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Impact of a New Metro Line in Amsterdam on Ridership, Travel Times, Reliability and Societal Costs and Benefits

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The north-south metro line in Amsterdam became operational in summer 2018, accompanied by changes to the existing bus, metro, and tram network in the city. In this paper we undertake an ex-post analysis of the transportation impacts of the network change. Using two sets of smart card transactions, of 5-6 weeks each, and corresponding Automatic Vehicle Location (AVL) data, a before-after comparison is made, concerning ridership, travel times, number of transfers, and travel time reliability. The results show a 4% increase in network wide working day ridership and a strong shift from tram and bus to metro. On an average working day, more than 6,000 hours of travel time is saved. 21% of travellers have more than 1 minute shorter travel time and 13% of travellers have more than 1 minute travel time increase. Furthermore, slightly fewer transfers are made, and the aggregated effect on travel time reliability is marginally positive. For an average working day (7am to 7pm), the resulting daily societal benefits of the new public transport network are approximately €54,200. On a yearly basis the transport related societal benefits are approximately 22 million euros. Doing an ex-post analysis is not common in the literature and in practice, and therefore in a lot of cases the realized benefits of large infrastructural investments remain unknown. This study provides an example of scientific methodology development using multiple data sources, that enables such ex-post evaluations, leading to improvements in public transport assessment and planning.

***Keywords**: Ex-post evaluation, public transport networks, metro, smart card data analysis, ridership, cost-benefit analysis.*

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1. Introduction

Large infrastructural projects are usually evaluated ex-ante before the decision to build the project is taken. However, after construction and opening of such projects, a thorough ex-post analysis is rare. Nicolaisen and Driscoll (2016) in their review of ex-post evaluations from around the world highlight that such studies receive much less attention from both practitioners and academics than ex-ante studies. This is remarkable, because such analysis is important to understand the mechanisms occurring after a large network change. Especially since the issue of optimism bias still remains prevalent in ex-ante analyses (Kelly et al., 2015), this kind of knowledge development is needed to be able to improve the transport system in general, and public transport (PT) system in particular, in terms of performance and efficiency. Multiple big data sources can be valuable for such work. First, we need to observe the system we study, which may lead to further understanding of it. Next step is to model the system, which enables improving predictions for the future to use when (re)designing the system.

In public transport in particular, estimating the transport benefits to the passengers is a non-trivial problem. Ingvardson and Nielsen (2018) provide an international comparison of effects of various new bus and rail rapid transit systems around the world. They differentiate between the direct operational impacts of ridership, mode-shift and travel times; and indirect impacts on the land-use and economy. Börjesson et al. (2014) provide an interesting example of an ex-post cost benefit analysis including land-use effects for the metro network of Stockholm, Sweden: over a time period of decades the influence of the metro system on the development of the city is evaluated. Adding capacity to the transport system is identified as an important benefit, while in Dutch cost-benefit analysis travel time gains are usually the most important benefits of (PT) infrastructural projects. In this paper we focus on the direct effects (travel times, reliability and transfers), which remains the primary aim of most new public transport infrastructure projects (Mackett and Edwards, 1998). In Van Oort and Yap (2020), other potential benefits of PT projects, such as increased capacity and comfort, and also wider benefits, such as economy and environment are discussed.

While the transit ridership data can typically be obtained from the operator, estimating the mode shift from private vehicles to public transport requires other data sources, including survey data (such as in Knowles (1996) and Wang et al. (2013)) and/or traffic counts (such as in Vuk, 2005) for both before and after scenarios. In most cases, the change in transit ridership and mode share cannot directly be attributed to the new transit lines, since other factors such as changes in rest of the transport network, land-use, policy etc. may have happened simultaneously. A series of studies have focussed on isolating the impact of the new lines on ridership, by comparing the changes against control area(s). For example, Knowles (1996) used control areas in their before and after surveys to isolate the impact of the new light rail system in Greater Manchester from other temporal changes. Similarly, Werner et al. (2016) also used a control group to isolate the additional ridership due to a new light rail line in the Salt Lake City, Utah, USA from mode-shift from other public transport modes. Lee et al. (2017) on the other hand compared two light rail corridors in Los Angeles, USA and found that the reduction in bus service along one of them resulted in a net decrease in public transport ridership over the years. However, the focus of these studies, and other similar ones (like Senior (2009) and Cao (2014)) was on isolating the impact of new transit lines, and for that they primarily analyse the ridership along the corridor of the new line only.

Few studies in the past have analysed the direct operational impacts of such a network change at a network-wide scale, possibly due to the absence of such data sources earlier. Recently, Fu and Gu (2018) analysed the impact of a new metro line in Nanjing, China in terms of changes in flows, travel times and travel time reliability using smart card. However, this was done at the trip level (without considering the transfers made). Arbex et al. (2019) also used historical smart card data to evaluate the impact of improvements to the late night bus network of Sao Paulo, Brazil. The study compared the changes in travel times, transfers and accessibility, and related them to the changes in demand for a large scale bus network. This study undertakes a similar before/after assessment in the context of a multi-modal transit network including transfers within and across modes.

We present the results of an ex-post evaluation study conducted in Amsterdam, capital of The Netherlands, where the new north-south metro line became operational on 22nd July 2018. Unlike some of the other previously mentioned work, this new metro line runs through the city centre replacing the previously existing tram and bus connections in the area. The changes to the whole PT network were intended to result in improvements to most routes, but deterioration to some others. Our study adds to the literature by analysing the impact of a major infrastructural change within a large scale multi-modal public transport network, on the travel patterns for all public transport travellers in the network, and monetizing these impacts. In doing so, it tackles the technical challenges with regards to the comparison across modes and time periods, such as ensuring comparable journey statistics across different smart card systems and time periods.

Since the new line serves an already transit dense area, one of the main benefits of the new line is the increased reliability compared to the existing trams which share the right-of-way with private vehicle traffic. A higher service reliability is expected to attract higher transit ridership (Chakrabarti, 2015). Despite this, as highlighted by van Oort (2016), reliability is not usually explicitly incorporated in cost-benefit analysis. In our study we include the reliability benefits to have a more comprehensive estimate of transport impacts as a result of the network changes.

The objective of this paper is to demonstrate how smart card data can be used to identify the main effects of a large infrastructural PT-project (like a new metro line) on existing and new passengers. The following research questions are to be answered to fulfil this objective.

- How do total travel numbers change and how does the modal share of PT-modes change?
- What are the aggregated travel time changes?
- How are these travel time changes distributed across the network?
- How does the number of transfers change?
- How does the travel time reliability of PT-journeys change?
- How do the above components add up to societal benefits and costs when monetized?

To answer the above, we use automated data sources: smart card data and automatic vehicle location (AVL) data, and compare the situation after opening of the metro with the before situation. The impact of the network changes is quantified in terms of travel time, transfer and reliability changes to see an overall impact. In addition, the distributional impact to different areas is also looked at. It includes all urban PT lines in the Amsterdam area, which is metro, tram, and bus. The results of the case study in Amsterdam provide valuable insights that could be useful in similar situations when designing a PT network - especially a situation where a trunk line (in combination with feeder lines) is introduced instead of a network of multiple branches of lines. The presented methods can be used in a growing number of cities or regions, since smart card systems (and therefore smart card data collection) is being introduced in more and more regions worldwide.

