Long-term impact of rail maintenance works on passenger patterns

A longitudinal analysis of individual passenger patterns in the Dutch main rail network

CIEM0500 MSc Thesis

Thijs Krijgsman van Spangenberg

Delft University of Technology

TU Delft

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A longitudinal analysis of individual passenger patterns in the Dutch main rail network

by

Thijs Krijgsman van Spangenberg

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Student number:	5596963	
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Thesis committee:	Dr. ir. N. (Niels) van Oort	TU Delft, chair
	Dr. ir. A. (Alexandra) Gavriilidou	TU Delft, daily supervisor
Company supervisors:	F.C.A (Freek) Verhoof MSc	Nederlandse Spoorwegen
	Ir. P. (Panagiotis) Spartalis	Nederlandse Spoorwegen

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Preface

This thesis marks the final work of my Master's in Civil Engineering, track Traffic and Transport Engineering. It has been written in collaboration with the network development department of Nederlandse Spoorwegen and has allowed me to investigate what has always fascinated me: how do people move through a mobility network. It was really cool to work with real data from a network that I have used throughout my entire life.

This would not have been possible without my supervisors. First of all, I would like to thank Freek Verhoof from NS. Your enthusiastic help is greatly appreciated. Your knowledge about the network, the data and your feedback helped me a lot. Panagiotis Spartalis, thank you for your critical questions and your willingness to always help. I had a great time with the both of you!

I also thank Alexandra Gavriilidou, my daily supervisor at the TU Delft. Our biweekly meetings helped me stay on track, and your knowledge and tips on how to write a thesis helped me a lot. Niels van Oort, my chair, thank you for your help in finding a thesis topic that I really liked, and your sharp feedback during the meetings. Thanks to all the supervisors for challenging me and pushing me towards a result that I am proud of.

I would also like to thank the colleagues of team *NO* at NS. I enjoyed going to the office and hearing about all the interesting projects you work on (and talking about football, of course). In addition, thank you to the colleagues in other departments who contributed to this thesis and showed their interest in my work. It was rewarding to see that my work was of value to different parts of the company.

It was also nice to share my internship at NS with fellow TU Delft students, especially Hugo with whom I spent many hours in the office working on our theses. Our discussions often led to new insights and fresh ideas for our projects, and contributed to many enjoyable memories of my time at NS. Besides, thank you Rona for your help with the front page and the countless days of working together at the TU.

Looking back, I enjoyed my time at the Master's. Thank you to Moritz, Martijn, Luke and all my other fellow TTE, MDP and DV mates, I enjoyed these last two years with you.

Finally, thanks to my family for supporting me throughout my entire time at the TU Delft and for listening to all the fun facts about transport over the years.

I hope you enjoy reading my thesis.

Thijs Krijgsman van Spangenberg
Delft, July 2026

Summary

Introduction

The rail system plays a critical role in the accessibility of the Netherlands. However, train traffic is sometimes suspended due to required rail maintenance, resulting in a train-free period, referred to as a rail possession. Recently, interest has grown in the potential long-term effects of these possessions on passenger patterns. Train passengers might find a suitable alternative during the maintenance, and continue to use it after the possession has ended. This has negative consequences for the environment and the revenue of the railway operator.

Previous studies have already found that passengers who frequently travelled by train before a (long) possession permanently reduce their number of trips. However, no studies have assessed the influence of different possession characteristics on this effect. In addition, there are no studies on the effects of these characteristics on different passenger groups. This thesis aims to fill these gaps in the literature by answering the following main research question:

Which rail possession characteristics have the greatest impact on permanent changes in passenger patterns on a specific line given the passenger group composition on that line?

Takeaway from literature

There are two types of possession characteristics that can permanently change passenger patterns: general possession characteristics (duration, length, time planning, frequency, simultaneous possessions) and passenger-dependent characteristics (quality of alternative travel options, such as the car, other public transport and the rail-replacement option).

The long-term effects of possessions can only be observed after at least two months. In this thesis, a post-possession period of six months is used, divided into three two-month periods. The passenger patterns in these periods are compared to a two-month pre-possession period, while it is also tested if passenger patterns change as time progresses.

Data analysis methodology

The analysis is performed for 23 cases of maintenance in the Netherlands. For each case, passengers who frequently use the line are analysed on an individual passenger level with pseudonymous automated fare collection data from smart cards. Passenger groups are defined based on their main subscription type (Business, Consumer, or Student) and the travel frequency (high, medium-high, medium-low, low) in the pre-possession period.

Equation 1 quantifies the change in the number of trips for a passenger i between the pre-possession period and one of the post-possession periods j. Seasonality is corrected for with the expected change in the number of trips, which is computed based on an unaffected reference group.

$$\Delta N^{\text{total}}_{i;\ \text{pre-}j} = \frac{N^{\text{total}}_{i,\ j} - \Delta N^{\text{total}}_{\text{passenger group ref};\ \text{pre-}j} - N^{\text{total}}_{i,\text{pre}}}{N^{\text{total}}_{i,\text{pre}}} \tag{1}$$

Equation 2 quantifies changes in route or station choice, comparing the Share of Trips on the affected Line (STL) among all trips between a passenger's main origin-destination zones, before and after the possession.

$$\Delta STL_{i;\ \text{pre-j}} = \frac{STL_{i,j} - STL_{i,\ \text{pre}}}{STL_{i,\ \text{pre}}} \tag{2}$$

Next, regression models are developed for the second and third post-possession periods. The base models estimate the number of trips in a post-possession period with one explanatory variable: the expected number of trips, which is the sum of the trips in the pre-possession period and the expected

change. Possession characteristics are added to these models, to determine whether they increase the model quality. This tests whether there is a long-term effect of the possessions, and which characteristics affect this. Passenger groups are added to determine whether different groups react differently to certain characteristics.

Results

Passenger patterns do not change after the possession for 21 of the 23 investigated cases. These are all of short- or mid-duration (seven days at most). Passengers return to their pre-possession travel patterns after the maintenance has ended, both in terms of travel frequency and route or station choice. However, for the two long-duration possessions (of at least eight days), passengers permanently make fewer trips than they were expected to make without the possession. This effect is larger for the Groningen-possession, which lasted 64 days, than for the Deventer-Zwolle case of nine days. For both the long-duration cases, business passengers gradually return to their pre-possession travel pattern as time progresses.

The regression models show that the addition of possession characteristics to the base models does not increase the model quality in a large way. This confirms that, in general, the investigated possessions do not have a permanent effect on passenger patterns. However, the long-duration characteristic is found to be significant: passengers make, in general, 3.59 fewer trips than expected in the second post-possession period after being faced with such a possession. Student and consumer passengers, averaging one to two tours per week, are less severely affected by long-duration possessions. Their number of trips in the second post-possession period is decreases slightly less (by 3.10) after a long possession.

Conclusion and implications

The main research question asks for the most influential possession characteristics on permanent changes in travel patterns, given the passenger group composition on a specific rail line. The duration is the only characteristic that is found to have an effect on permanent changes in passenger patterns, with long-duration possessions leading to reduced travel frequency. Therefore, there is no distinction between passenger groups about the most influential property.

However, only two possessions with a long duration are analysed. The boundary between mid- and long-duration possessions could not be adequately investigated. Moreover, the effect of other possession characteristics could not be investigated well, since the main distinction between possessions with and without permanent effects is the long duration. Therefore, more long-duration possessions should be investigated. The developed method is directly applicable to any possession in the Netherlands, and only requires small adjustments for cases in other countries.

The negative long-term effect of long possessions on travel frequency (and the corresponding lost revenue) gives reasons to consider these impacts when scheduling large maintenance projects. It is advised to divide long-duration maintenance work into two or multiple shorter possessions. Then, passengers are less inclined to find a suitable alternative during the possession, that they could continue to use, since the consecutive maintenance period is shorter. This strategy increases financial costs and requires collaboration between infrastructure managers and railway operators in order to find a system-optimum on the total costs of maintenance.

Moreover, NS and other railway operators are recommended to put more focus on the benefits of maintenance in the communication to passengers. Currently, alternative travel options during a possession are communicated, but the benefits for the passenger are not discussed as much by NS. Doing so might decrease the negative long-term effects of long-duration possessions, because passengers are informed about the advantages maintenance has for them.

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Introduction

1.1. Context and problem statement

The train is an important mode for many people to commute to work and to travel to other activities. Trains transport many people making efficient use of space. Transportation by rail requires 3.5 times less land use per passenger-kilometre than by car (European Environmental Agency, 2000). In addition, trains have a lower CO_2-emission per passenger-kilometre than electric and petrol cars (Milieu Centraal, n.d.), making it a more sustainable travel mode. The main train operator in the Netherlands is Nederlandse Spoorwegen (NS), which holds the concession to operate the train services on the main rail network of the Netherlands (Ministerie van Infrastructuur en Waterstaat, 2023). NS has used only green energy (wind and solar) since 2017 (Nederlandse Spoorwegen, n.d.-c), which further reduces the environmental impact of train travel in the country.

All together, for regional and interregional trips, it is desirable that many people use the train as travel mode instead of the private car, for sustainability and efficiency reasons. Besides, higher passenger volumes on the train lead to higher revenues for the operator, which ultimately leads to a higher quality of the network. Unfortunately, train traffic is sometimes suspended, due to required maintenance of the track. Rail maintenance often require a track possession, which is a train-free period that allows maintenance crews to work safely. Such a period is referred to as a rail possession. ProRail, the infrastructure manager in the Netherlands, tries to keep these periods as short as possible, to minimise the hindrance for passengers. Nights, weekends and (school) holidays are preferred time slots for these rail possessions (ProRail, n.d.-c). However, it is not always possible to schedule maintenance in these periods. Due to an increasing number of required construction works, ProRail expects to need more rail possessions during the day and during regular working weeks, and also longer rail possessions in the period 2026-2030 (ProRail, 2024). In 2023, 60% of Dutch train passengers experienced at least once hindrance due to a rail possession (Guis et al., 2024). This number will increase in the coming years due to the increasing number of maintenance projects. The substantial amount of necessary rail maintenance works is not unique to the Netherlands. For example, large rail possessions are also required in Germany and the United Kingdom (Kinkartz, 2026; National Rail, n.d.-a).

During a rail possession, train passengers cannot use their regular train route and need to find an alternative. This can be taking a detour by train, using rail-replacement services of the railway operator, using other forms of public transport, using a private mode, or not travelling at all, among others. Teleworking has become a popular alternative since the Covid-pandemic (Bickel et al., 2026). It is desirable that people return to the train once the maintenance period is over. However, this is not always the case, because train passengers might discover new travel options (or teleworking) and form new habits during a period of rail maintenance. This could lead to lower passenger volumes on trains after the rail possession, which leads to lower revenues from ticket fares for the railway operator, which harms its business case in the long-term. In addition, a potential increase in car traffic, caused by the modal shift from the train, leads to more pressure on the road network, with more congestion and emissions as a result. This potential modal shift from the train to other modes is especially interesting to investigate for frequent train passengers. They make the most trips, so changes in their travel patterns have the largest (negative) effect for the operator and society.

1.2. Literature gap and research questions

Much research has been done on the short-term effects of unplanned railway disruptions (e.g. Bickel et al., 2026; Currie and Muir, 2017; Lin, 2017; Mo et al., 2022; Nguyen-Phuoc et al., 2018; Saxena et al., 2019; Yap et al., 2017). The amount of research on planned railway disruptions (rail possessions) is limited. Pnevmatikou et al. (2015) analysed passenger behaviour during rail possessions. Van Exel and Rietveld (2001) suggested that railway strikes, which have comparable effects for passengers as possessions, negatively affect passengers' attitude to rail transit, which could reduce ridership. Recently, interest has grown in the long-term impact of planned rail possessions. Eltved et al. (2021) investigated the passenger volume on a rail link in the greater Copenhagen area after a rail possession of 13 weeks. Similarly, Nazem et al. (2018) studied a metro station usage after a four month maintenance period. Nijënstein and Hogenberg (2018) and Verhoof et al. (2023) investigated passenger volumes in an urban public transport network and on a specific rail line in the months after a possession respectively.

These studies have already shown that (long) rail possessions negatively affect long-term passenger volumes. However, no research has been done on the characteristics of rail possessions that influence the structural impacts on passenger patterns, since the studies investigated only a single possession each. Different characteristics (e.g. duration, length, etc.) of rail possessions are expected to have different effects on these long-term impacts. Currently, infrastructure managers and railway operators do not have insight into the long-term effects of maintenance on passenger patterns, and how different aspects of a possession relate to this. Knowledge about these relationships between possession characteristics and permanent changes in passenger patterns could be used to schedule maintenance in such a way that permanent, negative effects on passenger patterns are minimised. This benefits the train passengers (i.e. they do not have to change their preferred travel patterns due to maintenance), the railway operators (i.e. they do not lose passengers and therewith revenue), and ultimately the society, since rail transport is sustainable and relatively space-efficient compared to other modes for regional and interregional trips.

In addition, there has been no study on the effect of these maintenance characteristics for different passenger groups. The maintenance strategy could be adjusted further to the responses of the most common passenger groups on the line, in order to reduce the negative consequences for the largest group. Especially the behaviour of high-frequent passengers is interesting, because they are most prone to permanently changing their travel mode once they have found a good alternative, as suggested by Eltved et al. (2021). Moreover, high-frequent passengers are financially the most attractive for the railway operator.

Therefore, it is necessary to identify the long-term effects of rail possessions on passenger patterns and to determine the influence of different possession characteristics and different passenger groups on these long-term effects. This thesis aims to fill the gap in the literature, by analysing multiple possessions, using the Netherlands as a case study.

In short, the goal of this thesis is to find the possession characteristics that have the most effect on permanent changes in overall passenger patterns, given the composition of passenger groups on the affected line before the maintenance. This leads to the following main research question:

- Which rail possession characteristics have the greatest impact on structural changes in passenger patterns on a specific line given the passenger group composition on that line?

To answer the main question, the following sub-questions are formulated:

1. What characteristics of a planned rail possession influence passengers' post-possession travel patterns?
2. What time period before and after a rail possession should be considered when determining its long-term impact on passenger patterns?
3. How do passenger patterns of different passenger groups structurally change after a planned rail possession for selected rail possessions in the Dutch main rail network?
4. How do different passenger groups respond to different characteristics of a rail possession in the Dutch main rail network?

The first two research questions are initially answered through literature, while the other two research questions are answered through data analyses and the development of a regression model.

A comparison will be made between the travel patterns of individual passengers, who are affected by the maintenance, before and after the rail possession. This is done using Automated Fare Collection (AFC) data, provided by NS. The data are available at a pseudonymous passenger level, so it can be determined if a person who travelled on a certain rail section before it was closed for maintenance, also travels on it once it is opened again with a similar frequency. However, personal information like name, OV-chipkaart number, age and gender is not known, so travel patterns cannot be linked to an individual, to comply with privacy regulations.

In short, it is determined if the passenger returns to his or her old travel pattern. Combining this information with the characteristics of the rail possession and the passenger groups gives insight into the effect of different characteristics on the long-term impact on travel patterns. The methods for the latter two sub-questions are explained in detail in Chapter 3. This two-fold analysis on individual passenger patterns and how they are affected by maintenance properties has not been done before. Therefore, this thesis contributes to the existing field of research by developing a method that can be applied by railway operators in different countries.

1.3. Nederlandse Spoorwegen and ProRail

Nederlandse Spoorwegen (NS) is the main railway operator in the Netherlands. It has the exclusive right to operate train services on the Dutch main rail network, shown in Figure 1.1. NS currently has the concession for the main rail network for the period 2025-2033, awarded by the Ministry of Infrastructure and Water Management (Ministerie van Infrastructuur en Waterstaat, 2023). The company NS is organised according to private law, but is fully owned by the Dutch government (Van de Velde & Röntgen, 2009). The Ministry of Finance is the only shareholder of the company (Nederlandse Spoorwegen, n.d.-d).

Figure 1.1: Main rail network of the Netherlands in red. Adapted from NOS (2023)

NS is not responsible for the infrastructure, because the railway operator and infrastructure manager are vertically separated in the Netherlands, which was implemented to facilitate fair competition for track allocation, required by the European Union (Van de Velde & Röntgen, 2009). ProRail is the infrastructure manager in the Netherlands. ProRail is also organised according to private law, and fully owned by the Dutch government (Van de Velde & Röntgen, 2009). The Ministry of Infrastructure and Water Management is ProRail's only shareholder (ProRail, n.d.-a). One of the responsibilities of ProRail is the scheduling and execution of maintenance works. ProRail collaborates with contractors for the latter (ProRail, n.d.-b).

The rail market is organised similarly in other member states of the European Union. For example, Infrabel is the infrastructure manager in Belgium, while NMBS is the national railway operator (Infrabel, n.d.). Likewise, RFF and DB Netze are the infrastructure managers in France and Germany, respectively, while SNCF and DB Mobility Logistics are the railway operators (Van de Velde, 2015). Therefore, rail maintenance works are also not the responsibility of the railway operator in these countries.

1.4. Scope

The scope of this thesis is bounded to planned rail possessions for maintenance. This section discusses aspects related to planned possessions that are beyond of the scope of this thesis.

Short, unplanned incidents, such as temporary power outages and signalling failures, are excluded in this thesis. Due to the limited duration, these stand-alone incidents are likely not to have a long-term impact. Moreover, the findings related to the effect of different characteristics (of the possession) would not be useful, since incidents are, by definition, unplanned and their characteristics cannot be chosen.

There are also long, unplanned disruptions, for example due to train derailments, accidents on rail crossings, or emergency maintenance works (e.g. NOS, 2026; ProRail, 2023). These disruptions are similar to planned maintenance, but different in nature (i.e. passengers do not have full knowledge about it in the first hours or days after the disruptions starts). These disruptions are considered as incidents and are therefore excluded from this thesis. Moreover, findings on the effect of different characteristics are again not useful, since incidents cannot be planned. However, the method for deriving the long-term effects of maintenance on passenger patterns that is developed in this thesis, is also applicable to long, unplanned disruptions.

There are two types of planned possessions. The first type includes routine, short possessions, for example for inspection of the tracks and small repairs. This type of work is usually carried out during the night. The second type considers irregular maintenance or other larger projects that need to be carried out less frequently (De Weert et al., 2024). This thesis only considers the second type of planned possessions for maintenance and improvement of the network. This means that only rail possessions of at least one day (24 hours) are considered in this thesis. Maintenance with a shorter duration likely takes place during the night (first type of possession), with limited effect on passengers. Therefore, these possessions are not relevant for this study.

A rail possession could be a line closure or a station closure. This thesis only includes possessions where there is no train traffic in both directions. Train traffic has to be blocked between two stations; the length of the possession is not a selection criterion. Station closures are included in this thesis, and considered as separate line closures.

This thesis only considers frequent train passengers to possessions. These passengers make the most trips, and are, therefore, most interesting to investigate. Changes in their passenger patterns potentially have a large impact on overall ridership of the train, and thus the positive externalities of train travel and the railway operator's revenue. Moreover, a regular (frequent) travel pattern by train needs to be established to be able to determine whether someone changes his or her travel pattern permanently due to maintenance.

In addition, it is beyond the scope of this thesis to determine the alternative modes that regular train passengers use during and after (if they do not return to the train) a planned rail possession. This would require data from other sources (e.g. bus operators, highway vehicle counts and mobile phone providers), which are not available for this thesis.

Finally, the case study of this thesis only includes planned possessions on the main rail network of the Netherlands, where NS operates train services. The pseudonymous individual passenger records are only stored by NS for 18 months, according to Dutch privacy law. For this thesis, data are only available for a 15-month period; from January 2025 until March 2026.

1.5. Outline thesis

The remainder of this thesis is structured as follows. Chapter 2 includes the literature chapter. In this chapter, the literature gap is explained in more detail and the first two research questions are answered. Thereafter, Chapter 3 introduces the methods that are used to answer the next two research questions. Chapter 4 covers the case study to which the methods are applied. It includes the additional steps that need to be taken to apply the study on the Dutch main rail network, and gives an overview of the investigated possessions and passengers. Next, Chapter 5 gives the results of the analyses. This includes an overview of the permanent changes in passenger patterns after the investigated rail possessions, and the final regressions models that are developed. The implications of the findings of this thesis are given in Chapter 6, which also discusses the limitations of the study. Finally, Chapter 7 presents the conclusions of the thesis and gives recommendations for practice and science.

