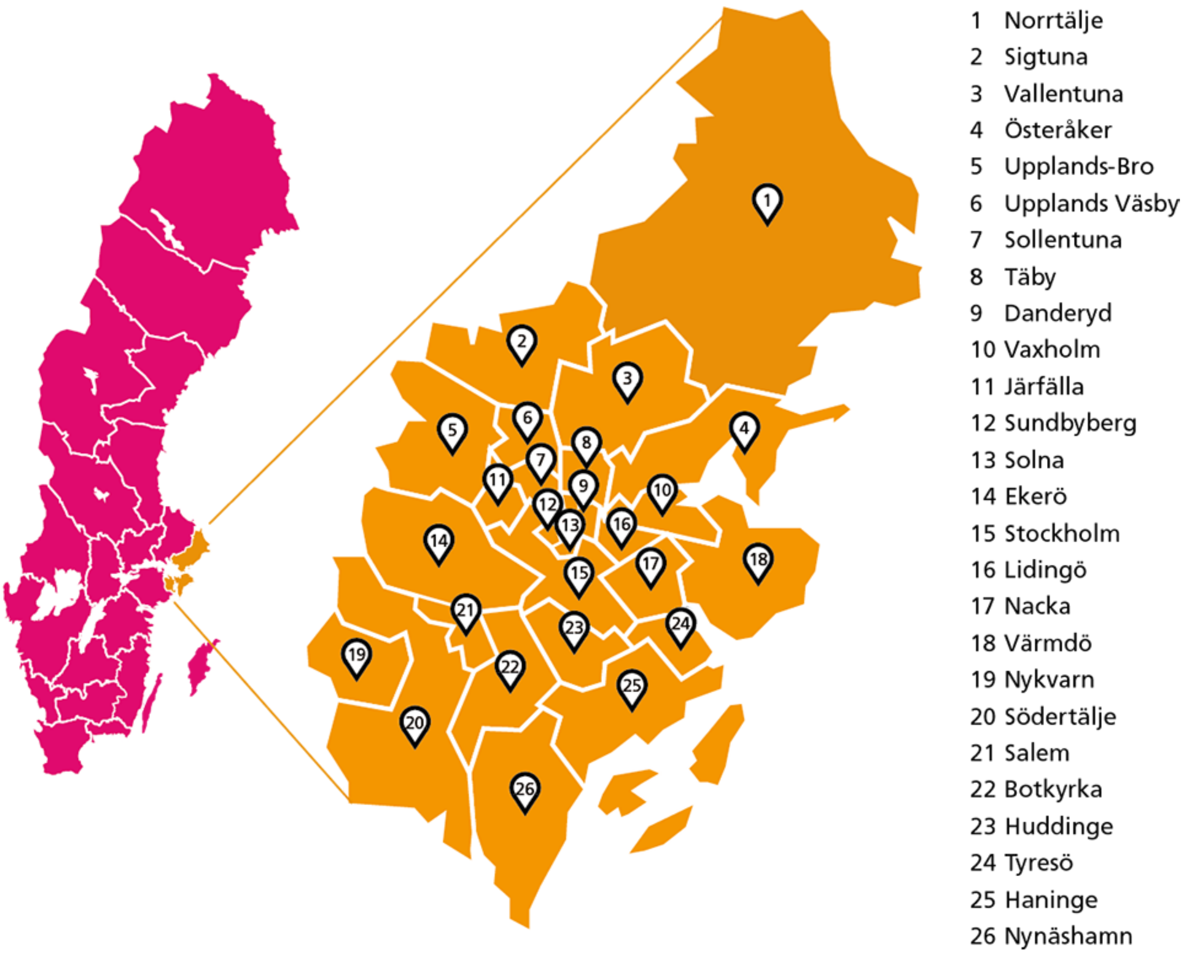


Figure 3.1: Stockholm County and its municipal structure (SLL, 2019a)

3.2. Public transport system in Stockholm County

Stockholm County has an extensive public transport system that is represented by metro (Tunnelbana), commuter trains (Pendeltåg), light rail (Roslagsbanan, Saltsjöbanan), tram (Lidingöbanan, Nockebybanan, Tvärbanan, Spårväg City), buses and boats.

The network has a clear hierarchy, where rail transport serves as a mass transit backbone both at the regional and local scale, accompanied by dense bus services (SLL, 2019b). The geographic allocation of the mass transit network in Stockholm County is presented in Figure 3.2 together with important urban areas and transfer points. Figure 3.3 displays the layout of the rail network in the region as well as the accumulative length of lines. In total, rail transport accounts for 469 km of line length along with 9.079 km of bus lines (SLL, 2019b). In terms of access to the public transport system, around 76% of the population live within a 1,2 km reach to the nearest train station (SLL, 2017).

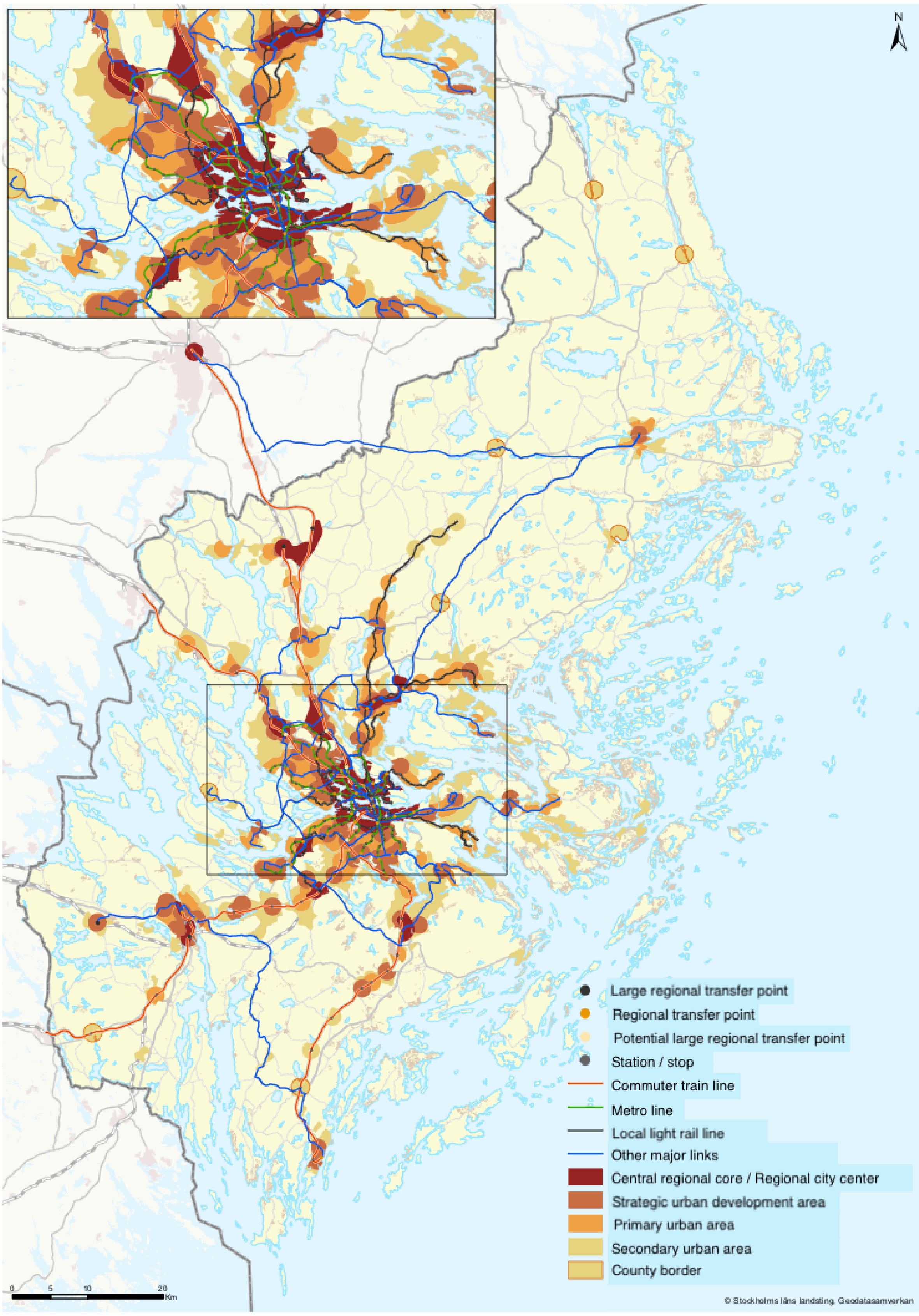
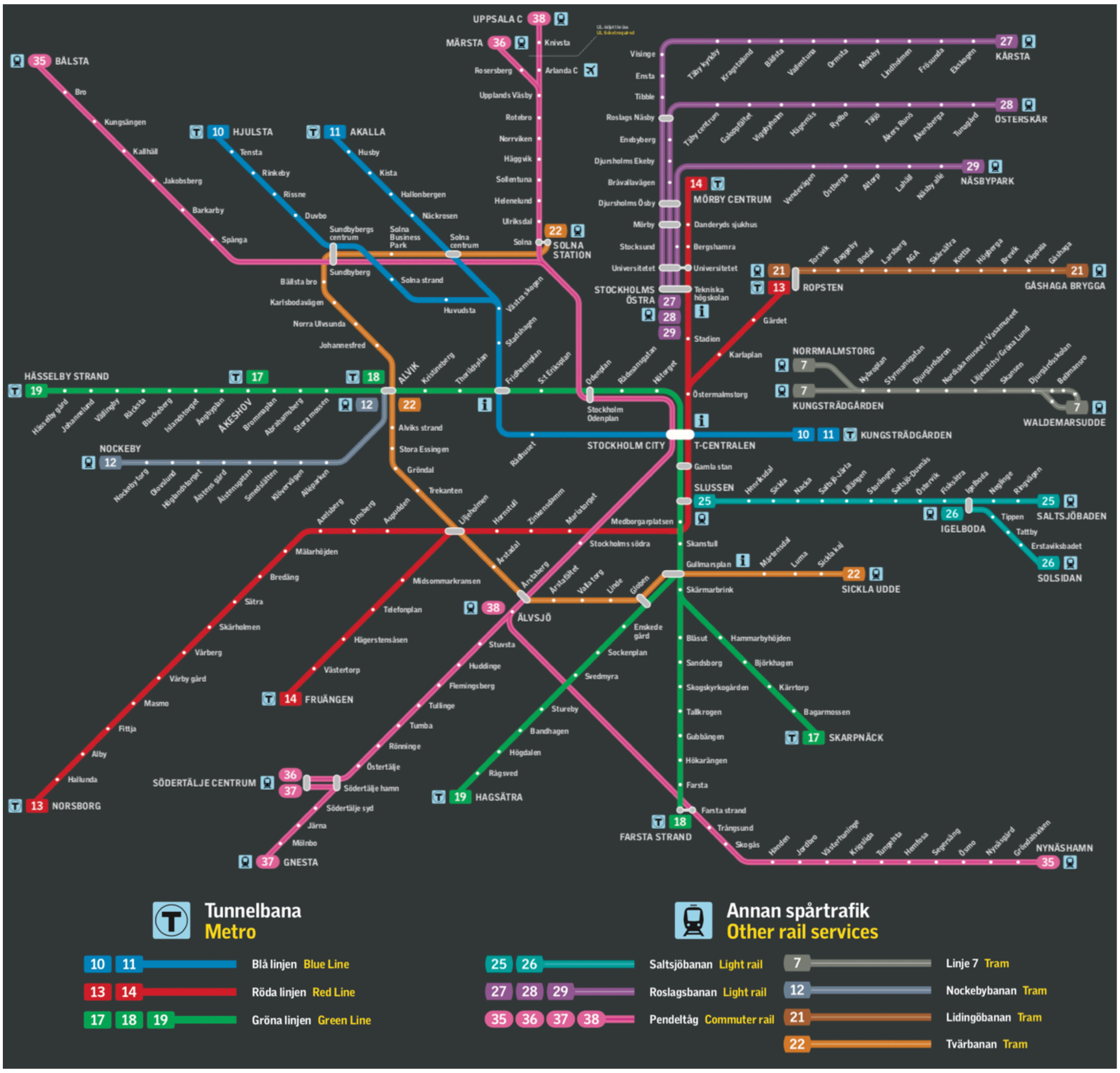


Figure 3.2: Geographic location of mass transit network (SLL, 2017)



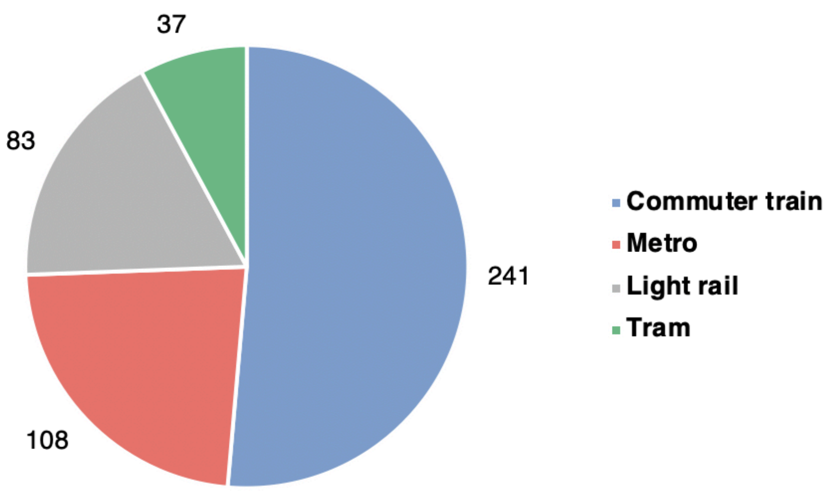


Figure 3.3: Line structure of rail transport (above) with according distribution of line length (below), in km (SL, 2019a; SLL, 2019b)

Regarding the performance of the public transport system of Stockholm County, there are a few important aspects to point out. First and foremost, there is a daily passenger flow of more than 800.000 people (SLL, 2019c). As presented in Figure 3.4, together with active modes this constitutes to 54% of all journeys made in the region (SLL, 2019b). Looking at the distribution of passenger-kilometers and average journey length (see Table 3.1), it can be noted that commuter trains operate for large groups of travelers on longer distances, metro serves the highest number of passengers mostly within the central core, whereas buses and light rail provide supply for local demand or work as a last-mile transport in conjunction with other modes.

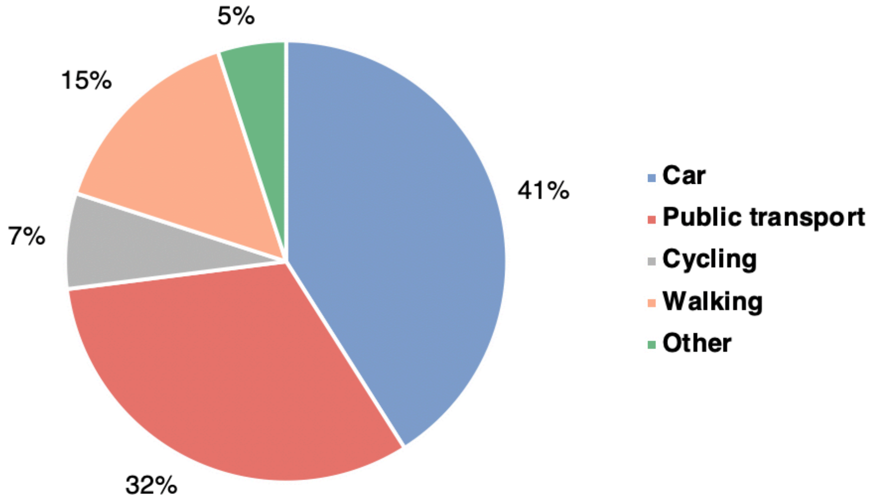


Figure 3.4: Modal split of journeys in 2015 (SLL, 2019b)

Table 3.1: Distribution of passenger-kilometers / average journey length between public transport modes on a winter day in 2017, in thousand pass-km / km (SLL, 2019b)

Transport mode	06.00 - 09.00	09.00 - 15.00	15.00 - 18.00	18.00 - 21.00	21.00 - 06.00	Day
Metro	1.674 / 6,1	1.952 / 5,3	2.048 / 5,6	1.023 / 5,5	469 / 5,6	7.146 / 5,6
Commuter train	1.667 / 18,6	1.770 / 18,2	1.721 / 18,4	657 / 19,0	594 / 21,1	6.409 / 18,7
Light rail & tram	279 / 6,3	275 / 5,3	303 / 6,1	129 / 6,4	73 / 6,8	1.060 / 6,0
Bus	1.812 / 6,1	1.702 / 4,9	1.785 / 5,6	642 / 5,4	516 / 7,0	6.458 / 5,6
All modes	5.427 / 7,7	5.693 / 6,6	5.850 / 7,1	2.449 / 6,8	1.650 / 8,4	21.048 / 7,1

Figure 3.5 elaborates on how public transport journeys in the Stockholm region are distributed by taking into account their spatial characteristics. In this way, public transport serves 47% of all journeys within one municipality (14% of which are in Stockholm City) and further 26% to connect the central core with other areas, bringing people to and out of Stockholm City. The fraction of 25% accounts for journeys between all municipalities except for the center, where 14% of them are exhibited within either the North or the South of the County (without crossing the center). These statistics support the statement that the region has a distinct monocentric structure (see Section 3.1) with local municipal centres playing an additional role, which can be observed as well in Figure 3.2 by the degree of urban development.

The administrative structure in the transportation domain is represented by several stakeholders. At the national level, The Swedish Transport Administration (Trafikverket) is responsible for strategic planning of transport systems as well as construction, operation and maintenance of public roads and railways. Nevertheless, regional administrations, namely Region Stockholm in this case, have the same degree of importance for the regional development. For Stockholm County, major directions and programs are put together in the spatial and economic plan RUFS that further provides general guidelines for the local development plans of 26 municipalities.

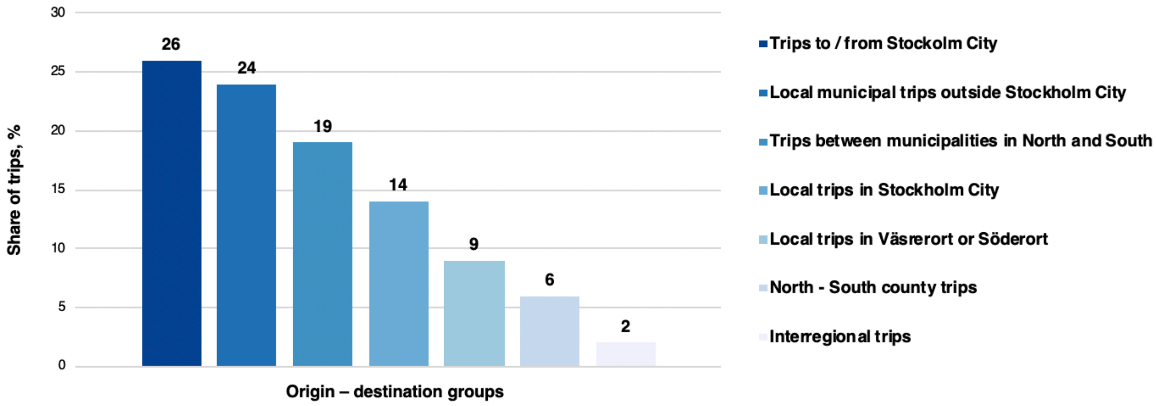


Figure 3.5: Spatial distribution of public transport journeys (SLL, 2019b)

Regarding public transport, the organisation Stockholm Public Transport (Storstockholms Lokaltrafik or SL) as a part of Region Stockholm is responsible for the provision of public transport services through long-term planning, procurement, establishment and control of standards for operation quality and sustainability. The public transport system is operated by a number of contractors, such as Arriva, Keolis, Nobina, MTR, to name a few (SLL, 2019c). Together with SL, which has provided uniform requirements and overseen each entity's work, they have maintained a satisfactory level of performance. As an example, in 2017 the punctuality of commuter trains, metro, light rail and buses was 90%, 98%, 96% and 88% respectively. The average perceived quality by passengers was assessed at the mark of 82% (SLL, 2019b).

When it comes to the future goals of public transport in Stockholm County, SL distinguishes three pillars that would characterise its development by 2030. First, the system must accommodate the constantly growing demand, encouraging more people to choose public transport as their main way of travel. Second, the sustainable side of public transport must be improved, including environmental impacts, safety and energy efficiency. Third, public transport must become more inclusive and attractive for a broader range of potential users, which can be realised by increased equity in access to work, service and leisure activities based on different needs and conditions (SLL, 2019c). The topic of this thesis is falling under the last goal, whereas the fare policy appears to be one of the instruments to achieve it.

3.3. Fare system

The public transport fare structure in Stockholm County is realtively complex as it provides a wide range of travel products that are designed for different areas, time periods, modes and user groups. As mentioned above, a new policy was introduced on the 10th of January 2017, that affected the fare basis, categories, price levels and methods of payment. Further, a focus is given on every individual part of the fare structure before and after the change, based on SL (2016) and SL (2019).

The fare structure of 2016 was organised on a zonal basis, with three fare zones A, B and C as displayed in Figure 3.6. Zone A covered the Stockholm City core and inner suburbs, zone B stretched over outer suburbs, whereas zone C included remote areas at the county's fringe. No zonal hierarchy was present in terms of pricing. It was only important how many zones a traveler wanted to cross. For example, a journey from zone A to zone B would cost the same as a journey from zone B to zone C. Arlanda Airport was assigned as a separate destination with a special price category. Moreover, traveling to the cities of Gnesta and Bålsta, that are located on the other side of the border with Uppsala County, implied an extra charge for county crossing. Going farther into Uppsala County was also possible via a combined journey with SL and UL (two regional public transport providers). The cross-county fare scheme included another large group of products, zone-, time- and user-based, however it will stay out of scope of this research.

Figure 3.6: Map of public transport fare zones in 2016 (SLL, 2019c)

The policy of January 2017 brought a shift from the zonal to a flat-fare basis. The fare zones got removed, and a single fare was applied to any journey within the county. In addition to that, journeys to Gnesta and Bålsta were also considered as single-county journeys. The specific conditions for Arlanda and Uppsala County remained, yet got changed.

In terms of transport modes, the fare structure described above applies to almost all services provided by SL, both in 2016 and 2017 (no changes in this matter). This includes bus, metro, commuter train, tram and light rail systems. The exceptions are the UL train service (cross-county journeys require a combined ticket), private airport services, such as Arlanda Express and Flygbussarna, and the water transport service by Waxholmsbolaget.