The outline of the remainder of this paper is as follows. In section 2 the method for data processing and analysis is described. In section 3 the case study in Amsterdam is described in more detail. Section 4 contains the results for the case study and section 5 contains conclusions.

2. Methodology

This chapter describes the applied methodology. First the data sources are described, and then the data processing. Next, the stop clustering procedure is explained. Finally, the method to monetize the effects of the infrastructural change is described.

2.1 Data sources

To answer the research questions, two sets of smart card data were analysed (for more information on Dutch smart card data, see Van Oort et al., 2015). These data sets are chosen such that the same period in the year before opening of the metro line is compared with the situation after opening (see Figure 1: 11th September 2017 - 15th October 2017 and 10th September 2018 - 21st October 2018). The 'after' data starts 7 weeks after opening, so the travellers had time to get used to the new situation. Both periods exclude school holidays in the Netherlands.

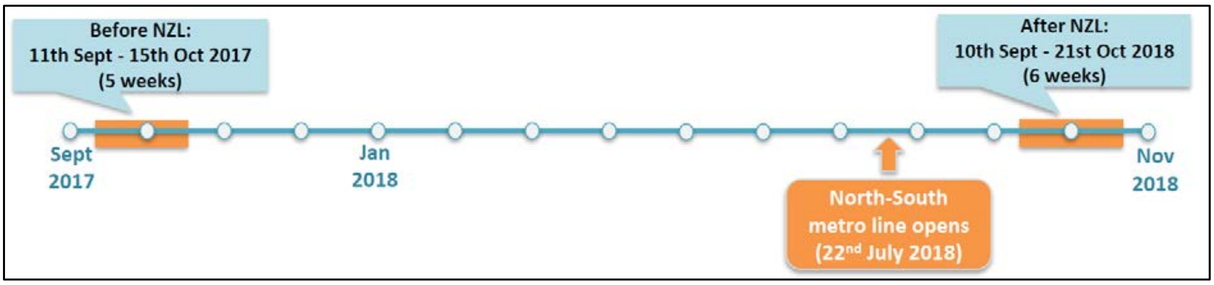


Figure 1. Time line of data collection period in relation to the network changes

The smart card data consists of individual trip transactions (tap in and tap out; approximately 700,000 per day) of all urban PT-lines in Amsterdam (operated by the urban transit operator GVB), including metro, tram and bus lines. For tram and bus, transactions from smart card devices take place inside the vehicle. For metro, transactions take place on the platform / in stations. The latter implies that transfers within the metro system cannot be identified directly from the smart card data. The following information is available per trip:

- (anonymous) smart card ID
- Check in and check out stop ID
- Line number ID (for bus and tram) and modality (metro, tram or bus)
- Check in and check out time

This implies that there is no information available in the smart card data on personal characteristics, like age, gender or journey purpose. Therefore, we cannot distinguish results based on these kinds of characteristics.

In addition to the smart card data, AVL data was used for the analysis. For all vehicle trips made in the network, AVL data provides the times at which the vehicles arrived and departed for each of the stops. The raw AVL data consists of approximately 190,000 and 180,000 records per day, respectively for the before and after periods. Before using for subsequent analysis, the data is cleaned to remove incomplete or erroneous records (4.5-5.5% in the data).

2.2 Data processing

The following steps describe the methodology used to process the data:

1. Data cleaning & fusion. This involved removing incomplete, invalid or unrealistic transactions from smart card and AVL data (~3.2% in the data). In addition, matching each smartcard transaction with corresponding AVL data was needed to obtain the realized arrival and departure times of the vehicle. The details of this step can be found in Dixit et al. (2019).
2. Destination inference. Although the Dutch smart card data provides the information on both check-in and check-out, ~3.7% of the transactions had missing check-outs. For these records, destination inference was carried out by combining the smartcard data with the

AVL data, using an existing method as described in Zhao et al. (2007). The transactions for which the destinations could not be inferred were removed from the data (~2.2%).

3. Transfer inference. It is important to analyse changes in travel patterns on the journey level (including transfers), instead of at the trip level, since many travellers will take different routes (in some cases involving an additional transfer) after a network change. Therefore, state-of-the-art transfer inference techniques were used to construct journeys, based on (Gordon et al., 2013 and Yap et al., 2017). The details of the criteria as well as the parameters used for Amsterdam case can be found in Dixit et al. (2019). The final database resulted in an average of 550,000 to 600,000 journeys per day in both before and after scenarios.

4. Waiting time estimation. In the Amsterdam metro, the check-in and check-out of the smartcard happens at the station. This means that the difference between the check-out and check-in times from the smart card measures the waiting time at the origin, the in-vehicle time for metro and the access/egress times to/from the platform and the fare gates. On the other hand, the check-in and check-out for buses and trams happens inside the vehicle, which means the travel time from smart card data only measures the in-vehicle time in that case. Current study looks at the total travel time experienced by the passenger from the time he/she arrived at the transit stop. Hence, for journeys starting with bus/trams, the waiting time at the origin is simulated and added to the travel time measured by the smart card data for each journey. Uniform arrivals of passengers to the transit stop are assumed: the waiting time is sampled from a uniform distribution between 0 and the realized headway (as derived from AVL data; with a maximum of 15 minutes). More details on this estimation are provided in Dixit et al. (2019).

The above steps result in a journey data base with the information on the total travel time for each journey – that includes the waiting time at the origin, in-vehicle time for the first leg, transfer walking and waiting times (if applicable) and in-vehicle time of subsequent legs (if applicable). These travel time components are shown in Figure 2. However, this study focuses on changes to the overall travel times and all travel time components have been assumed contribute equally to it.

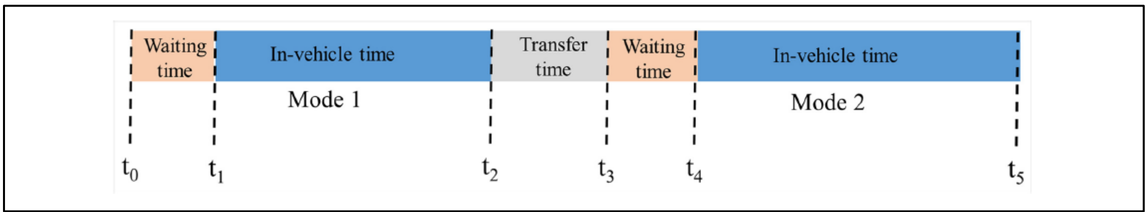


Figure 2. Components of passenger experienced travel time for a transit journey with two legs (Dixit et al., 2019)

2.3 Stop clustering

As a result of the network changes accompanying the new north-south metro line, some public transport stops are no longer used, and new stops have been added to the network in the after scenario, with the new metro stops as most important ones. In order to make the journey statistics comparable between the before and after scenarios, the public transport stops within close proximity of each other were aggregated to form stop clusters and the comparisons have been made at the stop cluster level. This was done by means of 'agglomerative hierarchical clustering' (for a general overview, see Jain et al., 1999), wherein starting with each public transport stop forming its own cluster, neighbouring clusters are merged together recursively, until a maximum distance threshold is reached between any two stops within a cluster. The clustering is expected to minimize the influence of changes in exact stop use on the results, and facilitate the ease of interpretation of results, while maintaining enough level of detail to calculate travel times and reliability. The stop clusters need to be large enough to have stop cluster pairs with enough observations for travel time and reliability calculation. On the other hand, they need to be small enough for the changes in travel time and reliability to not get averaged out.