2
Literature review

This chapter is structured as follows. Section 2.1 lists the search terms and data bases that are used for the literature review, both for the literature gap and the first two research questions. Section 2.2 then presents the literature gap for this thesis and finds relevant methods. Thereafter, Section 2.3 covers the rail possession characteristics that influence the post-possession passenger patterns, and therewith answers the first research question. The required time period for the analysis is found in Section 2.4, as well as the effects of seasonality.

2.1. Search methods

This section gives the search terms used in the literature review. ScienceDirect and Google Scholar are used as data bases. In addition, the repository of the *Colloquium Vervoersplanologisch Speurwerk*, a Dutch conference on transportation, is also used. The reference list of relevant articles is used to find more articles (snowballing principle).

The selection of papers is made based on the relevance of the title and the abstract. First, the literature gap and the identification of relevant methods is covered, followed by the first and second research questions.

2.1.1. Literature gap and relevant methods

The literature gap is already discussed in Section 1.2, but discussed in more detail in this chapter. The following questions are used to find the literature gap and to find methods that are used in similar studies:

- What research has already been done on the effect of railway disruptions or rail possessions on passenger behaviour or passenger numbers?
- What methods are used to determine the long-term impact of railway track closures on passenger volumes?

The following search terms are used:

- (“rail possession” OR “rail disruption” OR “service disruption”) AND (ridership OR “passenger behaviour”) AND “long-term effects”
- (“unplanned rail disruption” OR “unplanned rail service interruption” OR “rail network perturbation” OR “rail service disruption”) AND (“route choice” OR “mode choice” OR “passenger behaviour” OR “travel demand” OR “passenger response”)

Unplanned rail disruptions are also considered in the literature review, because studies on them likely cover relevant passenger behaviour and relevant methods.

2.1.2. Possession characteristics

Next, the first research question – “What characteristics of a planned rail possession influence passengers’ post-possession travel patterns?” – is answered by literature review. The result is a conceptual framework that visualises the relationships between characteristics of a rail possession and the passenger patterns before and after the rail possession. These characteristics are later used in the data analyses to answer the fourth research question. Other aspects, that are not related to the rail possession, but that have an effect on potential changing passenger patterns, are included as well. The characteristics have to be mutually exclusive and collectively exhaustive.

Identified characteristics might not have an effect on the post-possession passenger patterns, which would become apparent when analysing the impact of each characteristic on the long-term passenger patterns in the fourth research question with data.

It is not expected that there are (many) studies that mention different characteristics of planned railway possessions, because this is a new field of interest. Therefore, studies on unplanned disruptions are also considered to determine potential influencing factors of railway possession on the passenger return rate. Characteristics of an unplanned disruption that influence passenger behaviour in the short-term probably also have a long-term effect.

The same articles on unplanned disruptions as before (for the literature gap) are used to identify potential influencing factors, with the following search terms:

- (“unplanned rail disruption” OR “unplanned rail service interruption” OR “rail network perturbation” OR “rail service disruption”) AND (“route choice” OR “mode choice” OR “passenger behaviour” OR “travel demand” OR “passenger response”)

The studies on planned possessions that are found in the process of identifying the literature gap are also used for this part. These studies might suggest how different characteristics influence passenger behaviour, although it is not investigated in these studies.

2.1.3. Time period

The second research question – “What time period before and after a rail possession should be considered when determining its long-term impact on passenger patterns?” – is also answered by a literature review. The literature review results in the ideal time period, but the data availability is also a limiting factor in selecting the final time frames. In addition, the required time period can be changed after performing the data analyses in the third research question, if the period is deemed too long or short, for example if the passenger patterns are fluctuating a lot in the selected time period.

The answer to this question is required for a correct analysis, but also for the selection of possessions that are used in this thesis. AFC data need to be available for the entire period that should be considered. The time period before the possession is required in order to select passengers that regularly use the line before a possession and to determine their original travel patterns.

The result of this literature review could also be multiple post-possession time periods, for different order effects. There is only one pre-possession time period.

The review aims to answer three questions:

- What time periods before and after a rail possession are used in similar studies?
- After which time period are changes in passenger patterns considered to be permanent?
- What are the usual seasonal variations in passenger patterns and how should they be included in this thesis?

The first question on this list is answered using the studies found to define the research gap. These studies are also used to answer the second question in the list.

The following search term is used to answer the third question on the list above:

- “seasonal variation” AND (“passenger behaviour” OR “passenger pattern” OR ridership OR “passenger volume”) AND (AFC OR “smart card data”)
- “seasonal variation” AND “passenger volume” AND “public transport” AND “time-series”
- “smart card” AND “longitudinal analysis” AND behaviour AND (pattern OR habit)

Based on the literature and data availability, the time period(s) for investigating the long-term impact of rail possessions on passenger patterns in this study is selected.

2.2. Literature gap and relevant methods

This section covers the existing body of literature on passenger behaviour during and after rail disruptions. This section aims to explain the literature gap in more detail, and to find methods for this thesis. The gap is already discussed in Section 1.2, but discussed in more detail in this section.

Much research has been done on the short-term effects of unplanned railway disruptions (Bickel et al., 2026; Currie & Muir, 2017; Lin, 2017; Mo et al., 2022; Nguyen-Phuoc et al., 2018; Saxena et al., 2019; Yap et al., 2017). The amount of research on planned railway disruptions (rail possessions) is limited. Pnevmatikou et al. (2015) analysed passenger behaviour during rail possessions. Also, Van Exel and Rietveld (2001) suggested that railway strikes negatively affect passengers' attitude to rail transit, which could reduce ridership. Recently, interest has grown in the long-term impact of planned railway possessions. Eltved et al. (2021) investigated the passenger volume on a rail link in the greater Copenhagen area after a rail possession of 13 weeks. Similarly, Nazem et al. (2018) studied the metro station usage after a four month maintenance period. The remainder of this section covers the findings and methods of these and other studies.

Surveys are a common method for investigating the effects of public transport disruptions. They are used to determine satisfaction levels among passengers (Currie & Muir, 2017), to model passenger behaviour during a disruption (Currie & Muir, 2017; Lin, 2017; Saxena et al., 2019) and to compute the impact of public transport disruptions on congestion levels (Nguyen-Phuoc et al., 2018). Recently, Bickel et al. (2026) used a survey to investigate passenger behaviour during short, unplanned disruptions, also considering the option to telework, which has become a more popular alternative since the COVID pandemic. Revealed preference (RP) is often combined with stated preference (SP). Characteristics of respondents and their public transport usage are first inferred with RP, after which behaviour in hypothetical situations (service disruptions) is determined with SP (Lin, 2017; Saxena et al., 2019).

Other studies used a smart-card data-driven approach to investigate passenger behaviour during an unexpected rail disruption. Mo et al. (2022) developed a probabilistic framework to determine passenger responses during an unexpected disruption using historical and future smart-card check-in data in a metro system (Chicago, USA). Sun et al. (2016) analysed the behaviour of urban rail users during short disruptions in Beijing using AFC data and Yap et al. (2017) developed a transfer inference algorithm for journeys during a rail disruption by combining AFC and Automatic Vehicle Location (AVL) data.

Unexpected rail disruptions can last for a long period of time. These are similar to maintenance works in terms of duration and impact. After some time, passengers are informed about these situations, and can adapt their travel plans, as they do for regular maintenance. For example, the Hanzelijn between Lelystad and Dronten in the Netherlands was blocked for over three months because a high voltage cable unexpectedly fell on the catenary system and destroyed the electrical systems of the rail line. AFC data were used to investigate travel behaviour during this rail possession. Four months after the Hanzelijn opened again, demand was at the same level as in the year before. However, passenger numbers had increased with 15% nationwide, which could indicate that there is a permanent impact of the blockage on the ridership, but this has not been further investigated (Verhoof et al., 2023).

Finally, proxies can be used to determine the modal shift from rail to other modes during unexpected disruptions. For example, Ou et al. (2024) used NO_x levels to infer the increase in car traffic during an urban rail disruption in Hong Kong.

Surveys are also used to investigate passenger behaviour during planned disruptions. Models can be made based on stated preference and revealed preference data, as is done in Athens for a five month planned disruption in the metro system (Pnevmatikou et al., 2015). However, this research does not investigate the long-term effects of the planned possession on passenger numbers. Shires et al. (2018) asked respondents of a survey how planned disruptions from the past year influenced their further rail usage. They excluded commuters from their survey, because maintenance usually occurs during the weekend in Great Britain, so it is deemed unlikely that commuters are affected by them. Moreover, they only included short rail possessions (one or a few days), and excluded all major maintenance projects. They found a 10% to 13% long-term demand reduction. However, this could be different in other countries, like the Netherlands, where engineering works also happen during the week, and it could also be different when including the longer track possessions as well. Moreover, it is likely different for frequent train passengers (commuters).

AFC data can also be used to investigate passenger behaviour during a planned, long disruption. Yap and Cats (2022) used pseudonymous smart card data to compute generalised travel time and costs of individual passengers during a one-week possession in an urban tram network. They found that frequent passengers respond the least strongly to planned possessions, and still travel. This is likely due to the mandatory journey of their travel (e.g. work).

Strikes are comparable to planned rail possessions for maintenance, because train traffic is disrupted for both cases. A strike may lead to a negative attitude towards public transport and therefore lower modal shares, according to Van Exel and Rietveld (2001). However, Adler et al. (2017) found that there are no long-term impacts of short (one day or shorter) urban public transport strikes on mode choice in Rotterdam. For example, the number of cyclists, an alternative travel mode, already returned to its original level after two days. This does not mean that this is also the case for planned rail possessions for maintenance. The spatial scale (urban versus regional/national), duration and nature of the disruption of these examples are different than those of planned rail possessions, which could cause different long-term effects.

In recent years, interest in the long-term impacts of railway maintenance on passenger volumes has surged. Eltved et al. (2021) used AFC data to determine total passenger volumes on a disturbed rail link and a group of reference lines, before, during and after (12 weeks) a possession on a single line in the Greater Copenhagen area. They divided passengers into groups with similar travel behaviours (travel frequency, moments of travel during a week), using K-means clustering. It was found that especially the ridership of daily commuters is reduced after the possession. The use of reference lines is essential, because travel behaviour changes over time and throughout the year, even without large disruptions. Since Eltved et al. (2021) only used one case study, the effect of different possession characteristics is not investigated. Nazem et al. (2018) used AFC data to investigate the long-term effects of metro station closures in Montreal, Canada, using four months of post-possession data. They used a reference station to account for seasonality. They found that the total station usage after the disruption did not reach its original level, and suggested that effects are larger for larger disruptions, like full line closures. Nazem et al. (2018) also investigated the impact of the metro station closure on (before closure) frequent users. Passenger groups are defined based on the number of check-ins in the months prior to the maintenance period. Frequent users of the stations used less public transport during the disruption, which continued once the station was reopened, indicating that the passengers permanently left the system. Again, only one case was investigated, so the effect of different variables related to the possession is not tested.

Mojica (2008) used AFC data to analyse passenger levels after a large-scale maintenance project in the Chicago metro network. Multiple one-day station closures are investigated. The total check-ins at temporarily closed stations are lower than expected after reopening. In this study, AFC and AVL data is used to infer passenger behaviour of commuters before and during the maintenance project. An attempt is made to investigate the post-possession behaviour of passengers. However, only data of two weeks after finishing the (partial) project are used and there is a high rate of lost AFC cards, so accurate long-term effects cannot be determined in this study.

Combining AFC data with surveys provides more information. Nijënstein and Hogenberg (2018) asked respondents if they changed their travel frequency by tram after a half year period of maintenance on the tram tracks near The Hague Hollands Spoor train station in the Netherlands. 9% of the respondents indicated that they travelled less often, but this was not apparent from the (aggregated) AFC data. However, the authors indicate that new passengers (due to the better infrastructure and autonomous growth) likely make up for the lost passengers. The authors suggest that the long-term effect of possessions can only be inferred from AFC data when individual smart card IDs are used in the analysis.

Research on long-term passenger behaviour in public transport is also relevant in promotion strategies regarding the time of travel on a day. The long-term effects of a promotion strategy to shift passengers' time of travel are investigated for the Hong Kong urban heavy rail system. An AFC data set of two years is used for this research. However, passenger patterns are already approximately constant after a period of 6 to 12 months. It is found that 35-40% of passengers who initially changed their departure time returned to their original time (Ma et al., 2020), indicating that habits play an important role in passenger behaviour.

In conclusion, much research is done on passenger behaviour during a service disruption. Most of these studies cover an urban rail network (metro or light rail), and not a national rail system (train). Most of the authors investigated passenger behaviour during short, unplanned rail disruptions. There are only a few studies on long-term effects of planned rail possessions, but they are either on metro systems or only consider one possession (or both). There are no studies on the effect of different characteristics of planned rail possessions on long-term passenger volumes for different passenger groups in a nation-wide rail system. This thesis aims to fill these gaps in the literature. Table 2.1 gives an overview of studies on rail disruptions. Moreover, it shows how there have been no studies on the influence of different characteristics of a planned rail possession on passenger volumes. This is especially interesting, as it could be used to plan maintenance in such a way that it leads to an as high as possible passenger return rate. Finally, combining the effect of possession characteristics with passenger groups has never been done.

Table 2.1: Research gap table. A short disruption is defined as less than 24 hours.

Author(s), year	Disruption type	Topic	Investigated time period	Pas. groups[1]	Poss. chars.[2]	Data source	Mode(s)	Location
Currie and Muir, 2017	Short, unplanned	Short-term satisfaction level	During disruption	Yes	N/A	Survey, RP	Metro	Melbourne, Australia
Saxena et al., 2019	Short, unplanned	Short-term passenger behaviour	During disruption	Yes	N/A	Survey, RP & SP	Metro	Chicago, USA
Lin, 2017	Short, unplanned	Passenger mode choice	During disruption	Yes	N/A	Survey, RP & SP	Metro	Toronto, Canada
Nguyen-Phuoc et al., 2018	Announced strike	Mode choice related to congestion	During disruption	Yes	N/A	Survey	Train, tram and bus	Melbourne, Australia
Mo et al., 2022	Short, unplanned	Framework to infer passenger responses	During disruption	No	N/A	AFC	Bus, metro	Chicago, USA
Sun et al., 2016	Short, unplanned	Passenger behaviour	During disruption	No	N/A	AFC	Metro	Beijing, China
Ou et al., 2024	Short, unplanned	Mode choice	During disruption	No	N/A	Air quality	Metro	Hong Kong
Bickel et al., 2026	Short, unplanned	Passenger behaviour including teleworking option	During disruption	Yes	N/A	Survey, SP	Train	The Netherlands
Yap et al., 2017	Short, unplanned	Transfer inference algorithm	During disruption	No	No	AFC & AVL	Light-rail	The Hague, the Netherlands
Pnevmatikou et al., 2015	Long, planned	Passenger behaviour	During disruption	Yes	N/A	Survey, RP & SP	Metro	Athens, Greece
Yap and Cats, 2022	Long, planned	Passenger behaviour	During disruption	Yes	No	AFC & AVL	Tram	Amsterdam, the Netherlands
Eltved et al., 2021	Long, planned	Passenger volume	Before and after disruption	Yes	No	AFC	Train	Copenhagen, Denmark
Nazem et al., 2018	Long, planned	Passenger volume	Before & after disruption	No	No	AFC	Metro	Montreal, Canada
Mojica, 2008	Long, planned	Passenger volume	Before and after disruption	Yes	No	AFC & AVL	Metro	Chicago, USA
Ma et al., 2020	N/A	Change time of travel with promotion strategy	Before and after launch	Yes	No	AFC	Metro	Hong Kong
Shires et al., 2018	Long, planned	Immediate and long-term passenger behaviour	During and after disruption	Yes	No	Survey, RP & SP	Train	United Kingdom
Verhoof et al., 2023	Long, unplanned	Immediate and long-term passenger numbers	Before, during and after disruption	No	No	AFC	Train	The Netherlands
Nijënstein and Hogenberg, 2018	Long, planned	Immediate and long-term passenger numbers	Before, during and after disruption	No	No	Survey & AFC	Tram	The Hague, the Netherlands

(Continuation of Table 2.1)

Author(s), year	Disruption type	Topic	Investigated time frame	Pas. groups[1]	Poss. chars.[2]	Data source	Mode(s)	Location
This study	Long, planned	Long-term passenger patterns	Before and after disruption	Yes	Yes	AFC	Train	The Netherlands

[1] Passenger groups: includes different passenger groups (e.g. commuters, leisure passengers, etc.) or uses passenger demographics (e.g. age, gender, etc.)

[2] Possession characteristics: includes different characteristics of planned possession (e.g. duration, time period, detour possibilities, etc.)

2.3. Characteristics of rail possessions

This section answers the first research question. Subsection 2.3.1 discusses characteristics of rail possessions and external effects that potentially influence the post-possession travel patterns of train users. Next, Subsection 2.3.2 introduces a theoretical framework with the characteristics that are investigated. A definitive answer to the first research question is given after the regression model has been applied, for which the method is explained in Section 3.4.

2.3.1. Factors influencing return rate

Nazem et al. (2018) investigated station closures in an urban metro network during the summer period and found permanent changes in passenger behaviour. They suggest that the long-term impacts of the rail possession are larger if the rail possession continued for a longer period, outside the holiday period and if the geographical impacted area would be larger (e.g. a whole line instead of only few stations). ProRail is responsible for planning maintenance works in the Netherlands. Nights, weekends and school holidays are preferred periods for maintenance to the tracks (ProRail, n.d.-c). The planning of maintenance (in the week and/or year) is therefore one of the characteristics of a rail possession. Van Exel and Rietveld (2001) found that the negative attitudes formed due to a strike becomes more prominent with increasing strike duration and increasing spatial scale. This suggests that the duration, period in the year and length (impacted area) are characteristics of a rail possession that influence the long-term ridership changes, which Nazem et al. (2018) also implied. The period in the year (season) and the planning during school holidays are related to each other. Therefore, only the school holidays are used in the analysis. This is preferred over the season, because it gives more information on expected ridership than the period in the year. In relation to the spatial scale of the possession, the presence of a rail possession on another nearby line at the same time is also a characteristic that potentially has an effect.

For possessions with a long duration, people must deliberately decide on an alternative option for the duration of the maintenance, contradictory to the habitual travel pattern they normally perform. The so-called stable context of people's travel pattern is disturbed, which disrupts the passenger's habit and requires new decisions on travel options. This is referred to as the habit discontinuity hypothesis (Verplanken et al., 2008). Verplanken and Roy (2016) found that a behaviour change could occur within three months after a habit has been permanently broken. This time frame is not directly applicable to maintenance works, as habits are only temporarily broken. However, the (temporary) habit discontinuity allows new habits in passenger patterns to form, if the new pattern is continuously performed for a sufficiently long time. This is also suggested to happen by Eltved et al. (2021) and aligns with the suggestion of Van Exel and Rietveld (2001) and Nazem et al. (2018) that the duration has an effect on permanent changes in passenger patterns.

It is also hypothesised that the frequency of maintenance projects on a single line has a negative relation with the overall satisfaction level. ProRail tries to bundle different maintenance works as much as possible, to minimise the hindrance for passengers (ProRail, n.d.-d). The more sub-projects are bundled, the less often maintenance is required. Therefore, the time since the last possession is also a characteristic of a possession that might influence the permanent changes in travel patterns.

Moreover, the long-term effects are different for different passenger groups (Eltved et al., 2021; Shires et al., 2018). Different responses per passenger type were also found in a study on shifting departing time with a promotion strategy (Ma et al., 2020). Commuters are largely affected by maintenance, and are likely to find a new travel option and form a new habit during long disruptions, due to their frequent travel (Eltved et al., 2021) and the mandatory nature of their travel. However, Yap and Cats (2022) found that frequent passengers still travel within the network during a possession in an urban rail network, also caused by their mandatory travel motive. However, the smaller scale and higher density of an urban public transport network facilitates alternatives within the network, which is more rare in national rail networks. Van Exel and Rietveld (2001) suggest that people might try other transport modes during a strike, and continue using these alternatives once the strike is over. Therefore, if there is a good detour possibility by train during a possession, and people use that, it is likely that people return to the original route once the maintenance has finished. After all, people do not discover the benefits of other transport modes if they continue to use the train during a possession. Another alternative option is the replacement bus provided by the railway operator. During short-term disruptions, the level of satisfaction of passengers who are faced with a bus replacement service is lower than that of people who have a non-bus replacement option (Currie & Muir, 2017). Guis et al. (2024) found that passengers experience one minute on a replacement bus as 13% higher than on a train. Since the travel time by replacement bus is often much longer than the travel time by regular train, experienced travel times with a replacement bus during a possession are much higher than the regular travel time. Yap et al. (2018) found a similar increase in travel time valuation (+10%) for replacement buses in a urban tram network. It is arguable that the satisfaction level decreases even further if replacement buses have to be used for a longer time (during maintenance), which could lead to passenger losses.