Regarding individual fare categories, Table A.1 presents a comprehensive list of products with according prices in 2016 and 2017. The price got changed for all categories that were kept after the policy introduction. Periodic products allow to travel within Stockholm County for a certain number of days, with some limitations for a few areas in 2016 that got cancelled later in 2017. School products exist for different periods as well, and for two times of the day: the school pass is valid from Monday to Friday 04.30-19.00, the leisure pass is valid from Monday to Friday 16.00-4.30 and from Saturday to Sunday. Student products were cancelled in 2017 and got merged with the “reduced” group, which also includes the youth (people under 20 years), the elderly (people over 65 years) and holders of social or pension certificates. Single products vary based on the number of zones crossed in 2016 and the method of payment. Travel funds imply the use of the SL access card, which can be loaded with money along with a subscription. Apart from the general categories in Table A.1, the fare structure also includes special products, such as group tickets, event tickets, admission with no traveling and free tickets for organisations. These products go beyond the scope of this research.

3.4. Summary

To summarise the chapter, it delivers an overview of the research context of this thesis. Starting with the general description of the region, it gets narrowed to the public transport system and even further to the fare structure. The following highlights a few important aspects in each domain:

- Stockholm County accumulates 23% of Sweden’s total population and 32% of Swedish Gross Regional Product; the annual growth rates of the number of residents and the economy are stable and amount to 1,6% and 3,2% respectively.
- The general focus of policy-making in Stockholm County is set on sustainability and social responsibility in all major fields, including public transport.
- The public transport network of the region is represented by a variety of modes with rail transport serving as a backbone; the rail service is available within a 1,2 km reach to around 76% of the population; the reliability level stays in the 90-98% range.
- Public transport is very popular among the population with 54% of the total mobility share, mostly connecting the entire county with the main city core as well as providing services in local municipal centres.
- The fare structure in Stockholm county is complex as it includes a wide range of products for different areas, seasons, modes and user groups.
- In January 2017, a new policy brought a shift from the zonal to a flat-fare basis, which in turn affected categories, price levels and methods of payment.

The explained scientific background and research context finalise the conceptual framework of the study. This makes it possible to continue with the actual fare policy analysis. The first step in this procedure is data processing, which is the topic of the next chapter.

4
Data processing and exploration

This chapter presents the sequence of steps in data processing, starting with the initial data taken from various sources to the final and complete dataset through intermediate assumptions, cleaning, specified sorting, selection, enrichment and merging. However, apart from processing, working with data includes the simultaneous exploration of their different aspects that lead to insightful information on travel metrics and year-on-year changes between the two periods. Descriptive statistics and visualisation are used to highlight major findings. Following this logic, the first section describes what sources the data was taken from and their preliminary treatment. After that, a processing workflow is set up according to the framework specified in the literature review. It is followed by the section explaining how an analysis period is selected. An algorithm of transfer inference is then described. The next section focuses on the exploration of various travel metrics to select the most relevant parts for the research purpose, including the processing of time periods, journey lengths, frequency and modal split. The selection of products is presented afterwards, which is succeeded by a procedure of home zone estimation. The last section provides the final dataset with its qualitative assessment.

4.1. Data sources

The core data source of this research project is formed by previously constructed individual travel diaries within the entire public transport network of Stockholm County for the years 2016 and 2017. The work was done through a collaboration between KTH Royal Institute of Technology, Delft University of Technology and SL. Because the system in Stockholm County has boarding validation only, it was necessary to estimate the alighting point following the transactions sequence under some distance constraints. The assumptions were taken from the previous literature by Munizaga & Palma (2012), Barry et al. (2002), Zhao et al. (2007), and Trepanier et al. (2007), and applied to the complex multimodal network.

The inputs of the model are three main databases: transactions (boarding) from the automatic fare collection system (AFC data), a geocoded definition of the public transport network (stops, lines, locations) and vehicle position from the automatic vehicle location system (AVL data). The model incorporates three algorithms: a tap-out location inferring algorithm (TOLIA), a travel time estimation algorithm (TEA) and a vehicle inferring algorithm (VIA). First, TOLIA suggests the alighting location based on the assumption of a maximum walking distance from the next transaction, data gathered from the current transaction and geospatial network data. Second, TEA and VIA estimate times and couple vehicles respectively. The vehicle can be inferred either because the boarding transaction contains the information or because the location and time of the boarding transaction are known, as well as the location of the estimated alighting transaction.

The model eventually delivers a list of matched trips that form individual travel diaries. Every trip is described by mode, stop (station) and time of boarding and alighting, card identification number and the product used for validation. On average, the success rate of matching trips for one year of records is 87% which is considered more than satisfactory, according to Munizaga & Palma (2012). Travel diaries can be used in a transfer inference algorithm that takes into account the time gap between two adjacent trips. The algorithm would facilitate the construction of origin-destination matrices which are an essential input for demand and user behaviour analysis.

The second important data source is socioeconomic data collected by the national bureau Statistics Sweden (SCB), which is also used by SL for planning and evaluation purposes (SCB, 2019). The data is stored at the level of 1364 census zones. Census zones greatly vary in size and population. For instance, they can represent a single neighbourhood, a town or a major part of a commune. It generally depends on how homogeneous citizens and the use of this area are. In terms of population, the average number for a census zone is about 1.000-2.000 inhabitants, with the rare maximum up to 6.000-9.000. Figure 4.1 displays the zonal structure of Stockholm County with the zoomed-in city core and its suburbs.

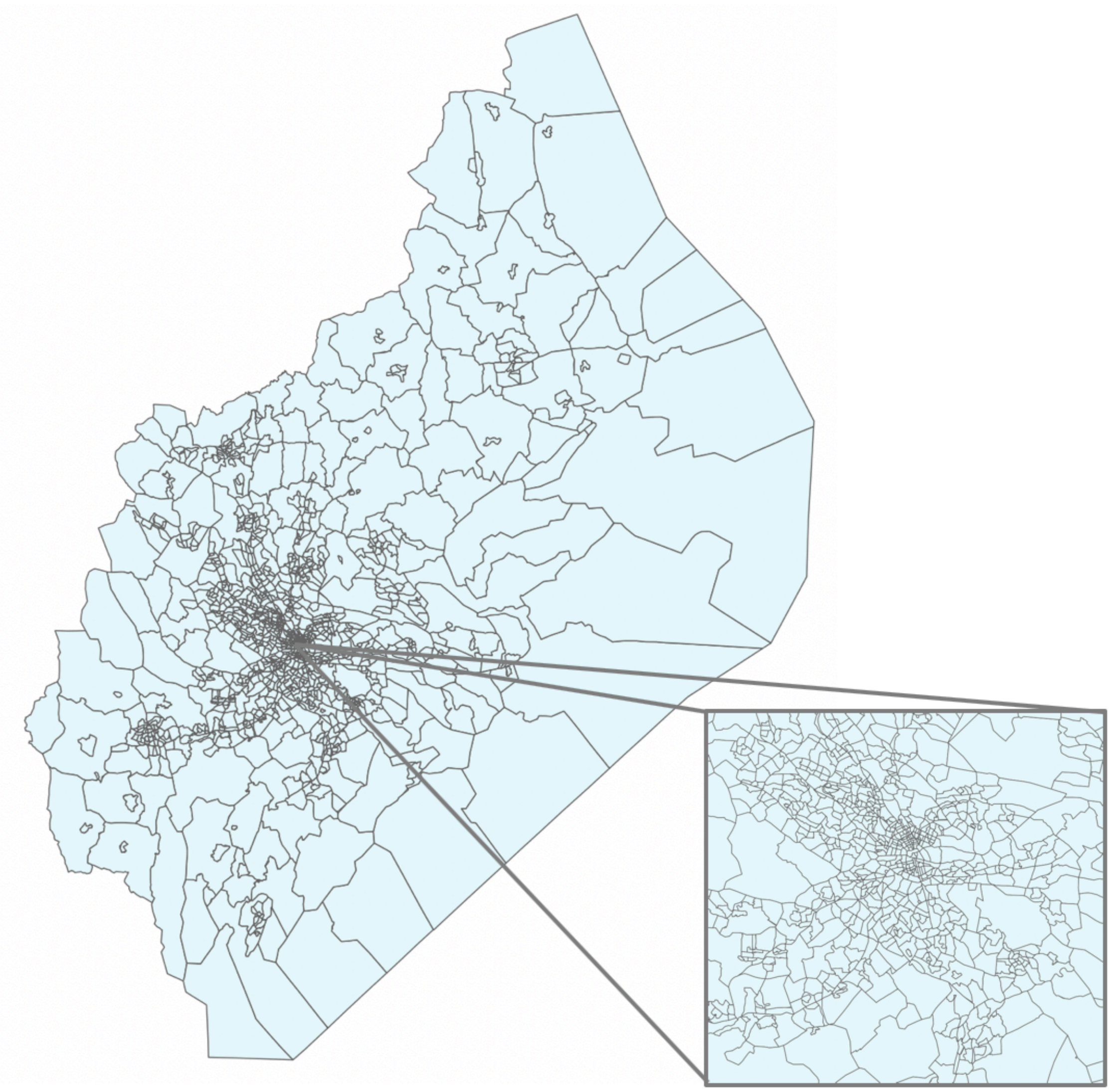


Figure 4.1: Census zone structure of Stockholm County (QGIS, based on data provided by SL)

For each census zone, the following data is available:

- name and codes (Planområde, Basområde and SAMSID15) of the zone as well as the commune this zone belongs to;
- geospatial data with coordinates, contours and geographic centers;
- population (years 2015-2017);
- population split by age, gender, citizenship, country of origin (year 2017);
- median income (year 2015);
- socioeconomic index, which is a complex indicator incorporating proportions of citizens of the age group 18-64 years with upper secondary education, employment and no financial assistance (year 2015);
- car and driver's licence ownership (year 2015).

4.2. Data processing setup

Before starting any processing of the available data, some fundamental decisions, assumptions and preparatory manipulations have to be made. First, travel diaries for the two years are sorted and stored as separate tables in a PostgreSQL database. Socioeconomic data are cleaned, standardised, and composed into one table together with zonal and communal coding. Zonal data are also put together, where each zone ID is assigned to its coding, geospatial perimeter and centroid, and according fare zone from the fare system in 2016. For the sake of the analysis' purpose, trips in 2017 are also allocated to the hypothetical fare zones, even though the zones were removed through the flat fare introduction.

Figure 4.2 presents a general workflow executed throughout the data processing, with its stages linked to the according sections of this chapter. At first, an analysis period is selected. Based on the previous experience of computational power constraints with the travel diary compilation and expected numerous alterations with this data set, it is decided to proceed with one month of records for each year. It helps to acquire representative results while optimising the time spent on running test versions of algorithms. The consistency between the two years is checked upon.

Afterwards, all departure and arrival stops (stations) of each trip are matched with census and fare zones. Having this, the most important procedure is performed, namely a transfer inference algorithm. It relies on the assumed transfer time thresholds that are identified based on the existing research practice. As an output, O-D matrices for both periods go through a selection of the relevant ones. In this case, each journey must have complete and different origins and destinations and must be taken within Stockholm County. Inbound and outbound journeys are excluded due to different characteristics, such as fares, operators, types of travelers, etc.

Having complete and selected journeys, an analysis of mobility metrics is executed. Daily demand split involves a consistency check between days of the month and times of the day for the right level of aggregation. Spatially, it is recommended to aggregate journeys by fare zones, as the number of census zones is too high and they cannot guarantee robust results, while between fare zones, major differences are expected in two years due to the price change. The modal split is investigated to sort out the most popular and representative modes in the system. Frequency, journey lengths and product split are analysed in conjunction to understand which types of users changed their behaviour with the transition between the fare systems.

Lastly, for each individual smartcard ID, a home census zone is identified in order to assign certain socioeconomic characteristics to the user. This task is solved through an application of one of the existing routine-based algorithms. At the very end of the data processing, the final dataset is revisited, including an assessment of its quality and significance.

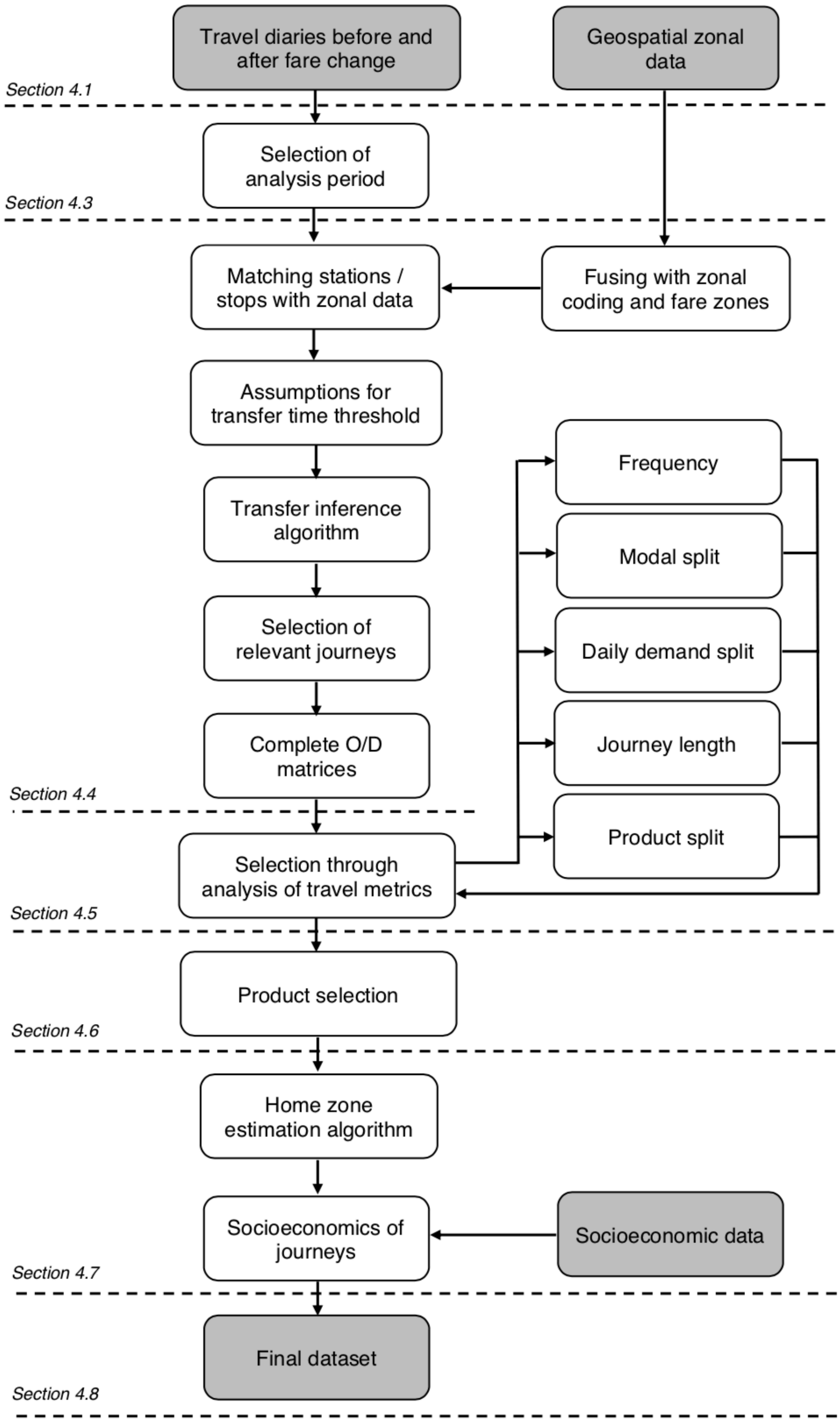


Figure 4.2: Data processing workflow

4.3. Selection of analysis period

To select a period which will be used in the further analysis, monthly demand split is extracted to Table A.2 followed by a diagram (see Figure 4.3). Table A.2 presents ridership in trips and cards as well as the number of trips per card. Moreover, total and average values are estimated for each year, accompanied by growth values. Figure 4.3 displays the according demand in trips. Following the SL's annual reports, seasonal variability have stayed remarkably stable since 2008, with December - February being considered average months, June - August as a period of significant decline (especially in July), and two peak periods in ridership, namely March - May and September - November (SLL, 2019b). The variability of the extracted data for 2016 and 2017 is in line with the official long-term trends.

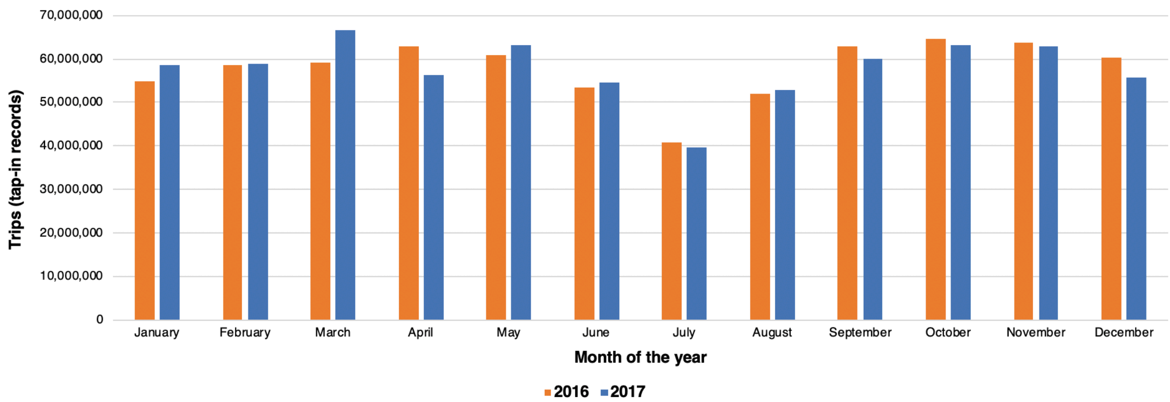


Figure 4.3: Monthly demand split

In order to reach coherence between the two years, one should account for all significant circumstances that might have affected regular operating conditions of the system or demand patterns at that time. The most common examples are holidays or public events, strikes, severe weather, public transport upgrades or breakdowns. Starting from July 2017, a few major changes were introduced affecting public transport, including the opening of the Stockholm City Line for commuter trains and the launch of a new schedule. Therefore, the months July - December are not suitable for the comparison. Moreover, April, May and June are the months with a large number of holidays that create demand fluctuation, which in turn varies between years. This might also not allow for robust and effective analysis.

Among the three months that are left, March 2017 exhibits failed records of cards due to a system error. This can be clearly seen from Table A.2, where all trips made are assigned to 1.008 cards only. The fare change was introduced on the 9th of January 2017, hence the first month of the year is also taken out of consideration. All in all, February appears to be the optimal month to continue with. Looking at the detailed numbers in the aforementioned table, February is one of the closest to the annual average (deviation does not exceed 2%) as well as to the total growth of trips and cards (0,9% versus 0,8% and -0,2% versus 0,2% for month and year respectively). In the official annual reports, SL chooses an "average winter month" for evaluation purposes (SL, 2017). The month of February satisfies this condition as well.

In February 2016 and 2017, the demand profiles looks very stable and comparable, which can be observed from Figure 4.4. It is easy to distinguish weekends and specific weekdays due to a very high consistency between weeks. The only point of attention are the two last days in 2017 with a relatively lower demand than usual. This period is the start of a winter sport holiday that takes place in the end of February / March. Excluding these days from the analysis in 2017 requires to pick the analogous set in 2016. In Figure 4.4, the final analysis period is highlighted in red. It comprises 26 days, 8 weekend and 18 working days.

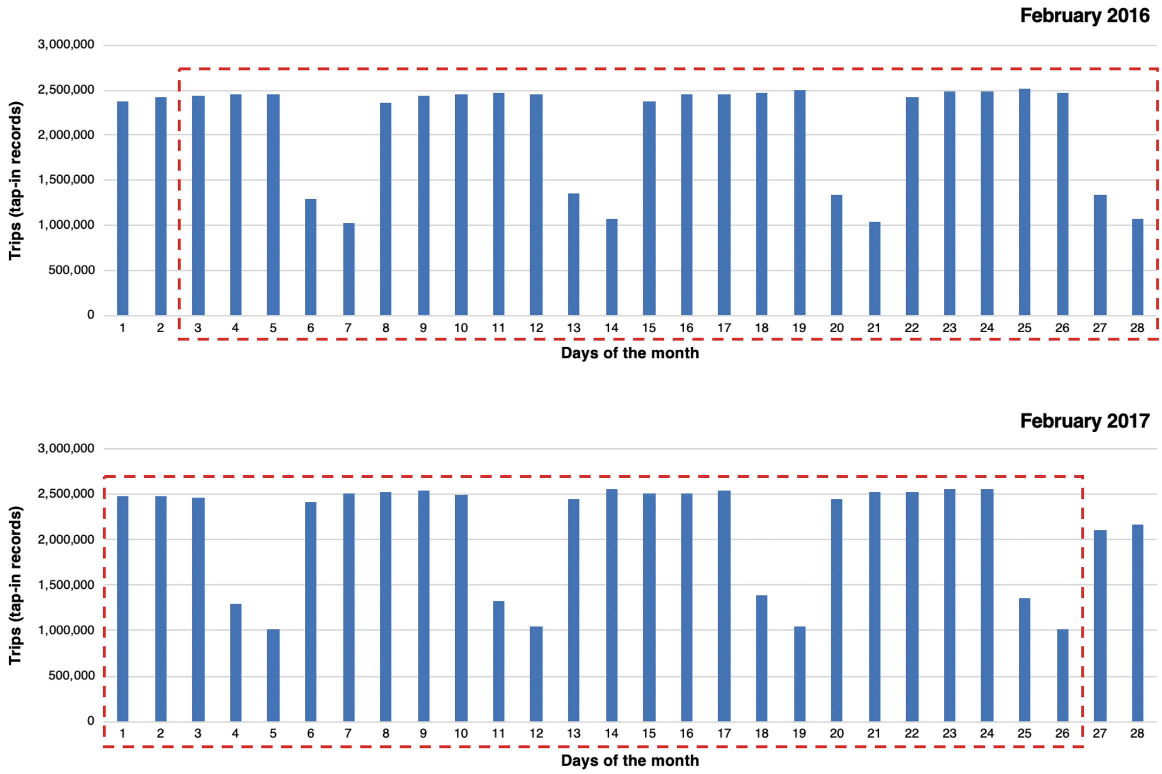


Figure 4.4: Daily demand split in February

4.4. Transfer inference

One step that should be taken prior to transfer inference is the assignment of all stops and stations in the system to the according census and fare zones. This procedure is relatively easy, as geospatial data is available for both categories. Therefore, if the coordinates of a certain stop (station) fall into the polygon of a zone, they get matched. The success rate for the assignment of 18.990 locations is 99%.

For the actual compilation of trips into journeys, the approach used by Seaborn, Attanucci & Wilson (2009) is adopted. It defines a transfer as the change 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 its duration.

The goal of the algorithm is to select the right time threshold that would allow to identify whether there is only an accidental activity involved 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 linked into a journey.

As smartcard data do not provide any information on activities during travel time, it is recommended to rely on a networkwide analysis of the available time gap distribution. This opens up some insightful relations which lead to a decision on 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 does not seem sufficient, because tap-out time is estimated for only 60% of the trips. In this case, it can be complemented with tap-in/next tap-in gaps that, apart from the pure transfer time and activities, include the in-vehicle time.