In this paper, results are presented for an average working day, but further distinctions may be made, for example AM peak, PM peak, off-peak period, Saturday, Sunday. The following information is available for each pair of stop clusters:

- Number of travellers;
- Average travel time from stop to stop, aggregated over stop clusters. This travel time contains the following components, which may be analysed separately based on the data available from smartcard transactions:
    - In-vehicle time, where in case of the metro, this includes waiting time at the platform;
    - Waiting time at first stop (simulated for bus and tram), excluding metro waiting time;
    - Transfer time.
- Travel time variance aggregated over stop clusters, as an indication for travel time reliability. We count all deviations from the average travel time on the individual stop-stop level, and then aggregate these deviations over all stop-stop pairs in a stop cluster pair.

2.4 *Monetization of effects*

Final step in the analysis is to translate travel time savings (in time units) to monetary values using a value of time. The value of time in the Dutch context is taken from Significance et al. (2012). Additionally, transfer valuation is used to monetize the gains of fewer transfers and the burden of additional transfers. Until we receive Amsterdam specific data from survey results in our project, we use 10 minutes. This is the lower bound reported in Schakenbos et al. (2015); lower bound because the Amsterdam network mainly has high frequent services. The value of 10 minutes falls within the bandwidth for transfer valuation as reported in Wardman (2014). Finally, using a reliability ratio (also available in Significance et al., 2012), the changes in reliability / travel time variability are added to the societal effects.

3. Case study

In this chapter the case study is described in more detail. First the city and PT-network of Amsterdam are described. Next, the evaluated network change is described in more detail. Finally the stop clustering that is used in the case study is presented.

3.1 *Amsterdam and its PT network*

Amsterdam has about 850,000 inhabitants within its municipality borders. Including the surrounding areas the number of inhabitants is about 1,350,000, covering an area of about 250 km^2. Before opening of the new metro line, the area was served by 13 train stations, 4 metro lines with 51 metro stations, 15 tram lines and 25 urban bus lines. The broad river IJ divides the city into two parts, where the city centre is situated in the larger southern part (see Figure 1). The northern part of the city was only served by buses; it is also connected to the rest of the city by 6 ferry connections. All metro, tram and bus lines have the same fare system (a fixed start fare combined with a distance based fare). The ferries are free of charge, and therefore not included in the smart card data. Also, it is allowed to take a bicycle on these ferries free of charge. In fact, these ferries may be seen as a part of the bicycle and walking network rather than of the PT network.

3.2 The north-south metro line

The new metro line connects the Amsterdam Zuid station to the Noord neighbourhood, passing through the Amsterdam central station and the dense city centre. The opening of the new line was accompanied by changes to the existing bus and tram network to provide feeder services to the new line, as well as to remove duplicate routes (Stadsregio Amsterdam, 2015). Especially in the northern area, buses are now designed as feeder services for the metro line: a traveller crossing the river can now only take the metro (or ferry). Removal of duplicate routes mainly applies to tram routes in the city centre, to and from the central train station. A conceptual visualization of these network changes are shown in Figure 3. The PT networks before and after opening of the metro line are shown in detail in Figure 4.

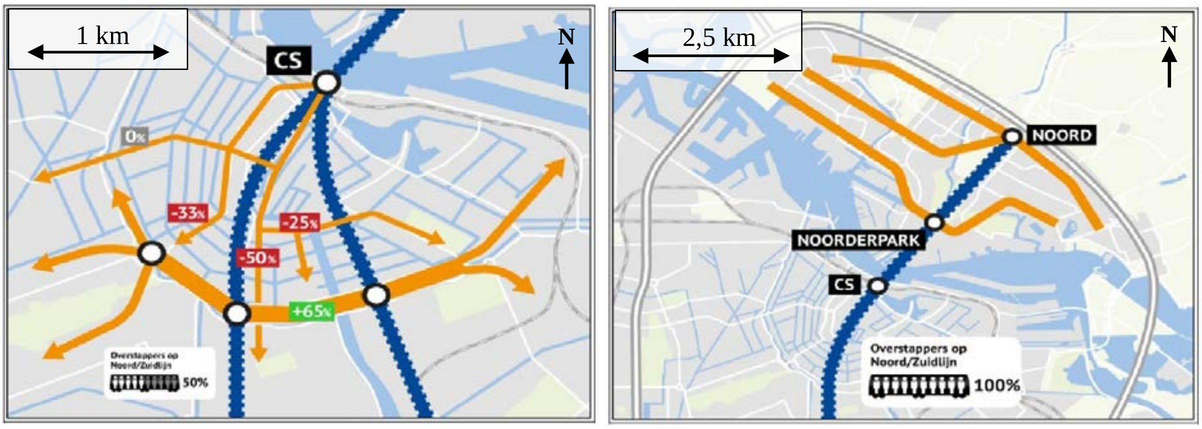


Figure 3. Conceptual visualisation of network changes in the tram network (left) and the bus network (right). Metro is shown in blue (the most Western metro line is the new north-south line) and trams and buses are shown in orange (Stadsregio Amsterdam, 2015)