In the Netherlands, railway operators (such as NS) arrange alternative travel options for each possession. This is also common practice in other European countries (e.g. Deutsche Bahn (n.d.), National Rail (n.d.-b), and NMBS (n.d.)). In the Netherlands, this is either a detour by train or the use of replacement buses (ProRail, n.d.-d). NS is required by the concession to offer a detour by train or arrange another public transport option (for which an NS-ticket is valid in that case) with at most 45 minutes of additional travel time. If this is not possible, replacement buses (or taxis) must be offered, which must be aimed at a maximum of 45 minutes of additional travel time (Ministerie van Infrastructuur en Waterstaat, 2023). In practice, replacement buses are often used, as smaller stations cannot be reached by other NS trains (because there is only a single rail line) or public transport options (within 45 minutes). A detour by train is likely more attractive, which could increase the probability that a passenger returns to his/her original travel patterns. The alternative option, arranged by NS (a detour by train, a replacement bus or other public transport (often metro) for which an NS-ticket is valid), is, therefore, potentially a characteristic that has an effect on post-possession passenger patterns. Since buses are experienced differently to trains, and travel time is important to passengers, both the option itself (train, bus, metro) and the additional travel time are included as characteristics.

During an unplanned disruption, affected passengers can change their route by rail, delay their trip, switch to other public transport modes, or leave the public transport system (Mo et al., 2022). The popularity of teleworking has increased as an option since the Covid pandemic (Bickel et al., 2026). People have the same options during a planned disruption, they are only better informed. People are likely to choose the option with the lowest (generalised) travel time or not travel at all. Following the same reasoning as above, people might stick with their alternative option after the maintenance is finished. Therefore, the quality of the alternative options outside the rail network might also have an effect on permanent changes in passenger behaviour. The car and other public transport are included as alternative modes in this thesis. The travel time by these mode from station to station are used as proxy to measure the quality of those alternatives.

Finally, long-term impacts of rail maintenance can be hard to quantify. Changes in passenger patterns are not necessarily caused by a possession. People could, for example, change jobs or move houses, at the same time as the maintenance period. These changes lead to new travel patterns (Shires et al., 2018). Similarly, long-term effects of a railway possession could be influenced by other projects that were close to the considered one (geographically and time-wise), like highway maintenance.

In conclusion, the literature review identified the characteristics of a possession that influence the change in passenger patterns due to a rail possession. There are two main groups of characteristics: the general characteristics (e.g. duration) and the passenger-dependent characteristics (e.g. detour options). Subsection 2.3.2 presents a framework in which the relationships of these variables with the change in passenger patterns are shown.

2.3.2. Theoretical framework
Based on the literature on the types of railway possessions for maintenance in the Netherlands, the following characteristics that differ per railway possession are identified:

- General rail possession characteristics
  - Duration
  - Length
  - Time planning
    - Planned during a school holiday
    - Planned fully during the weekend
  - Time since the last possession
  - The presence of (an)other possession(s) at the same time in the same region
- Passenger-dependent characteristics
  - The (quality of the) alternative travel option during the possession provided by the railway operator
    - The option itself (e.g. bus, metro or detour by train)
    - The travel time
  - The (quality of the) other alternative travel options
    - Travel time by car
    - Travel time by other public transport
  - The passenger group

In addition, there are external effects, unrelated to the possession, that have an effect on passenger patterns:

- Seasonality
- Demographic changes (e.g. moving houses, switching jobs)

The before-mentioned aspects and their influence on the change in passenger patterns are visualised in Figure 2.1.

The location in the country also likely has an effect on the potential changes in travel patterns. However, this has already been incorporated in other characteristics. For example, the holiday periods are determined by the location (region), and the quality of the alternative travel options (within and outside of the rail network) also differ per region. Therefore, it is chosen to exclude the location as a separate characteristic.

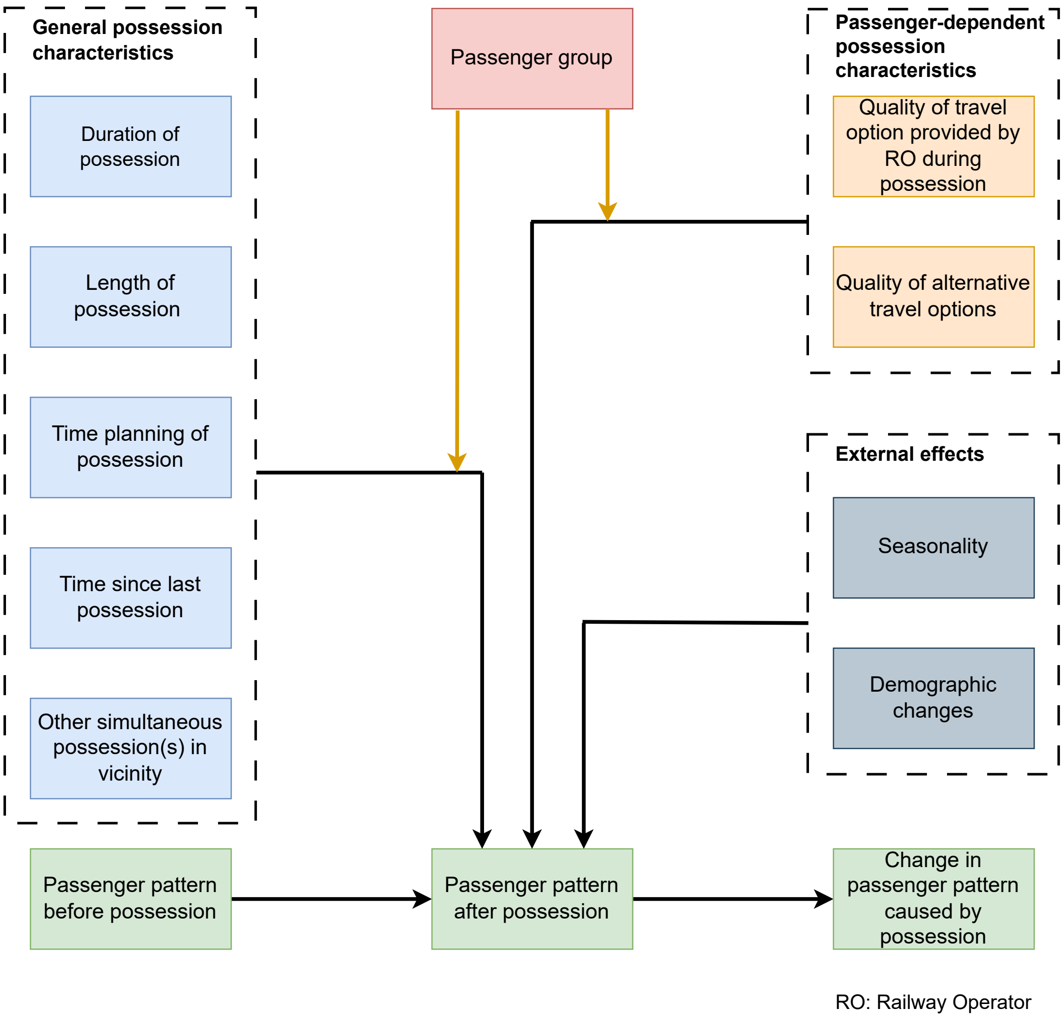


Figure 2.1: Conceptual framework: factors that influence individual passenger's post-possession travel patterns.

2.4. Pre and post-possession time period

This section answers the second research question on the time period(s) that should be investigated. It also discusses how seasonality should be included in the analysis.

2.4.1. Time periods in similar studies

Different studies use different time frames to investigate the long-term effects of rail disruptions. The start of the investigated pre-disruption periods range from five months to two weeks prior to the disruption, whereas the post-disruption periods vary between two weeks and twelve months. Some studies compare the travel patterns after maintenance to a reference period that is not directly before the rail disruption. An overview of the used time periods per study is given in Figure 2.2.

Ma et al. (2020) used 23 months of data to investigate the long-term impacts of a promotion strategy to shift time of travel. They only investigated passengers who changed their departure time in the month after introduction of the programme. They found near-constant passenger patterns already after six to twelve months, indicating that (new) habits have formed within this period. However, this period could be different for maintenance situations than for promotion strategies. Promotion strategies are specifically aimed at changing people's travel patterns, contrary to maintenance. The direct effects of a promotion strategy are longer present than the direct effects (hindrance) of maintenance. So, passengers can adapt to the strategy at their own pace. Therefore, it is likely that potential changes in

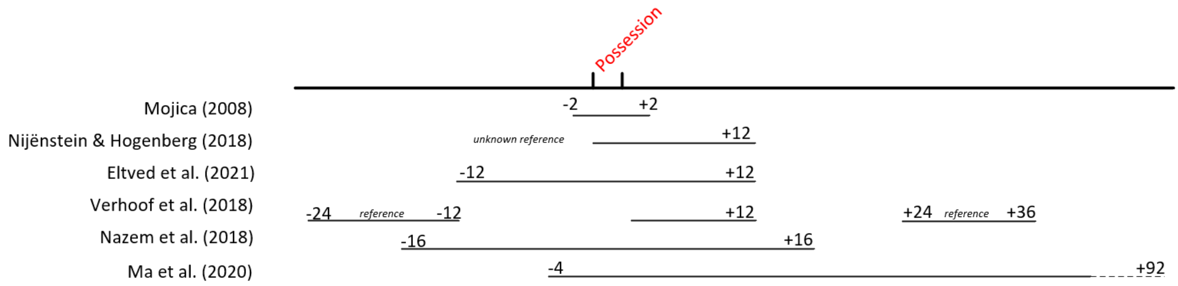


Figure 2.2: Investigated time periods in the literature, with the number of weeks before and after the possession indicated with numbers

behaviour due to maintenance are permanent after a shorter period, so a shorter time period can be investigated. For example, Eltved et al. (2021) used a period of 12 weeks before and after the planned disruption of 13 weeks they investigated. This was considered to be sufficient to investigate the travel behaviour of frequent and infrequent rail users. Nazem et al. (2018) uses four months before and four months after the disruption. For future research, they suggest that the post-possession investigation period could be extended, with the downside that it becomes harder to isolate the effect of the maintenance. It gives, however, more insights in the permanency of changes in passenger patterns. Verhoof et al. (2023) also found that passenger volumes had not reached normal levels yet four months after a possession. They compared the passenger numbers in the four months after the rail disruption to reference periods a half year before and after the disruption.

Shires et al. (2018) asked respondents of an online survey about the long-term impacts of rail possessions in the last 12 months. However, this does not necessarily mean that the relevant possession occurred 12 months ago, nor that the respondents considered a single possession. Nijënstein and Hogenberg (2018) compared the number of trips during a tram and bus disruption to an undefined reference period. They also used three months of AFC data after a tram disruption to investigate a potential long-term effect. The total number of trips recovered quickly after the possession ended, but they did not consider individual passengers. They state that autonomous growth and external effects likely compensated for the permanently lost passengers. Mojica (2008) only considered two weeks prior to and two weeks after the maintenance. No conclusions are drawn about the permanence of passenger changes, due to the limited time frame after the possession.

There is a period of approximately two months between the end of the rail possession and (relatively) constant passenger volumes (Eltved et al., 2021; Nazem et al., 2018). This corresponds to the concept of a resilience triangle and indicates that structural effects cannot be identified in the first two months after a possession.

2.4.2. Seasonality and autonomic growth

Usual seasonal variations in passenger behaviour should be considered when comparing travel patterns before and after a rail possession. Figure 2.3 shows the variation in the number of NS passengers in 2025. The lowest ridership is in the summer months, while the highest passenger numbers occur from September to November. The lower passenger volumes in the summer period are caused by the (school) summer holiday.

Verhoof et al. (2023) state that making year-to-year comparisons to study the effect of rail possessions is methodologically more sound than using other reference periods, to account for the effect of seasonality. However, they used a reference period of approximately half a year before and half a year after their studied possession in autumn 2022. They considered the data from autumn 2021 not representative due to COVID-measures, which decreased passenger volumes. They also indicate that the total ridership in 2023 was higher than in the year before, due to autonomous growth. This shows that making year-to-year comparisons is not always possible, because external effects and autonomous growth influence the passenger numbers as well. This last point is not relevant for this study, because the study is performed on an individual passenger level. New passengers, due to, for example, autonomous growth, are not considered.

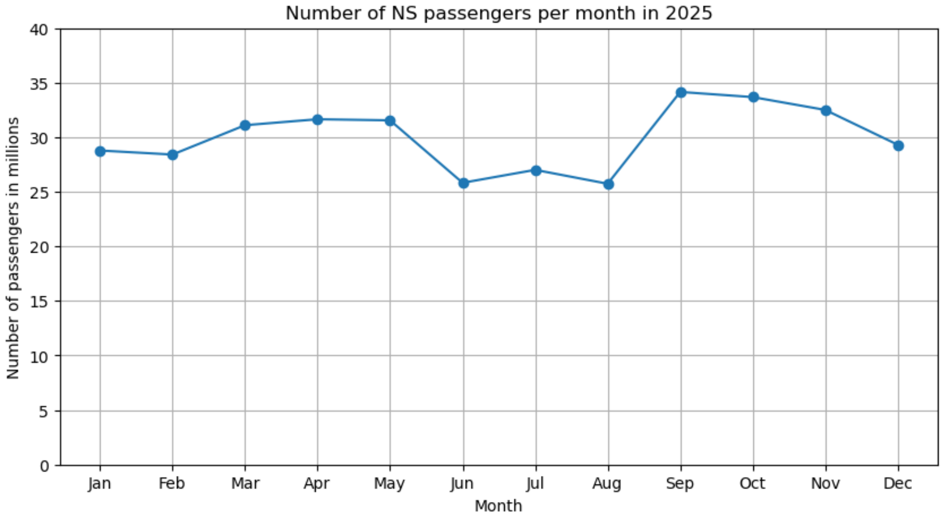


Figure 2.3: Number of NS passengers per month in 2025. Numbers from Nederlandse Spoorwegen (2025b)

When making a year-to-year comparison of the travel behaviour of individual passengers, the assumption is made that the passengers' travel patterns remain constant under normal conditions (i.e. without the investigated rail possession). There are multiple reasons why this assumption might not be valid.
First of all, the timetable of NS changes each year in December (Nederlandse Spoorwegen, n.d.-a). Often, this leads to an improvement of the service, which could lead to an increased frequency of train travel for an individual passenger. This effect could then cancel out the potential negative effects of a rail possession on the trip frequency.
Secondly, changes in travel patterns can be caused by major life changes, such as moving houses or changing jobs (Shires et al., 2018). This could overestimate the potential (negative) effect of rail possessions. Passengers could have a reduced trip frequency of zero, which in that case would not be caused by a rail possession, but rather by the life event.
Thirdly, there is rarely one single rail possession per year on a specific route in the Netherlands. There was, for example, four times a rail possession of at least 24 hours between Haarlem and Amsterdam Sloterdijk in 2025, all in different months. Isolating the effect of a single possession might prove difficult in such situations when making year-to-year comparisons.

The hypothesis that travel patterns do not remain constant over a year in normal situations is confirmed by Egu and Bonnel (2020) who classified approximately 40% of individual urban public transport users in Lyon as intermittent transit users, based on AFC data from a six-month period. These users first frequently used the transit system, but suddenly stopped doing so, or they did not use the public transport, but suddenly started doing so, without a direct cause.

In a longitudinal analysis of the responses of individuals to fare incentives, Wang et al. (2025) removed individuals who changed their origin or destination station during the investigated period to account for life events. They also removed passengers with seasonal variation in their travel habits from their identified time of travel adapters, by comparing the same months in different years. However, their AFC data set ranges from July 2014 to December 2015, while the promotion strategy started in September 2014. It is unclear which data they used to determine seasonality for passengers, and how they isolated this from the fare incentives.

Finally, when the investigation period is too short, the results could be affected by the weather, as suggested by Mojica (2008), which is also related to the season in the year. People might use the car more often after a rail possession due to bad weather, and not use an active mode to reach a station or public transport stop. This is unrelated to the possession itself.

2.4.3. Conclusion on investigation period

Long-term effects can only be observed after at least two months after the end of the maintenance. Few studies have investigated the long-term effects of rail possessions on passenger patterns. Mojica (2008) could not identify long-term effects in a post-possession period of two weeks. The studies of Eltved et al. (2021) and Nazem et al. (2018) are pioneering in the field of long-term effects of maintenance. They use a post-possession period of three and four months respectively, but a longer period is recommended, by the latter. A time frame of three and four months is used as well as pre-possession period.

It is established that comparing travel patterns over yearly periods cannot be used to investigate the long-term effects of a single rail possession due to a combination of factors. First of all, because there are often multiple possessions on the same route in a year. This complicates isolating the effect of one possession. In addition, because the timetable changes each year, and finally because travel patterns are often not constant over a year in regular situations (Egu & Bonnel, 2020).

Moreover, from Subsection 2.4.2 it follows that there are seasonal variations in passenger volumes on an aggregated level, which indicates that individuals also have varying patterns throughout the year. This must be incorporated into the comparison between passenger patterns before and after a possession.

From the literature, it follows that a four month period after the possession is the minimum to determine whether passenger patterns have changed structurally. However, it is interesting to determine whether negative effects fade after a longer period than has been investigated before. However, a longer post-possession period complicates isolating the effect of a single possession.

Structural effects cannot be identified by studying the first two months after a possession. This is the intermittent period, where people are adapting to the new situation. Therefore, long-term effects only become apparent after at least two months after the end of a possession.

2.5. Take-away from literature

In conclusion, the literature review found the answers to the first two research questions, which are used for the data analyses, explained in Chapter 3. In addition, it discussed methods that are used in previous studies on similar topics.

Section 2.2 showed that there are two main data sources to investigate passenger behaviour: AFC data and survey data. AFC data are used more often to follow individual passenger patterns over time, which aligns with the research needs of this thesis.

Section 2.3 found rail possession characteristics that influence the changes in passenger patterns due to the maintenance period. These characteristics are computed for the cases that are investigated in this thesis, which is explained in Section 3.3. Next, Section 3.4 describes how it is tested if these characteristics indeed have an effect on changes in passenger patterns.

Section 2.4 found the ideal time period that should be investigated to identify long-term effects of possessions. A period of at least four months after the possession is needed, but the first two months cannot be used to find long-term effects. A longer post-possession period has never been investigated before, but is recommended. The incorporation of these findings into the method for the data analyses is explained in Subsection 3.1.4. That section also discusses the limitations related to data availability, that also influence the time period that can be investigated.

3 Data analysis methodology

This chapter describes the methodology for answering the third and fourth research questions with data analyses. Section 3.1 covers the method that is used to quantify changes in passenger patterns (i.e. the third research question), using the literature on the required time period found in Section 2.4. Next, Section 3.2 describes how cases (possessions) are selected to be analysed. Thereafter, Section 3.3 is about the computation of possession characteristics, which were found in Section 2.3. In Section 3.4, the method for developing a regression model is given, which is used to determine the effect of possession characteristics and passenger groups on permanent changes of passenger patterns (i.e. the fourth research question). Next, Section 3.5 discusses the application possibilities of the regression models, which are identifying the possession characteristics with the largest effect on changes in passenger patterns and the estimation of permanent passenger loses due to maintenance for future possessions. Finally, Section 3.6 summarises the key methodological steps of this thesis.

3.1. Analysis of travel patterns

This section covers the computation of the indicators that are used to quantify the changes in passenger patterns due to a rail possession. The analysis of permanent changes in passenger patterns is performed on an individual passenger level with AFC data. This allows for determining whether people who (frequently) travel on a rail segment that is possessed continue to do so after the maintenance has ended or whether they decrease their travel frequency or leave the rail system entirely. To do so, cases are required to be able to analyse the potential permanent change in travel patterns of individual passengers (see Section 3.2) after maintenance projects. By analysing multiple possessions, the effect of different possession characteristics on changes in passenger patterns can be investigated.