The logic behind the transfer inference algorithm is presented in Figure 4.5. The algorithm runs through a set of potential time gaps and assigns a transfer status to those which fall below a certain threshold. The priority is given to the inferred tap-out/next tap-in rule, and only if the tap-out information is not available, the tap-in/next tap-in condition gets checked. A journey is compiled when either the next time gap exceeds the transfer threshold, or there is no next tap-in available.

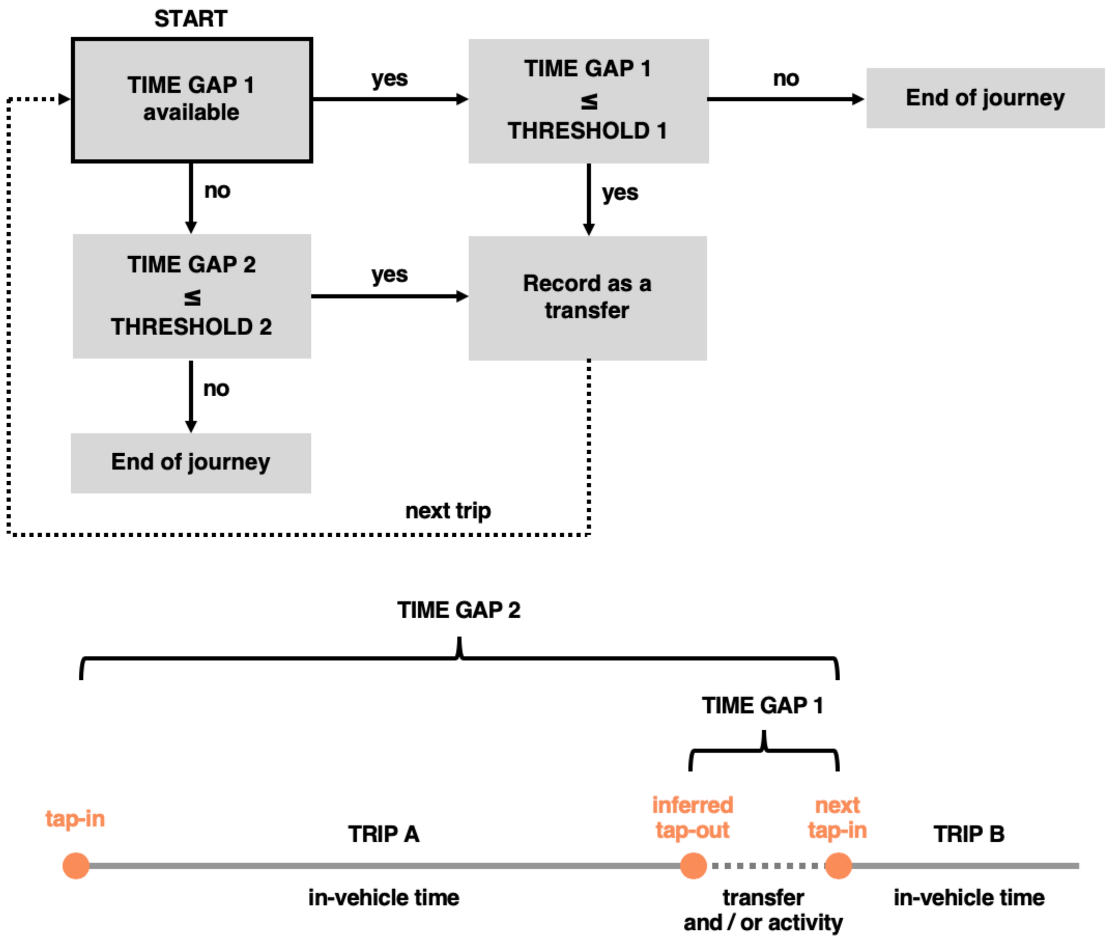


Figure 4.5: Logic of transfer inference algorithm

Figure 4.6 presents the distribution of all available time gaps between adjacent trips, both for the tap-in/next tap-in and inferred tap-out/next tap-in combinations. The almost absolute similarity between the years becomes evident. 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 and home (leisure) 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 deliver an average of 11,4 minutes (11,1 minutes for 2017) and 80% gaps within 20 minutes. Most of the transfers are done within the first few minutes, whereas the in-vehicle time is more evenly distributed among the hour. It is facilitated by the highly efficient and frequent public transport system.

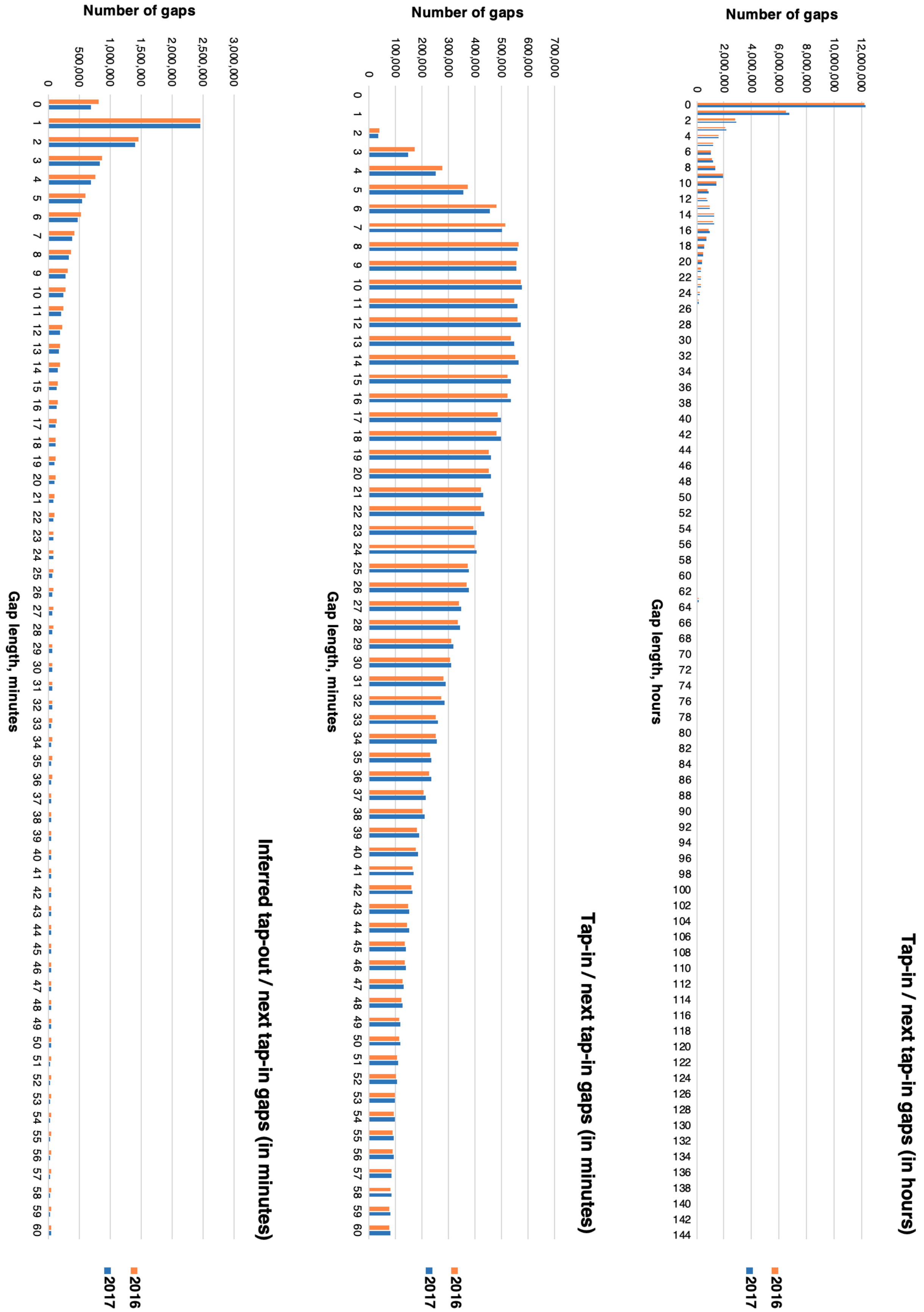


Figure 4.6: Distribution of available time gaps between trips

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 should be plotted, based on a certain parameter (Seaborn, 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 influence the total transfer time. Table 4.1 presents top-eight combinations of three modes (metro, bus, commuter train) that yield 95% of all available gaps of the first hour.

Table 4.1: Split of available time gaps by mode combination (top-eight results)

Mode combination		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

The cumulative distribution of inferred tap-out/next tap-in time gaps for the aforementioned mode combinations is displayed in Figure 4.7. As explained in Seaborn (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 4.7, four clusters are distinguished due to their similar distribution: bus-train and bus-metro; metro-train, train-metro, metro-bus and train-bus; bus-bus; metro-metro. 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 as 5 minutes. All results are listed in Table 4.2.

For tap-in/next tap-in gaps, the distribution is plotted in Figure 4.8. What matters is the duration of in-vehicle time that is much longer than an average transfer (refer to Figure 4.6). The O/D combination affects the length of a trip, therefore fare zones are chosen to be the defining parameter. In this way, three clusters are clearly visible, each of them representing trips within one zone, between two or three zones. Thresholds for each cluster are set in the similar way to the inferred tap-out/next tap-in case and listed in Table 4.2.

As the decision on time thresholds is made, one can continue with the application of transfer inference. The algorithm is realised in the programming language Python with an external assistance at KTH. Table 4.3 presents the performance results of the algorithm. The success rate will be evaluated later, but at this stage it is important to see how the additional use of tap-in/next tap-in gaps substantially improves the data quality. In particular, trips without tap-out recordings can still be associated with a transfer based on their tap-in information, which is the case for 46,4% (37,0% plus 9,4%) and 53,5% (42,4% plus 11,1%) of journeys in 2016 and 2017 respectively.

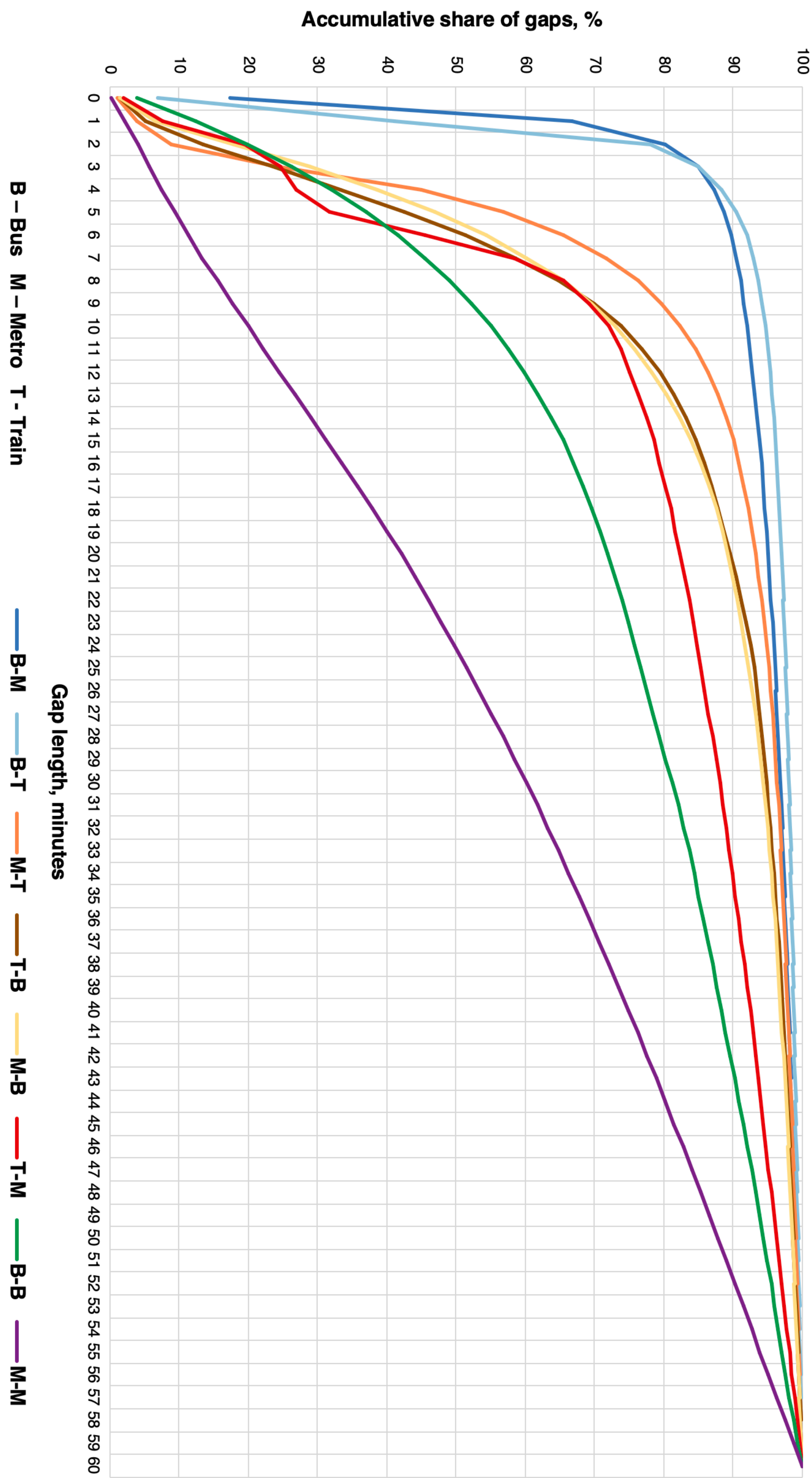


Figure 4.7: Cumulative distribution of available inferred tap-out / next tap-in time gaps based on mode combination

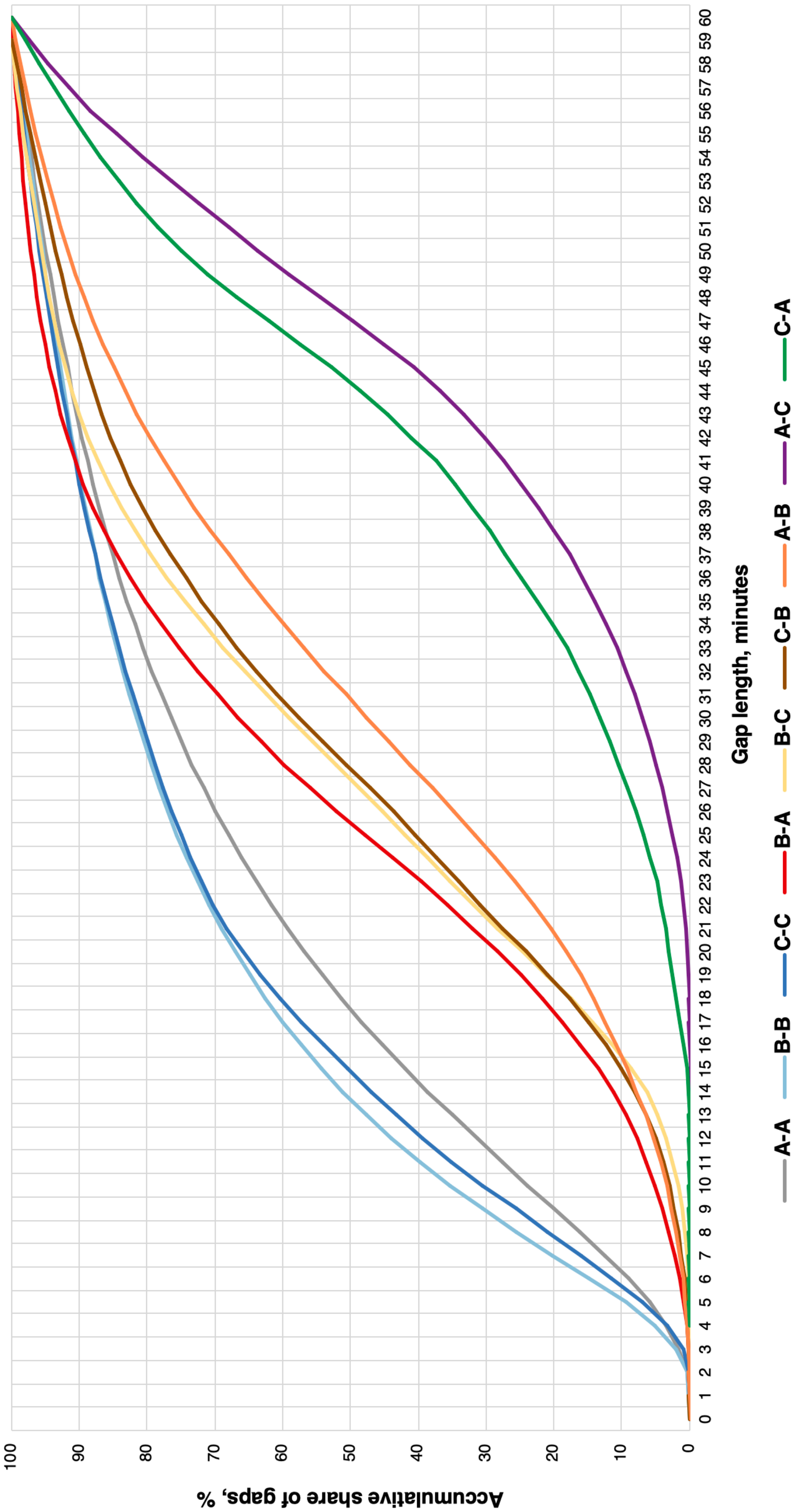


Figure 4.8: Cumulative distribution of available tap-in / next tap-in time gaps based on fare zone O/D

Table 4.2: Time thresholds for transfer inference

Inferred tap-out / next tap-in			Tap-in / next tap-in		
Tap-out mode	**Next tap-in mode**	**Threshold, min**	**Tap-in fare zone**	**Next tap-in fare zone**	**Threshold, min**
Metro	Metro	5	A	A	35
Bus	Metro	10	B	B	
Bus	Rail	10	C	C	
Bus	Bus	30	A	B	45
Default (Rest of modes)		20	B	A	
			B	C	
			C	B	
			A	C	55
			C	A	

Table 4.3: Performance results of transfer inference

Transfer inference condition		Number of journeys, 2016	Share in 2016, %	Number of journeys, 2017	Share in 2017, %
Tap-out available	Large gap	20.218.612	48,6	17.899.697	42,5
	No next tap-in	2.077.551	5,0	1.647.668	3,9
Tap-out not available	Large gap	15.423.403	37,0	17.862.318	42,4
	No next tap-in	3.920.051	9,4	4.684.019	11,1
Total		41.639.617	-	42.093.702	-

The last step after O/D pairs are acquired is to sort out the irrelevant journeys, namely those with an incomplete origin or destination, same origin and destination and an origin or a destination located outside of Stockholm County. The complete and relevant journeys are stored in the corresponding tables of the PostgreSQL database.

4.5. Analysis of travel metrics

As it is stated above, the aim of this section is to underline performance of the public transport system and main trends in user behaviour through several travel metrics. By comparing values among the years, one can conclude what changes occurred with the fare scheme transition.

Table 4.4 represents the general demand split between fare zones as well as average journey composition for each O/D pair. Figures 4.9 and 4.10 visually complement a couple of particular aspects in the table. The passenger flow for the O/D pair A-A is by far the highest, contributing to around 71% of the total ridership. The second most popular route is A-B in both directions with around 8-9% each. The internal ridership within the zone B also poses some relevance with its share of 6%, whereas other routes vary within the range of 0,5-2%. A significant growth in absolute terms is noted for the O/D pairs A-A, C-C and A-B (B-A), and in relative terms for the O/D pair A-C (C-A) which is higher than the total average. This proves that travel patterns in Stockholm County are very core-oriented, and this trend gets reinforced throughout time, along with some local development in the remote areas.

Table 4.4: General demand split between fare zones

Origin	Destination	2016			2017			Growth in journeys		Growth in trips / journey	
		Number of journeys	Share, %	Trips / journey	Number of journeys	Share, %	Trips / journey	Absolute	Relative, %	Absolute	Relative, %
A	A	21.349.146	71,8	1,28	21.594.290	71,2	1,28	245.144	1,1	0,00	0,0
A	B	2.414.181	8,1	1,75	2.484.079	8,2	1,74	69.898	2,9	-0,01	-0,6
A	C	319.622	1,1	1,95	336.560	1,1	1,92	16.938	5,3	-0,03	-1,5
B	A	2.643.079	8,9	1,79	2.745.688	9,1	1,79	102.609	3,9	0,00	0,0
B	B	1.836.971	6,2	1,31	1.879.501	6,2	1,30	42.530	2,3	-0,01	-0,8
B	C	140.137	0,5	1,79	143.663	0,5	1,78	3.526	2,5	-0,01	-0,6
C	A	340.081	1,1	1,94	365.910	1,2	1,91	25.829	7,6	-0,03	-1,5
C	B	128.264	0,4	1,77	135.023	0,4	1,75	6.759	5,3	-0,02	-1,1
C	C	545.176	1,8	1,23	623.950	2,1	1,23	78.774	14,4	0,00	0,0

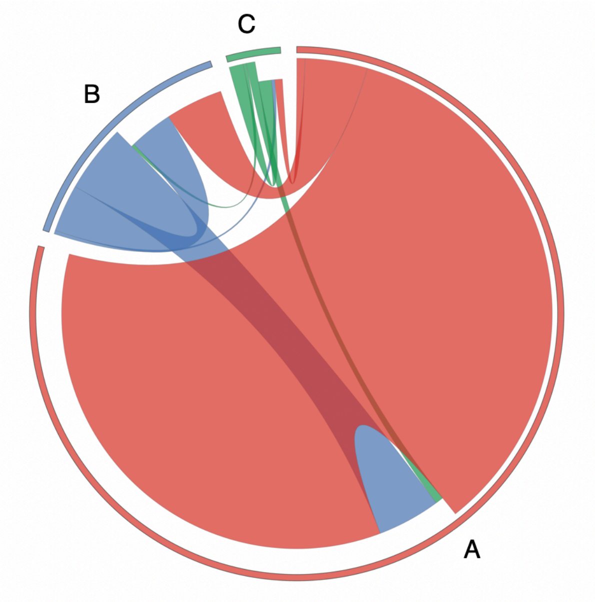


Figure 4.9: Chord diagram of demand split between fare zones in 2016 and 2017

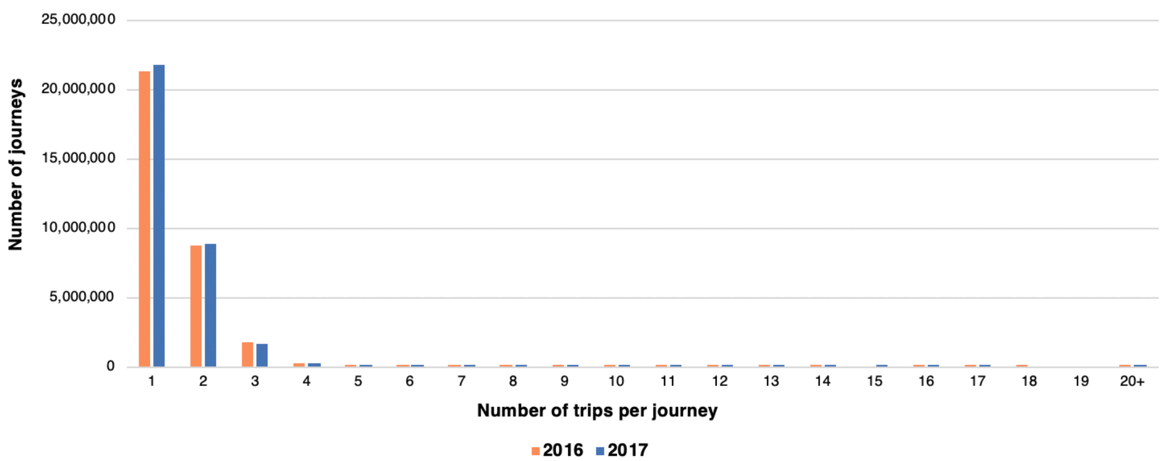


Figure 4.10: Distribution of journeys with a certain number of trips

The journey composition (Table 4.4 and Figure 4.10) stays stable throughout time and generally does not exceed 3 trips for 99% of the journeys. Every third journey in the system is a multi-trip one. Furthermore, the average number of trips per journey depends on the O/D combination, with numbers of 1,2-1,3 trips within one zone, 1,7-1,8 trips within two zones and 1,9-2,0 within three zones. In order to exclude outliers and algorithm mistakes, it is decided to proceed with journeys composed of 1-3 trips.