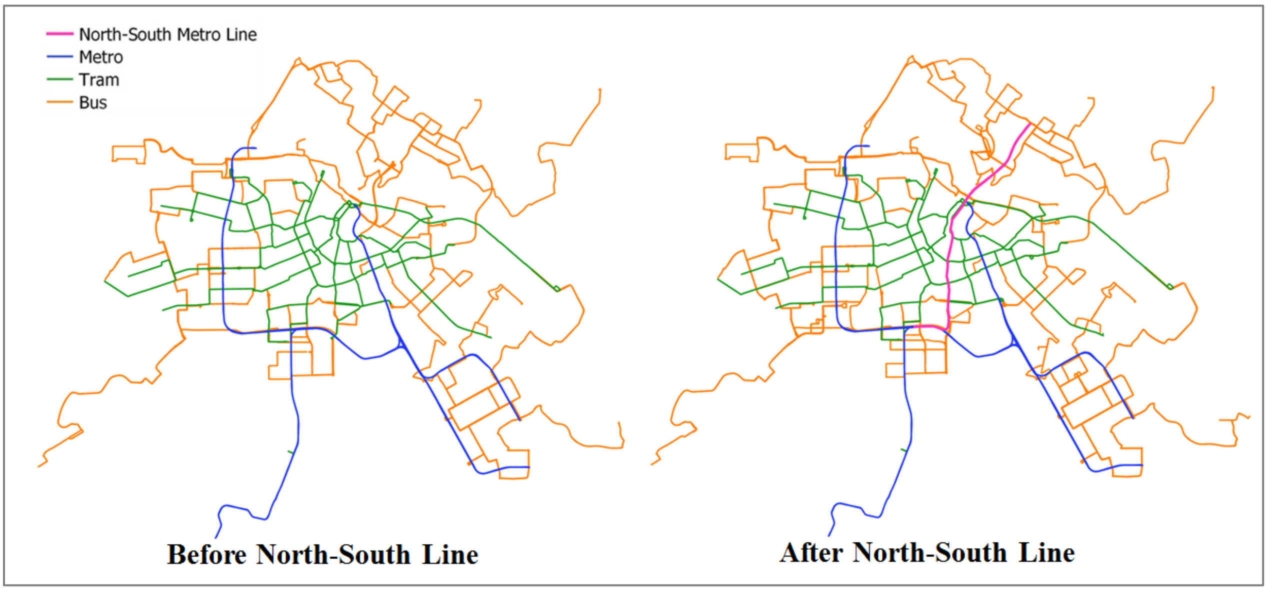


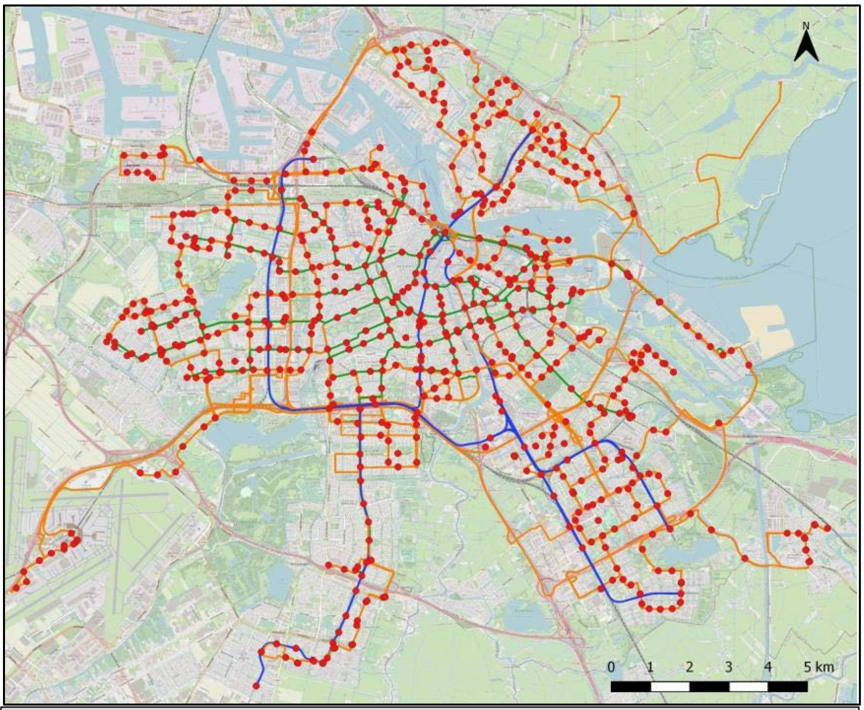
Figure 4. The public transport network of Amsterdam before and after opening of the north-south metro line (data provided by GVB)

Apart from adding significant capacity to the PT-network, the new line and the accompanying changes to the network are expected to improve travel times, reliability and accessibility (Stadsregio Amsterdam, 2015). These improvements are expected on average, not for all individual travellers. The changes in such service quality attributes is expected to lead to a change in travel behaviour in terms of PT route choice, mode choice (between PT and private modes or within PT), destination choice, departure time choice or addition of new trips (induced demand).

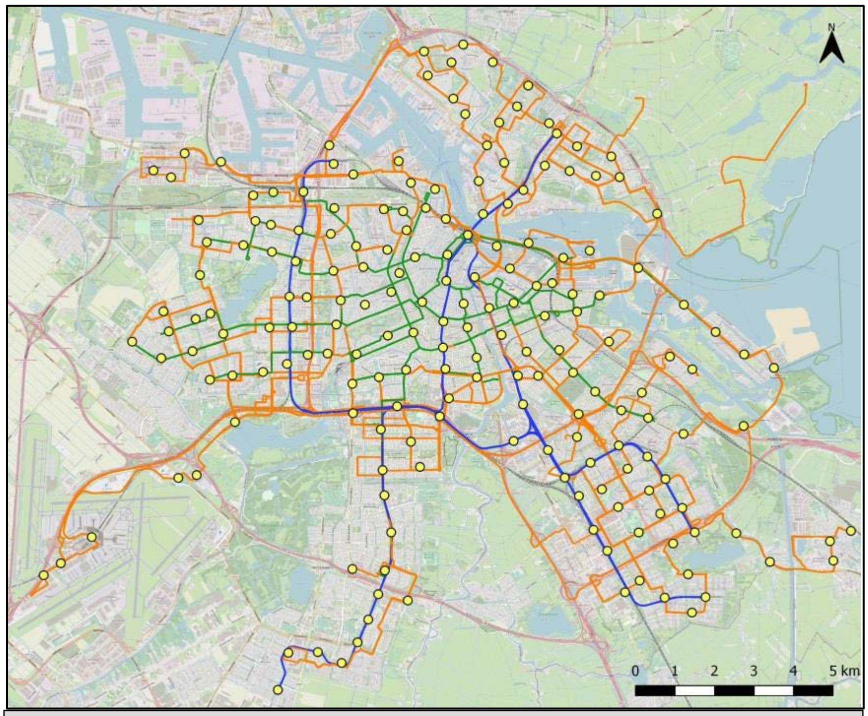
It should be noted that the 'before' analysis in this study is not impacted by infrastructure work and disruption from the new metro line, because the construction mostly took place underground, and all heavy infrastructural works were already finished.

3.3 *Stop clusters*

Figure 5(a) shows the transit stops in Amsterdam, which were clustered together based on agglomerative hierarchical clustering, as described earlier. A maximum (Euclidean) distance threshold of 750m was used for clustering to ensure compact clustering, as measured by the Silhouette score of the clusters. As a result, 651 public transport stops and stations in the city of Amsterdam were grouped into 192 stop clusters (see Figure 5(b)).



(a) Public transport stops before clustering (651)



(b) Public transport stop clusters (192)

Figure 5. Public transport stops (a) and stop clusters (b) in Amsterdam (Base map and data from OpenStreetMap and OpenStreetMap Foundation)

4. Results

In this section the results of the before-after comparison are presented. First, the effects on number of travellers are presented, including the effects per mode. After that, the effects on travel times, number of transfers and travel time reliability are shown. Finally, the effects are monetized and aggregated into social welfare effects.

4.1 Number of travellers

After the network change, total ridership in the Amsterdam PT-network (in terms of journeys) has increased by approximately 4.0% per average working day. Although the bus and tram services along the new metro line were modified, an overall positive impact on metro ridership was obtained. This is different than the observations in Los Angeles, USA (Lee et al., 2017), where a reduction in bus service along with the introduction of a new metro line resulted in a net decrease in public transport ridership. We cannot isolate the effect of the new PT-network from other developments that may have occurred in the area, like changes in number of inhabitants and visitors, changes in fuel costs or parking fares or general societal trends like possible change of attitude towards certain modes. However, the following more detailed results show that the changes of the network likely had a significant effect on ridership. New travellers may have shifted from other modes, like car, bicycle and walking, and may also be newly generated (induced demand).

The geographical distribution of ridership growth is shown in Figure 6. We can observe that the stop clusters in the city with a new metro station now produce more trips than before, indicating that ridership growth is indeed related to the line. On the other hand, some stop clusters next to the new line show a decrease in ridership, indicating that travellers have changed routes, including departure station and therefore also their access and egress leg on foot/bike. Overall, the number of stop clusters with increase in ridership is roughly the same as the number of clusters with a decrease, but a few stop clusters show a strong increase (more than 3,000 journeys), which explains the network wide increase of travellers.