The remainder of this section is structured as follows. First, the required time periods for the investigation are discussed in Subsection 3.1.1, which is based on Section 2.4. Next, criteria that passengers must satisfy to be investigated are discussed in Subsection 3.1.2. Thereafter, Subsection 3.1.3 discusses the indicators that are used to quantify a potential change in passenger patterns due to the rail possession. The incorporation of seasonality in the computations is discussed in Subsection 3.1.4.

3.1.1. Time periods

It is concluded in Subsection 2.4.3 that a minimum of four months should be used as post-possession period, and that the first two months after a possession cannot be used to determine its long-term effects. A longer post-possession period than four months is recommended. In addition, the entire investigation period should not be too long, to isolate the effect of a single possession as much as possible and to decrease the chance of external effects influencing the passenger patterns. Moreover, data availability is limited, which also leads to the desire to have relatively short investigation periods.

Therefore, a post-possession period of six months is used in this thesis, to fulfil the desire of a longer post-possession period than in previous studies is used. The pre-possession period is chosen as the two months before the maintenance starts, which is shorter than in previous studies. This is done to minimise the total duration of the investigation period, for the reasons mentioned above. Moreover, the strict selection criteria in Subsection 3.1.2 ensure that only regular passengers are included in the analysis, for whom two months is long enough to identify their (regular) passenger pattern.

The six-month post-possession period is divided into three periods of two months ($T(0)$ to $T(2)$), see Figure 3.1. In this way, the short-term effects are separated from the long-term effects, and changes in the response to the possession can be followed over time. By using post-possession periods of the same duration as the pre-possession period, a fair comparison between the travel patterns can be made. One month is defined as four weeks (28 days), to ensure that each day of the week is included the same number of times in each period. The boundary between short-term and long-term effects is set at the start of the third month (i.e. $T(2)$ and $T(3)$ are considered as long-term).

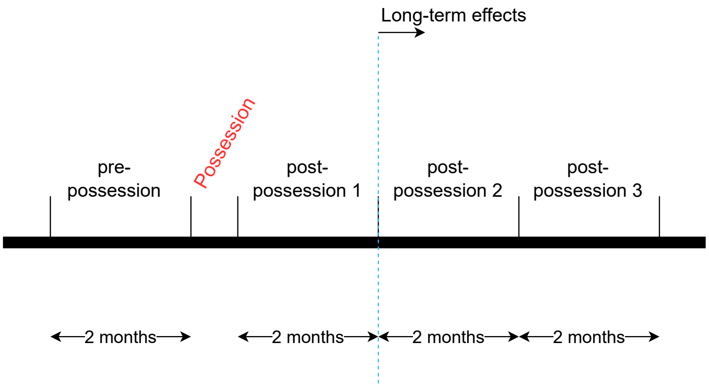


Figure 3.1: Time line pre- and post-possession periods

Each passenger's travel pattern in each of the three two-month post-possession periods ($T(1)$ to $T(3)$) is compared to the travel pattern in the two-month pre-possession period ($T(-1)$), as explained in Subsection 3.1.3.

3.1.2. Passenger selection and passenger groups

This section describes the general criteria that a passenger needs to satisfy to be investigated in this thesis.

First of all, only passengers who travel with a smart card that can be followed over time (i.e. a card that has the same pseudonymous ID every time it is used) can be used in the analysis.

To compare passenger patterns before and after a possession, only passengers with an identifiable pattern are selected for the analysis. Passengers must make regular use of the impacted line, because they must have a regular travel pattern that is affected by the possession, which is used to compare the travel behaviour in the post-possession period with. Nazem et al. (2018) only used frequent passengers for their analysis, which they defined as making on average one tour a week during a four month pre-possession period. However, they did not consider the distribution of the trips during this period, which means someone who made eight tours (16 trips) during one week is considered a frequent passenger.

In this thesis, the distribution of trips over the pre-possession is considered. All passengers who travel more than eight times over the blocked route in the two-month pre-possession period (i.e. once every week on average) and who travel in more than four (of the eight) weeks are selected. The minimum average number of trips per week is reduced compared to the threshold of Nazem et al. (2018), to account for passengers who travel regularly biweekly and potential periods of reduced travel (e.g. holidays) in the pre-possession period. However, the threshold for active weeks ensures only regular passenger are selected. Passengers who make one tour (two trips) every two weeks are included in this analysis. They are considered regular passengers, because they make that tour (over the affected line) consistently in multiple weeks in the pre-possession period. So, the following criteria related to a passenger's trips have to be satisfied:

- $N_{\text{trips over affected line}} \geq 8$ trips in eight-week pre-possession period;
- $N_{\text{weeks with trip over affected line}} \geq 4$ in eight-week pre-possession period.

In addition, the selected passengers should not be affected by another possession in the post-possession period. This would directly impact the number of trips they can make in the post-possession period (a lower number of trips would be explained by another possession on their regular route), and it could also indirectly lead to reduced train travel frequency due to repeated possessions and building annoyance. In the filtering steps for the selection of the cases, it is already ensured that the selected route itself does not have a new possession in the six months after the investigated possession, see Section 3.2. In addition to this, all passengers whose trips, during the pre-possession period, are for more than 10% over a line that is possessed for at least three days in the six month post-possession period are not included in the analysis.

This threshold is chosen as follows. All selected passengers make at least eight trips (four tours) over the affected line. The threshold for trips over another affected line is, for these lowest-frequency passengers, 0.8 trips, meaning that if they make one tour (two trips) over another affected line, they are filtered out. They are filtered out even if they make only one trip over another affected line, because that accounts for 12.5% of their trips. Passengers with 20 trips can make one tour over another affected line without being filtered out. One tour is likely an incidental trip, and the possession on the other route will therefore not have an effect on regular passenger patterns.

Figure 3.2 shows an example. The line A-B is investigated, but there is also a possession between B and C within its post-possession period. Two passengers both make 22 trips over the affected line (A-B). However, for one passenger, two of those trips are also over the line B-C, while the other passenger makes four trips over that line. The latter passenger has a too high share of trips over another impacted line, and is therefore not considered in the analysis of the A-B possession. For the former passenger, the single tour to C is considered an incidental trip, while two tours within eight weeks are not considered incidental for the latter passenger.

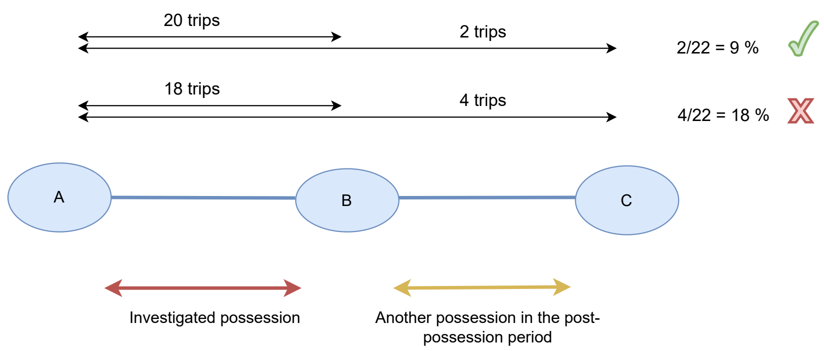


Figure 3.2: Example of filtering passengers based on number of trips over another affected line in the post-possession period

Passengers affected by another possession in the pre-possession period of the investigated possession might travel less often than usual. These passengers are, however, not removed from the investigated group. This choice leads to potentially less negative impacts of the investigated possession (so it is a conservative choice). The choice is made to save computational time.

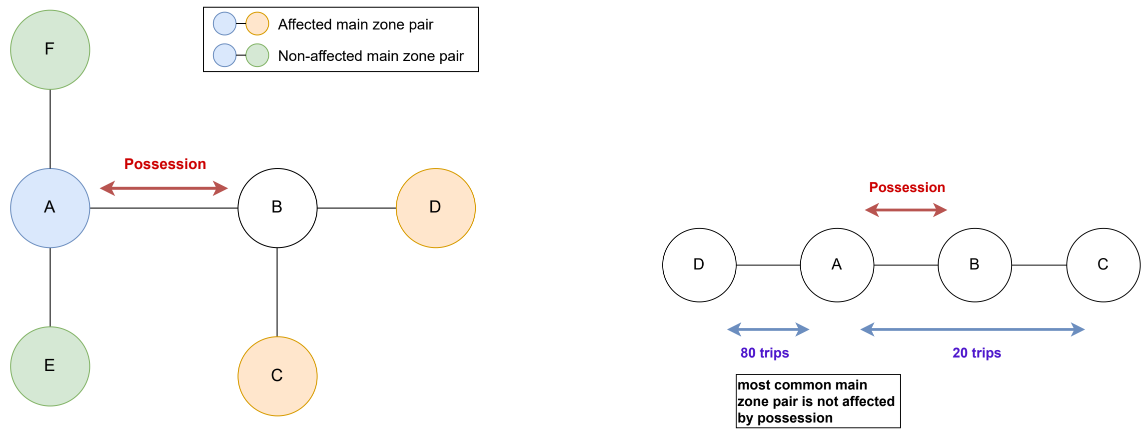
Moreover, only passengers with a geographically distinct travel pattern are included in the analysis. This is required, because this thesis aims to determine the effect of passenger-dependent possession characteristics (e.g. quality of alternative travel options) on the long-term impact of the possession on passenger patterns. Therefore, passengers must have a distinct OD-pair for which these characteristics can be computed. So, at least 50% of a passenger's trips over the affected line (i.e. trips that are affected by the possession) must be between the same two main zones for a passenger to be included in the analysis. Note that the previously mentioned threshold for the number of trips ensures that the selected passengers travel often enough over the affected line, so the trips that do not use the affected line are not considered for the criterion on main zones.

All stations in the same city are grouped into the same main zone. Smaller stations, in another town, close to a large (intercity) station are also grouped into the main zone of that larger station. The exact implementation of the main zones differs per railway operator.

Table 3.1 shows an example of the main zone requirement for a possession between station A and station B. Only the first two zone pairs are considered for the requirement, since the affected line is used for these pairs. The zone pair A-C accounts for 75% of the trips. The example passenger therefore meets the requirement and goes through this filtering step. Figure 3.3a visualises this example.

Table 3.1: Example of main zone requirement for a possession, for one passenger

Zone pair	Affected by possession	Number of trips	Main zone pair
A-C	Yes	30	Yes
A-D	Yes	10	No
A-E	No	2	No
A-F	No	4	No



(a) Visualisation of example in Table 3.1.

(b) Example of unaffected main zone pair.

Figure 3.3: Examples of main zone requirements in filtering of passengers.

In addition, a passenger may not have a most common origin-destination zone pair that is not affected by the possession (i.e. the passenger's most common trip has to be affected by the maintenance). The example in Figure 3.3b shows a passenger who travels 20 times between A and C, over the affected line, which is A-B. The passenger also travels 80 times from A to D. The passenger satisfies all before-mentioned criteria. However, A-D is the passenger's most common main zone pair, but this pair is not affected by the possession. Therefore, the passenger is not used for this case, because the majority of this person's trips is not affected by the possession.

After selecting the passengers for the analysis, they are put into passenger groups. These groups are based on subscription type and travel frequency in the pre-possession period. The subscription types differ per railway operator, so no general groups exist. However, a distinction between business, leisure and student passengers should be made. The definition of the passenger groups for the Netherlands is given in Subsection 4.2.3.

Next, the groups are divided into sub-groups based on the number of trips of an individual passenger in the pre-possession period (of eight weeks, as defined in Subsection 3.1.1), using Equation 3.1. The low-frequency group includes passengers who, on average, make one or less tours per week in the eight-week pre-possession period, resulting in at most 16 trips. The medium-low frequency group has between one and two tours per week (16 to 32 trips). The medium-high frequency group has between two and three tours per week (32 to 48 trips), and the high frequency group has more than three tours per week on average (48+ trips).

$$\text{Frequency group} = \begin{cases} LOW & \text{if } N_{\text{trips}} \leq 16 \\ MEDIUM - LOW & \text{if } 16 < N_{\text{trips}} \leq 32 \\ MEDIUM - HIGH & \text{if } 32 < N_{\text{trips}} \leq 48 \\ HIGH & \text{if } N_{\text{trips}} > 48 \end{cases} \tag{3.1}$$

In conclusion, the filtering steps ensure that only passengers who frequently use the affected track (i.e. at least one tour every two weeks) and who travel with a smart card (that can be followed over time) are included in the analysis. Moreover, the filtering steps ensure that the passengers have a distinct travel pattern, between two main zones. Lastly, the selected passengers are not affected by other maintenance projects in the investigated period. Figure 3.4 shows the filtering steps that are taken to obtain the investigated group for each case, based on the pre-possession period. Finally, passenger groups are made based on the subscription type and travel frequency in the pre-possession period.

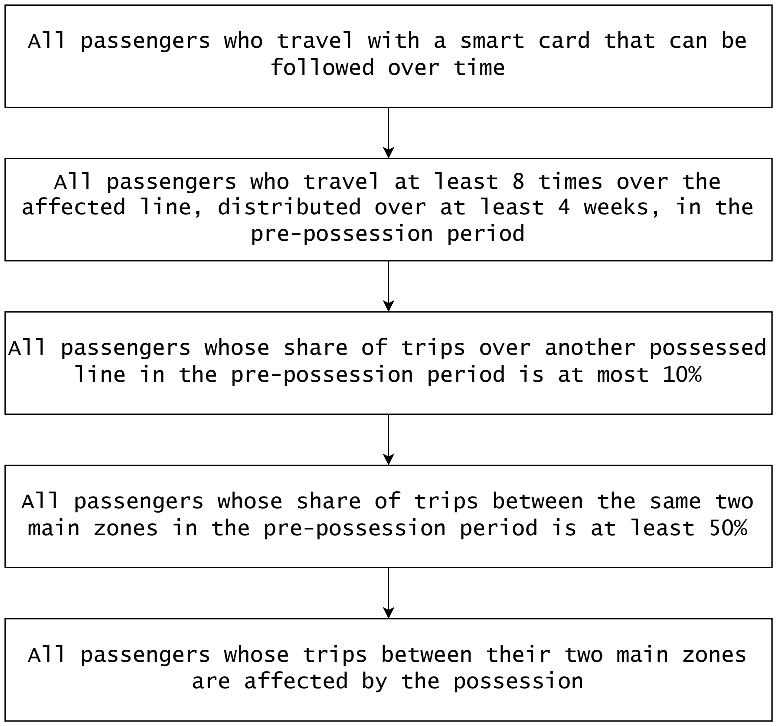


Figure 3.4: Filtering steps (top to bottom) to obtain the investigated passenger group for each possession

3.1.3. Travel pattern indicators

Quantification of travel patterns is required to determine whether passengers' travel patterns change due to a possession.

The passenger patterns are quantified for the pre-possession period and the three post-possession periods ($T(-1)$ to $T(2)$). However, only the last two post-possession periods are used to identify potential long-term effects of possessions, as described in Subsection 3.1.1. Still the indicators are computed for the first post-possession period, to identify a potential growth path. A passenger pattern is described by the following aspects:

- The total number of trips. This quantifies a potential change in travel frequency;
- The share of trips that use the affected line among all trips between a passenger's most common origin and destination main zones. This quantifies potential changes in route or station choice.

The main interest lies in a potential change in the number of total trips, caused by the maintenance period. This directly relates to the positive externalities of the train (sustainable and efficient travel mode) compared to travel by car and it also relates to the revenue of the railway operator. Passengers whose number of trips is reduced after the possession likely have found an alternative travel mode, or reduced their frequency of train travel. Other potential effects of a possession are the change in the transfer station or even the origin and destination station, as suggested by Eltved et al. (2021) for future work. Changing the transfer station is related to route choice. Changes in origin and destination station likely only occur in major cities with multiple stations and sufficient urban public transport options for the access and egress trips (e.g. Amsterdam, Rotterdam, Den Haag, Utrecht in the Netherlands).

The first two potential changes in behaviour (other mode or less frequent travel) are directly identified by comparing the total number of trips that a passenger makes before and after the possession, visualised in Figure 3.5. Seasonality must be considered in this comparison. The incorporation of this is explained in detail in Subsection 3.1.4.

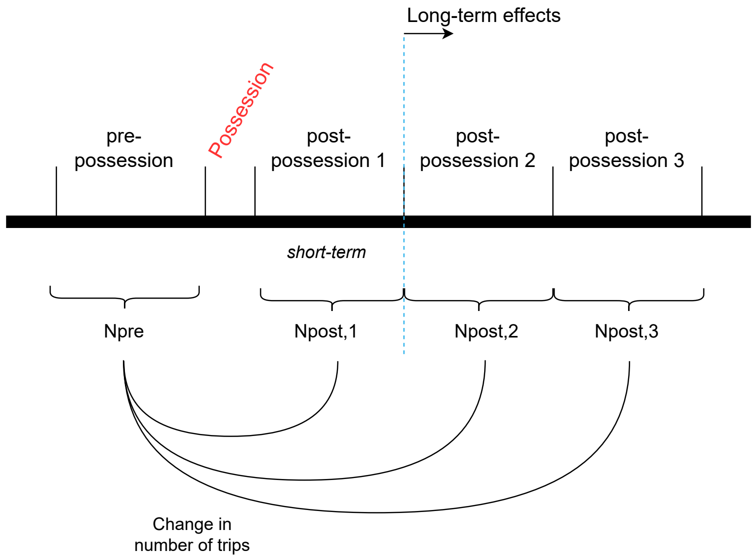


Figure 3.5: Comparison of the number of trips between the pre- and a post-possession period.

A new route choice is identified by comparing the percentage of trips over the affected line among all trips between the two most common main zones of a passenger. If a passenger travels in the pre-possession period 30 times between two main zones, of which 25 trips over the affected line, his or her percentage of trips over the affected line is 83%. Now, in the post-possession period, he or she travels 20 times between the main zones, of which 10 over the affected line. This is only 50% of the trips, so the original route is relatively less often used than before.

The change in the number of trips between the pre-possession period and the post-possession period is measured as the difference between the observed change and the expected change in the number of trips. This indicator accounts for seasonality by incorporating the expected change in the number of trips. This is further explained in Subsection 3.1.4. The difference between the observed and expected change is normalised by a passenger's pre-possession number of trips. By doing so, the relative magnitude of the change is obtained. The indicator is computed with Equation 3.2.

$$\Delta N^{\text{total}}_{i;\ \text{pre-}j} = \frac{N^{\text{total}}_{i,\ j} - \Delta N^{\text{total}}_{\text{passenger group ref; pre-}j} - N^{\text{total}}_{i,\text{pre}}}{N^{\text{total}}_{i,\text{pre}}} \tag{3.2}$$

for post-possession period j, with N^{total} the total number of trips made by passenger i in either the pre-possession period or post-possession period j, and $\Delta N^{\text{total}}_{\text{passenger group ref; pre-}j}$ the correction factor for seasonality for the passenger group to which passenger i belongs (i.e. the expected change in number of trips for passenger i). The definition of the correction factor is given in Subsection 3.1.4.

A negative value indicates that the passenger's change in number of trips was more negative than expected. This can occur even if the passenger increased his or her number of trips, for example when the expected change was +8 trips, but the observed change was only +6. The magnitude of the indicator tells how large the difference between the observed and expected change in number of trips is, relative to a passenger's number of trips in the pre-possession period. Larger absolute values indicate larger deviations from the expected change in the number of trips. The inclusion of the denominator facilitates quantification of how large the deviation from the expected change is relative to a passenger's pre-possession number of trips. If the difference between the observed and expected number of trips for two passengers is both -5, but one travelled 10 times in the pre-possession period, and the other 50 times, then the deviation from the passenger's pre-possession travel pattern is much larger for the first passenger than for the second (i.e. -0.5 versus -0.1).

Secondly, the change in the share of trips over the affected line (STL for Share Trips Line) for trips between a passenger's most common origin-destination main zone pair is computed for each passenger i with Equation 3.3.

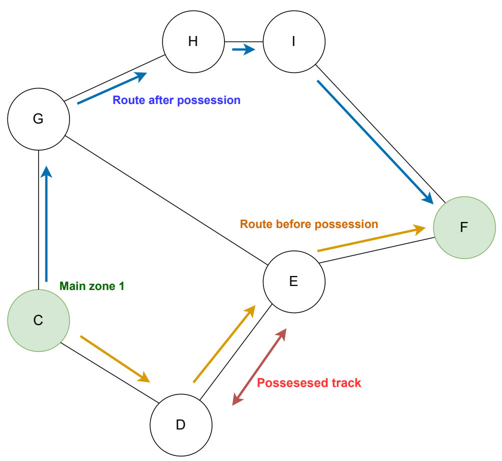
$$\Delta STL_{i;\ \text{pre-j}} = \frac{STL_{i,j} - STL_{i,\ \text{pre}}}{STL_{i,\ \text{pre}}} \tag{3.3}$$

with the share of trips over the affected line among all the trips between the two most common main zones of a passenger computed with Equation 3.4.