The travel frequency (see Figure 4.11) is remarkably consistent between the two years exhibiting a slight growth of the total average from 21,2 journeys in 2016 to 21,7 journeys in 2017. Three general groups of users can be distinguished from the graph: occasional users who traveled less than 10 times in the analysis period (44% of cards and 8% of journeys), regular users with a frequency between 10 and 40 journeys that are evenly distributed and make up more than 38% of cards and 45% of journeys, and frequent users with up to 68 journeys, 16% and 39% of the total card and journey share respectively. Other irregular cases fall into the remaining 2% of cards and 8% of journeys.

The modal split is analysed from two different perspectives: the pure modal share considering single trips within journeys (Table 4.5) and the combination of multiple modes used in each journey. For the former, the two major modes are metro and bus, with an aggregate share of 86% trips and steady average growth of 1-2%, followed by rail which is fairly significant in share (around 12% of the trips) and demonstrates a growth rate of 5% between the two years. Tram (including light rail) contributes to only 2% of all trips; the negative growth of -7,6% is explained by the closure of Roslagsbanan for maintenance in early 2017. A low share of ridership, local function and the biased year-on-year growth values of tram and light rail are the reasons to exclude this mode from the further analysis. The same decision is made for water transport that constitutes to not even 0,2% of the trip share.

Table 4.5: Modal split for trips within journeys

Transport mode	Number of journeys, 2016	Share 2016, %	Number of journeys, 2017	Share 2017, %	Absolute growth	Relative growth, %
Metro	20.123.119	49,3	20.493.484	49,3	370.365	1,8
Bus	14.988.397	36,7	15.157.354	36,5	168.957	1,1
Train	4.782.284	11,7	5.024.854	12,1	242.570	5,1
Tram	920.942	2,3	850.633	2,0	-70.309	-7,6
Ferry	11.200	0,0	13.294	0,0	2.094	18,7
Ship	672	0,0	31.350	0,1	30.678	4.565,2
Total	40.826.614	100,0	41.570.969	100,0	744.355	1,8

In regard to mode combination, 60% of journeys are taken directly with metro or bus, with the former being distinctly dominant. Bus is most frequently used in multi-trip journeys, being combined with itself, metro or rail (25% in total). Three modes to be used in one journey is a very rare observation, with the combination of metro, rail and bus accounting for only 1,5% of journeys. As in the previous case, rail and tram stand out with their growth rates higher than the average (positive and negative respectively).

Figure 4.12 displays the distribution of journey length in the network. As most of the previously mentioned indicators, the distribution of journey length did not change in time substantially either, which explains overlapping lines on the graph. Almost 95% of all journeys are done within a 20 km range. The distribution of length among fare zones is very consistent for each O/D combination: 5,0-5,5 km for one zone, 13,5-14,0 km for A-B and B-A, 20,0-20,5 km for B-C and C-B (also two zones, yet the scale of zone C is larger), and 32,5-33,5 km for three zones. The growth rates can be considered irrelevant.

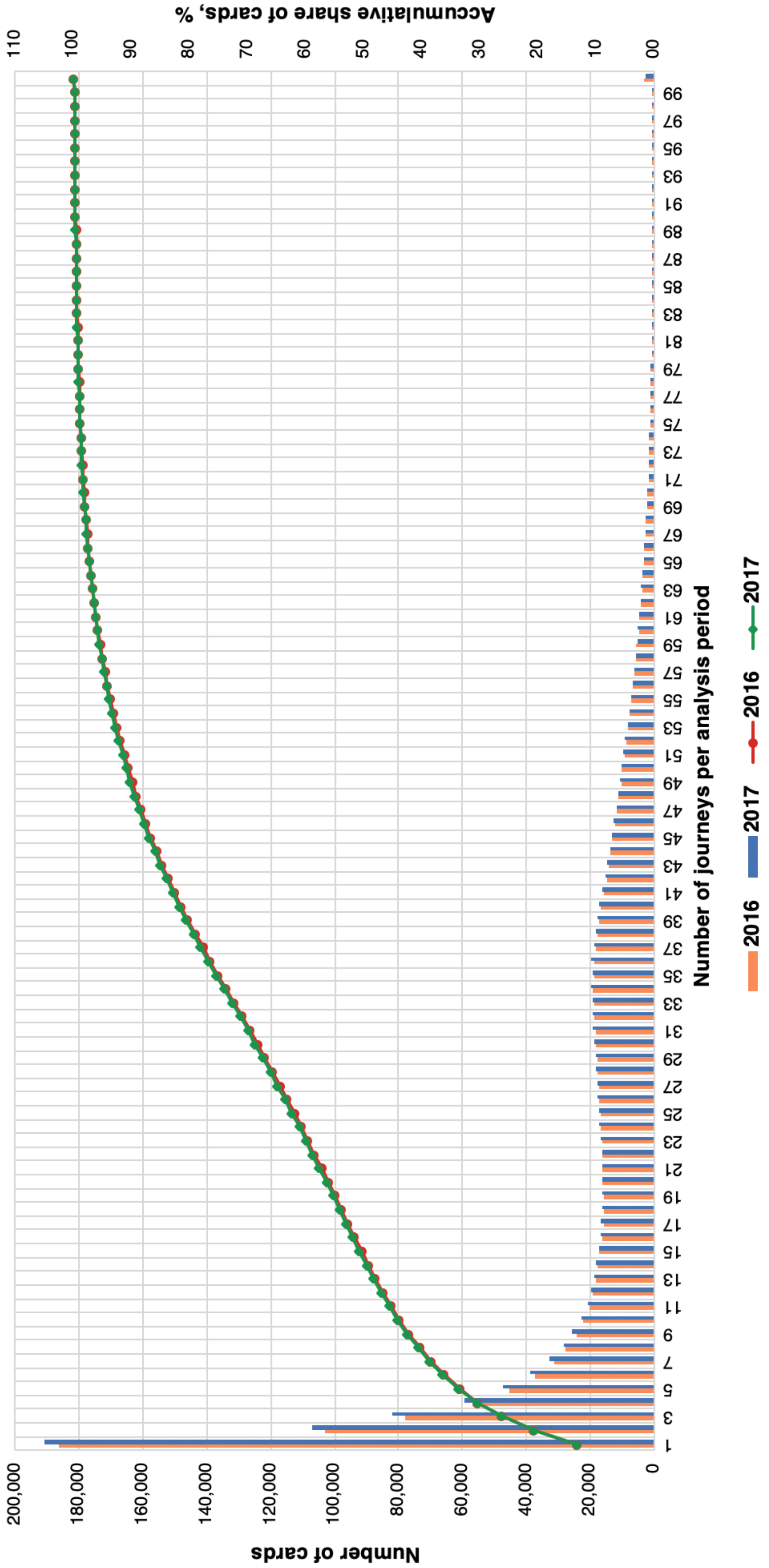


Figure 4.11: Cumulative distribution of cards by frequency

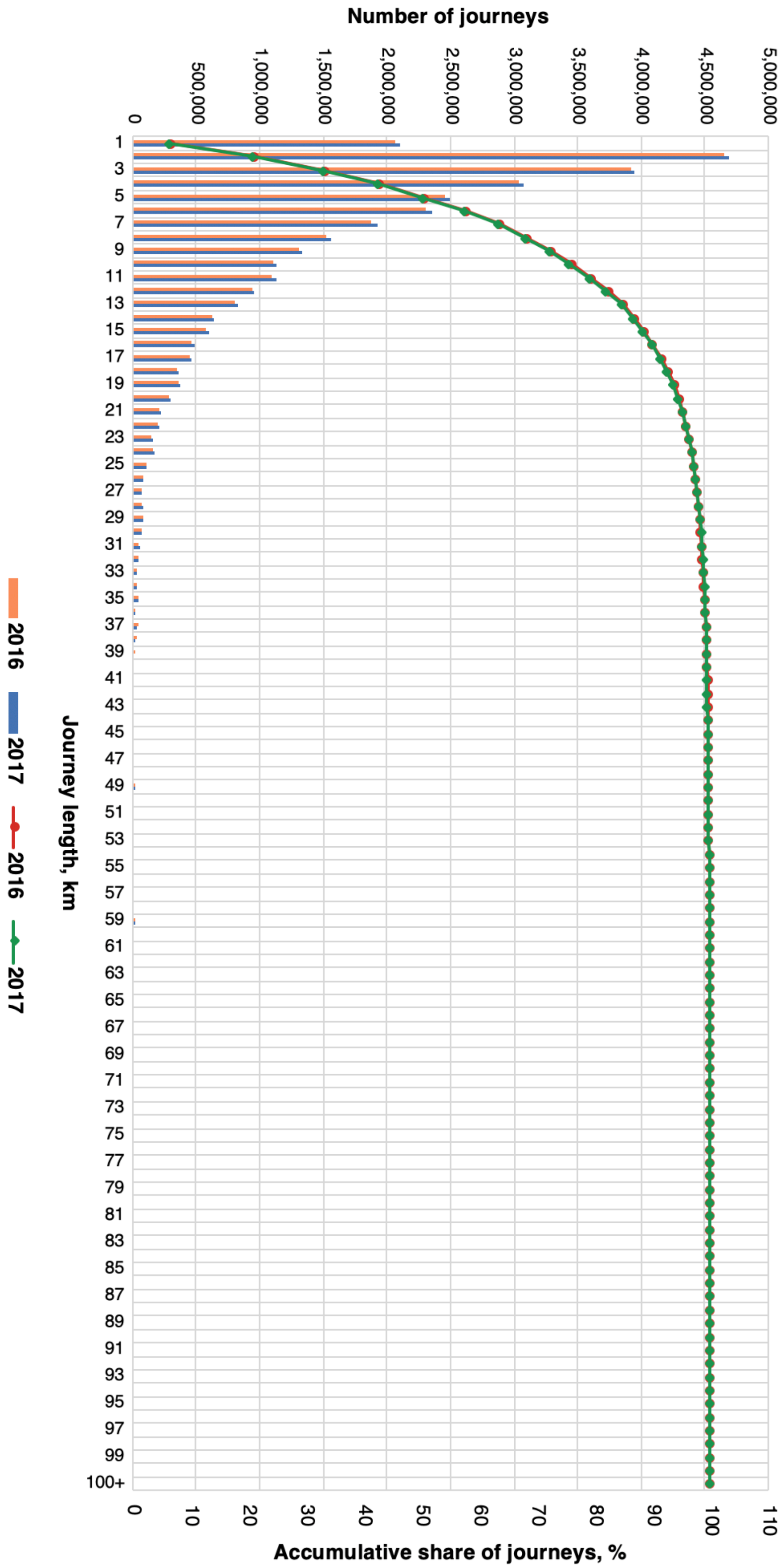


Figure 4.12: Cumulative distribution of journeys by length

The next metric to be analysed is the demand split within the analysis period. In terms of the variability of daily demand, weekdays are very consistent between each other, fluctuating in a 1-3% range around the average value. Weekends, in turn, differentiate more, exhibiting common boundaries of 10-15%. It is assumed that the average values for both weekdays and weekends are representative enough to use them in the analysis as an acceptable level of aggregation. Moreover, the growth of 2,5% is noted for weekdays in 2017, whereas weekend ridership slightly decreased by 0,7%.

On weekdays, a few time periods should be distinguished due to specific travel patterns taking place at each of them, namely morning and evening peaks, interpeak, early and late off-peak. Figure 4.13 presents the 15-minute demand profile for the average weekday. It allows to approximately identify the required periods through empirically observed patterns. The morning peak appears to be very sharp and short, and lies between 7.00 am and 8.45 am, whereas the evening peak is less intense, smoother and quite evenly spread between 3.00 pm and 5.45 pm.

According to the assumed peak times, Table 4.6 delivers a journey split for each of the periods. More than 40% of the entire demand falls under the peak times, while one third constitutes to the interpeak. For the off-peak times, demand becomes significant after 6.00 am or until 9.00 pm. In terms of growth, the peak periods and the second half of the early off-peak demonstrate the highest rates (3-4%).

Table 4.6: Demand split between weekday time periods

Time period	Number of journeys, 2016	Share in 2016, %	Number of journeys, 2017	Share in 2017, %	Absolute growth	Relative growth, %
Early off-peak	117.858	8,1	122.403	8,2	4.545	3,9
Morning peak	249.441	17,1	259.668	17,3	10.227	4,1
Interpeak	443.161	30,3	447.950	29,9	4.789	1,1
Evening peak	354.776	24,2	366.290	24,4	11.514	3,3
Late off-peak	298.171	20,4	302.986	20,2	4.815	1,6

The last travel metric considered is the product split. Generally, almost all cards in the system are loaded with one product only (around 91%), with some cases of two products (see Table 4.7). The latter is observed to become slightly more popular in 2017. Another common practice among travelers in Stockholm County is to get two separate smartcards with one product each, for instance, a combination of a subscription with travel funds. This is done in order to avoid the automatic validation of a wrong product while using a multi-product card. However, with the existing data, it is impossible to match cards with actual users, so each card is treated as an individual traveler.

Table 4.7: Distribution of cards by number of products

Number of products	Number of cards, 2016	Share in 2016, %	Number of cards, 2017	Share in 2017, %	Absolute growth	Relative growth, %
1	1.402.902	90,9	1.426.963	90,3	24.061	1,7
2	136.298	8,8	148.165	9,4	11.867	8,7
3	4.323	0,3	5.169	0,3	846	19,6
4+	290	0,0	294	0,0	4	1,4
Total	1.543.813	100,0	1.580.591	100,0	36.778	2,4

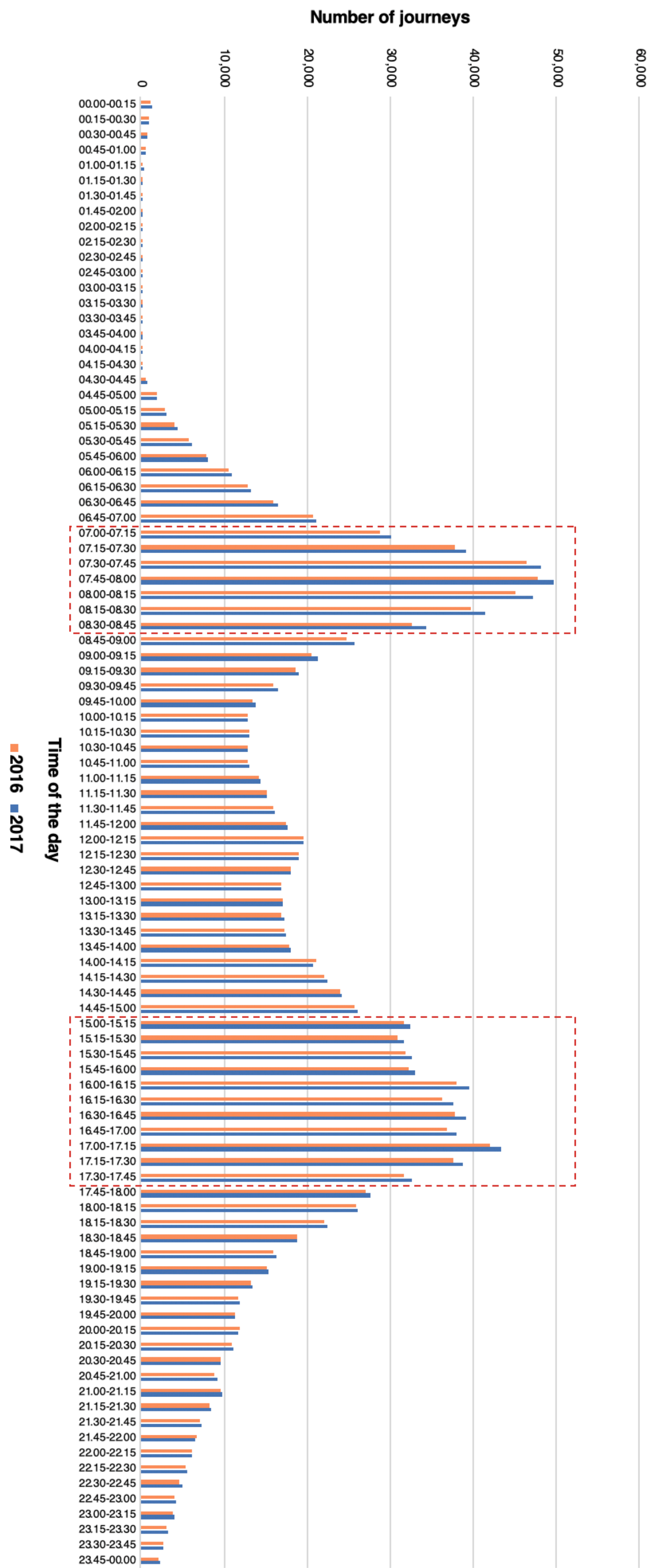


Figure 4.13: Demand distribution for average weekday with highlighted peak times

4.6. Product selection

Among the entire product range, the top-14 are chosen as a compromise between a great coverage of ridership (around 93% of journeys and 90% of cards) and the feasibility of the analysis. This includes full and reduced options of the 30-day, 90-day and annual subscriptions, travel funds, general and leisure school passes. As student passes became a part of the reduced group after the fare scheme change, there was a mix of old and new products present in February 2017. Therefore, demand for both products is combined to enable a comprehensive comparison.

Figure 4.14 shows that five products form the demand basis, namely: 30-day pass with the full and reduced fare, together accounting for 60% of the journeys and 35% of the cards; travel funds (full and reduced) with much lower share of journeys 11%, but the largest share of cards 40%; general school pass with significant 9% of the journeys and 7% of the cards. In terms of frequency, all subscriptions have the same pattern of regular usage between 32 and 35 times during the analysis period, most likely for commuting and leisure purposes. The school category involves less frequent yet still regular traveling (23 journeys for studying and 17 for leisure). Travel funds, in turn, are used very infrequently - around 5 times on average. They appear to be used rather as a secondary product, either for conventional public transport users as a backup, or for occasional users with lower mobility or preferences for personal transport.

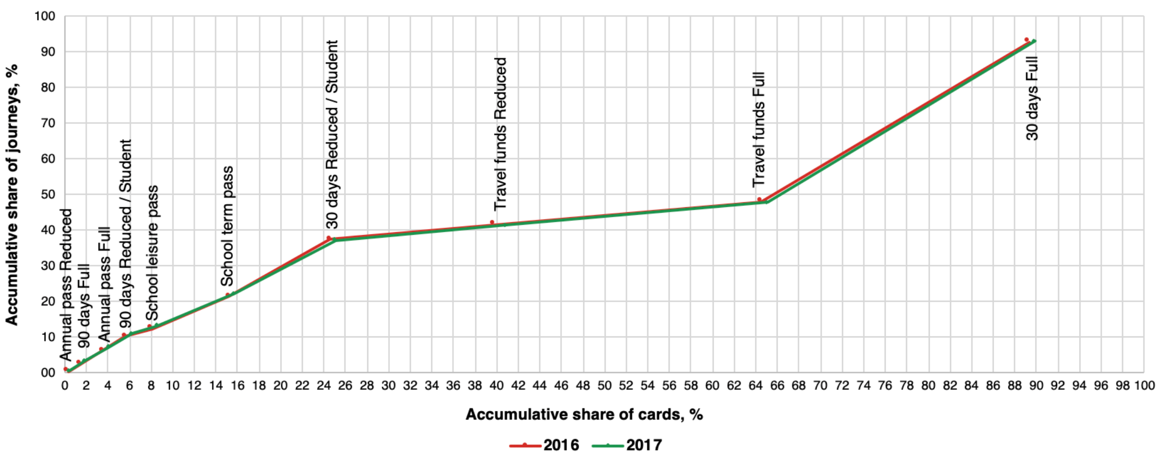


Figure 4.14: Cumulative distribution of cards and journeys by products

In terms of change, a few important aspects need to be addressed. Generally, the frequency of travelling in the system has a tendency for negative growth, which appears to be stronger in the reduced range. The full 30-day pass demonstrates a steady growth that results in a substantial part of the total increase of cards and journeys. The full 90-day pass also brings a great share of growth with a rate of more than 37% in 2017. Both products show a consistent increase between journeys and cards, thus the personal usage level does not change in time, which can not be noted for products' reduced fares. With a negative growth in journeys, the number of cards still rises, altogether greatly affecting frequency by 7-8%. In the school range, the usage of the general pass steadily grows along with the steady decline of the leisure pass. 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. An example for travel funds is presented in Figure 4.15. 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.

Table 4.8 demonstrates the internal demand split within each chosen product in time that explains in what periods a certain product is used more often. On average, the split between weekdays and weekends is 80% to 20% respectively. Only the school range follows another logic due to the specifics of general and leisure passes. For subscriptions, full fares are more commonly used on weekdays, particularly at peak times (50% of the entire day), whereas reduced fares appear more frequently on weekends (by 5%) and at off-peak times (by 10-20%). Travel funds, both full and reduced, get chosen for weekends and off-peak periods slightly more often than subscriptions.