If we look at the change in ridership by mode(s) used, we see a clear modal shift towards metro after the introduction of the new north-south metro line. This is shown in Figure 7, where there is an increase in journeys by metro and decrease in journeys by bus and trams. The intermodal transfers to/from metro also increase in the 'after' scenario. Especially the combination of bus, tram and metro strongly increases, but the share in total modal split remains small. It is worth noting that after the introduction of the new line, more than half of the journeys include a leg by metro – making metro the backbone of the network.

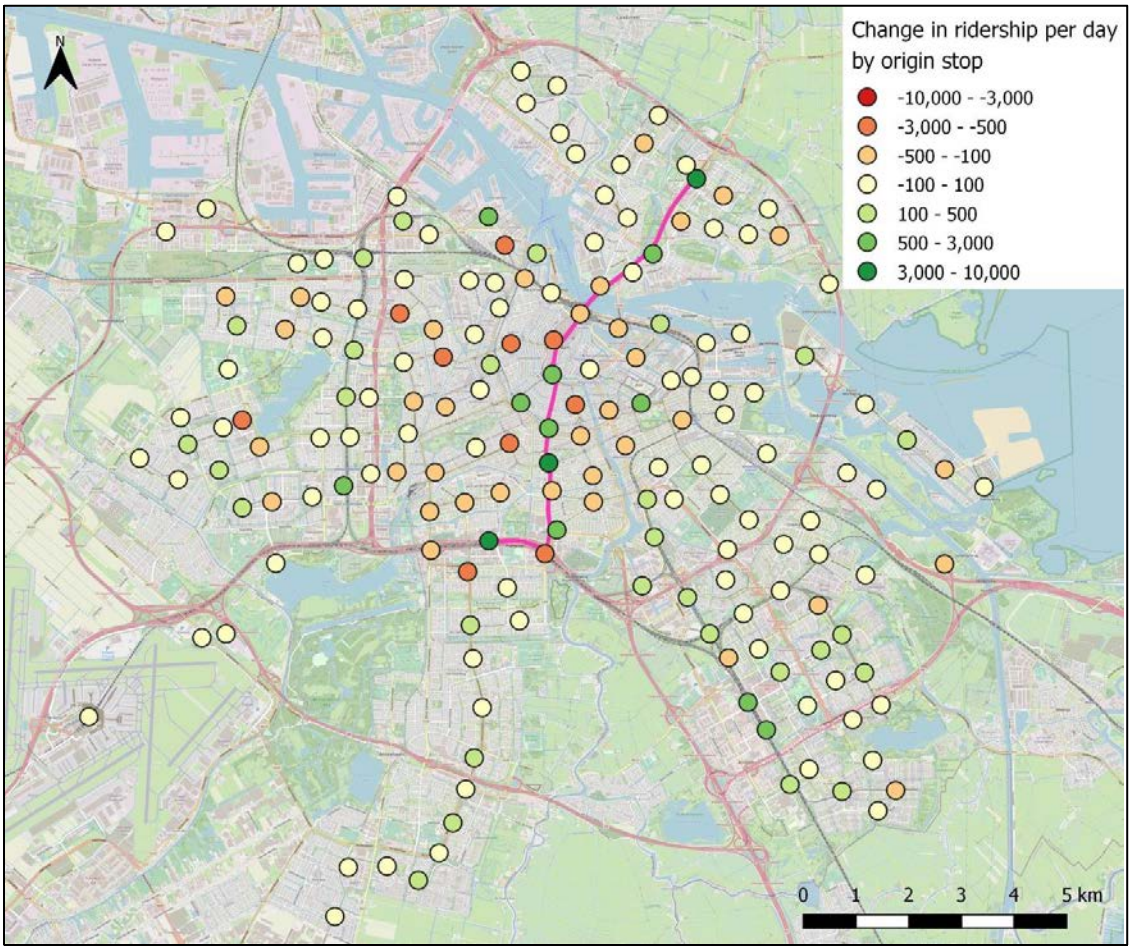


Figure 6. Ridership growth or decline per stop cluster as absolute difference in number of journeys (weekday 7am to 7pm) (Base map and data from OpenStreetMap and OpenStreetMap Foundation)

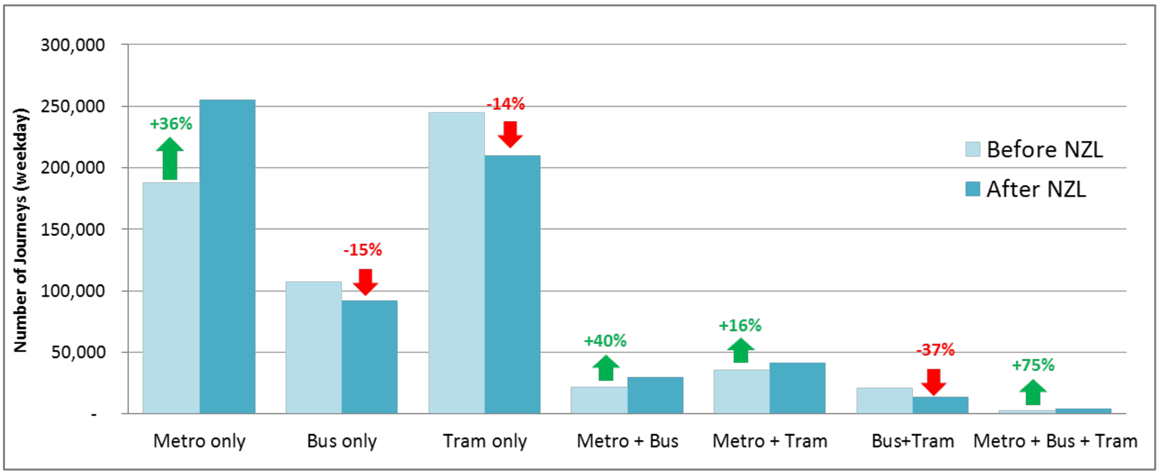


Figure 7. Change in ridership by mode(s) used

4.2 Travel time changes

From all 36,672 stop cluster-stop cluster relations, 13,373 have enough observations both before and after opening of the north-south metro line to observe the travel time in a reliably way and to comply with privacy regulations (at least 40 observations on working days between 7am and 7pm).

For each of these 13,373 relations, the difference in travel time was determined. Considering the number of travellers per relation, it is possible to determine the number of people with shorter travel times, and the number of people with longer travel times. The result is summarized in Figure 8, showing (in ranges) to which extent travellers have better or worse travel times. We note from the figure that majority of travellers in the network (approximately 70%) do not have a significant change to the experienced travel times (change of -1 to 1 mins). Amongst the rest of the population, more travellers experience a decrease in travel times, than an increase. We especially see this for a travel time savings/loss of 2 mins or more per journey, implying that the aggregated travel time savings are due to a minority of travellers experiencing high gains in travel time: almost 3% of travellers have a travel time gain larger than 10 minutes. For the 30% of travellers affected by the network changes, the average travel time gain is almost 3 minutes.