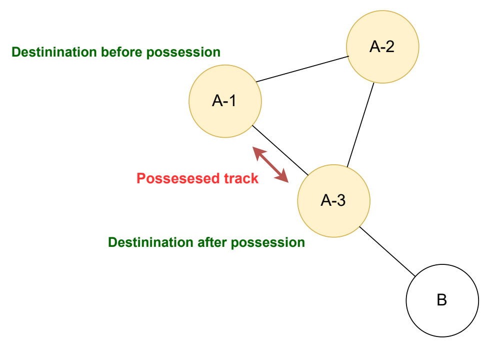
$$STL = \frac{N_{\text{line}}^{\text{main zones}}}{N_{\text{total}}^{\text{main zones}}} \tag{3.4}$$

In some situations, the route of a passenger is not known for sure. Some operators assign probabilities to each travel option and thus to each route (e.g. NS, see Subsection 4.2.2). These probabilities are then used as the frequency in this indicator. For example, there is a 65% probability that a passenger used a specific route for trip A, and a 45% probability for trip B, and there are no other trips over the line, then the total frequency in that post-possession period over that line is $0.65 + 0.45 = 1.10$.

A value of zero for this indicator means that the passenger did not change his or her route choice. A negative value indicates that the passenger decreased the share of trips over the affected line among all trips between his or her two main zones. This could be by taking a detour (e.g. going from C to F via G, H and I instead of via D and E after a maintenance period on the DE-segment) or by using another station within the same main zone for access or egress (e.g. stop using A-1 as origin/destination, and start using A-3, after a possession between A-1 and A-3). These examples are visualised in Figure 3.6a and Figure 3.6b respectively.



(a) Example of change in route after possession. Passenger travelling between main zones C and F switches route from via D and E to via G, H and I.



(b) Example of change in station choice. Passenger originating from B switches from A-1 to A-2 as destination station after the possession.

Figure 3.6: Two possible behavioural changes that are captured by the second indicator on share of trips over the affected route.

This indicator is only computed for the passengers who have at least one trip between their two main zones in the post-possession period, since the indicator is undefined for passengers with zero trips in the post-possession period, see Equation 3.4. However, the effect of not using the train any more in the post-possession period is captured with the first indicator, Equation 3.2.

3.1.4. Seasonality correction factor

The indicators introduced in Subsection 3.1.3 are based on (1) the total number of trips and (2) the share of trips over the affected line among all trips between a passenger's main zones. The first needs to be corrected for seasonality effects. The second indicator does not need to be corrected for seasonality.

A seasonality correction factor is used in the computation of the first indicator, see Equation 3.2. The correction factor computes the expected change in the number of trips between different periods for each investigated passenger. This expected change is then incorporated into the comparison between pre- and post-possession travel patterns, to remove the effect of seasonality from the comparison, as already introduced in Subsection 3.1.3.

The correction factor is computed per passenger group. Each (investigated) passenger is assigned to a passenger group, as introduced in Subsection 3.1.2.

It is assumed that the seasonality of a passenger group on a specific line is equal to the seasonality of the same passenger group in the same region of the country, and that the seasonality of each individual passenger is equal to that of the group. Different regions of a country are used to account for potential differences between holiday regions (i.e. school holidays do not occur entirely simultaneously), which has an effect on travel patterns. The implementation of these regions differs per country. Chapter 4 explains how this is implemented in the Netherlands.

Figure 3.7 visualises the incorporation of the correction factor into the indicator on the change in the number of trips, introduced in Subsection 3.1.3. The correction factor differs per passenger group of the investigated passengers, per case, and per post-possession period.

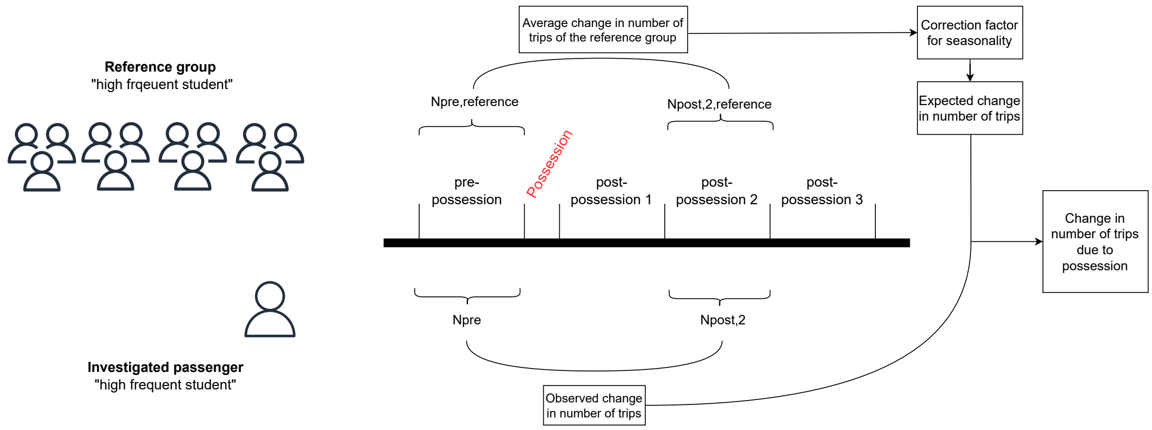


Figure 3.7: Comparing post-possession period with pre-possession period while accounting for seasonality. Example for a passenger who is part of the passenger group 'high frequent student', for post-possession period 2.

The correction factor for a certain passenger group for a certain case is computed with Equation 3.5.

$$\Delta N^{\text{total}}_{\text{passenger group k ref; pre-}j} = \frac{\sum_i (N_{i,\,j} - N_{i,\,\text{pre}})}{n_k} \tag{3.5}$$

with i a passenger of passenger group k in the reference group, and n_k the number of passengers in the reference for passenger group k.

The reference group has to meet certain criteria, in order to have similar travel patterns as the investigated group. The only difference between the investigated group and the reference group must be the possession that the investigated group is faced with. Therefore, similar filtering steps are performed for the reference group as for the investigated group (see Figure 3.4). So, the primary criteria for passengers to be included in the reference group are the following:

- Passengers who travel with a smart card that can be followed over time;
- Passengers who travel at least eight times in at least four weeks in the pre-possession period;
- Passengers who make at least 50% of their trips between the same two main zones.

The requirement on trips between the same main zones is to ensure that the reference group consists only of passengers who have a distinct (geographical) travel pattern, similar to the investigated group that consists of passengers travelling often over a specific line.

In addition, the reference group must consist of passengers from regions with similar holiday periods as the investigated possessions. In other words, the passengers from the investigated group and the reference group must have the same amount of vacation (days) in each investigated period, for a fair comparison between the two groups.

Passengers affected by the possession under investigation, and passengers affected by another possession that has at least one overlapping day are excluded from the reference group, to ensure that the reference group is not affected by maintenance.

In addition, the reference group can be affected by other possessions during the pre-possession period of the investigated maintenance. This would lead to reduced train travel of the reference, and therefore potentially overestimating of the effect of the investigated maintenance, because the number of trips of the reference groups changes, between the pre-possession and post-possession periods, not only due to seasonality, but also because they could not travel in a part of the pre-possession period. Therefore, all passengers who use a rail line that is possessed for at least three days in the pre-possession period of the investigated maintenance, are excluded from the reference group. Short possessions (one or two days) are unlikely to affect the passenger patterns of the reference group in the pre-possession period much, since these are usually in the weekend and since the reference group consists only of passengers that travel frequently, which is for most people during the week. Therefore, the potential reduced travel frequency in the pre-possession period of the reference group is limited. In addition, reducing this threshold from five to three (which is tested for a few cases) has negligible effect. So, reducing the threshold to two or one is assumed to also have a negligible effect, while it does reduce the size of the reference group, which is not desired.

Maintenance also affects the reference group during the post-possession period of the investigated possession. The passengers who are affected by this are, however, not excluded from the reference. This would lead to a too small reference group. Therefore, the reference group could have a lower trip frequency in the post-possession period, due to them not being able to travel. So, the indicators give a conservative view of the effect of the possession, because the reference group might be affected by maintenance in the post-possession period. However, if the reference group is sufficiently large, the effect on the indicators is limited, since there are many reference passengers not affected by any possessions. It is unlikely that all reference passengers are affected by maintenance, due to the separation in time and location of maintenance works.

Short, unplanned disruptions and strikes can occur during the pre-possession period and post-possession period, for the investigated passengers and the reference group. Potentially lower use of the train by the investigated group due to unplanned disruptions in the post-possession period is compensated for by the reference group, because they are also affected by these disruptions, assuming that the occurrence of these disruptions is equally distributed over the rail network. Strikes always occur on the same days in the same region, so the reference group corrects the lower travel frequency due to them.

In short, passengers in the reference group satisfy the following criteria:

- They meet the criteria in the list above;
- They travel in the same holiday region as the possession is in;
- They are not affected by another possession of at least three days in the pre-possession period;
- They are not affected by another possession with at least one overlapping day of the investigated possession;
- They are not affected by the investigated possession itself.

These selected passengers for the reference group are then placed into passenger groups, based on their travel pattern in the pre-possession period, similar to the investigated group, explained in Subsection 4.2.3.

Next, the travel patterns in the pre-possessions period of the reference group are compared to the travel patterns of the investigated group, per case and per passenger group, with the Kolmogorov-Smirnov (KS) test. The distribution of the number of trips in the pre-possession period should be approximately equal, per passenger group, for the investigated group and the reference group in order to establish a fair correction term. The empirical cumulative distribution function (ECDF) of the number of trips in the pre-possession period is constructed for both the investigated group and the reference group, per pre-defined passenger group. The KS-test computes the largest distance, $D_{n,m}$, between the distributions n and m with Equation 3.6 (Massey, 1951).

$$D_{n,m} = max|F_{\text{investigated group}}(x) - F_{\text{reference group}}(x)| \tag{3.6}$$

with $F_{\text{investigated group}}(x)$ and $F_{\text{reference group}}(x)$ the ECDF of the number of trips per passenger in the pre-possession period for the investigated group and the reference group respectively.

The null hypothesis (H_0) is that both distributions are the same, and is rejected if Equation 3.7 holds. The test statistic D must be statistically significant ($\alpha = 0.05$) (Massey, 1951), and large enough for practice. Equation 3.8 shows that the KS-test is sensitive for large sample sizes. The reference group is for all cases large ($m = 10^3$ to 10^4), and the investigated group is for some cases also large ($n > 10^3$). Therefore, small differences between the distributions are already significant, even though the distributions are very similar. The practical threshold T is added to address this problem.

$$D_{n,m} > c(\alpha) \cdot \sqrt{\frac{n+m}{n \cdot m}} \;\cap\; D_{n,m} > \text{T} \tag{3.7}$$

with n and m the sizes of the investigated and reference group respectively (per passenger group), T the practical threshold, and

$$c(\alpha) = \sqrt{-\frac{1}{2} \cdot ln(\frac{\alpha}{2})} \tag{3.8}$$

The practical threshold, T, is chosen as 0.10. This means that, for a certain number of trips in the pre-possession period, the difference between the cumulative share of number of trips of the investigated group and the reference group may at most be 0.10. This corresponds to visually clearly different distributions of the reference and investigated group, and therefore differentiates between negligible and substantial differences in the distributions.

Only the passenger groups, defined in Subsection 4.2.3, for which Equation 3.7 does not hold are considered in the analysis. For these passenger groups, the reference group behaves similarly to the investigated group in the pre-possession period. For the selected reference passengers, the number of trips in the post-possession periods is computed, after which the average change of the number of trips between the pre-possession period and each post-possession period is computed per passenger group with Equation 3.5.

3.2. Selection criteria for cases

This section describes the general selection criteria that need to be met for a case to be used in the analysis. Therefore, an overview of all possessions within a certain period should be made before selecting the relevant cases.

As stated in Section 1.4, only possessions of at least one day (24 hours) are considered in this study.

In addition, the most important criteria are related to data availability. Data must be available for a sufficiently long time before and after the rail possession. The required duration of the pre-possession period and the post-possession period is two months and six months respectively, as determined in Subsection 3.1.1.

Thirdly, there should not be a new possession on the same route in the post-possession period. This would directly affect the number of trips of passengers (because they cannot travel on their regular route), regardless of the effect of the original, investigated possession. Besides, the effect of the first possession cannot be isolated from the subsequent possessions in these situations. So, a possession is not investigated if there is a new possession on the same route within six months. Note that an individual passenger could be affected by another possession on his or her route during the post-possession period. Passengers who travel often over such a route are not included in the analysis, as explained in Subsection 3.1.2.

In addition, the same holds for the pre-possession period. There may not be a possession on the same track in the pre-possession period.

Moreover, cases with other major external factors (e.g. highway maintenance) should be excluded, because it is not possible in such cases to isolate the effect of the rail possession.

There are also (partial) station closures. In these situations, more than one line connected to the same station is possessed. It should be prevented that one passenger affected by both line closures is included twice (for both possessions) in the analysis of the effects of different possession characteristics on changes in passenger patterns (see Section 3.4). Therefore, if there are multiple line closures connected to the same station, only one is used in the analysis: the possession with the longest duration. This possession presumably has the largest negative effect on passengers, and is therefore most interesting to investigate. If the durations are equal, the possession with the highest number of unique passengers that can be used in the analysis (i.e. passengers that travel with a smart card) is used, which is taken directly from the data.

Simultaneous possessions are usually geographically separated (except for lines connected to the same station). Therefore, it is unlikely that a passenger is affected by two or more simultaneous possessions that are included after the previous filtering steps, but it is not impossible. However, only passengers who frequently use an affected line are included in the analysis (see Subsection 3.1.2). It is considered very unlikely that a passenger frequently travels over two geographically -much- separated lines that are also possessed at the same time. This effect is therefore neglected.

There are cases for which the same maintenance project has different phases of closures. In those situations, the track is possessed between A and B for the entire duration of the project, but also between B and C during a part of the project (which means that the track is closed between A and C), see Figure 3.8. In these situations, a rule-based approach is used to determine the normative possession. A choice has to be made between the duration and the length of the possession. The option expected to have the largest effect on changes in passenger patterns, and the most affected passengers, is selected. Only if the phase with a shorter length of possessed track (i.e. A-B) lasts seven or more days more than the phase with the full track closure (i.e. A-C), the short track closure is used as a case, which in that case is assumed to have a larger total impact. This means that not all affected passengers are selected for the analysis (the ones that only use B-C are not selected), and that the effect of the possession characteristics (duration, length, etc.) might be underestimated or overestimated. In all other cases, the shorter phase with the full route bocked (A-C) is used.

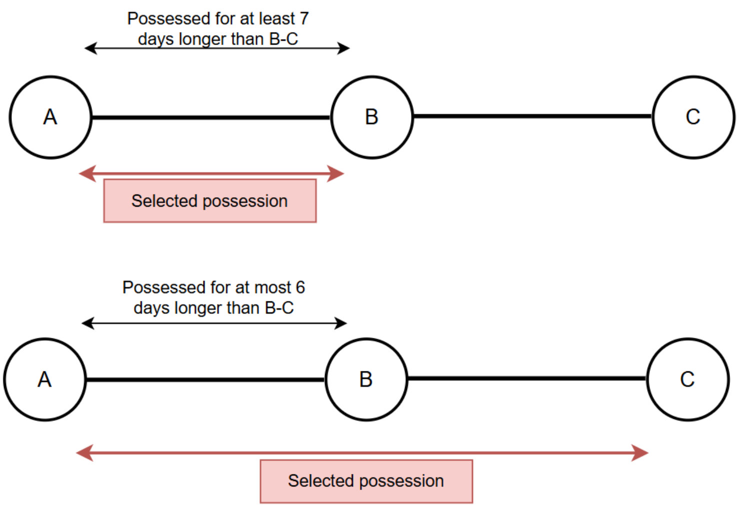


Figure 3.8: Selection of possession for maintenance with different phases

Finally, there are maintenance projects with multiple phases, that overlap geographically and/or time-wise. If no normative possession can be determined for a maintenance project, with the mentioned criteria, the project is not considered at all in this thesis.

Figure 3.9 shows the filtering steps that are taken to select the possessions for the analysis. These steps ensure that the cases can be investigated adequately and that their long-term effects can be well isolated.

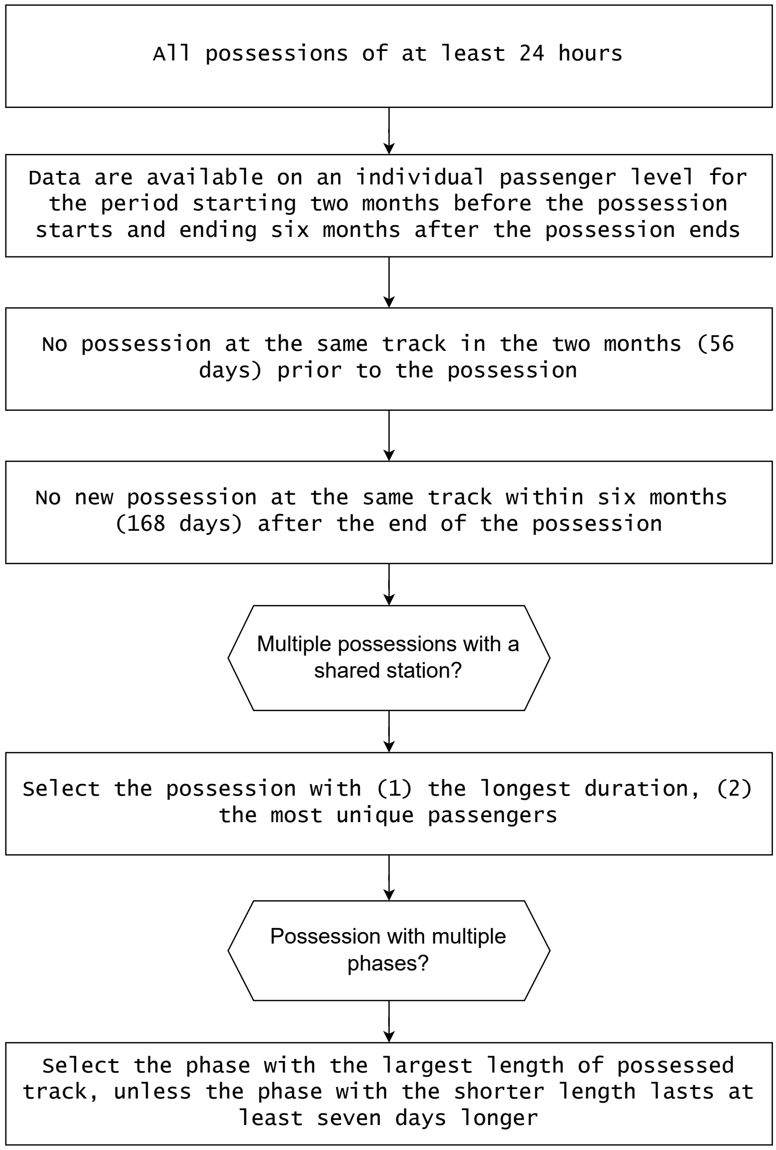


Figure 3.9: Filtering steps for selecting possessions for the analysis

3.3. Rail possession characteristics

This section explains how the possession characteristics are computed. Subsection 3.3.1 covers the general characteristics, and Subsection 3.3.2 the passenger-specific ones.

3.3.1. General rail possession characteristics

The length, L, in kilometers of a possession is determined by comparing the coordinates (on a one-dimensional scale) between the start and end stations (Equation 3.9). The duration, T, in days is computed by counting the days from the start date to the end date, see Equation 3.10, and subsequently categorised according to Equation 3.11.

$$L = x_{\text{end-station}} - x_{\text{begin-station}} \tag{3.9}$$

$$T = T_{\text{end}} - T_{\text{begin}} \tag{3.10}$$

$$T = \begin{cases} SHORT & \text{if} \quad T \leq 2 \text{ days} \\ MID & \text{if} \quad 3 \leq T \leq 7 \text{ days} \\ LONG & \text{if} \quad T \geq 8 \text{ days} \end{cases} \tag{3.11}$$

These categories are determined using the following logic. Short possessions (1-2 days) can occur within a weekend, which does not impact most commuters. For mid duration possessions, passengers are one week affected by it, which does not lead to too much hindrance. Passengers can, for example, temporarily work (more) from home or accept a longer travel time for a few days. Long possessions lead to hindrance in at least two weeks (e.g. two successive Mondays), which require people to find a good alternative, since they cannot skip their activities for such a period.