Table 4.8: Time split of demand within each product

Product ID	Product name	Weekend		Weekday		Morning peak		Evening peak		Off-peak	
		Split 2016, %	Split 2017, %	Split 2016, %	Split 2017, %	Split 2016, %	Split 2017, %	Split 2016, %	Split 2017, %	Split 2016, %	Split 2017, %
1022	30 days Full	17,0	16,7	83,0	83,3	21,3	21,3	27,3	27,4	51,4	51,3
1024 / 1356	30 days Reduced / Student	21,1	20,5	78,9	79,5	12,5	13,0	24,5	24,6	62,9	62,4
1064	90 days Full	16,3	16,1	83,7	83,9	23,7	23,9	27,5	27,9	48,8	48,2
1065 / 1357	90 days Reduced / Student	20,6	20,1	79,4	79,9	13,7	13,7	24,2	24,4	62,1	61,9
1104 / 1107	Annual pass Full	15,5	15,3	84,5	84,7	22,5	22,8	27,7	27,8	49,8	49,3
1108	Annual pass Reduced	20,2	19,9	79,8	80,1	9,4	9,5	24,3	24,6	66,3	65,9
1250 / 1266	School term pass	0,0	0,0	100,0	100,0	27,0	27,3	28,3	28,8	44,7	43,9
1309	School leisure pass	42,0	41,2	58,0	58,8	12,3	12,5	20,6	20,4	67,1	67,1
40_1	Travel funds Full	21,6	21,2	78,4	78,8	17,5	17,6	25,1	25,2	57,4	57,2
40_2	Travel funds Reduced	22,3	22,2	77,7	77,8	7,1	7,3	24,4	24,5	68,6	68,2
Total		17,4	16,9	82,6	83,1	19,2	19,5	26,5	26,6	54,3	53,9

What is also important to look at is the product split from the O/D perspective, as exhibited in Table 4.9. 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.

Nevertheless, explaining hidden relations behind this phenomenon for all products is a challenging task due to the volume of data and lack of their specific aspects. 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.

4.7. Home zone estimation

In order to assign socioeconomic characteristics to each card, its home location should be identified at the census zone level. The algorithm applied in this study partly utilises the methodology from Aslam et al. (2018), adapted to the conditions of the tap-in validation system. Essentially, spatial and temporal regularity of usage should be investigated, which helps to set up the right threshold that separates sporadic travelers from regular ones. This creates a meaningful dataset of cards assigned to home zones with a sufficient degree of confidence.

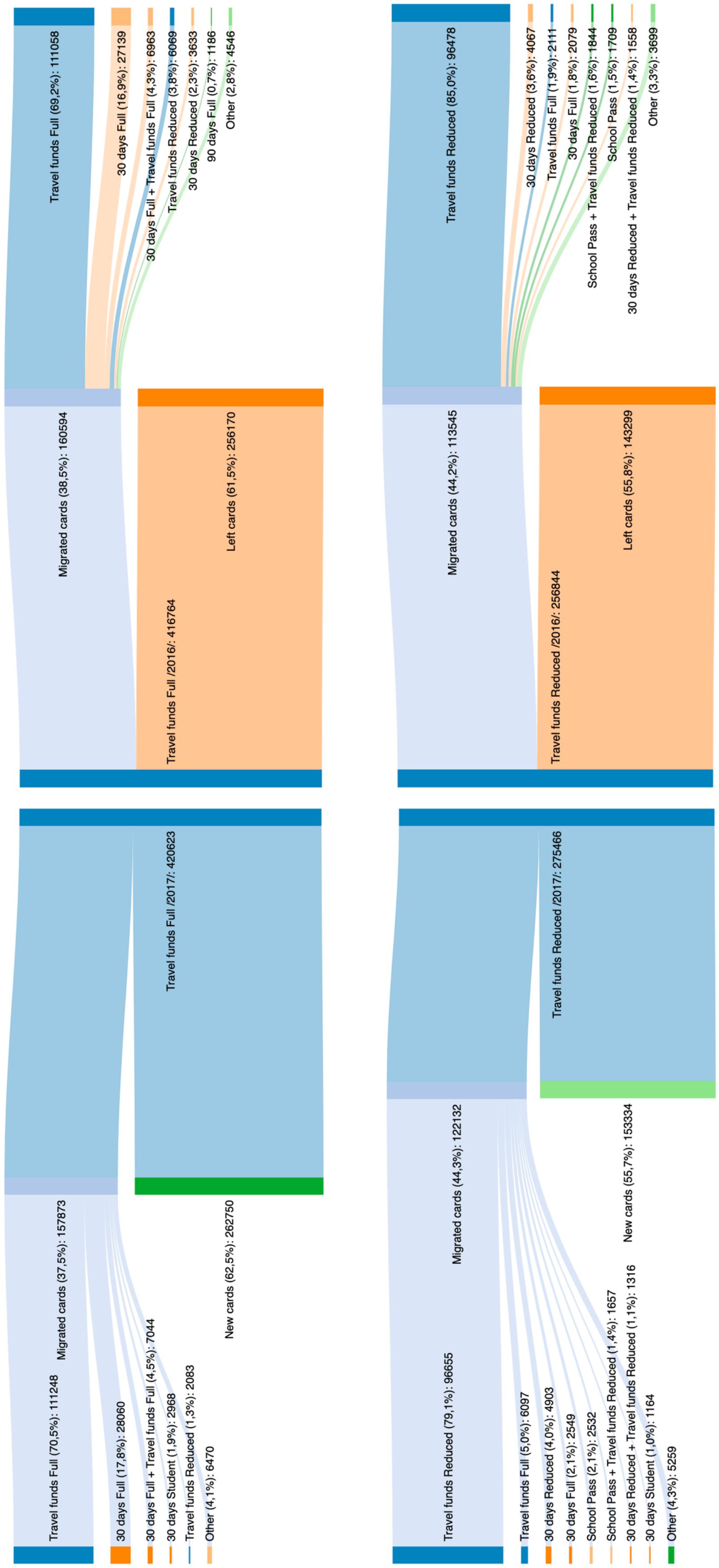


Figure 4.15: Migration flow of travel funds cards

Table 4.9: Demand growth for each product split by fare zones

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

The algorithm is realised in the programming language Python with an external assistance at KTH. It is based on the general assumption that the first journey of the day starting from 5 am always originates from home. Journey destinations are not considered to avoid reinforcement of any mistakes brought by the travel diary compilation. For each card, 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 a home location for this card.

The selection of a threshold stems from the empirical data of four months: January, February, April and May. Figure 4.16 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 separation point, after which the number of cards decreases at a slower and more even rate than before. This distinguishes regular travelers, hence the threshold of visit frequency is set to be 9. It is in line with the research by Aslam et al. (2018), which found a threshold of 5 for a two-month period. The threshold is half as high, so is the analysis period (two months instead of four).

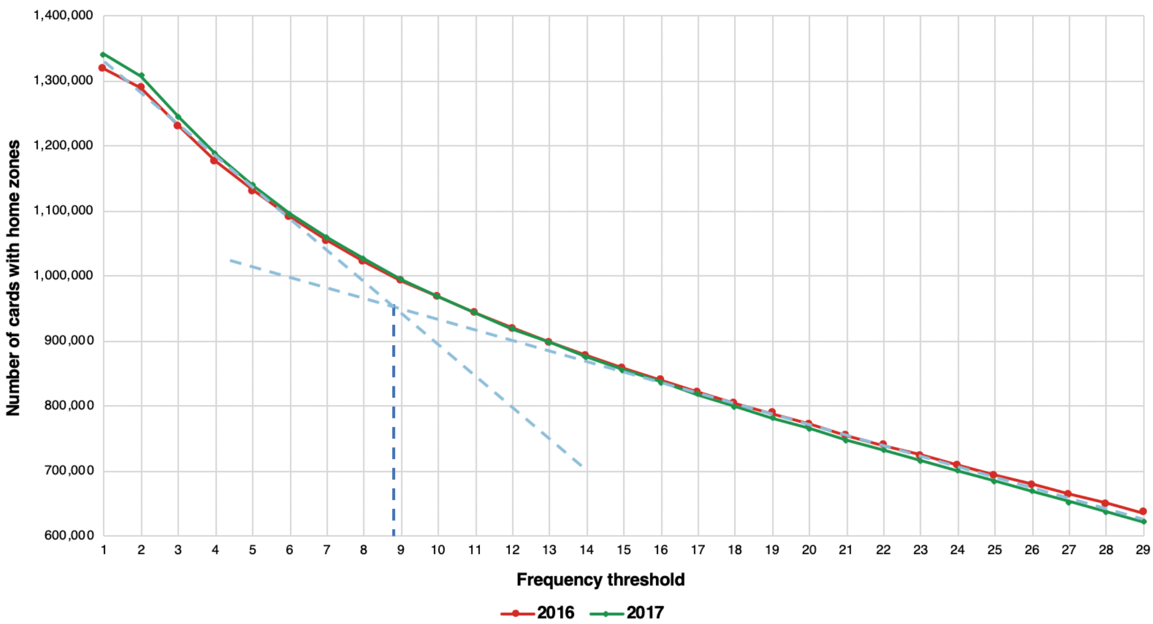


Figure 4.16: Number of cards with identified home zones based on frequency threshold

Afterwards, the home zone estimation is performed under the frequency threshold 9. The location is found for 70% of cards that produce 95% of all journeys. Thus, the removal of a significant number of infrequent travelers does not lead to a great reduction in journeys. The cards with assigned home zones are aggregated at the communal level and juxtaposed to the total population. The ratio of cards/capita varies between 7% and 66% with an average value of 46%, which seems fairly realistic considering the official statistics on public transport share in Section 3.2. The ratio is very stable between the years. There are only slight changes for some communes within the 3% limit.

Another aspect of visit frequency is the home zone observation rate. It indicates the fraction of the estimated home zone in 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 4.17, around 75% of all cards have their home location visited more than 50% of all times (rate higher than 0,5), and 90% of cards more than 40% of all times (rate higher than 0,4).

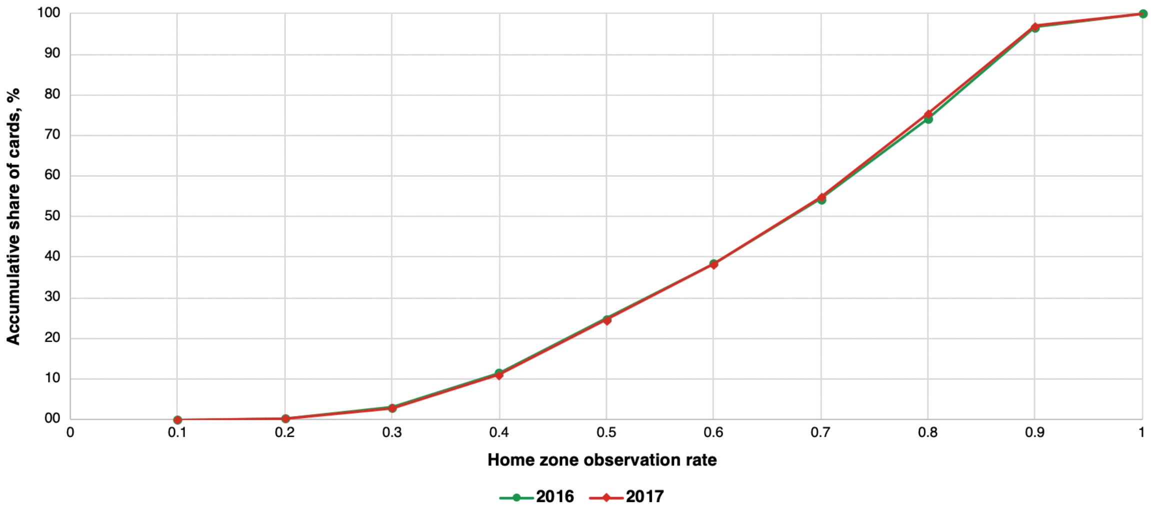


Figure 4.17: Cumulative distribution of cards by home zone observation rate

4.8. Final dataset

In the previous sections of this chapter, the initial set of travel diaries (trip records) of the entire network in 2016 and 2017 goes through the multi-stage processing and thorough selection based on various criteria. This section evaluates quality of the final dataset and its consistency with the initial input.

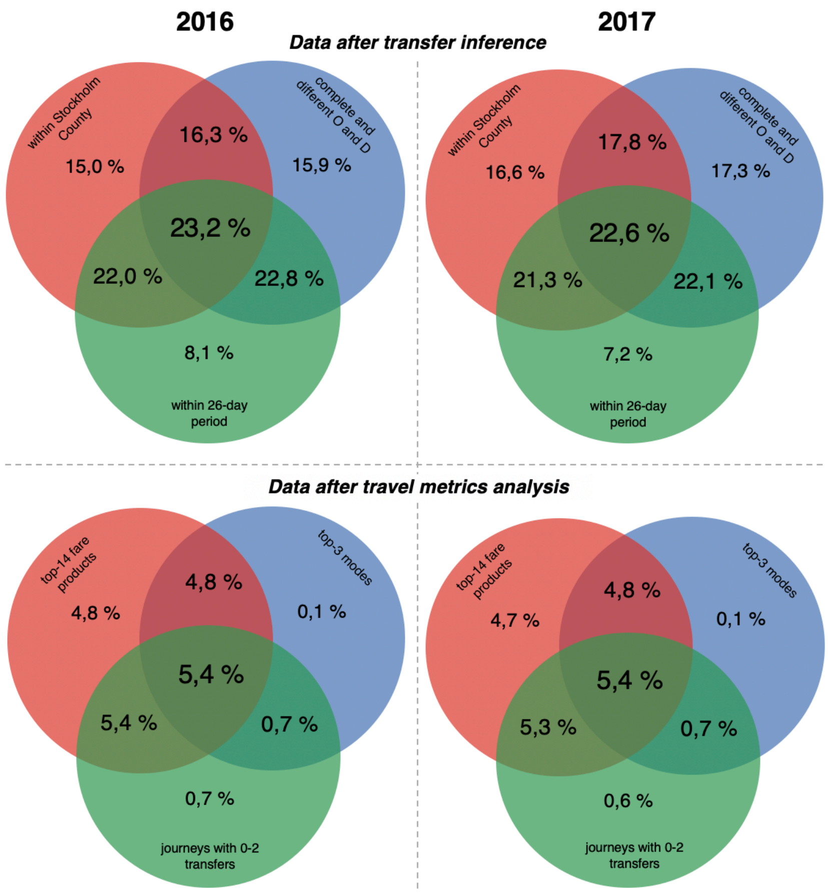


Figure 4.18: Share of excluded journeys throughout selection process for 2016 (left) and 2017 (right)

At first, the analysis period is limited to 26 days in February, followed by the transfer inference. Next, journeys with origins and destinations that are identical, incomplete or located outside Stockholm County, get excluded from the overall results. The analysis of travel metrics entails an additional filtering, such as the set of modes, products and maximum number of transfers per journey. Altogether, the selection procedure delivers 71,4% and 72% of the initial number of journeys for the years 2016 and 2017 respectively. Figure 4.18 visually represents how each criterion affects the outcome.

Nevertheless, the loss of almost 30% of journeys does not represent a loss in quality to the same extent. Table 4.10 elaborates on this matter. Most importantly, it refers back to the trip tables which are used for the transfer inference. Extracting only "useful" trips, namely those with different origins and destinations, within Stockholm County and the defined 26-day period, leads to 78-79% of trips and 84-85% of cards from the initial dataset. Technically, this is the scale of an original input that bears some potential value for the current study. Compared to the number of trips and cards that the selected journeys contain, the loss accounts for 8% and 11% accordingly. In addition, even though the growth rate experiences some distortion, the trend line is still maintained: 1,9% for original against 2,0% for selected trips; 2,4% for original against 3,0% for selected cards.

Table 4.10: Quality and consistency of processed data

Element	2016	2017	Absolute growth	Relative growth, %
Original dataset				
Number of journeys	41.639.617	42.093.702	454.085	1,1
• where trips	58.477.224	58.981.653	504.429	0,9
• where cards	1.926.723	1.930.978	4.255	0,2
"Useful" trips from initial table	45.822.908	46.676.287	853.379	1,9
share, %	78,4	79,1	0,7	-
• where cards	1.612.351	1.645.478	33.127	2,4
share, %	83,7	85,2	1,5	-
Dataset with filtered journeys				
Number of journeys	29.716.657	30.308.664	592.007	2,0
share, %	71,4	72,0	0,6	-
Number of trips	41.220.028	41.894.817	674.789	1,6
share, %	70,5	71,0	0,5	-
Number of cards	1.399.245	1.440.532	41.287	3,0
share, %	72,6	74,6	2,0	-
Dataset with estimated home zones				
Number of journeys	28.222.580	28.677.149	454.569	1,6
share, %	67,8	68,1	0,3	-
Number of trips	39.240.901	39.727.535	486.634	1,2
share, %	67,1	67,4	0,3	-
Number of cards	982.132	995.927	13.795	1,4
share, %	51,0	51,6	0,6	-

Table 4.10 also contains information on the set of cards with the estimated home location. As mentioned previously, the additional loss of journeys is only 4%, with a similar loss of trips of around 4%, while the number of cards got reduced by 22%, all compared to the original dataset. The growth rates slightly differ from the initial ones and are still representative for regular users.

4.9. Summary

To conclude, the chapter explicitly presents all major steps that are undertaken throughout data processing with the use of two data sources, namely individual travel diaries of the public transport system in Stockholm County and socioeconomic statistics of the region. The analysis period is chosen to encompass 26 days in February in both 2016 and 2017, which delivers consistent and comparable demand profiles. The initial trips are combined into journeys with a transfer inference algorithm. Afterwards, a sorting and selection process takes place to form the final dataset. This includes journeys with two or fewer transfers, complete and different origin and destination, taken within the analysis period and inside Stockholm County. Moreover, top-3 modes and top-14 products are selected. As an extension to the first, a second dataset is created that contains estimated home zone locations for individual cards, which allows to assign socioeconomic characteristics to travelers. Essentially, the processing brings a loss of 8% of trips and 11% of cards for the final dataset, and additional 4% of trips and 22% of cards for the dataset with home zones. Despite some distortion in the growth rates, the initial trend line is still maintained.

The work also includes the exploration of travel metrics, which delivers a number of insightful observations, such as:

- all metrics demonstrate high consistency among the two years together with the steady ridership growth, which indicates no significant effect of the fare policy on the overall travel patterns;
- travel patterns in Stockholm County are very core-oriented, with the O/D pair A-A being extremely dominant (71% of the ridership);
- three groups of users can be distinguished based on the travel frequency: occasional (44% of cards and 8% of journeys), regular (38% of cards and 45% of journeys), and frequent (16% of cards and 39% of journeys);
- three modes, namely metro, bus and commuter train, serve almost 98% of the total demand;
- the peak hours are 7.00 am to 8.45 am and 3.00pm to 5.45 pm, accounting for more than 40% of the entire demand;
- almost all cards in the system are loaded with one product only (around 91%).

Analysing the product split in a more elaborate manner revealed the high relevance of travel funds to the current study. It is one of the five products that form the demand basis, with 40% of cards and 11% of journeys. Due to the high influx of new users, travel funds reach a disproportionate development of journeys and cards which also reduces average frequency. Most importantly, it is the only product that demonstrates a non-coherent demand growth among fare zones, reaching great disparity between one-zone O/D and two- or three-zone O/Ds (0-5% against 20-60%). These findings are in line with the expectations on the main fare policy effects and create favourable conditions for the policy evaluation, which is described in the next chapter.

5 Fare policy evaluation

The last stage of the study is explained in detail in the following chapter. It elucidates the fare policy assessment process focusing on the category of travel funds. This product seems to be the most indicative when it comes to the short-term outcomes of the policy, as it got directly affected by the introduced changes.

Due to the new fare basis, traveling within one fare zone became more expensive whilst traveling through two and three former fare zones got reduced in price. According to Section 2.1, the price factor appears to be one of the major drivers in the traveler's choice. It is thus expected that the demand levels for each fare zone O/D pair changed according to the price. The extent of this change as well as the importance of additional influential factors (spatial, temporal and socioeconomic) are measured through the fare elasticity. Looking further, the price change could possibly lead to redistribution of fare expenses and mobility benefits among various social groups. The degree of redistribution is evaluated through the equity perspective following the principles from Section 2.2.

The fare policy assessment is generally split into two parts: the first looks into user sensitivity to the fare change based on different factors, while the second explores the effects on equity. Essentially, several values of demand elasticity and distribution indices are determined, that are subject to further analysis of their casual relationships and fit into the existing research framework.

5.1. Fare elasticity analysis

This section delivers the analysis of the fare elasticity that can be derived for the travel funds category. It starts with a description of the estimation procedure, including the factors of influence, an acceptable level of aggregation, and the computational steps to be taken. Afterwards, the results are presented together with important findings. Lastly, the acquired elasticity values are juxtaposed to the ones from the existing research, which allows to assess the outcome quality through the goodness of fit.

5.1.1. Elasticity estimation

Stemming from Section 2.1, 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. Based on this, several key decisions are made on how the input and output data should be sorted and presented.

First and foremost, the regularity of usage incorporates the frequency visit threshold identified in Section 4.7. Therefore, by extracting the subset with a frequency value of 9 and higher (number of journeys in four months), one selects regular users only, whereas removing the frequency filter would include all types of travelers, regular and sporadic. For the purpose of the comparison at a general level, both subsets with and without the threshold are used for the elasticity calculation. However, with all other factors, only the subset of regular users is utilised.

Within the elasticity of every factor, a split is made between fare categories and O/D fare zones. For the former, this means that full, reduced and combined fares of travel funds are distinguished. It is assumed that the reduced group mostly covers the youth, the elderly and students, which by default are more dependant on public transport. The full group is generally represented by mid-age adults, the majority of whom are daily commuters with very distinct travel patterns.

The O/D pairs indicate how many fare zones a user crosses. This aspect carries a lot of importance, as journeys within one zone became more expensive in 2017 along with the reduced price of journeys through two and three zones. Due to the relatively low ridership of the two- and three-zone groups, each incremental change of demand would bring a higher value to the elasticity coefficient compared to the more robust one-zone group. Thus, elasticity values are weighted based on a ridership share of each group,

$$TE = \sum_{i=1}^{3} E_i * \frac{D_i}{TD} \tag{5.1}$$

where TD and TE are the total demand and elasticity respectively, D and E are the corresponding demand and unweighted elasticity values for each fare zone O/D group, and i is the number of O/D group (1, 2 or 3 fare zones). The weighted elasticity only represents the contribution of an element in the total quantity. It cannot be compared among O/D pairs, yet might be compared among various user groups and fare categories, which essentially allows to investigate the directionality of sensitivity.

The selection of travel metrics as sensitivity factors is done according to Section 4.5. The transport modes are metro, bus and commuter train. The time periods are an average weekday and weekend, with the weekday also split into morning peak, evening peak and off-peak. When it comes to travel distance, the journey accumulative share and features of each range are considered. Eventually the distance groups are: 0-1 km (walking distance, 6% share), 1-3 km (short urban journey, 33% share), 3-5 km (average distance within a city, 50% share), 5-10 km (long urban journey, 75% share), 10-20 km (interzonal distance for two zones, 95% share), 20+ km (interzonal distance for three zones).