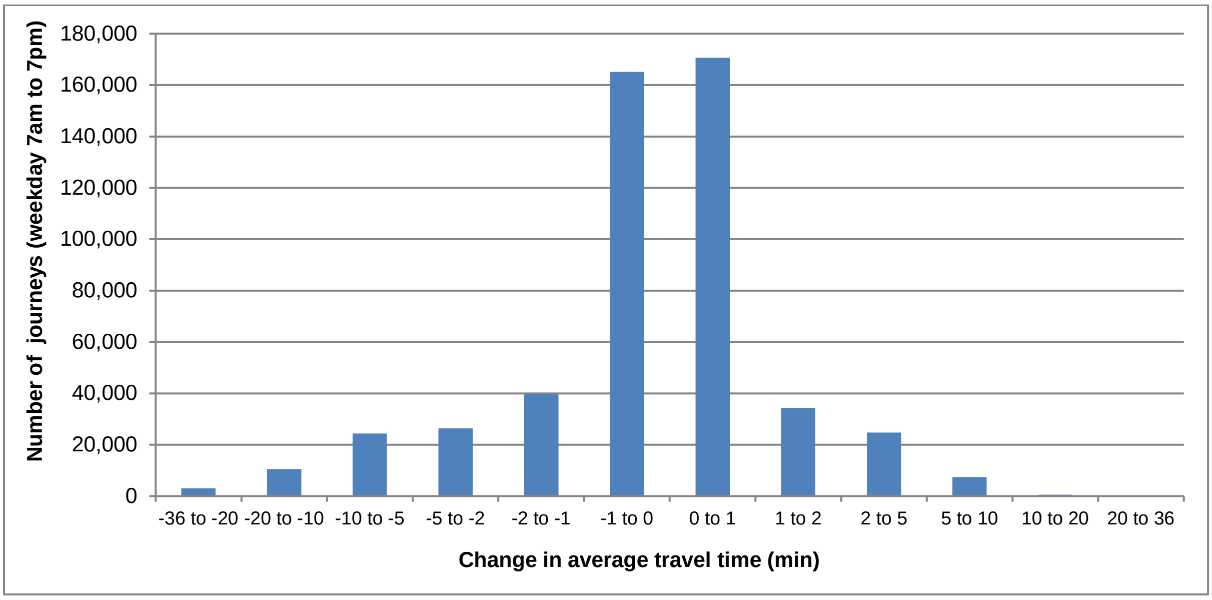


Figure 8. Distribution of travel time savings and losses over travellers

The total travel time changes are calculated on the stop cluster level, by multiplying the travel time difference by the number of travellers. Note that the number of travellers differs between the before and after situation. For existing travellers (number of travellers in the before situation) the full travel time changes are taken into account. For new travellers, the 'rule of half' is applied: for these travellers only half of the travel time changes are taken into account. The resulting network wide travel time changes (7am to 7pm period) are approximately 6,000 hours per working day.

The geographical distribution of these travel time changes is shown in Figure 9. The highest gain of travel times is found along the stops of the new metro line. From the map it can be seen that most stop clusters have benefitted in terms of travel times changes, with the decreases restricted to outskirts of the city. It should also be noted that the stop clusters in Weesp and Schiphol are mainly served by train, so the travel times by bus are less important (also because the passenger numbers are small in these stop clusters). The stop clusters right next to the new metro line have a neutral or slightly negative impact on their travel times.

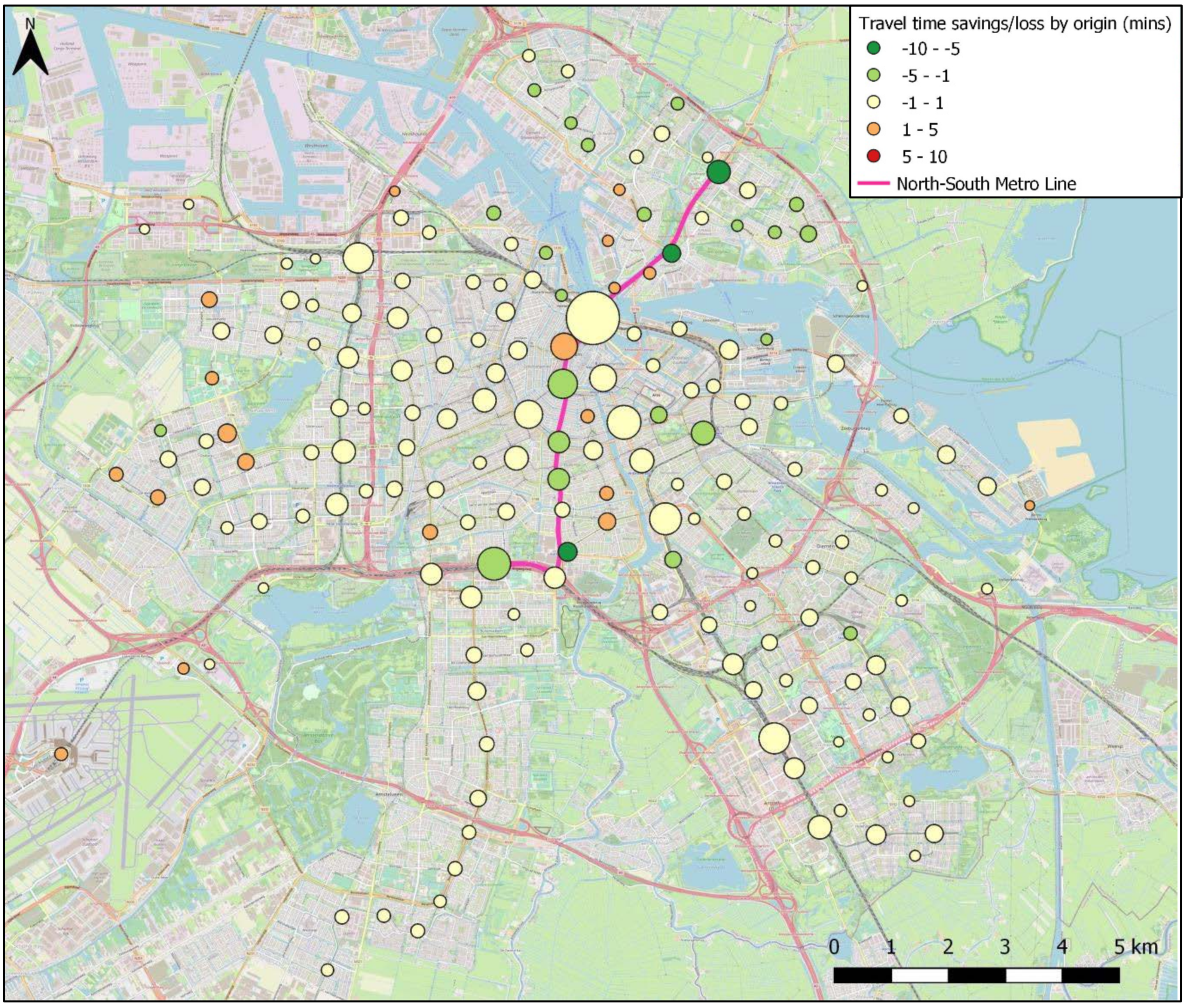


Figure 9. Geographical distribution of travel time changes by origin stop cluster (weekday 7am to 7pm) (Base map and data from OpenStreetMap and OpenStreetMap Foundation)

4.3 Number of transfers changes

Comparable with the analysis for travel time, the effect of the new PT-network on the number of transfers is determined. The result is summarized in Figure 10, showing (in ranges) to which extent travellers have more or fewer transfers. Again, we see that the vast majority of the journeys remain relatively unaffected in terms of number of transfers. However, overall there is a decrease in the total number of transfers made with a larger proportion of passengers have fewer rather than more transfers with the new network.