The dates of the possession are also used to determine if a possession took place on the weekend and/or holiday. This results in two dummy variables as possession characteristics, computed with Equation 3.12 and Equation 3.13. For both characteristics, the possession has to take place fully during the relevant period. A possession that started on a Friday and ended on the next Wednesday is, for example, not considered as weekend-possession.

For the weekend-characteristic, possessions are assigned a value of 1 for the dummy variable if the possession has a start and end day of Saturday or Sunday and lasted one or two days (filtering out any possessions that started on a Saturday and ended on the next Saturday, for example):

$$\text{Weekend} = \begin{cases} 1 & \text{if start and end date are a Saturday or Sunday and duration is one or two days} \\ 0 & \text{otherwise} \end{cases} \tag{3.12}$$

A possession is only considered to be during a holiday if the start date and end date are both a public holiday in the relevant region and there are no non-holiday days in between. For possessions where one end is located in a different holiday region than the other end, the possession is registered as in a holiday if one or both of the regions have holiday at that time.

$$\text{Holiday} = \begin{cases} 1 & \text{if possession is fully during school holidays in the relevant region} \\ 0 & \text{otherwise} \end{cases} \tag{3.13}$$

The number of days since the last possession on the same route is also one of the characteristics, and computed with Equation 3.14. This is taken as the number of days between the start date of the new possession and the end date of the last possession. If 75% of the currently affected stations was also affected by a previous possession, the previous possession is considered to be the same, and is used to compute the days since the last possession. This is done to ensure that possessions on the same line, but between different stations are included in this characteristic.

For example, there have been possessions between station A and station D, but also between station A and station E. The former consists of the route *A-B-C-D*, while the latter is the route *A-B-C-D-E*. When considering the former, the latter has 100% the same stations. When considering the latter, the former has 80% the same stations. Therefore, the other possession meets the criterion for both cases, and is used to compute the duration since the last possession. This is desirable, since the same route and passengers are affected by both possessions in practice, although the possessed track is not entirely the same.

Besides, there have to be at least five days between both possessions, otherwise they are likely the same project. Five days is chosen as the threshold to allow maintenance in consecutive weekends to be considered for this possession characteristic. An overview of maintenance works per route might not be available for an indefinite period in the past, as data are only stored for a limited period. Therefore, there might not be a known previous possession for all cases. If that is the case, the time since the moment from which data are known is used instead.

$$\Delta T = \begin{cases} T_{\text{start possession}} - T_{\text{end last possession}} & \text{if there has been a possession} \\ & \text{with the same route since the data set starts} \\ T_{\text{start possession}} - T_{\text{start data set}} & \text{otherwise} \end{cases} \tag{3.14}$$

Next, the time since the last possession (T_{LP}) is categorised according to Equation 3.15, similar to the the duration of the possession. The boundaries are set at half a year and a full year. The half year (six months) is used because it is as long as the full post-possession period that is used for the analyses of long-term effects. Long-term effects are thought to be observable within a six-month period, so it is also interesting to investigate if a past possession influences the effect of a new possession within a period of equal duration. The category *long* is chosen as double the time.

$$T_{LP} = \begin{cases} SHORT & \text{if} \quad \Delta T \leq 6 \text{ months (168 days)} \\ MID & \text{if} \quad 6 \text{ months (168 days) } < \Delta T < 12 \text{ months (336 days)} \\ LONG & \text{if} \quad \Delta T \geq 12 \text{ months (336 days)} \end{cases} \tag{3.15}$$

Other maintenance projects in the same area are also one of the possession characteristics, represented with a dummy variable, see Equation 3.16. A possession is assigned a value of 1 for this characteristic if at least one of the affected stations is also affected by another possession (on another line), on at least one day of the possession.

$$\text{OTHER-MAINTENANCE} = \begin{cases} 1 & \text{if one of the affected stations is also affected by another pos-} \\ & \text{session on at least one overlapping day} \\ 0 & \text{otherwise} \end{cases} \tag{3.16}$$

3.3.2. Passenger-specific possession characteristics

This section covers the computation of the passenger-dependent possession characteristics. For these characteristics, a passenger's most common origin-destination pair in the pre-possession period is used. If there is not a distinct OD-pair, the average value to each station of the passenger's main zone is used instead. Each passenger has a distinct main zone OD-pair, after filtering.

The alternative travel option provided by the railway operator (RO) is represented in two characteristics: the option itself and the travel time. The computation of these variables differs per country or railway operator, because it depends on the way the data are structured. The methodology for NS in the Netherlands is given in Subsection 4.3.2. There are usually three possible alternative modes that a RO can offer: (a detour by) train, bus or metro. Moreover, it could be that there is not an alternative option provided, or that it is not included in the data, for certain OD-pairs (and thus passengers). Therefore, a fourth option *missing* is included. These are included in the analysis as three dummy variables, see Equation 3.17, Equation 3.18 and Equation 3.19.

$$BUS = \begin{cases} 1 & \text{if the shortest RO-alternative includes a replacement bus} \\ 0 & \text{otherwise} \end{cases} \tag{3.17}$$

$$METRO = \begin{cases} 1 & \text{if the shortest RO-alternative includes a metro} \\ 0 & \text{otherwise} \end{cases} \tag{3.18}$$

$$MISSING = \begin{cases} 1 & \text{if there is not an alternative option provided by the RO or} \\ & \text{it is not included in the data} \\ 0 & \text{otherwise} \end{cases} \tag{3.19}$$

If both BUS, $METRO$ and $MISSING$ are zero, but there was an alternative travel option of the RO available, the alternative option included only the train. This option is not included as a separate variable in the model (see Section 3.4) to prevent multicollinearity of the variables.

The quality of the other alternative travel options is included in the model with the travel time of these options.

The travel time by car between two stations is computed using the Open Source Routing Machine (OSRM) (OSRM, n.d.), an extension of OpenStreetMap. This method is generally applicable, regardless of the country or railway operator. This routing machine returns the travel time by car between two coordinates, assuming that there is no congestion. For this thesis, the coordinates of the stations are used as origin and destination. For each passenger, its regular origin and destination (zone) (from the pre-possession period) are used to compute the travel time by car between the stations, as one of the possession characteristics. This is a simplification because a passenger's origin and destination is not exactly at the station. The computed travel time can therefore be over- or under-estimated. This effect increases for larger access and egress distances. However, a passenger's exact origin and destination are unknown, so using the stations as origin and destination is the best option. For each station, the travel time to all other stations is computed, using a Python script that connects to the OSRM server. The travel time between each combination of stations is computed once, so the day and time on the day are not considered.

Finally, the approach to compute the travel time by other public transport differs per country. In all cases, it involves a public transport routing machine that has the option to exclude the train as mode. Subsection 4.3.2 covers the methodology for the Netherlands.

3.4. Effect of possession characteristics and passenger groups on post-possession passenger patterns

Next, it is determined whether the selected rail possession characteristics from the literature review in Section 2.3 actually have an effect on the post-possession travel patterns, and whether the passenger type influences these relationships between characteristics and changes in travel patterns. This is tested by developing regression models.

Subsection 3.4.1 introduces the ANOVA test that is used to test whether there is a difference in values of the indicators between passenger groups, and the post-hoc test that is used to determine which passenger groups have statistically different indicators. Subsequently, Subsection 3.4.2 explains the ordinary least squares method that is used in the regression models. Finally, Subsection 3.4.3 covers the model estimation strategy.

3.4.1. Effect of passenger groups

One-way ANOVA tests are used to determine whether the passenger groups influence the value of the indicator on the (change in the) number of trips (see Equation 3.2). The ANOVA test is performed separately for both long-term post-possession periods (i.e. month 3-4 and month 5-6).

The null hypothesis in this test is that the mean value of an indicator is the same throughout the different passenger groups (Ostertagova & Ostertag, 2013):

$$H_0 : \mu_{\text{pass.group 1}} = \mu_{\text{pass.group 2}} = ... = \mu_{\text{pass.group N}}$$

In other words, it is tested whether the variation between passenger groups is (much) larger than the variation within a passenger group. The alternative hypothesis (H_A) is that at least one passenger group has a different value for the indicator. The F-statistic is used to test the null hypothesis (Ostertagova & Ostertag, 2013).

$$F = \frac{MS_{\text{between groups}}}{MS_{\text{within groups}}} = \frac{SS_{\text{between groups}}/df_{\text{between groups}}}{SS_{\text{within groups}}/df_{\text{within groups}}} \tag{3.20}$$

with MS the mean squares, SS the sum of squares and df the degrees of freedom

Then, the p-value is computed using the F-distribution table. A significance level (α) of 0.05 is used. The *statsmodels* package in Python (Seabold & Perktold, 2010) is used to perform the ANOVA test.

Next, Equation 3.21 gives the formula for the η^2 statistic, which is used to compute the effect size of the sample. The statistic quantifies how large the effect is that the factor (i.e. the passenger group) has on the indicators. The η^2 statistic can be interpreted as the fraction of the overall variance (Richardson, 2011) explained by the passenger group.

$$\eta^2 = \frac{SS_{\text{between groups}}}{SS_{\text{total}}} \tag{3.21}$$

Next, post-hoc analyses are performed to determine which overarching passenger groups are relevant to include in the regression model. The Games-Howell test is used to identify the groups between which significant differences in changes in passenger patterns occur. The pre-defined groups that do not have a significant different distribution of indicator-values, are grouped together in overarching passenger groups. The Games-Howell test does not assume equal sample sizes and equal variances for the groups (Agbangba et al., 2024), and is therefore preferred over the commonly used Tukey's Honestly Significant Difference (HSD) test in this thesis, since the sizes of the passenger groups are not equal.

The difference in the mean value (μ) of the indicator for two groups A and B is statistically significant if Equation 3.22 is satisfied (Games & Howell, 1976; Sauder et al., 2017).

$$|\mu_A - \mu_B| \geq Q^*_{A,B} \frac{S_{\alpha,k,v}}{\sqrt{2}} \tag{3.22}$$

with $S_{\alpha,k,v}$ the Studentised range value for a total of k groups, v degrees of freedom, and a significance level α (α = 0.05), and

$$Q^*_{A.B} = \sqrt{\frac{SS_A^2}{n_A} + \frac{SS_B^2}{n_B}} \tag{3.23}$$

with SS_A and SS_B the variance of passenger group A and B, and n_A and n_B the size of the groups (Games & Howell, 1976; Sauder et al., 2017).

The results of the Games-Howell test are used to select the relevant passenger groups for the regression model of each indicator (Subsection 3.4.2). If two or more pre-defined passenger groups do not have a significant difference in response to a possession ($p > 0.05$), they form a new, overarching group together. The overarching groups are primarily determined using the second investigated post-possession period (3-4 month), because this is the closest period to the possession itself, in which potential changes are considered to be permanent.

The results of the Games-Howell test are visually supported with box plots with the computed indicators, per case and per pre-defined passenger group. These box plots include the mean value, interquartile range, minima, maxima and outliers. Pre-defined groups that are similar in response according to the Games-Howell test must have similar box plots (for most of the cases).

3.4.2. Linear regression model

For the two post-possession periods that are considered long-term (i.e. the second and third post-possession periods), a regression model is developed that estimates the number of trips of a passenger in a post-possession period j. First, base models are developed, with only the expected number of trips for a passenger as an explanatory variable. This is defined for a passenger i as the sum of the number of trips in the pre-possession period and the expected change in the number of trips, see Equation 3.24. The expected change is equal to the seasonality correction factor defined in Equation 3.5 in Subsection 3.1.4.

$$N_{\text{expected},i,j} = N_{i,\text{pre}} + \Delta N^{\text{total}}_{\text{passenger group k ref; pre-}j} \tag{3.24}$$

with j the post-possession period, k the passenger group that the relevant passenger belongs to, and $\Delta N^{\text{total}}_{\text{passenger group k ref; pre-}j}$ the expected change in the number of trips.

The general and passenger-dependent possession characteristics, as well as the passenger groups are added to the models after developing the base models. By doing this, it is tested whether the possession characteristics increase the model performance. The possessions have an effect on passenger patterns, in terms of number of trips, if the quality of the model, expressed with the R^2, increases.

Figure 3.10 shows the regression framework with the dependent and independent variables.

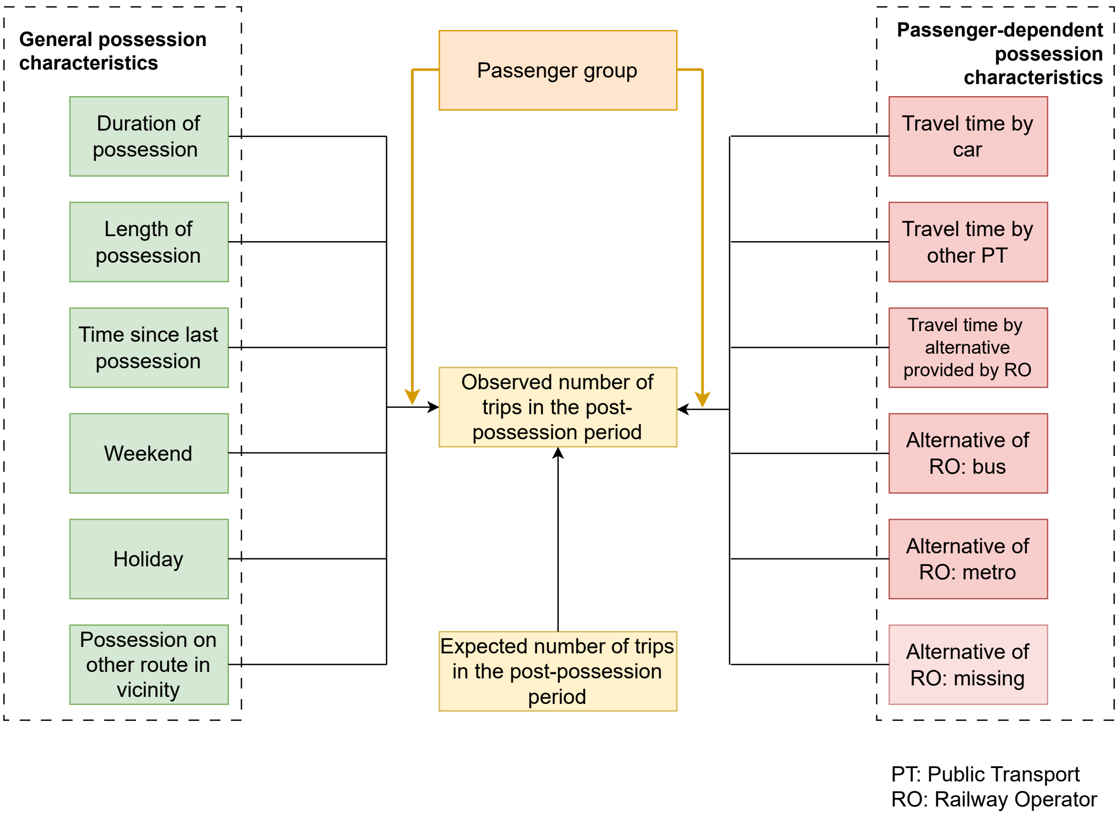


Figure 3.10: Regression framework. The passenger type is only included for an indicator if it is significant in the ANOVA test.

Equation 3.25 shows the equation for the regression model.

$$\boldsymbol{y} = \boldsymbol{\beta X} + \boldsymbol{\epsilon} \tag{3.25}$$

- with y an $n \times 1$ vector with the dependent variables (the observed number of trips of a passenger);
- and with β an $(m+1) \times 1$ vector for the m parameters and the intercept (β_0) that are estimated;
- and with X an $n \times (m+1)$ matrix with the independent variables (each row contains the value of the m characteristics for that passenger, with the first column containing only ones for the intercept);
- and with ϵ an $n \times 1$ matrix containing the error terms (Hansen, 2021).

An Ordinary Least Squares (OLS) method is used. This minimises the squared differences between the observed and estimated values of the indicators ($\boldsymbol{y}$). This method is linear in its parameters, but it can handle non-linear relationships (Pohlmann & Leitner, 2003). The (potential) correlation between observations (passengers) from the same case is accounted for by using Cluster Robust Standard Errors (CRSE). Controlling for these correlations prevents over-estimating the precision of confidence intervals and prevents deceptively low p-values (Cameron & Miller, 2015).

The overarching passenger groups, based on the Games-Howell test (see Subsection 3.4.1), are included as interaction variables in the regression model. This enables testing whether the effect of an independent variable (i.e. a possession characteristics) differs for different values of other independent variables (i.e. per passenger group) (Burks et al., 2019). Equation 3.26 shows how the interaction variable between a passenger group and possession characteristic X_1 is calculated.

$$X_{1,\text{interaction}} = GROUP \cdot X_1 \tag{3.26}$$

The linear regression cannot be performed with missing data (Nahhas, 2026). This means that each possession characteristics needs to be known to be able to perform the analysis. Therefore, handling missing data is an important aspect. A suitable approach must be used depending on the nature of the missing data, i.e. whether it is missing at random (MAR), missing completely at random (MCAR), or missing not at random (MNAR), see Hyun (2013). Subsection 4.3.2 discusses how missing variables are handled for the case study in the Netherlands.

3.4.3. Model estimation strategy

The possession characteristics are added to the model using hierarchical multiple regression, with five blocks of variables, in combination with backward elimination per block. For both long-term post-possession periods, the regression model that estimates the number of trips in the post-possession period is built in steps. Hierarchical regression ensures reproducibility of the method, since the order of addition of variables is based on theory instead of the data (Kioko, 2021).

Five successive models (A to E) are developed based on the five blocks. Model A consists only of the variable from the first block, which contains the expected number of trips. This is expected to be the best estimator of the number of trips in the post-possession period, and therefore included in the first block. Next, model B includes the first and second blocks. The second block contains the general possession characteristics. Thereafter, the third block contains the interaction terms of the passenger groups and the general possession characteristics. This block is added in model C. Model D also contains the fourth block, which contains the passenger-dependent characteristics. Finally, the fifth block, with the interaction terms between the passenger-dependent characteristics and the passenger groups, is added in model E. The process is shown in Figure 3.11, while the variables per block are listed in Table 3.2.

The general possession characteristics are added to the model before the passenger-dependent characteristics. The possession characteristics are added first, because they can be chosen (to a certain extent) when scheduling maintenance. The passenger-dependent properties are mostly fixed due to the context and chosen general characteristics. For example, the travel time by car cannot be influenced, whereas the time planning of the possession can be chosen.