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.

Elasticity is calculated with the mid-arc formula described in Section 2.1. One of the important conditions of using the shrinkage analysis is the assumption on static environment. This means that any changes in travel patterns and user behaviour take place due to the introduced policy. However, this can not be fully stated, as the real situation is rather more complex. Even with the carefully chosen analysis period in Section 4.3 that minimises the effect of the transport service updates, there is an ever-present economic and demographic background. Looking at the mid-term statistical data of the region between years 2009 and 2017 (SCB, 2019; SLL, 2017; Trakifanalys, 2019), the annual growth of the population and

Gross Regional Product demonstrates steady rates of 1,7% and 3,2% respectively. This in turn results in a steady increase in public transport ridership by 1,5-2,5% per year. The statistical data is in line with the findings of the current study (see Table 4.10), which proves the existence of the natural demand growth. Despite the general factors, the policy still brings a significant and observable effect that becomes evident for the travel funds category in Section 4.6. This effect dominates over the overall trends due to the great disparity between fare zones (from -5% up to 70% growth). It makes feasible to continue with the shrinkage analysis, yet still without clear distinction of the policy share in the overall change.

With the aforementioned assumptions and settings, the corresponding journey data is extracted for both years and each factor, and further separated by user groups, O/D pairs and fare categories. Elasticity is then calculated and weighted based on the demand share. Finally, aggregate elasticity values are obtained by summarising relevant elements. As the next step, one can proceed with the user sensitivity analysis.

5.1.2. Elasticity results and findings

All elasticity values estimated in this study are shown in Tables A.3 and A.4. 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.

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 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 more 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 (Balcombe et al., 2004). 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. Full fare travelers are hence less sensitive to the changes. 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 incentivises travelers, especially commuters, to consider other available options, for instance private transport. This reasoning is underlined by Figure 5.1 that evidently displays areas with higher rate of car ownership located primarily in fare zones B and C. Asymmetry in values should not be taken into account 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.

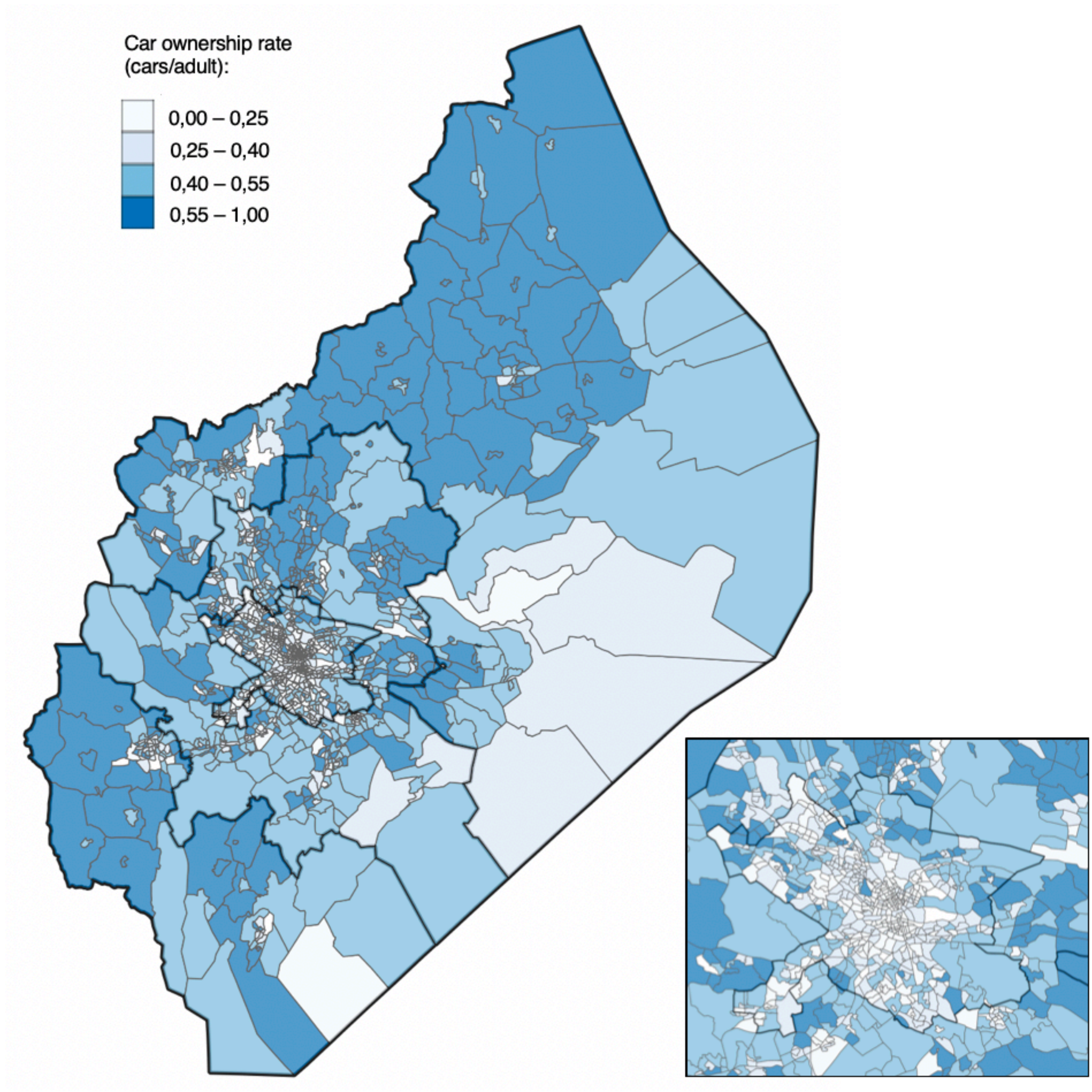


Figure 5.1: Spatial distribution of car ownership in Stockholm County
(on the right: fare zone A enlarged)

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). In the full fare group, the price increase elements dominate. It means that users might consider to reduce their mobility or to opt for alternative transport, as in the case of weekends, or to switch to other fare options for the morning peaks. Conversely, for the reduced group price decrease stands out more. Users who are temporally constrained, students for instance, could see it as an incentive for traveling. 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.

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 5.2 presents the elasticity ranges from Section 2.1 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.

The trends among each factor's user groups are generally followed, even though in a few cases they become less distinct or unclear, as with socioeconomics or time periods. This issue can be partly resolved by introducing disaggregated elasticity which specifies directionality of fare change. Besides, it should be emphasised that the current evaluation study focuses on one particular product due to the specific fare policy. Hence, elasticity reflects not only on travelers leaving and joining the public transport system, but also on existing users changing their product choice. This circumstance certainly adds some variability to the outcomes.

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 5.1 delivers unweighted elasticity for the dataset of regular users. Directionality creates an enormous 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 (Balcombe et al., 2004). 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 behaviour, especially in the case of the reduced fare users. With the current study's scope and input, it is not possible to fully distinguish impacts of the two sensitivities.

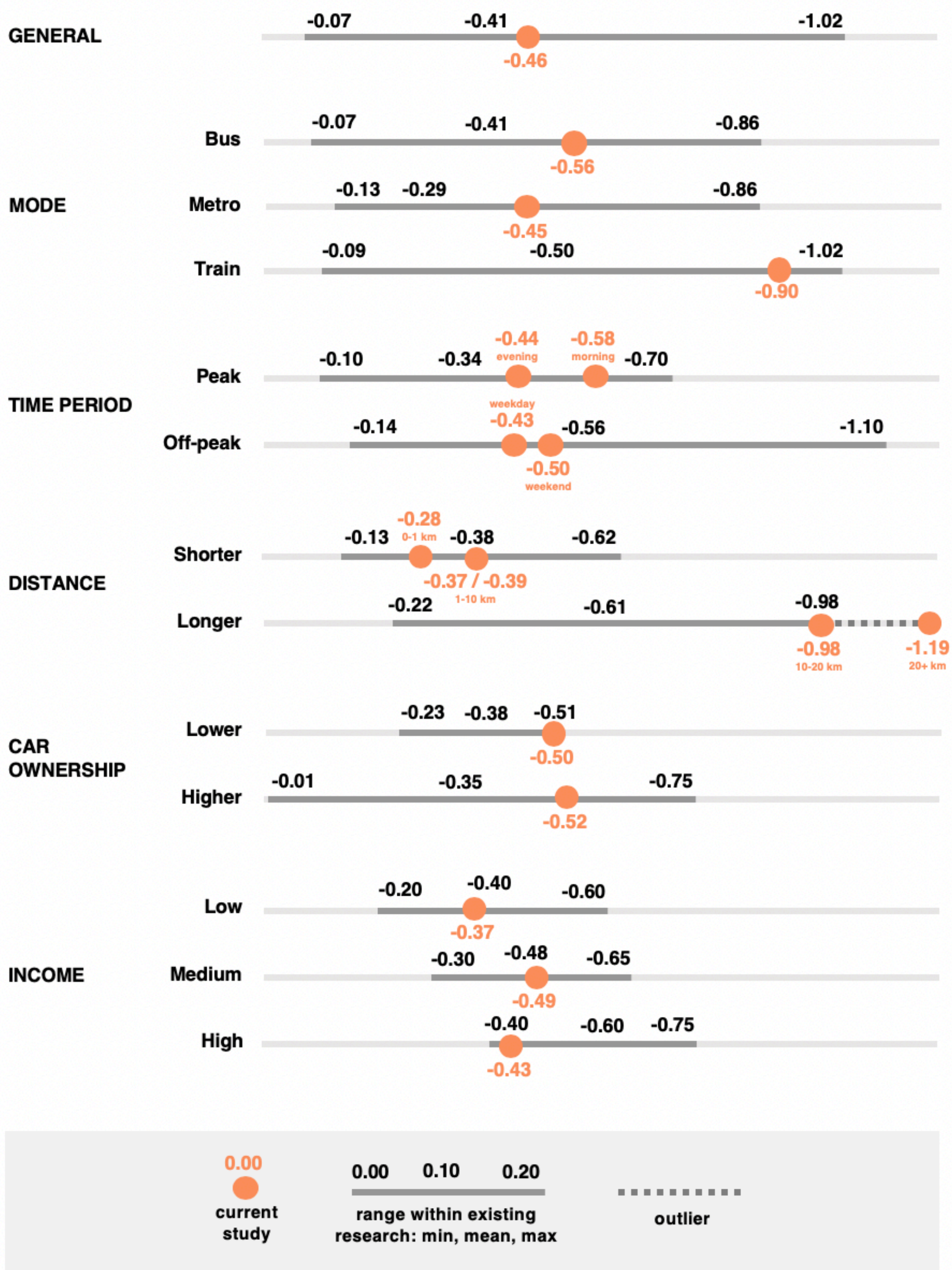


Figure 5.2: Fit of estimated elasticity values into existing research

Table 5.1: 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

5.2. Equity evaluation

As the policy introduced in 2017 affected the price of the travel funds product and consequently led to changes in ridership, this research 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.

In this study, equity analysis focuses on travel expenses as one of the most important outcomes of the public transport system. Based on the principles outlined in Section 2.2, both horizontal and vertical equity are elaborated on. The distribution of expenses for horizontal equity implies that the general population is ordered by the expense magnitude per capita. For vertical equity, it grasps several user groups ordered by their income level, socioeconomic index, car ownership rate and distance from home to the city centre. These factors are supposed to distinguish socioeconomic population cohorts. For each category, the Gini or Suits indices are computed along with plotted Lorenz curves. This allows to identify how evenly expenditures are distributed as well as how the situation changed between the two years, thus how the fare policy contributed to equity reformation. Apart from travel funds, all products are also used together for the sake of comparison, both in terms of evenness and year-on-year change.

However, a change in the degree of uniformity can be triggered by both an increase or a decrease of the overall expenses. For instance, more uniform conditions after a fare policy might be caused by higher expenses of low-income users. What is also important is that the amount of expenses gets formed not only by the fare cost, but also by the frequency of product use. It might be the case when expenses of a group do not change in time, but are associated with an increased mobility (more journeys are done with the same total cost). Under these circumstances, equity analysis requires a more detailed investigation of the journey and expense distribution. This also includes the estimation of the average journey cost, which appears to be the most objective indicator as it covers both changes in frequency and changes in price for each user group. Eventually, by taking into account the aforementioned elements, one can derive the equity implications of a fare policy.

Data processing for equity evaluation seems rather straightforward. 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 centre 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 5.2). 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 A.5). Altogether, this information can serve as an input for the equity evaluation.

Table 5.2: Overview of equity indices

Equity 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 centre	-0,561	-0,562	-0,217	-0,208

Looking at the horizontal equity (Table 5.2 and Figure 5.3), there is a disparity within the general population in terms of travel expenses, which grows significantly for travel funds. This observation is not surprising, as 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 (in line with the statistics from Section 3.2).

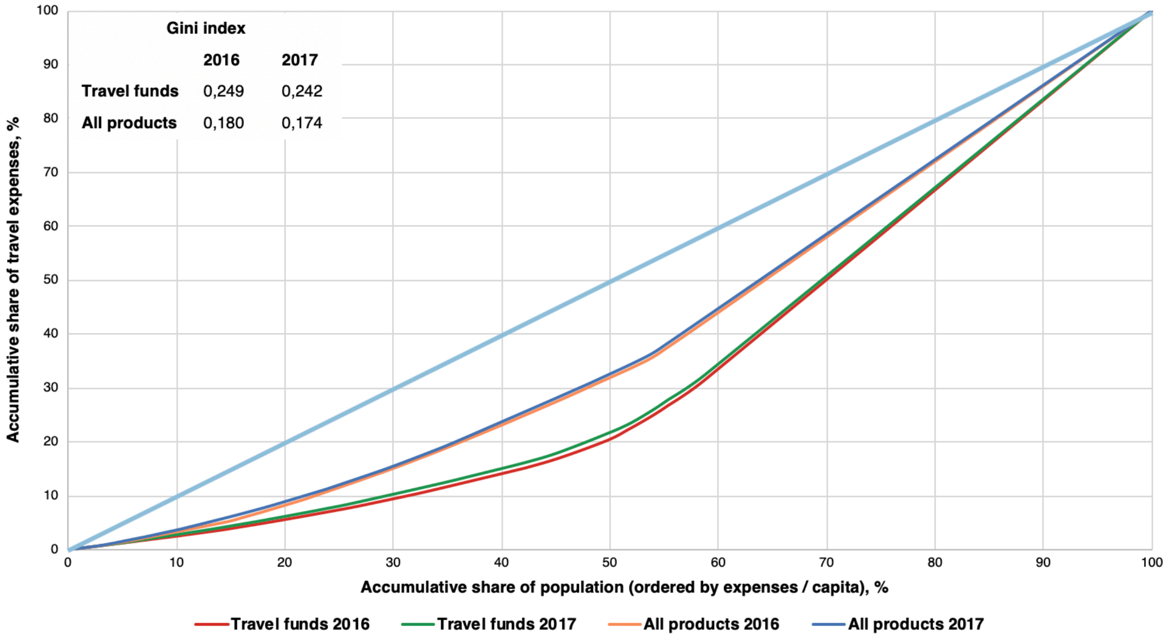


Figure 5.3: Lorenz curves for horizontal equity

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 5.4 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 can not 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.

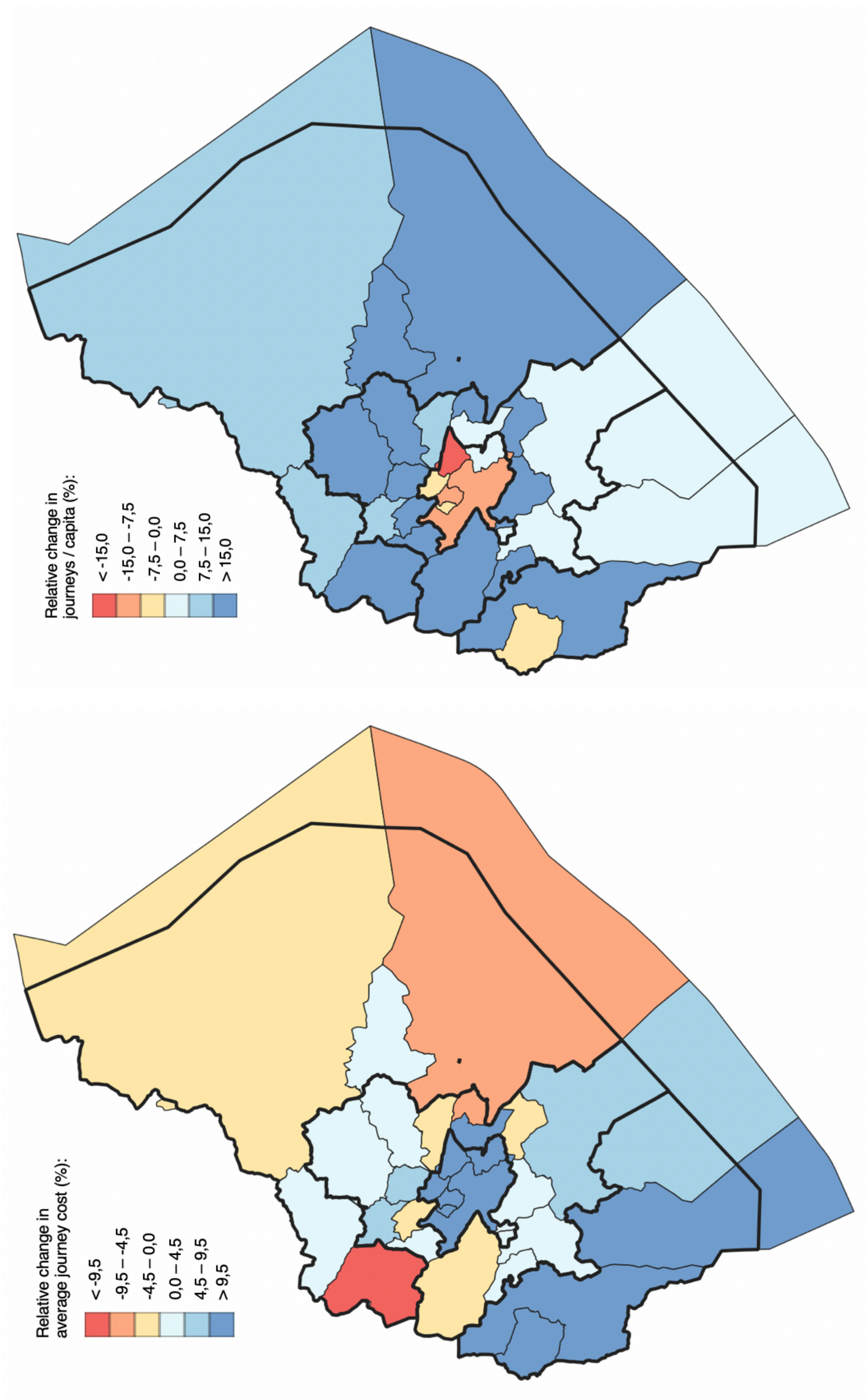


Figure 5.4: Year-on-year (2016 vs 2017) change of expenses (left) and mobility (right) at the communal level (fare zones highlighted in bold)

In terms of income category (Figure 5.5), 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 A.5, 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 behaviour, 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 equity improvements.

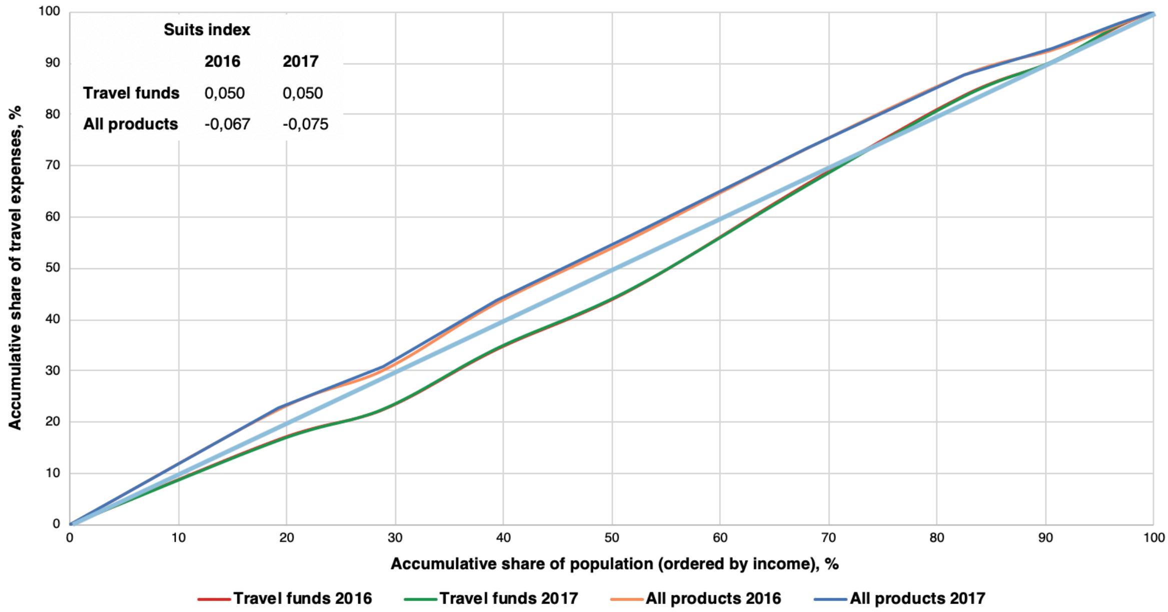


Figure 5.5: Lorenz curves for vertical equity by income

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 5.6). The indicators in Table A.5 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 equity can be establish for socioeconomic index either.

The two other factors, namely car ownership rate and distance from the city centre, pose more interest due to their diversity between user groups and temporal development. Figure 5.7 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 A.5 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.