The aggregated effect on the number of transfers is that an average journey has 0.004 fewer transfers in the after situation, when aggregated across a working day. It should be noted that this decrease is entirely caused by new travellers: especially on those relations with a new direct metro connection, additional passengers are attracted. When only travellers in the before situation are included in the analysis, a slight increase in number of transfers (0.041 on average) is to be observed.

Figure 10. Distribution of change in number of transfers over travellers

The geographical distribution of effect on transfers is shown in Figure 11. First we observe that in most stop clusters, the effect on number of transfers is neutral. Furthermore, as expected in parts of the Noord area more transfers are made by travellers to reach their destinations. Stop clusters that include the new metro line show considerable decreases in number of transfers, probably because travellers from Noord to the city centre do not have to transfer at Central station any more. Also, the Southern stations of the new line show a decrease in transfers, perhaps due to the trip generation effect to and from these stop clusters. West of the city centre, some stop clusters with an increase in transfers appear, probably less destinations are directly (i.e. with no transfer) accessible by tram. The effects in the far West area are probably due to the changes in the bus network in that area.

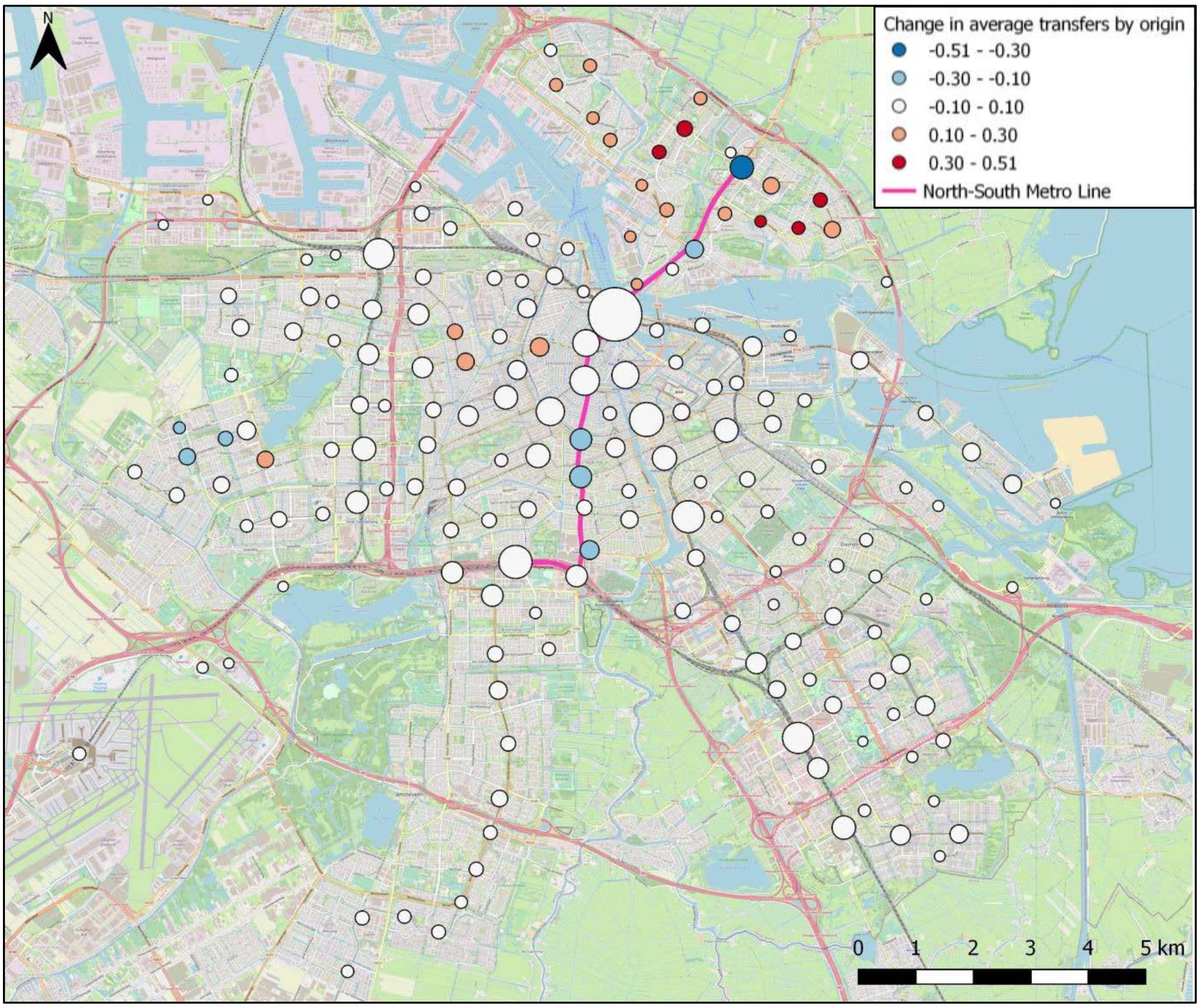


Figure 11. Geographical distribution of changes in number of transfers by origin stop cluster (weekday 7am to 7pm) (Base map and data from OpenStreetMap and OpenStreetMap Foundation)

4.4 Reliability changes

Comparable with the analysis for travel time, the effect of the new PT-network on travel time variance is determined, as an indicator for reliability of travel time. Again, we use only the day period (7am to 7pm) for this analysis. The service level (in terms of frequency) goes down significantly in the evening, hence restricting our analysis to day period excludes the variability of travel time due to different service levels from the analysis.

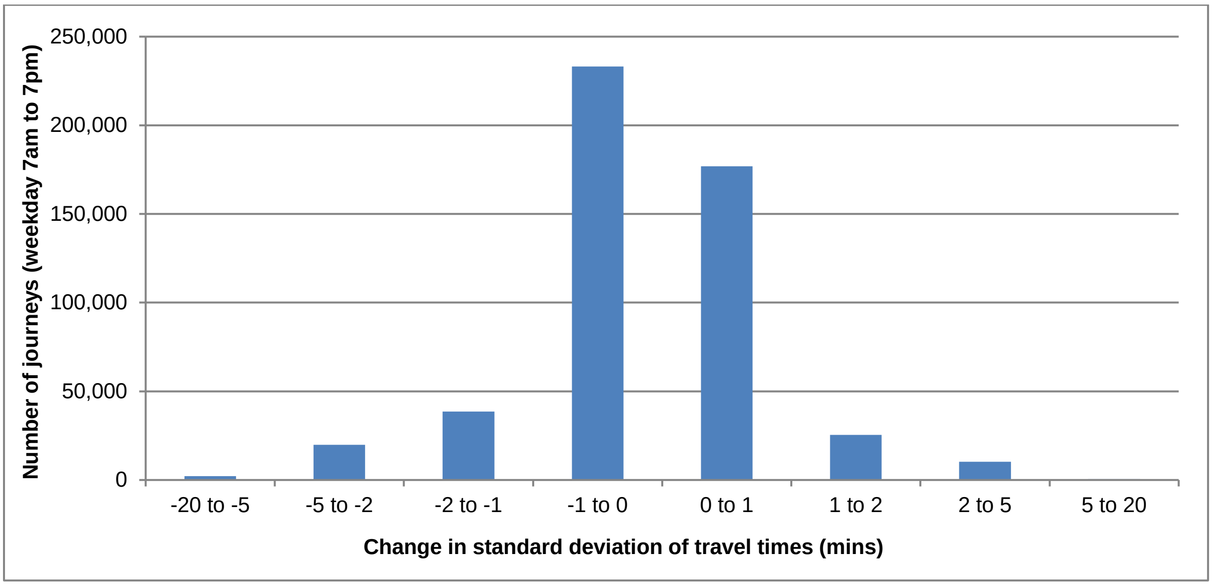


Figure 12. Distribution of change in standard deviation of travel time over travellers

Figure 12 shows the change in reliability as measured by the change in standard deviation of travel times between stop clusters. As with travel time changes, we note that majority of journeys (80%) are not significantly impacted by the network change, with a change in standard deviation of travel time of +/- 1 minute. Overall, the number of passengers facing an improvement is slightly more than the number of passengers facing a decline, making the average standard deviation of travel time per journey in the 'after' scenario slightly lower than that for 'before'. The resulting network wide reliability changes (7am to 7pm period) are approximately 1,300 hours of travel time variability per working day.