Table 3.2: Variables included in the hierarchical regression

No.	Block	Variables
1	Expected number of trips	Expected number of trips
2	General possession characteristics	Duration (category), length, holiday, weekend, work other route, time since the last possession (category)
3	Interaction group and general characs.	Passenger group × general possession characteristics
4	Passenger-dependent characteristics	Alternative travel option provided by RO: bus, metro, missing; travel time of the alternative provided by RO; travel time by car; travel time by other public transport
5	Interaction group and pass.-dep. characs.	Passenger group × passenger-dependent characteristics

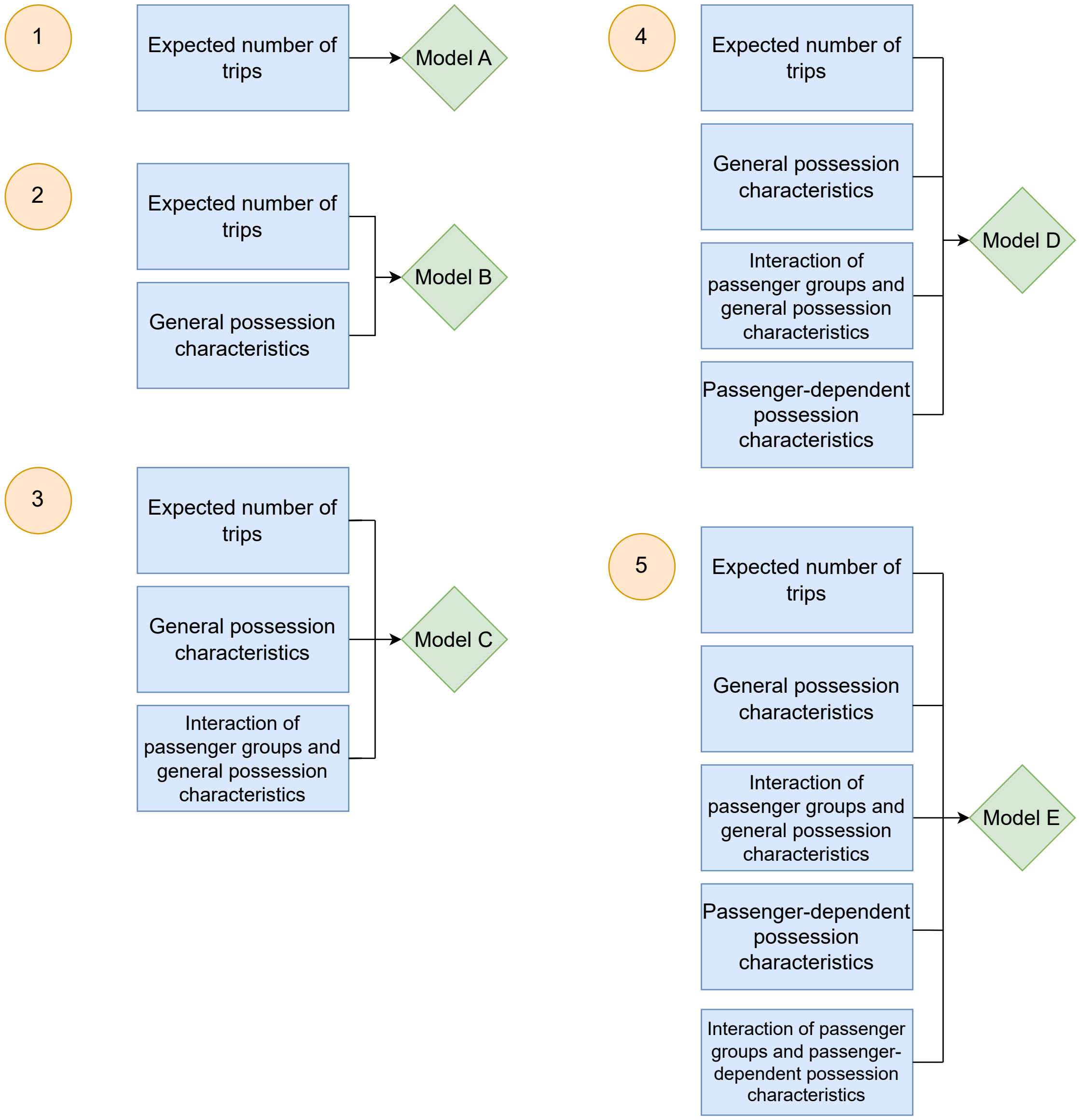


Figure 3.11: Hierarchical regression: order of model development

Per model (A to E), backward elimination is used to eliminate insignificant variables. A significance level (α) of 0.05 is used. The Variance Inflation Factor (VIF) is used to determine which independent variable should be removed first per hierarchical block. The VIF measures how much the variance of a coefficient (β) increases due to the correlations with other variables. The VIF of a variable j is computed with Equation 3.27 (Fox & Monette, 1992).

$$VIF_j = \frac{1}{1 - R_j^2} \tag{3.27}$$

in which R_j^2 is the coefficient of determination when estimating variable x_j with all other included variables, i.e. when estimating the parameters β in Equation 3.28 (Pardoe, 2018).

$$x_j = \beta_0 + \beta_1 x_1 + ... + \beta_{j-1} x_{j-1} + \beta_{j+1} x_{j+1} + \epsilon \tag{3.28}$$

A VIF of 1 indicates that a variable is uncorrelated with other variables, while a VIF greater than 1 indicates that it is correlated with (some) variables (Taboga, 2021).

However, the genaralised VIF (GVIF) must be used for a group of dummy variables with more than two categories (e.g. the three duration categories), because the value of the regular VIF depends on which category is used as reference (and excluded from the regression model) (Fox & Monette, 1992; Nahhas, 2026). In that case, the regression formula (Equation 3.25) is rewritten to Equation 3.29 (Fox & Monette, 1992) to be able to compute the GVIF.

$$\boldsymbol{y} = \boldsymbol{\beta_0 X_0} + \boldsymbol{\beta_1 X_1} + \boldsymbol{\beta_2 X_2} + \boldsymbol{\epsilon} \tag{3.29}$$

in which $\boldsymbol{X_1}$ consists of the group of binary variables, in which $\boldsymbol{X_2}$ consists of the other variables in the regression model, and in which $\boldsymbol{X_0}$ consists of 'fixed' variables (e.g. the intercept).

The GVIF of a group of at least three binary variables is computed with Equation 3.30 (Fox & Monette, 1992).

$$GVIF = \frac{det(R_{11}) \times det(R_{22})}{det(R)} \tag{3.30}$$

with $det(.)$ the determinant of a matrix, and R_{11} the correlation matrix of the variables within the group of binary variables of the same category, R_{22} the correlation matrix of all other variables in the model, and R the overall correlation matrix (Fox & Monette, 1992).

Next, the adjusted GVIF (aGVIF) is calculated, which considers the number of categories (p_1) within a group of binary variables, and allows comparison with other variables (Fox & Monette, 1992; Nahhas, 2026). The aGVIF is computed with Equation 3.31 (Fox & Monette, 1992).

$$aGVIF = GVIF^{\frac{1}{2p_1}} \tag{3.31}$$

The variable with the highest VIF or aGVIF among the insignificant variables is removed from the model, because that variable adds the least information to it. Then, the regression is performed again, and the VIF and aGVIF of the remaining estimators is computed again. This process repeats until only significant variables are included in the regression model, per hierarchical block. If a category of binary variables has the highest VIF, while not all categories are insignificant (e.g. the duration category has the largest VIF / aGVIF, but only the mid duration is insignificant), only the insignificant binary variables of that category are removed as intermediate step. This prevents unnecessary removal of significant variables from the model.

Interaction terms are inherently correlated with its parent variables (i.e. the interaction term between a passenger group and a possession characteristic is correlated to that group and characteristic). However, the VIF or aGVIF can be computed for these terms as well, to determine which (insignificant) interaction variables should be removed. In models C and E of the hierarchical development (Figure 3.11), interaction terms are removed before the potential removal of their corresponding general or passenger-dependent characteristic, even though the interaction term might have a lower (aG)VIF, since the possession characteristic has a higher hierarchical level.

The difference in model quality (between successive models in the model development) is assessed with the difference in R^2, the difference in the F statistic and the significance of these changes. This comparison is performed after the new model only has significant variables. ANOVA is used to compare the successive models. All explanatory variables of the prior model need to be included in the new model, for the ANOVA test to be applicable. The new model is accepted if the R^2 and F statistic increase, and if this increase is significant ($p \leq 0.05$) (Phillips, 2026).

The process does not stop if adding a block of variables does not lead to model improvement. In that case, the next block of variables is added to the previous model, so the block without significant variables or without improving the model is skipped.

The hierarchical regression model development is performed in Python with the *stats.models* package (Seabold & Perktold, 2010). In short, variables are added in hierarchical blocks to the model. General possession characteristics are added before the passenger-dependent possession properties. Insignificant variables are removed in each block based on the multicollinearity with other variables, using the VIF and aGVIF as measures. The final result consists of two regression models: one for each long-term post-possession period (e.g. the month 3-4 and month 5-6 after the maintenance has been completed).

3.5. Application model

This section discusses the applications of the final regression models. Subsection 3.5.1 gives the post-hoc application possibilities, while Subsection 3.5.2 discusses the predictive possibilities of the model.

3.5.1. Most influential possession characteristics

The final regression models give insight into the possession characteristics that influence the number of trips, and thus the passenger patterns, in the post-possession periods. These results are used to answer the main research question, that asks which characteristics have the greatest impact on structural changes on a specific line given the passenger composition on that line.

The insights in the effect of different characteristics and the magnitude of these effects can be used to schedule maintenance in such a way that the maintenance has the least negative impact on passenger patterns.

3.5.2. Extension to predictive model

The described method in Section 3.1 to Section 3.4 is a post-hoc analysis. The method is used to determine how past possessions led to permanent changes in passenger patterns and what the effect of different possession characteristics on these changes is. However, the method can also be used ‘reversely’ to predict the permanent changes in passenger patterns (in terms of number of trips) for future possessions. This requires some changes to the method, which are discussed in this section.

First of all, the passengers who frequently use the line to be possessed in the future must be selected. However, since the prediction will likely be made more than a few days in advance, the passengers who frequently use the line in the two months before the possession cannot be determined. Instead, the passengers who frequently use the line in the same two months, but a year before, should be used. It is assumed that the composition of passenger groups is approximately equal in successive years, although the individual passengers might differ.

Next, in the post-hoc analysis, passengers who, in addition to the investigated line, also use another rail line that is possessed in the two months before, six months after or during the possession are excluded, to isolate the effect of a single possession. However, this is not required for a predictive model, since there are no observations (i.e. passengers) that contaminate the data.

Moreover, the reference group cannot be used in a similar way as in the post-hoc analysis. The average change in the number of trips is not known beforehand. Therefore, again, the reference group is selected in the period a year before, and the average change in their number of trips from the year-before pre-possession period to the year-before post-possession period is computed and used as the expected change in number of trips per passenger group. The seasonality pattern is assumed to be equal in successive years. Moreover, people affected by other maintenance projects in the (year-before) pre-possession period are excluded from the reference group, as described in Subsection 3.1.4. Since the seasonality pattern is based on the pattern of the year before, the possessions in the year before in the pre-possession period are used. This ensures a representative reference group for the prediction.

Next, the investigated group of passengers is distributed into the pre-defined passenger groups. Then, the expected change in the number of trips is computed using Equation 3.24 in Subsection 3.4.2.

Thereafter, the general possession characteristics and passenger-dependent characteristics for the possession under investigation must then be computed. Finally, the regression model can be reversely used. The coefficients β in Equation 3.25 are known, as well as the matrix $\boldsymbol{X}$ with possession characteristics. Then, the dependent variable $\boldsymbol{y}$ is computed for each passenger selected for the analysis. This is the observed number of trips in the post-hoc analysis, but the predicted number of trips in the predictive model. This is not only based on the coefficients found in the regression analysis, but also on an error term ϵ as shown in Equation 3.25. This represents the randomness of passengers in terms of number of trips. The error term is computed per overarching passenger group (see Subsection 3.4.1) with Equation 3.32. It is assumed that the error term follows a normal distribution.

$$\epsilon_k = \mathcal{N}(0,\ \sigma_k^2) \tag{3.32}$$

in which σ_k is the standard deviation of the difference between the observed and expected change in the number of trips, for passenger group k, based on all observations from the post-hoc analysis (i.e. the post-hoc analysis results in the values of σ_k).

Therefore, the predicted number of trips of an individual passenger i of the overarching passenger group k is calculated with Equation 3.33.

$$N_{\text{predicted},i} = \boldsymbol{\beta X} + \epsilon_k \tag{3.33}$$

Then, a comparison is made between the predicted change in the number of trips (using the result of the regression model) and the expected change in the number of trips (based on the pre-possession number of trips and the average change of the reference group), similar to Equation 3.2 in Subsection 3.1.3, but without the denominator. The difference between these is caused by the possession.

Computing this for all passengers leads to a distribution of differences between the predicted and expected change in the number of trips, which is an estimate of the effect of a future possession. This can be used to show the negative, permanent effects of maintenance works. Simulations with different combinations of possession characteristics can be performed to determine the optimal (i.e. least damaging) maintenance strategy.

3.6. Summary of methodology

In summary, a six month post-possession period is used to analyse changes in travel patterns due to possessions. This period is split into three two-month periods. A pre-possession period of two months is used to compare the post-possession travel patterns with.

Changes in travel frequency are observed by comparing the number of trips in the post-possession period to the number of trips in the pre-possession period. Seasonality is accounted for by using an unaffected reference group. Changes in route or station choice are identified by comparing the share of trips over the affected line among all trips between a passenger's two main zones before and after the possession. Passengers are divided into overarching passenger groups using the Games-Howell test.

The regression model gives insight in the most influential possession characteristics on permanent changes in passenger patterns, and whether this differs per overarching passenger group. To do so, multiple possessions are analysed. Finally, the regression model can be used inversely to estimate the 'lost' trips in a post-possession period due to the maintenance.

The methodology is applied to possessions in the Netherlands. Chapter 4 explains some additional, context-specific methodological steps, and presents the cases and passengers that are investigated.

4 Case study

Chapter 3 described the methodology that is followed to quantify permanent changes in passenger patterns due to possessions (i.e. to answer the third research question) and to determine the effect of different possession characteristics and passenger groups to these changes (i.e. the fourth research question). As described in Chapter 3, these methods are applied to cases to find the answers on the third and fourth research questions.

The main rail network of the Netherlands, on which Nederlandse Spoorwegen (NS) operates, is used as a case study. This chapter describes the additional steps that are taken to identify suitable possessions to investigate, as well as an overview of the selected cases (Section 4.1). Then, Section 4.2 describes pre-processing steps of the AFC data, to be able to select the relevant passengers and perform the analysis. Next, Section 4.3 describes additional filtering steps to select the relevant passengers for the Netherlands specifically, and gives an overview of the selected passengers. Finally, Section 4.4 gives additional filtering steps to obtain the reference groups for the Netherlands specifically.

4.1. Selection of cases for analysis

Case studies are required to perform the analysis. There are multiple criteria that a period of maintenance must satisfy in order to be used in this study, which are discussed in Section 3.2. Subsection 4.1.2 adds additional criteria for the Netherlands specifically. First, Subsection 4.1.1 explains how an overview of possessions in the Dutch main rail network is made. Finally, Subsection 4.1.3 discusses the possessions that passed the selection criteria and are therefore used in the analysis. Subsection 4.1.3 also describes the general possession characteristics of those possessions.

4.1.1. Overview of rail possessions

There is no complete and reliable internal NS overview of possessions in recent years. Therefore, an overview of the possessions is retrieved from other sources: the SD (from the Dutch *Specifieke Dag*), BDu (from the Dutch *Basis Dag update*) and realisation data. The SD and BDu are two types of timetables used by NS, and the realisation data includes all trains (and their routes) that have operated in the past.

Rail possessions are identified by comparing the standard timetable with the day-specific timetable. The BDu is a timetable for normal days, developed for a three-month period. There is, for example, a BDu for all Wednesdays in the winter. These timetables are defined three months in advance. SDs are defined closer to the operation day, and take all special situations, like rail possessions or large events, into account. Incidents do not influence the SD, since incidents are not planned and therefore not considered in the timetable.

All NS-operated trains have a train-basis-series number, which belongs to the route it operates on. For example, all trains operating on the route Dordrecht - Arnhem Centraal (in either direction) have 6600 as train-basis-series. On regular days, with a frequency of twice per hour, there are 36 to 38 circulations in total (per direction) per day for a train-basis-series number (Treinposities, n.d.). A circulation is one trip from the start to the end station (e.g. from Dordrecht to Arnhem Centraal).

In this thesis, a track segment is defined as the track between two stations, regardless of whether a train-basis-series has a planned stop at those stations. Figure 4.1 shows an example of track segments.

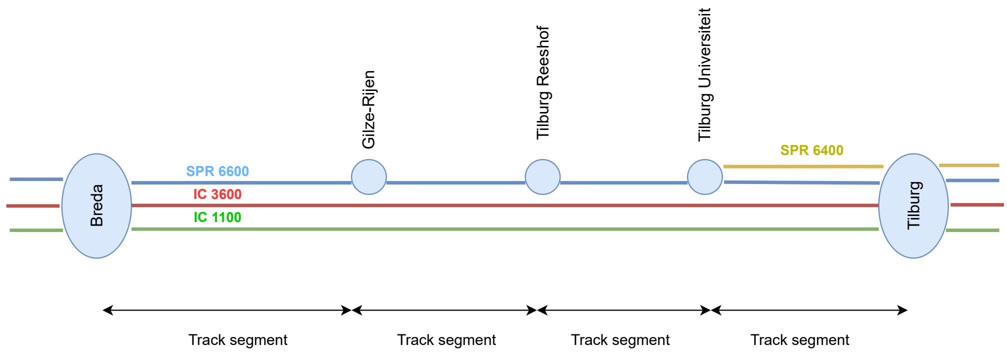


Figure 4.1: Example of track segment definition, including stations and train-basis-series

For each train-basis-series, the number of scheduled circulations on each track segment in the BDu (both directions together) is compared to the number of scheduled circulations in the SD, for each day. In other words, the number of times a train-series-basis is supposed to pass a track segment in the BDu is compared to the number of times it passes it in the SD.

A train-basis-series is assumed to not operate on a day due to maintenance, on a specific track segment, when on that segment it holds that:

- *There are more than five scheduled circulations in the BDu and there are less than five scheduled circulations in the SD* ($BDu > 5$ *and* $SD < 5$)

The threshold of five is used for the BDu to only consider trains-basis-series that would have operated the entire day on a track segment in normal situations. The threshold of five in the SD is used to account for trains that have operated the night before (between 0.00h and 4.00h). It holds for both thresholds that the number of trains would be much higher if the train would have operated in a normal way.

Next, the realisation data are added. These are used to check whether the train-basis-series indeed has not operated on the selected day and track segment, and, whether on the selected day and track segment, other train-basis-series have also not operated. It could be that one train-basis-series does not operate on a track segment, because there is a possession on another part of its regular route. In that case, other train-basis-series can still drive on the selected track segment, which indicates that there is no possession there. Again, a threshold of five trains is used for the realisation data.

Now, for each date, and for each train-basis-series, all track segments are known on which trains were originally scheduled to operate, but did not do so. Each blocked track segment consists of the two stations (abbreviations) between which the track is blocked, for example 'Sptn-Drh'. Each section occurs twice in the overview, if train traffic is blocked in both directions (e.g. 'Sptn-Drh' and 'Drh-Sptn' are both outputs of the previous step). The next step is to group all track segments with the same day and the same train-basis-series, in order to find the entire route that was possessed.

This is done by counting, per train-basis-series and per date, the station abbreviations and selecting the two that occur the fewest. This works under the assumption that the train traffic is always blocked in both directions at the same time.

For example, the train-basis-series 4800 normally operates between Amsterdam Centraal (Asd) and Hoorn (Hn), via Haarlem (Hlm) and Uitgeest (Utg). Figure 4.2 visually gives the output of the previous steps, in which all track segments between Haarlem and Beverwijk (Bv) are blocked, hence *Hlm-Bll*, *Bll-Sptz*, *Sptz-Sptn*, *Sptn-Drh* and *Drh-Bv* (and in the opposite direction) are outputs. All stations (abbreviations) are counted. Haarlem (Hlm) and Beverwijk (Bv) occur only twice, because the track is only blocked in one direction from those stations. The other (intermediate) stations occur four times in the output, because the track is possessed in both directions from those stations. Therefore, it is concluded that the track between Haarlem and Beverwijk is fully blocked.

It is also known that there are no trains with other train-basis-series operating on that route on that day, because otherwise the separate track segments would have been filtered out in the previous step.

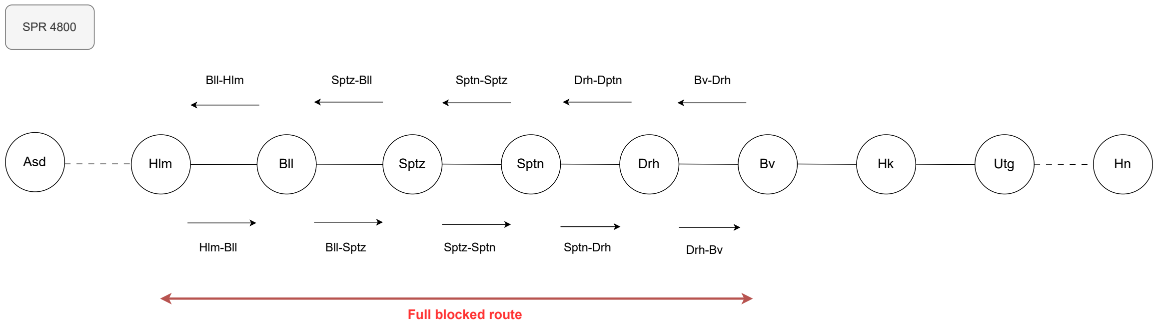


Figure 4.2: Example of inferring the total blocked route based on blocked track segments

There are also cases for which two, or more, separate parts of the route of a train-basis-series are possessed. In that case, four (or six, eight, etc.) stations are returned. For example, if Gs-Hlm-Ledn-Rsd is returned for the 2200, then Goes (Gs) - Roosendaal (Rsd) and Haarlem (Hlm) - Leiden (Ledn) are blocked. This requires a manual check of the route, and selecting the only logical option, based on knowledge of the rail network. This could be automatised by adding the order of stations based on the departure and arrival times, but this is not done for this thesis.