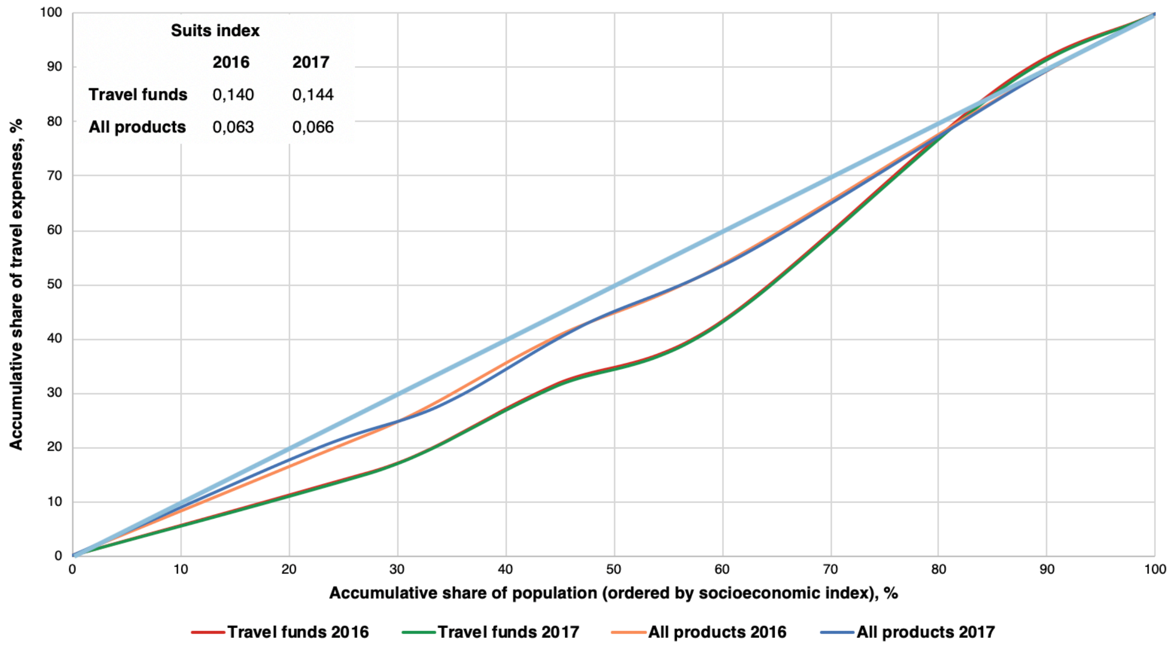


Figure 5.6: Lorenz curves for vertical equity by socioeconomic index

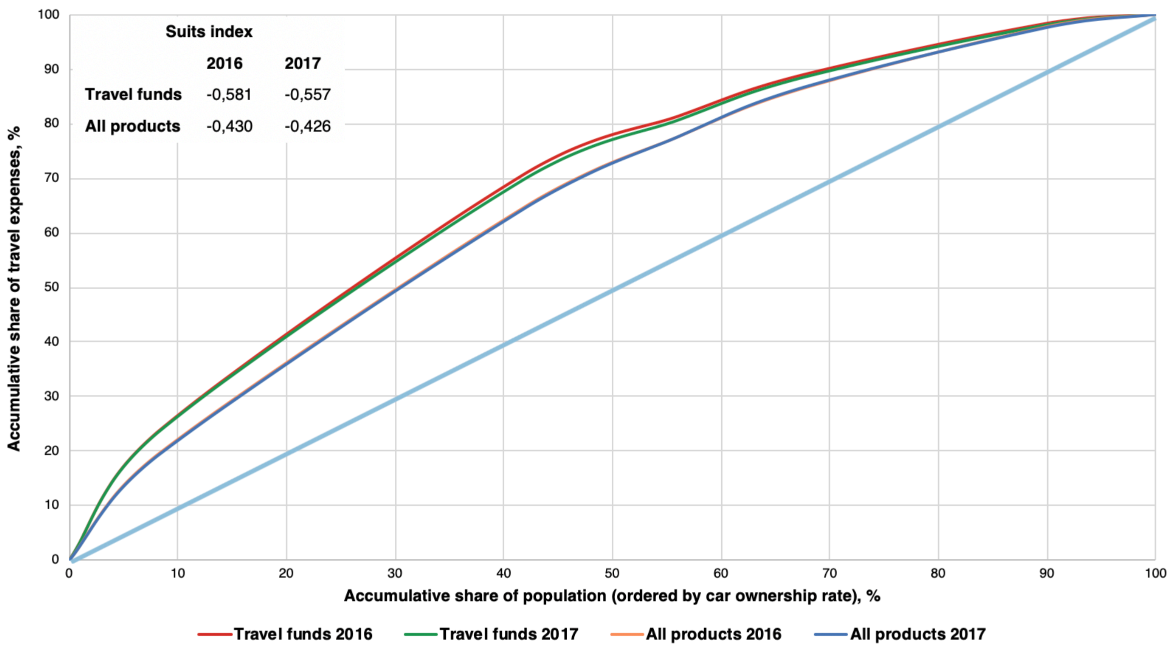


Figure 5.7: Lorenz curves for vertical equity by car ownership rate

The last factor in the equity evaluation procedure is distance from the city centre. It has a very distinct Lorenz curve (see Figure 5.8), 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 A.5 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.

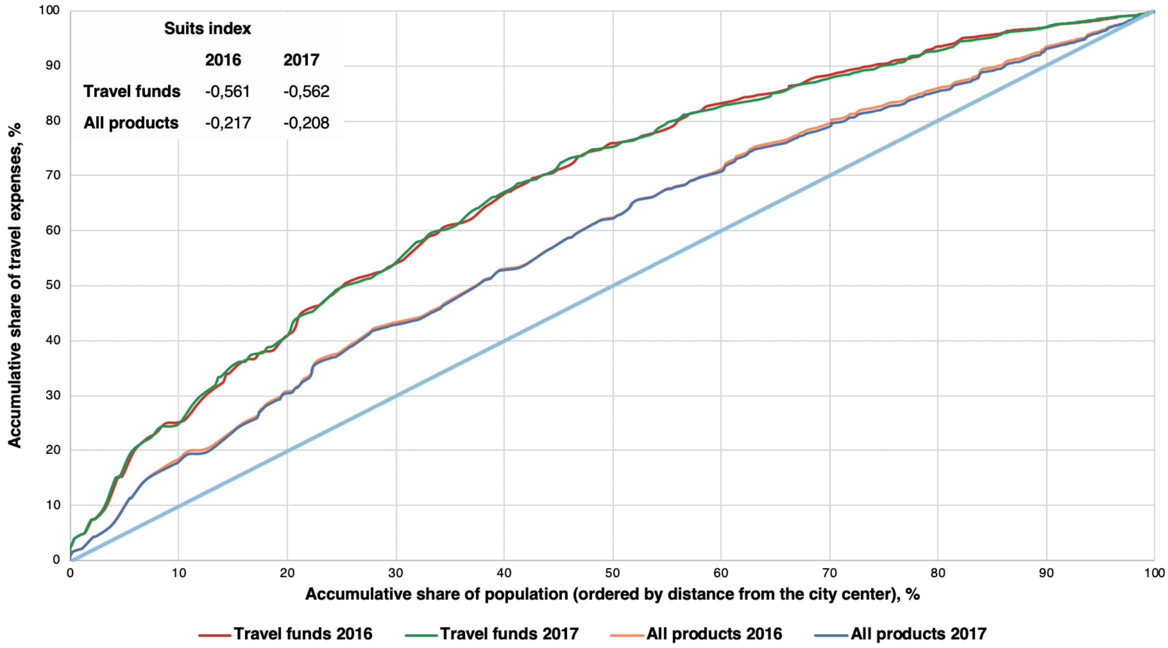


Figure 5.8: Lorenz curves for vertical equity by distance from the city centre

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 (see Figure 5.9). 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 incentivises 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 5.4, but also exhibit some differences due to the various ways of aggregation, namely zonal and radial. The former better describes localised changes, as within zone B or between the south and the north of zone C, whereas the latter elaborates on heterogeneity within one area, for instance northern communes.

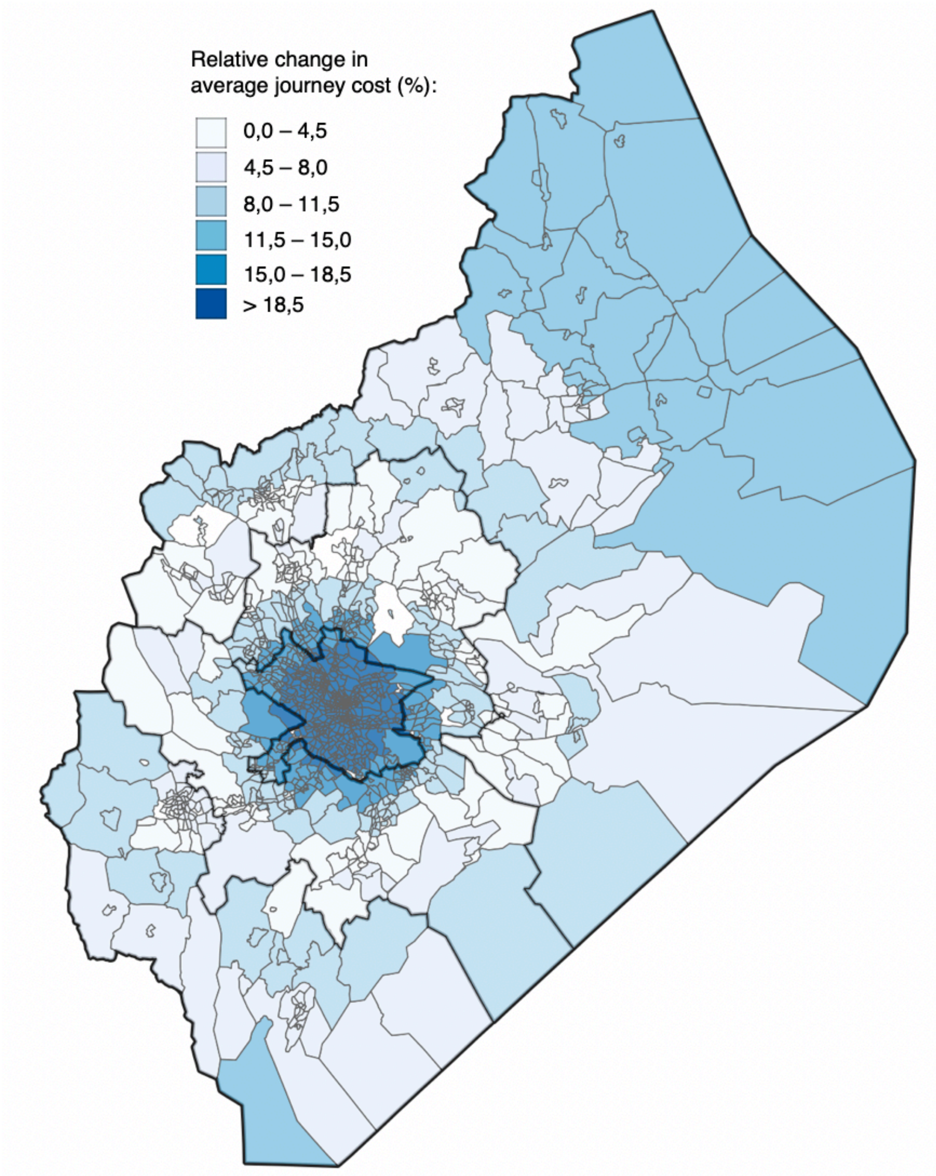


Figure 5.9: Year-on-year (2016 vs 2017) change of expenses by distance from the city centre (fare zones highlighted in bold)

5.3. Summary

This chapter delivers a fare policy evaluation procedure through a user sensitivity and equity analysis. The evaluation is performed for the travel funds product, as it got directly affected by the introduced changes. First, fare elasticity is estimated for different factors and split by fare categories (full and reduced) and the number of fare zones crossed. Looking at the elasticity values, a few important findings can be highlighted:

- The overall fare elasticity of travel funds equals -0,46, which perfectly matches with the most common value in the existing scientific framework. For most of the factors, the fit of the elasticity values into the existing research is noted to be satisfactory, as the values either match with the common averages or stay fairly close to them; the trends among each factor's user groups are generally followed.
- Groups of regular users and users with the full product are more sensitive to the fare policy for all factors, be that travel or socioeconomic ones.

- Metro users demonstrate the lowest sensitivity, followed by a slightly higher value for bus users and train riders who are by far the most sensitive.
- User sensitivity grows along with the journey distance and substantially rises after the 10-km mark; this finding correlates to the policy-predicted situation with a large number of potential travelers in fare zones B and C, where the car ownership rate increases due to the less developed public transport system.
- Sensitivity of users in time does not have a lot of variation, which can be explained by the product's specific use.
- Within the socioeconomic factors, the low-factor groups are very sensitive to price increases and do not adjust their behaviour with a price decrease (due to the already high patronage rate), whereas the high-factor groups' sensitivity is exactly the opposite (a price increase has no influence, but a price decrease incentivises traveling).
- The directionality of the price change creates a significant asymmetry, where a price decrease has a few times larger impact; this observation is contrary to the existing practice, however it clearly demonstrates the importance of travel funds' convenience brought by the fare policy.

Second, equity implications are derived through the detailed analysis of the mobility and travel expenses distribution. The analysis incorporates different factors of influence, which allows to investigate both horizontal and vertical types of equity. The main findings are:

- Generally, despite the uneven distribution of travel expenses among the population, public transport is widely used everywhere in Stockholm County. The disparity becomes larger among the users split by car ownership rate or by the distance from the city centre. Travel funds in particular has a more specific group of users (smaller number of travelers spend larger share of expenses).
- The distribution of fare expenses at the aggregate level did not get affected by the fare policy neither for the general community, nor for most of the factors (income level, socioeconomic index, distance from the city centre). Car ownership is the only factor that is found relevant to the changes in vertical equity. The distribution of expenses becomes more uniform after the policy by around 5%. Nevertheless, it is mostly caused by the higher expenses of the low-rate users. Being imposed with a higher journey cost, they reduce their travel frequency, yet still have a larger financial burden.
- At the disaggregated level, the fare policy induces a higher journey cost in zone A which directly leads to the lower travel frequency. In zones B and C, a moderate to large rise in frequency is observed, however some areas experience an increasing journey cost due to the growing share of single-zone journeys. This means that the ridership is not only promoted by the price change, but most likely by the improved convenience of the product.

The analysis of user sensitivity as well as equity effects marks the end of fare policy evaluation. All results and findings should be collected together in order to draw conclusions, answer research questions and formulate recommendations. This is done in the next closing chapter.

6 Conclusions and recommendations

This study investigated the potential of ex-post fare policy evaluation utilising smartcard data. It looked into how to identify and measure the actual outcomes of a policy, define the degree of its success, and even find some unexpected side-effects of high importance. Altogether, these insights could be transformed into lessons for designing a more advanced evaluation approach and future policy-making. The study was based on a case of the public transport fare policy introduced by the regional administration of Stockholm County in January, 2017. The policy focused on changing the fare structure basis, in particular switching from a zonal to a flat-fare scheme. The goal of the study was to determine how the policy affected the traveling behavior of different public transport user groups and what equity implications it brought. The availability of smartcard data granted by Stockholm Public Transport, together with socioeconomic data allowed to perform an extensive and detailed policy evaluation.

Data processing was performed to obtain a complete and representative dataset. It started with a combination of initial individual trip diaries into journeys through a transfer inference algorithm. Afterwards, sorting and selection were undertaken. This involved decision-making on the analysis time period, a reasonable maximum number of transfers, particular origins and destinations, modes and products. Home zone locations for individual cards were estimated to assign socioeconomic characteristics to travelers. The work also explored various travel metrics (e.g. demand split, journey length, frequency etc.) that delivered a number of insights, including the high relevance of one particular product "travel funds" to the current study. Therefore, it was decided to perform a policy evaluation for this product, as it got directly affected by the introduced changes.

The evaluation process was done through a user sensitivity and equity analysis. In the former, fare elasticity was estimated for different factors (travel and socioeconomic) and split by fare categories and the number of fare zones crossed. In the latter, equity implications were derived through the detailed analysis of the mobility and travel expenses distribution. Both horizontal and vertical equity were investigated incorporating several factors of influence. The distribution for horizontal equity implied that the general population is ordered by the expense magnitude per capita. For vertical equity, it grasped several user groups ordered by their income level, socioeconomic index, car ownership rate and distance from home to the the city centre.

Section 6.1 summarises main findings by answering the research questions and concluding on the fare policy outcomes. This is followed by a presentation of the study's main scientific and practical contributions in Section 6.2. Next, Section 6.3 reflects on research limitations, which consequently lead to a set of suggestions for future research and policy-making in Section 6.4.

6.1. Main findings

This section presents the highlights of the whole study in a form of main findings. First, it accumulates the essential information and results by answering the research questions. Second, having all outcomes together, it comments on the degree of the policy success, concluding the evaluation procedure.

6.1.1. Answers to research questions

As a result of this study, the research questions formulated in Section 1.4 are answered. The sub-questions help to gain supportive knowledge for answering the main question and are, therefore, discussed first.

1. *What were the main public transport user groups in Stockholm County to be distinguished, based on travel, geographic and socioeconomic data?*

   The literature review, in particular Section 2.3, delivered general categories of users in the field of public transport fare policy evaluation. From these, a certain set was selected that is relevant to the current study, and it included the following:

   - travel choices brought a split by products used (users of periodic, school and student passes, single-use products), fare category (users of full and reduced products) and frequency (sporadic and regular users);
   - geographic information defined a split by place of residence (26 user groups representing communes) and a split by distance from the home location to the city centre (10 user groups in the range from 0 to 60+ km with a 5 km step);
   - socioeconomic data allowed to distinguish users at the statistical zonal level with a certain car ownership rate (6 groups in the range from 0.2 to 0.6+ with a 0.1 step), income (9 groups in the range from 225.000 SEK to 400.000+ SEK with a 25.000 SEK step) and socioeconomic index (6 groups in the range from 3 to 15 with a 2 step).

2. *What were the travel patterns of the user groups expressed through metrics in the spatial and temporal dimensions, before and after the fare scheme change?*

   The estimation of travel metrics and analysis of their year-on-year change was described in detail in Section 4.5. All metrics demonstrated a high consistency among the two years, followed by a steady ridership increase of 2% for journeys and 3% for cards. Travel patterns in Stockholm County were very core-oriented, with the fare zone O/D pair A-A being extremely dominant (71% of the ridership). A significant growth (higher than average) was noted for the fare zone O/D pairs A-A, C-C, A-B and A-C. The journey composition did not exceed 3 trips for 99% of journeys and depended on the O/D combination, where directness became lower with more fare zones crossed. Every third journey in the system was a multi-trip one. The peak hours were 7.00 am to 8.45 am and 3.00pm to 5.45 pm, forming more than 40% of the entire demand and having the highest growth rate.

   In terms of frequency, three general groups of users could be distinguished: occasional users with less than 10 journeys in the analysis period (44% of cards and 8% of journeys), regular users whose frequency was between 10 and 40 journeys (38% of cards and 45% of journeys), and frequent users with up to 68 journeys (16% of cards and 39% of journeys). Almost 95% of all journeys were done within a 20 km range. The journey length was very consistent for each O/D combination: 5,0 km for one zone (A, B or C), 14,0 km for A-B, 20,0 km for B-C, and 30,0 km for A-C. Three modes, namely metro, bus and commuter train, served almost 98% of the total demand. In regard to mode combination, 60% of journeys were taken directly with metro or bus. The latter appeared most frequently in multi-trip journeys (25% of total).

Almost all cards in the system were loaded with one product only (around 91%). The top-five products formed the demand basis, namely: the 30-day pass with full and reduced fares (60% of journeys and 35% of cards); travel funds (full and reduced) with a much lower share of journeys 11%, but the largest share of cards 40%; and the general school pass (9% of journeys and 7% of cards). Full fares were more commonly used on weekdays, particularly at peak times (50% of the entire day), whereas reduced fares appeared more frequently on weekends (by 5%) and at off-peak times (by 10-20%). Different product groups demonstrated a distinct frequency: 32-35 times for subscriptions, 17-23 times for the school category, and around 5 times for travel funds. Frequency of travelling in the system had a tendency for negative growth, which appeared to be stronger in the reduced range. Most importantly, travel funds was the only product that demonstrated a non-coherent demand growth among fare zones, reaching great disparity between the one-zone O/D and the two- or three-zone O/Ds (20-60% against 0-5% for other products).

3. *What was the degree of the fare policy impact on the change in travel patterns for each user group?*

   Analysing the product split in a more elaborate manner revealed that travel funds should be chosen for the fare policy evaluation. The impact of the policy was estimated through the user sensitivity to fare change, which was expressed as the fare elasticity, namely a ratio of the change in demand to the change in price. It did not consider all other side factors that induced a natural demand growth in the background. Nevertheless, the policy effect for travel funds was found to be significant and dominant, which made the evaluation feasible yet without clear distinction of the policy share in the overall change.

   The general fare elasticity of travel funds was found to be -0,46, which means that every 1% increase of price entailed a 0,46% decrease in demand, and vice versa for the opposite sign. The group of regular users was more sensitive to the fare policy (-0,46 compared to -0,29 for occasional), as well as users with the full product (-0,57 versus -0,31 for reduced). The sensitivity of users in time did not have a lot of variation and stayed within a range of -0,43 to -0,58. The user sensitivity grew along with the journey distance starting from -0,28 for 0-1 km and -0,38 for 1-10 km, and substantially rose afterwards to -0,98 for 10-20 km and -1,19 for 20 km and more. Metro users demonstrated the lowest sensitivity -0,45, followed by a slightly higher value for bus (-0,56) and by far the most sensitive commuter train riders (-0,90).

   The directionality of the price change created a significant asymmetry, where the price decrease had a few times larger impact. The sensitivity to a price increase was -0,51 and -0,11 whilst it lied between -1,10 and -1,81 in case of a price decrease, for the full and reduced fare categories respectively. This observation was contrary to the existing practice, in which price increase usually bears a larger value. However, it demonstrated the importance of product convenience brought by the fare policy, because convenience got improved for the fare zones B and C, exactly where price decrease is observed. For the socioeconomic factors, the aggregated elasticity values were similar to the overall one. However, the low-factor groups (i.e. low income, socioeconomic index, car ownership rate) were very sensitive to a price increase and did not adjust their behaviour with a price decrease, whereas the high-factor groups' sensitivity was exactly the opposite (for exact values, see Section 5.1).

4. *What equity effects did the fare policy bring to the public transport user groups?*

   The methodology for equity assessment stemmed from Sections 2.2 and 2.3. As the fare policy affected the price of travel funds and consequently led to changes in ridership, it was decided to look into two intertwined aspects, namely distribution of product usage and travel expenses. Both horizontal and vertical equity were elaborated on. The distribution of expenses for horizontal equity implied that the general population was ordered by the expense magnitude per capita. For vertical equity, it grasped user groups ordered by several factors that distinguished socioeconomic population cohorts. For each factor, the Gini or Suits indices were computed along with the plotted Lorenz curves. For a more detailed investigation, three indicators were computed for every user group: journeys/capita, expenses/capita and the average journey cost. Eventually, by taking into account changes in the aggregate distribution along with the growth split among population groups, one could derive equity implications of a fare policy.

Looking at the aggregate distribution of travel expenses, there was no change in the degree of equity between the two years. After a more detailed analysis, it could be observed that the expenses grew for every commune, with a rate ranging from 3% to 43%. The fare policy induced a higher journey cost in the fare zone A which directly led to a lower travel frequency. In the fare zones B and C, a moderate to large rise in frequency was noted, yet some areas experienced an increasing journey cost due to the growing share of single-zone journeys. This nevertheless did not stop travelers from using travel funds more often, which was most likely promoted by the improved convenience of the product.

Car ownership was the only socioeconomic factor that was found relevant to the changes in vertical equity. The distribution of expenses became more uniform after the policy by around 5%. However, it was mostly caused by the higher expenses of the low-rate users. Being imposed with a higher journey cost (growth of 19,4% compared to 10,0% for high-rate users), they reduced their travel frequency, yet still had a larger financial burden.