4.5 Societal benefits

In this section the travel time savings (and losses) are translated into societal benefits (and costs), including the effects of transfers and travel reliability. The aggregated travel time changes, changes in number of transfers and changes in travel time reliability are monetized using the values in Table 1. These values are taken from Significance et al. (2012), specifically for bus, tram and metro modes, and Schakenbos et al. (2015) and corrected for inflation between 2010 and 2018.

Table 1. Travel time, transfer and reliability savings translated into monetary values, using Value of Time, Value of Reliability and Value of Transfer (weekdays 7am to 7pm)

Component of societal travel costs	Savings	Monetary value per unit	Societal benefits per day
Travel time savings (hours)	6,045 hours	€ 7.62	€ 46,000
Transfer savings	1,940 transfers	€ 1.27	€ 2,500
Reliability savings (hours standard deviation)	1,343 hours	€ 4.24	€ 5,700
Total	-	-	€ 54,200

For an average working day (7am to 7pm), this results in a daily societal effect of the new PT-network of approximately €54,200, consisting of €46,000 travel time savings, €5,700 reliability savings and €2,500 savings due to transfers. These effects are the main direct effects for existing and new travellers. 20% of daily passenger number are not included in the 7am to 7pm analysis. Assuming similar benefits for those travellers, the daily societal effect (24 hours) is approximately €68,000. Using a conversion factor of 330, these benefits may be translated from average working day to yearly benefits, leading to a yearly benefit of approximately 22 million euros. Other potential benefits, such as increased capacity and comfort, and also wider benefits, such as economic and environmental benefits (as discussed by Van Oort and Yap, 2020) are not included in this analysis.

5. Conclusions

This study analysed the main direct transportation impacts of a major infrastructural change in the urban multi-modal public transport network of Amsterdam involving the introduction of a new metro line through the city centre. As expected, after the introduction of the new metro an increase in total PT ridership (4% increase network wide) is observed. A strong shift from tram and bus to metro could be seen as well. In the situation after opening, more than half of the journeys involve at least one metro leg. A geographical analysis shows that changes in access / egress patterns also occurred, since journeys were shifted from stop clusters without a new metro station to those with a new metro station.

Since the introduction of a new metro line in this case (and probably in most cases) also involves a change in the existing PT-network (consisting of buses and trams), not all effects on individual travellers are positive: 13% of travellers have more than 1 minute travel time increase, while 21% of travellers have more than 1 minute travel time decrease. Analysing the stop clusters where travellers benefit and where travel quality declines helps to understand consequences for travellers. Overall, on an average working day (7am to 7pm) more than 6,000 hours of travel time is saved.

Furthermore, in the after situation slightly fewer transfers are made, solely due to new travellers, who appear especially on OD pairs with no transfers. Almost 95% of travellers are not affected considering travel time variability / reliability. However, the aggregated effect on reliability is slightly positive.

For an average working day (7am to 7pm), the transport related societal benefits of the new PT-network are €54,200 per day, consisting of €46,000 travel time savings, €5,700 reliability savings and €2,500 savings due to transfers. On a yearly basis these benefits are approximately 22 million euros. This only relates to travel time, reliability and transfer impacts: other potential impacts, such as increased capacity or environmental and economic impacts, were not part of this study.

Doing an ex-post analysis is still not common in the literature and in practice, and therefore in a lot of cases the realized benefits of large infrastructural investments remain unknown. This study provides an example of scientific methodology development, using multiple data sources, that enables doing such ex-post evaluations especially in context of urban multi-modal networks, enabling improvements in public transport assessment and planning.

5.1 Limitations

In this study, we present the impact of the opening of a new metro line on ridership by different public transport modes. However, we have not isolated the effect of the network change from other developments that may have occurred in the area, like changes in number of inhabitants and visitors, changes in fuel costs or parking fares or general societal trends like possible change of attitude towards certain modes. As an extension to this study, it will be valuable to isolate the effect of the network change based on methods such as causal inference. This would also provide more insight in the relation of public transport with other modes, like bicycle, car and walking.

The data set after opening of the new metro line was gathered relatively soon after opening of the line. Travellers may need more time to get used to the new situation and use the full possibilities of the new network. Therefore, it would be good to repeat the analysis for a later time period in spring (2019 vs. 2018).

Smart card data does not included personal characteristics like age, gender and travel purpose. These kinds of characteristics are typically included in survey based evaluation studies. However, a drawback of survey based studies is that a survey is always limited to a sample of the population, while our data based approach measures all journeys made.

A data specific limitation concerning the transfer results is the fact that transfers within the metro system could not be identified since for metro check-in and check-out is taking place on the platform. This could underestimate the number of transfers, especially in the situation with new metro line, since then the metro network is larger. Moreover, for the monetization of transfer savings, we use a single value of transfer valuation, irrespective of the type or quality of transfer. Garcia-Martinez et al. (2018) provide mode-specific transfer penalties for Madrid, Spain, and Guo et al. (2011) look at how the transfer penalties vary as a function of transfer environment for the metro network of London. Furthermore, Cheng and Tseng (2016) relate the perceived value of metro–bus transfer service to various network properties like timetable coordination between metro and bus, passenger guidance information, comfortable waiting environment provisions, low-floor bus services, and smart card integration between the metro and buses. Such context specific transfer valuations, when estimated for our case study location, can further improve the calculation of societal costs and benefits.

5.2 Further research

It is important to note here that this analysis was conducted only for the GVB network – which is the urban PT-operator of Amsterdam. However, the outskirts of the city are also served by regional bus services, especially in the northern part which has the most significant impact in terms of travel times and ridership for the GVB network. Hence, some of this increase in ridership is likely due to a shift from the regional bus services to the GVB network – which is not captured by our data. Also the effect on the use of train services (i.e. station choice) is relevant to take into account. For future research we plan to include more PT-operators to make the analyses more complete.

Three further related extensions for future research are foreseen in the current research project. The first is to use Value of Time and Value of Transfer specifically for the Amsterdam region: in this paper general values for The Netherlands are used, while the values in the Amsterdam may be different. The second is to investigate the differences between realized travel time (as measured by big data sources) and how these travel times are perceived by the travellers, as reported by respondents in a survey. The third is to investigate equity effects of the network change by relating gains and losses in the network to socio-economic data of residents (like average income) in corresponding geographical areas.

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