With all the sub-questions answered, the main research question can be addressed, which concludes this study:

To what extent did the change from zonal to flat fare scheme in Stockholm County affect travel patterns of different public transport user groups, and what were its equity implications?

Along with a few additional changes, the fare policy mostly focused on the removal of the zonal structure for single tickets. The study confirmed that among the top-14 products in the system only travel funds (as the most popular in the single category) got directly affected by the introduced fare basis. The main changes were of a spatial nature. Travel funds demonstrated a very disproportionate growth rates between different O/D combinations of fare zones. In particular, one-zone pairs' relative growth varied between -5% to 5%, whereas for two- and three-zone pairs it stayed within a range of 20% to 70%. A particularly notable change was observed for the pairs A-A (decrease), A-B and B-A (increase). The increasing ridership was mostly formed by an influx of new cards. However, the new users took fewer journeys per card than on average, which eventually led to a slightly declining frequency in 2017.

Considering the policy impacts from the equity perspective, they fell into the horizontal domain, as there was no clear separation of effects between different user groups, but between geographic areas. Even in the case of car ownership, the change took place due to the high correlation between fare zones and the ownership rate (see Figure 5.1). The fare policy induced more journeys in the zones B and C, however also imposed a larger journey cost on some areas with a preference for local traveling. This nevertheless did not stop customers from using travel funds more often, which proved the prevailing importance of the improved convenience aspect in public transport users' behaviour.

6.1.2. Conclusions on fare policy

Ultimately, the evaluation results were compared to the SLL's policy objectives outlined in Section 1.2. Not all of the three were successfully met, as some deviation was noted from the initial prognosis. First and foremost, there was 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 in Table 1.1 appeared to be quite inaccurate compared to the actual rates found empirically. A much larger growth was 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 the 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 became the main driver of the great demand increase despite the higher journey costs, as in the case with intrazonal 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 reached a positive balance, as the ticket revenues within the analysis period grew by almost 7 million SEK or 13,5%. The distribution of travel expenses highlighted the points of attention. The highest increase in the average journey cost was observed for the fare zone A, where users mostly traveled within one zone and hence tried to compensate for the price increase by reducing the frequency of their product use. For the zones B and C, travelers used the product more often, being stimulated by its improved convenience, but ended up paying a higher price in some areas where local journeys still prevailed. Therefore, the policy contributed to the reduction of geographical disparity in terms of mobility, yet brought an additional inconsistency when it came 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 component was underestimated which resulted in the price adjustments being not in line with the mobility effects.

6.2. Main contributions

With its methodology and findings, the current study delivered certain contribution to the scientific and practical fields. From the scientific perspective, it provided an explicit workflow of public transport fare policy evaluation through an analysis of mobility and equity implications. The most important component was the investigation of user sensitivity to the fare change expressed through the fare elasticity. Moreover, instead of focusing solely on the ridership or fare levels, the work simultaneously looked into the degree of demand and fare expenses change through the lens of fair and just distribution in the society. To diversify the perspective, the bifold concept of equity was introduced, where the horizontal and vertical domains complement each other and reduced the level of bias.

In terms of the range and diversity of categories utilized, the study established a sufficient and multilayered structure. In particular, a spatial and temporal distribution of travel patterns was introduced, as well as several user groups based on the travel, social, geographic and economic characteristics. As an outcome, a large number of mobility metrics was estimated for all major categories and at different levels of aggregation, with further examination of significant impacts and trends.

When it comes to a combination of data sources, the work incorporated smartcard records as a modern and rich source of transport data. They were eventually fused with socioeconomic and geospatial sources to create a representative, detailed and reliable dataset. The workflow of smartcard data processing for fare policy evaluation is a major part of the study's overall contribution.

In the context of a small number of studies on fare policy evaluation in Europe and the Nordics, the current research has additional importance. Its methodological workflow can be used as a sequence of steps to be followed in user sensitivity and equity analysis. In addition to this, the estimated elasticity and distribution values might be considered comparable and applicable for cities of similar scale, structure and function.

From the practical perspective, the analysis of disaggregated group-specific travel data brought numerous empirical insights on travelling behavior of different users in Stockholm County. This includes origin-destination patterns, product choice, distance, and frequency of journeys, to name a few. Having an opportunity to observe and estimate these metrics, the public transport authority SL and the regional administration SLL could improve their evaluation and planning processes. For instance, the elasticity values could be used to quantify the impacts of a fare policy as well as to predict possible scenarios under alternative conditions.

Moreover, considering the increasing attention to sustainable and socially responsible policy-making in Stockholm County, equity evaluation becomes a focal point of the public transport development. The assessment of demand and fare expense distribution from various perspectives provided a facilitating input to decision-makers striving for accessible and inclusive transport.

6.3. Limitations

Despite the explicitness and valuable findings of this study, it still has a number of limitations. They stem from different elements of the work, such as system inputs, data processing and policy evaluation, have various reasons (lack of data, limited time and resources, unavailability of alternatives) and degree of impact on the results. A selection of the main limitations is presented in Table 6.1, each of them is elaborated on below.

Policy specifics

The fare policy in this study was quite narrow and focused, meaning that it directly affected only one product category - single tickets, in which travel funds was the only product with a significant ridership share. Moreover, along with the new pricing, it removed fare zones, therefore brought an improved convenience and transparency of product use. Consequently, this led to a few types of user sensitivity that could be observed simultaneously. First, travelers might have joined or left the public transport system, but also switched to another product, for instance, a subscription. Second, travelers could have reacted according to the changes in price, yet also adjusted their behaviour because of the better level of service. With the available data and methodology used, it seems rather impossible to distinguish the exact nature of user sensitivity, and thus to build clear casual connections.

Aggregation at the census zonal level

As socioeconomic data was available for census zones, the aggregation of journeys was done at the same level of detail. The analysis in this case became fairly granular and accurate, as each zone represented around 1.000-2.000 inhabitants only, yet still entailed some bias. The entire zone population was considered to be absolutely homogeneous in terms of any characteristic, which is not realistic even in very segregated communities. In addition to this, travelers might have started their journeys from a neighbouring zone (e.g. due to the location of the closest train station), thus got assigned to a wrong home location and different socioeconomics.

Non-personalised smartcards

In the public transport system of Stockholm County, most of the smartcards did not have any personal identification element, which meant they could be used not only by their owner, but a few other customers as well (e.g. one card per household). On the other hand, according to the common practice, travelers tended to have more than one card, where each of those was loaded with a different product. Eventually, the assumption that one smartcard represents one actual user can not be fully followed. Considering the fact that travel funds might have been used as a backup, it would be more logical to analyse its usage patterns in conjunction with other products at the personal level.

Initial travel diaries based on tap-in records

Because of the tap-in validation system in Stockholm County, a trip inference model was applied to prepare individual travel diaries that served as the main input for the current study. Even though the model demonstrated a robust performance with a relatively high success rate, it still incorporated a number of assumptions, such as time thresholds for trip chaining and vehicle assignment, maximum walking distance to the nearest stop (station), etc. As a result, all outcomes and findings of the study relied on the quality of this assumptions.

One-dimensional transfer inference algorithm

The transfer inference algorithm attempted to distinguish a group of specific time thresholds that helped to improve the quality of journey compilation. The split between two types of time gaps with their own defining factor (sequence of modes or journey distance) resulted in a clear clustering of gaps available in the system. Nevertheless, each cluster was built based on one dimension only which resulted in generic thresholds. There are a few more factors that have a lot of importance, such as time variation (transfers during peak hours and at late night vary significantly), station type (transfers at major hubs and local stops are incomparable) as well as the combination of mode and distance (in-vehicle travel time for busses has larger share due to lower speed).

Ambiguous identification of regular users

The home zone estimation algorithm aimed to identify regular users based on the most visited census zone. However, most of the cards with travel funds in the system were used 1-3 times a month, which undoubtedly impacted the total number of visits and their variability. Eventually, the visit frequency and home observation rate in some cases did not provide distinct results on one zone being the only home location possible. The regularity boundary was rather vague and required another assumption to set up a sensible threshold.

Fare policy as an exclusive demand-changing factor

One of the important conditions of using the shrinkage analysis in elasticity computation was the assumption of a static environment. This meant that any changes in travel patterns and user behaviour took place due to the introduced policy. The real situation is however much more complex, as it includes an ever-changing economic and demographic background along with personal development (relocation, change of occupation). Even when the policy brings a significant and observable effect, other general factors are present too. With the available data and methodology used, it was challenging to estimate the share of the policy in the overall change.

Selection of the analysis period

Because of computational power constraints, major changes of the public transport system in the second part of 2017, and some data failures, 26 days in February were selected as the analysis period. This appeared to be satisfactory, as the data of the two years were consistent and comparable, and the period duration was longer than in the common practice. Notwithstanding, the decision still had some limiting consequences. The fare policy was introduced in January 2017, so February marked only the second month of the active changes in the system. Hence, the analysis only revealed very short-term outcomes of the policy that could not account for any behavioural inertia. Furthermore, due to the imbalanced demand between fare zones, even a 26-day period appeared to be insufficient to make a robust representation of the ridership through two and three zones. This led to larger elasticity values and a slightly overestimated effect of price decrease.

Incomplete equity evaluation

The equity evaluation performed as the last part of the analysis was a fairly complicated procedure and relied on numerous factors. Some of them were mentioned before in this section and played a limiting role: the single-category fare policy, the simultaneous change in price and level of service, the relatively high aggregation level, to name a few. This study examined equity through the lens of the expenses to mobility ratio, yet both of these indicators were not the end-product of public transport usage. As an example, a user might have started taking more journeys of higher price because of the improved convenience. Even though they ended up spending more on a single journey, the new price still stayed within their affordability range, and after the policy change they could perform more activities and access new areas. Having some factors with multiple interpretations and others simply unavailable, one could not draw qualitative conclusions on equity. The study therefore provided equity implications for further consideration that are found with the available dataset.

Table 6.1: Limitations of current study

Source	Limitation	Influence	Degree of impact
System input	Policy specifics	Indistinguishable types of user sensitivity	Large
	Aggregation at the census zonal level	Homogeneous population within each zone and possibility of the assignment of wrong socioeconomics	Medium
	Non-personalised smartcards	One card does not represent one actual user	Small
Data processing	Initial travel diaries based on tap-in records	Incorrect or inaccurate estimated travel patterns	Large
	One-dimensional transfer inference algorithm	Incorrect journey compilation	Small
	Ambiguous identification of regular users	Exclusion of representative users from the final dataset	Medium
Policy evaluation	Fare policy as an exclusive demand-changing factor	Unseparated effects of fare policy from other factors	Small
	Selection of the analysis period	Analysis of very short-term effects only and overestimated elasticity results	Medium
	Incomplete equity evaluation	Impossible to draw qualitative conclusions on equity	None

6.4. Recommendations

The identified policy outcomes and limitations of this study paved the way for further research in the field of fare policy evaluation with smartcard data as well as future policy-making for public transport fares. This section sheds the light on both of these aspects which are consecutively described below.

6.4.1. Future research

In terms of recommendations for future research, two main directions can be discerned, namely methodology improvement and study extension. Both of them are described in detail below.

First and foremost, a longer time period could be chosen for the analysis under the condition that data for the two years are valid and comparable. This would bring more robust and insightful results on changes in user behaviour. Besides, the transfer inference algorithm is open for more elaborate time thresholds, which could be validated for different time periods and station types. If such correlation is observed, it becomes crucial to continue the estimation with separate time gap categories. Regarding the home zone identification algorithm and its challenge to distinguish regular users, an additional criterion could be checked upon. With this, not only the number of visits to each zone is counted, but the duration of stay in each location as well. The so-called stay-time is proven to be consistent for each user, both in its duration and the part of the day it takes place (Aslam et al., 2018). Eventually, it complements the visit frequency and significantly improves the algorithm's quality.

Another two important issues, the unseparated types of user sensitivity and the effects of the fare policy and other factors, could be tackled with the application of an econometric method. As the most common example, a regression analysis could be performed instead of a shrinkage analysis. In this case, the relationship between a set of factors and the change in ridership is expressed in a mathematical form that allows to isolate to a certain extent the impacts of each factor, including the price change. Fare elasticity computed with such an alternative method should be compared to the values of the current research in order to assess its contribution to the degree of unbiasedness.

When it comes to the extensive direction, there are a few ideas to consider. The equity implications outlined throughout the policy evaluation could be validated and supplemented with an additional study. It could for instance incorporate stated preference surveys on subjective well-being and an accessibility analysis. Furthermore, the entire data processing and evaluation framework could be organised in a more automated and user-friendly environment, such as a dashboard. This would deliver actual travel statistics and analytics for any defined period.

The outcomes of the fare evaluation methodology described in this study could be significantly improved if it is applied with another ticket validation system. First, the tap-in/tap-out validation would remove the necessity of trip diary recreation and transfer inference, thus exclude an intermediate step full of assumptions and data processing. A comprehensive set of correct journey records would become available for evaluation. Second, personalised smartcards would allow to acquire more precise information on individual socioeconomic and travel characteristics, yet to an extent that complies with the data privacy regulations (e.g. user ID, age category, area of residence).

Going beyond the boundaries of this research, the final dataset poses a great potential for the estimation of additional travel metrics and the investigation of a few other public transport system elements. It could for instance be used as a basis for vehicle crowding assessment, travel time variability analysis, development of a prediction algorithm through historical data, to name a few.

6.4.2. Future policy-making

Before the year 2017, Stockholm was the only European capital with a zonal single-use product category (SLL, 2016). The introduction of a new policy in Stockholm County that completed the uniform fare scheme built on a flat basis was proven to deliver a number of beneficial effects. The outcomes of this case could be transformed into lessons for future policy-making in Stockholm as well as in other cities of the world.

In order to further improve the SLL's fare policy, it is suggested to set a focus on the imbalanced pricing strategy. Understanding the importance of the product's service component and its direct demand effects, it would be useful to reestimate the level of the flat fare for each single-use product. The elasticity values presented in this study could serve as a starting point in the new estimation. However, for more precise results the price and service aspects of user sensitivity should be separated first (as discussed in Subsection 6.4.1). The adjusted pricing scheme would increase the product usage even more and improve the spatial uniformity of travel expenses, while staying at the level of neutrally-balanced economy.

As it was outlined previously, the study revealed a high value of public transport's user-friendliness and convenience among various user groups. Looking from a broader perspective, this could mean a potential to improve the general level of service without large investments in the physical infrastructure. Therefore, it is recommended to consider additional opportunities in the development of high-quality travel information, advanced means of payment, personalised digital services, and so forth.

Elaborating further on the Stockholm County's experience with the flat fare introduction, it suggests a policy direction for other regions. It might allow to reduce the geographic disparity of public transport travel and attract new users from remote areas who are more prone to be car owners. This policy direction nevertheless highly relies on three interconnected factors, such as the region's geography, level of public transport service and authority's political vision.

The Stockholm region is characterised by a clear single-core geographic structure that defines the major travel patterns, high variability of population density in urban and remote areas and thus the level of public transport development. This justifies the reasoning behind the fare policy, which attempts to compensate for the lower transport supply through the flat fare, rather than to relate the fare to the level of service consumption. Hence, a region with analogous specifics can consider the implementation of a flat fare scheme.

The opposite case can be represented by the Province of South Holland in the Netherlands, which plays a similar role in the country as Stockholm County and has an equivalent scale of the area. However, South Holland comprises several major cores (e.g. Rotterdam, The Hague, Leiden, Dordrecht), with complex and diverse travel patterns between them. The degree of urbanisation and population density is significantly higher, which creates favorable conditions for public transport development. As a result, the average level of transport supply is notably higher (Province Zuid-Holland, 2019). It is therefore not logical to implement a flat fare in this region, as a more categorised and user-tailored fare scheme is required.

In the case when a region appears to be suitable for a certain fare introduction, a preliminary policy investigation could be organised in the similar way as described in SLL (2016). However, the findings of this thesis should also be incorporated in the investigation procedure, including the service component of a product with the according elasticities as well as the distributional effects in mobility and travel expenses. The evaluation based on smartcard data is highly recommended on every stage of the fare policy implementation (for short- and long-term effects), which could be executed by following the relevant steps of the workflow presented in the current study.

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Appendix

Table A.1: General fare categories and according price list (SL, 2016; SL, 2019)

Fare category	Price 2016, SEK		Price 2017, SEK		Absolute price growth, SEK		Relative price growth, %	
	Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced
Periodic products								
24 hours	115	70	120	80	5	10	4,3	14,3
72 hours	230	140	240	160	10	20	4,3	14,3
7 days	300	180	315	210	15	30	5,0	16,7
30 days	790	490	830	550	40	60	5,1	12,2
30 days Bålsta	1.160	700	-	-	-	-	-	-
30 days Norrtälje	570	340	-	-	-	-	-	-
30 days Södertälje	570	340	-	-	-	-	-	-
30 days Arlanda	1.090	790	1.130	850	40	60	3,7	7,6
90 days	2.300	1.400	2.420	1.600	120	200	5,2	14,3
Annual pass	8.300	4.990	8.720	5.840	420	850	5,1	17,0
Summer pass (May 1 - August 31)	2.400	1.450	-	-	-	-	-	-
School products								
School pass (spring term)	-	840	-	880	-	40	-	4,8
School pass (autumn term)	-	670	-	700	-	30	-	4,5
School pass Bålsta (spring term)	-	1.430	-	-	-	-	-	-
School pass Bålsta (autumn term)	-	1.300	-	-	-	-	-	-
School pass (90 days)	-	510	-	540	-	30	-	5,9
School pass (120 days)	-	630	-	660	-	30	-	4,8
Leisure pass (spring term)	-	880	-	920	-	40	-	4,5
Leisure pass (autumn term)	-	720	-	760	-	40	-	5,6
Leisure pass Bålsta (spring term)	-	1.180	-	-	-	-	-	-
Leisure pass Bålsta (autumn term)	-	1.020	-	-	-	-	-	-
Leisure pass (90 days)	-	630	-	660	-	30	-	4,8
Leisure pass (120 days)	-	690	-	720	-	30	-	4,3
Summer holiday pass	-	630	-	-	-	-	-	-
Student products								
Student pass (30 days)	-	560	-	-	-	-	-	-
Student pass (90 days)	-	1.540	-	-	-	-	-	-
Single tickets								
Ticket office*, conductor (1 zone)	50	32			10	8	20,0	25,0
Ticket office*, conductor (2 zones)	75	48	60	40	-15	-8	-20,0	-16,7
Ticket office*, conductor (3 zones)	100	64			-40	-24	-40,0	-37,5
Ticket machine, app, SMS** (1 zone)	36	20			7	9	19,4	45,0
Ticket machine, app, SMS** (2 zones)	54	30	43	29	-11	-1	-20,4	-3,3
Ticket machine, app, SMS** (3 zones)	72	40			-29	-11	-40,3	-27,5
Travel funds (1 zone)	25	15			5	5	20,0	33,3
Travel funds (2 zones)	37,5	22,5	30	20	-7,5	-2,5	-20,0	-11,1
Travel funds (3 zones)	50	30			-20	-10	-40,0	-33,3
County border crossing	36	20	-	-	-	-	-	-
Arlanda pass	85	-	120	-	35	-	41,2	-
Ticket 3 zones + Arlanda pass	110	75	150	140	40	65	36,4	86,7

1 SEK ≈ 0,1 EUR; orange color indicates fare categories removed in 2017;
* - ticket office is moved to the group of machine and app payment in 2017; ** - SMS is removed as a payment method in 2017

Table A.2: Overview of monthly demand split

Month	Trips (tap-in records)						Smartcards						Trips per card			
	2016	Deviation from '16 AVG, %	2017	Deviation from '17 AVG, %	Absolute growth	Relative growth, %	2016	Deviation from '16 AVG, %	2017	Deviation from '17 AVG, %	Absolute growth	Relative growth, %	2016	2017	Absolute growth	Relative growth, %
January	55.012.362	-7,4	58.527.529	-1,4	3.515.167	6,4	17.738.099	-1,7	18.858.503	0,0	1.120.404	6,3	3,10	3,10	0,00	0,1
February	58.477.224	-1,6	58.983.352	-0,7	506.128	0,9	18.509.996	-0,4	18.649.615	-0,3	139.619	0,8	3,16	3,16	0,00	0,1
March	59.228.976	-0,3	66.721.233	12,4	7.492.257	12,6	18.717.240	-0,1	1.008	-31,8	-18.716.232	-100,0	3,16	66.191,70	66.188,53	2.091.656
April	62.870.348	5,8	56.449.613	-4,9	-6.420.735	-10,2	19.740.184	1,6	17.877.954	-1,6	-1.862.230	-9,4	3,18	3,16	-0,03	-0,9
May	60.973.747	2,6	63.315.365	6,6	2.341.618	3,8	19.193.413	0,7	19.247.837	0,7	54.424	0,3	3,18	3,29	0,11	3,5
June	53.573.731	-9,8	54.457.393	-8,3	883.662	1,6	16.007.799	-4,7	17.056.592	-3,0	1.048.793	6,6	3,35	3,19	-0,15	-4,6
July	40.953.952	-31,1	39.692.705	-33,1	-1.261.247	-3,1	13.000.761	-9,7	12.573.752	-10,6	-427.009	-3,3	3,15	3,16	0,01	0,2
August	51.923.909	-12,6	52.847.624	-11,0	923.715	1,8	16.568.552	-3,7	17.124.367	-2,9	555.815	3,4	3,13	3,09	-0,05	-1,5
September	62.827.705	5,7	60.062.151	1,2	-2.765.554	-4,4	19.890.355	1,9	19.701.719	1,4	-188.636	-0,9	3,16	3,05	-0,11	-3,5
October	64.499.959	8,6	63.124.384	6,3	-1.375.575	-2,1	20.438.440	2,8	20.763.364	3,2	324.924	1,6	3,16	3,04	-0,12	-3,7
November	63.706.164	7,2	62.971.456	6,1	-734.708	-1,2	20.421.115	2,8	20.710.037	3,1	288.922	1,4	3,12	3,04	-0,08	-2,5
December	60.458.529	1,8	55.654.587	-6,3	-4.803.942	-7,9	19.280.601	0,9	18.557.100	-0,5	-723.501	-3,8	3,14	3,00	-0,14	-4,4
Total (without March for cards)	694.506.606	-	692.807.392	-	-1.699.214	-0,2	200.789.315	-	201.120.840	-	331.525	0,2	3,16	3,11	-0,05	-1,6
Average (without July)	59.413.878	-	59.374.062	-	-39.815	-0,1	18.773.254	-	18.854.810	-	81.556	0,4	3,17	3,11	-0,05	-1,7

Table A.3: Fare elasticity results for travel funds (part 1)

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	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

Table A.4: Fare elasticity results for travel funds (part 2)

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

Table A.5: Distribution of journeys and travel expenses among population groups

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