Finally, consecutive days with the same blocked track segments are grouped. This results in the final overview of the rail possessions, including the start date, the end date and the blocked route.

This method does not work for possessions that are so long (in duration), that they are included in the BDu. These cases are rare, but they presumably have a large impact, and should, therefore, be manually added to the overview, which is a matter of adding an extra line with the start date, end date, start station and end station to the output of the method described above. Since these cases have a high impact, they are assumed to be known by practitioners, who should be consulted. There are no such cases in the selected investigation period. However, the rail possession Alphen aan den Rijn - Bodegraven from October 2026 to mid 2027 is, for example, included in the BDu. This method also does not work for emergency repair works (that take more than one day), because these are not included in the SD (for example, the maintenance near Amsterdam Bijlmer Arena in March 2026). These cases are also rare, and known by the operator. However, these cases are considered as incidents, since they are unplanned, because they are not included in the SD. Therefore, these cases are outside the scope of this thesis.

4.1.2. Filtering steps possessions for case study

Section 3.2 described the general selection criteria for the cases to be included in the analysis. This section adds additional criteria for the Dutch main rail network. The cases are then described in Subsection 4.1.3, which also includes an overview of how many cases are filtered out in each filtering step.

The most important selection criterion from Section 3.2 was data availability. Individual passenger data must be available for a period from two months before the maintenance to six months after completion. For this thesis, data are provided by NS. Therefore, only possessions on the Dutch main rail network can be used. The data are available from January 2025 to March 2026 (15 months) for cases on the Dutch main rail network. This relatively short period is due to the strict Dutch privacy laws. The data availability leads to cases between March 2025 and August 2025 being suitable for analysis. Moreover, possessions longer than seven months cannot be investigated, since the total required period before and after the possession (two months before until six months after) is eight months. There are no such cases (partly) in the period for which data are available (January 2025 to March 2026). However, the before-mentioned possession between Alphen aan den Rijn and Bodegraven starting in October 2026 is too long to be investigated. However, there are options to extend the data availability period at NS, but this requires additional privacy regulations.

In Section 3.2 it was stated that cases with major external factors (like a simultaneous highway maintenance project) must be excluded. However, ProRail and Rijkswaterstaat (the infrastructure manager of highways in the Netherlands) coordinate their maintenance projects, in order to reduce hindrance for commuters and other car or train passengers. They do not schedule major maintenance projects on the road and rail in the same region simultaneously, for most cases (Rijkswaterstaat, n.d.). However, there are simultaneous maintenance works on parallel rail lines and highways in rare occasions, but these are done only on weekends, with lower overall impact. Therefore, the absence of highway maintenance projects is not a selection criterion for the rail maintenance projects, because they, in principle, do not occur simultaneously.

In short, mainly the criteria in Section 3.2 apply for this thesis. This section presented additional criteria that apply for this thesis only.

4.1.3. Selected possessions and their general characteristics

This section describes the possessions that are selected according to Section 3.2 and Subsection 4.1.2 for the analysis.

There are 23 possessions selected for the analysis. Appendix A provides an overview of the cases, including the general possession characteristics per case. Due to limited data availability, all cases occurred between March 2025 and August 2025.

Table 4.1 shows the number of cases lost per filtering step. Only 22% of all possessions within the data availability period meet the criteria to be used. Selecting at most one possession connected to each station (e.g. use only one of the simultaneous possessions *Den Haag Centraal - Den Haag Hollands Spoor* and *Den Haag Centraal - Den Haag Laan van NOI*) and selecting only one normative phase of each possession (e.g. use only one of the partly overlapping possessions *Haarlem - Santpoort Noord* and *Haarlem - Uitgeest*) removes relatively many cases. These filtering steps are performed simultaneously, so the distribution between the two is unknown, but both situations occur regularly. However, the criterion of using only one normative possession cannot be relaxed. This criterion ensures that the same maintenance project is not investigated twice. Relaxing the filter on at most one possession connected to the same station is possible, but requires additional filtering steps on passengers. It should be prevented that an individual passenger is used for two possessions (i.e. a passenger who uses both possessed rail lines), because his or her response would 'count' double in the regression model. This might over-estimate the total effect, and the characteristics of a single possession cannot be investigated well if a passenger is also affected by another possession.

Next, requiring no new possessions in the pre- and post-possession periods filters even more cases out. Subsection 6.3.2 explains how this filter could be relaxed to investigate more cases, and also explains the downsides of this relaxation.

Table 4.1: Effect of filtering steps on number of selected possessions

Filtering step	Number of possessions	Percentage of total
All possessions between March and August 2025 of at least 24 hours on the Dutch main rail network	105	100%
No simultaneous possessions with a shared station and merging possessions with different phases	70	67%
And no new possessions on same track in two months prior or six months after the possession	23	22%

Figure 4.3 shows the distribution of cases over the country. There have not been possessions that meet the requirements in the south-east of the country. The majority of the selected possessions is in the Randstad-region, with high passenger volumes and, therefore, potentially largest effects on ridership. There is only one case in the north of the country (Groningen), but this possession has the longest duration (64 days). There are two cases in the outer ends of the rail network (near Den Helder in the north-west and Zeeland in the south-west), where detour options per train are not possible. Finally, some cases are on consecutive routes (e.g. Breukelen-Woerden, Woerden-Alphen aan den Rijn and Alphen aan den Rijn-Leiden Centraal). Note that for each of those cases, only passengers who do not regularly use one of the other lines are selected for the analysis, as explained in Subsection 3.1.2.

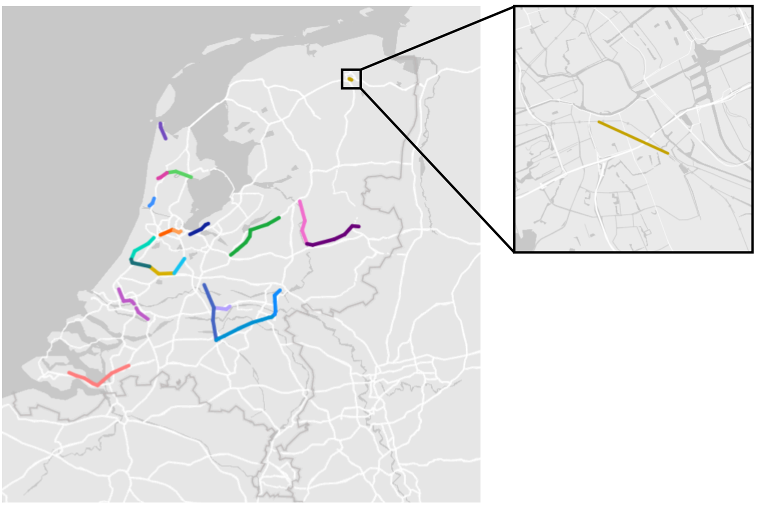


Figure 4.3: Map with selected possessions. Each colour represents one case.

Figure 4.4 shows the distribution of the length in kilometres of the possessions. There is a wide spread variation in the length of the possession, ranging from one to fifty kilometres.

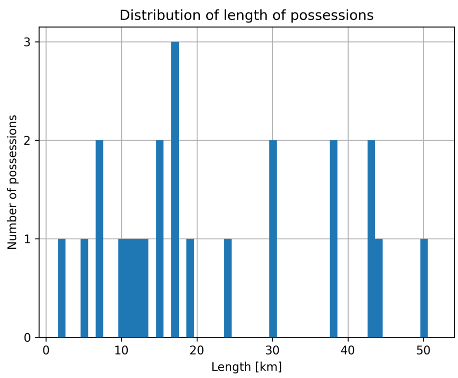


Figure 4.4: Length of possessions

Table 4.2 shows the number of possessions per duration category. There are only two possessions in the 'long'-category, the longest being 64 days in Groningen, and the other being nine days between Deventer and Zwolle. Most investigated possessions are short, with a duration of one or two days.

Table 4.3 shows the number of possessions per category of the time since the last possession on the same track. The data set with past possessions starts on June 13th, 2021, which is required input for Equation 3.14 in Subsection 3.3.1. For most cases, there was a possession less than half a year ago (12), but the other categories are also observed.

Table 4.2: Duration categories

Duration category	Number of possessions
Short (≤ 2 days)	14
Mid (3 to 7 days)	7
Long (≥ 8 days)	2

Table 4.3: Time since last possession categories

Duration category	Number of possessions
Short (≤ 6 months)	12
Mid (6 to 12 months)	5
Long (≥ 12 months)	6

The Netherlands has three holiday regions: *North*, *Centre* and *South*, in which school holidays are not scheduled (fully) simultaneously (Rijksoverheid, n.d.). An overview of these regions and the stations in each region is included in Appendix F.

Table 4.4 shows the distribution of the other dummy variables. Most of the selected possessions took place during the weekend, and during non-holiday periods. In addition, approximately one third of the possessions occurred simultaneously with another possession that shared at least one station.

Table 4.4: Descriptive statistics for the dummy variables

Characteristic	Yes	No
Fully during weekend	14	9
Fully during holiday	5	18
Other possession nearby same time	7	16

4.2. Preprocessing AFC data

This section briefly describes the processing steps that have already been performed with the raw data before they are obtained (Subsection 4.2.1) or before they are used in the analysis (Subsection 4.2.2 and Subsection 4.2.3). The raw data consists of the location and time of check-in and check-out of a trip, and the type of card and subscription. This is processed to trips (sequence of specific trains) and passenger types.

4.2.1. Route choice with FLUX model

Passenger routes are necessary to be determined for the analysis of their travel patterns. It is required to know the route of a train passenger to determine if he or she is negatively impacted by a rail possession (e.g. if he or she normally uses the affected rail line), and if he or she returns to the rail line after the rail possession has ended. The method of inferring the route choice differs per operator and country. The method of NS in the Netherlands is explained in this section.

The main rail network in the Netherlands is a closed, station-based network. For people who travel with an OV-chipkaart, OV-pas[1] or debit or credit card, checking in and checking out is required at the stations, not in the vehicles, which means that routes (and vehicles) are not directly observed. Most stations have barriers, that only open after checking in or out. However, there are also stations without barriers, but just a pole for checking-in and checking-out.

The NS model FLUX is used to infer the routes. A trip is defined with four variables: the origin, the destination, the check-in (CI) time and the check-out (CO) time. These four variables are known for more than 80% of the trips (Brands et al., 2024).

The first step of the model is to infer missing data (CI and/or CO location and/or time), see Brands et al. (2024). In the next step, the model generates ten possible (geographical) routes based on a passenger's check-in and check-out location, using a shortest-path algorithm, with the number of transfers as decision-making variable. Next, 100 combinations of specific trains and transfer stations are generated per route (travel options). Finally, a probability is assigned to each travel option, using the number of transfers, intercity-ratio (time in intercity / total travel time), inflow time (time from check-in until departure) and outflow time (time from arrival to check-out) (Brands et al., 2024).

The FLUX model distinguishes between eight types of trips, depending on the available data of the trip. A trip for which the origin, destination, check-in time and check-out time are known is classified as type 1. All other trips miss at least one of the four data inputs. This is mainly the case for passengers who do not travel with an OV-chipkaart, OV-pas or debit card. For passengers who travel with one of those payment options, forgetting to check out results in data loss. The FLUX model infers the missing data based on historical passenger patterns, but inferred check-in/check-out locations and times are not always correct.

4.2.2. Passengers with missing data and aggregating travel options

Only passengers who travel with an OV-chipkaart, OV-pas, or debit or credit card are included in the analysis. People who travel with a paper (single-time) ticket or online bought ticket do not have the same passenger ID each time they travel, so their behaviour cannot be followed over time. These

[1]The OV-pas is the successor to the OV-chipkaart, and was introduced in 2026 (Nederlandse Spoorwegen, n.d.-e).

passengers are removed from the data. A large share of unique passengers is removed by only considering passengers with an OV-chipaart, OV-pas or debit or credit card, but only a small share of the trips is removed. *Exact numbers or percentages cannot be listed for confidentiality reasons.*

Next, all non-type 1 trips are filtered out of the data. In 2025, the average share of type 1 trips among all trips for the passengers travelling with an OV-chipkaart, OV-pas or debit or credit card is very high. Therefore, the data loss due to filtering on type 1 trips alone is limited, while the accuracy of the data increases.

Only the passenger's route is required for the analysis. The FLUX model returns all possible travel options separately. For this thesis, the probabilities of all travel options that have the same route are summed to obtain the total probability that a passenger uses a certain route. Two or more travel options have the same route if and only if they have the exact same sequence of stations passed and the exact same total distance.

A simplified example of the pre-processed output of the FLUX model is shown in Table 4.5. In this example, all travel options for passenger 1 (ID 1) make use of the same route (Amsterdam Centraal (Asd) - Haarlem (Hlm) - Leiden Centraal (Ledn) - De Vink (Dvnk)), so the route is known (the probability is 1.0). However, the travel options make use of different specific trains (indicated with *Train series* in Table 4.5). There are two route options for passenger 2 (ID 2): from Nieuw-Vennep (Nvp) via Hoofddorp (Hfd)/Schiphol (Shl) and Amsterdam Sloterdijk (Asa) to Haarlem (Hlm), or from Nieuw-Vennep via Leiden (Ledn) to Haarlem. Since only the route is relevant for this thesis, the probabilities of the options are summed per route. The route via Amsterdam Sloterdijk is assigned a 0.35 probability, and the route via Leiden a 0.65 probability. These examples are visualised in Figure 4.5.

Table 4.5: Simplified example of preprocessed output FLUX model (fictitious data).

ID	Origin	Dest.	CI time	CO time	Train series	Route	Prob.
ID 1	Asd	Dvnk	10:49	12:08	2131-4330	Asd-Ass-Hwzb-Hlms-Hlm-Had-Hil-Vh-Ledn-Dvnk	0.35
ID 1	Asd	Dvnk	10:49	12:08	2333-4330	Asd-Ass-Hwzb-Hlms-Hlm-Had-Hil-Vh-Ledn-Dvnk	0.20
ID 1	Asd	Dvnk	10:49	12:08	2133-4332	Asd-Ass-Hwzb-Hlms-Hlm-Had-Hil-Vh-Ledn-Dvnk	0.45
ID 2	Nvp	Hlm	11:00	12:15	5739-4132-4833	Nvp-Hfd-Shl-Asdl-Ass-Hwzb-Hlms-Hlm	0.15
ID 2	Nvp	Hlm	11:00	12:15	5741-4134-4835	Nvp-Hfd-Shl-Asdl-Ass-Hwzb-Hlms-Hlm	0.20
ID 2	Nvp	Hlm	11:00	12:15	4330-2130	Nvp-Ssh-Ledn-Vh-Hil-Had-Hlm	0.30
ID 2	Nvp	Hlm	11:00	12:15	5730-2330	Nvp-Ssh-Ledn-Vh-Hil-Had-Hlm	0.35

4.2.3. Passenger groups

The analysis is performed per passenger group. Groups are already assigned to all passengers based on their subscription type. These groups are the following, with the Dutch name in brackets:

- Consumer ('Consument')
- Business ('Zakelijk')
- Student ('Student')
- International ('Internationaal')
- Plan ('Plan')

All passengers in the first three groups (in the left column) are relevant for this thesis. Passengers from the group 'international' travel with international trains or national trains as part of an international trip, and are not relevant for this thesis, because one can only travel once with a ticket of this category. Finally, most passengers in the group 'Plan' are also international passengers, who are not relevant for this thesis. This group also includes single-use e-tickets sold by third parties, which are also not relevant. However, the group 'Plan' also includes OV-chip cards that are sold by a third party (e.g. Shuttel, Reisbalans, etc.) to companies, which distribute them to their employees. Therefore, these passengers who use these cards are actually business passengers, and are therefore included in the group 'Business'.

It is possible that passengers switch their subscription type, but keep the same card. In most cases, the group does not change (e.g. a consumer buys another type of consumer subscription). Switching from student to consumer or vice versa does occur. If a passenger makes such a switch during an

[1]The percentages exceed 100% due to rounding

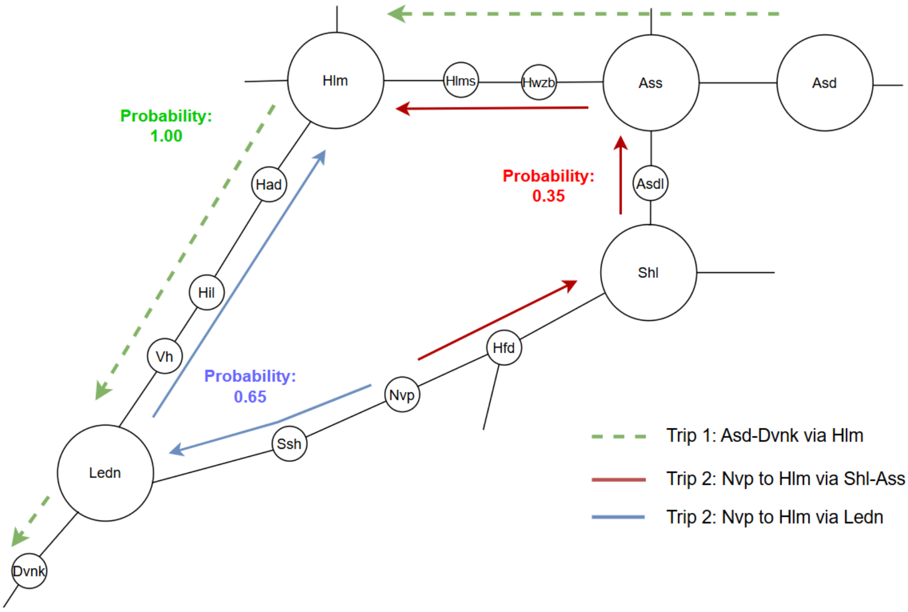


Figure 4.5: Examples of Table 4.5 on the map.

investigation period for a possession, the passenger is removed from the data. The passenger's subscription type is included in the data for all trips, so changes in subscription type are easily observed. It is assumed that any changes in travel patterns are caused by the life event that corresponds to the switch in subscription (student to consumer or vice versa).

Next, subgroups are made based on the travel frequency of the passengers in the pre-possession period (see Equation 3.1 in Subsection 3.1.2). This results in twelve subgroups (four for each of the three selected NS-defined groups) that are used in the analysis.

In short, Subsection 3.1.2 introduced that passenger groups are used in the analysis. This subsection provided the 12 passenger groups that are used in the case study of the Netherlands, based on the subscription types of NS.

4.3. Selection of passengers for analysis and passenger-dependent characteristics

This section describes the passengers who are investigated in the case study. First, Subsection 4.3.1 describes additional filtering steps for the passengers for the Dutch case study specifically. Thereafter, Subsection 4.3.2 discusses the computation of the passenger-dependent possession characteristics, specifically for the Dutch case. Next, Subsection 4.3.3 describes the extent of data loss due to the filtering steps, and gives a description of the final data set that is used for the analysis.

4.3.1. Filtering steps passengers for case study

Subsection 3.1.2 described the general selection criteria for passengers to be investigated. This section describes the steps that are taken in the case study to obtain these passengers.

The first step is to select all passengers who travel at least once over the affected line in the pre-possession period and can be tracked over time (e.g. travel with an OV-chipkaart, OV-pas or debit card). This is a relatively small group compared to the entire population of train users, which reduces computational time in the subsequent filtering steps. The possibly relevant passengers are identified in the following steps:

- Select all passengers who make at least one trip that passes at least one of the impacted stations, or one of the 'main stations' further down the affected line, in the pre-possession period[2];

[2]Example: for a possession 's Hertogenbosch - Houten Castellum, first passengers with at least one trip from/to/via one of

- Select all passengers who travel with an OV-chipkaart, OV-pas or debit card;
- Select all passengers who have a subscription type Business, Student, Consumer or Plan (business);
- Select all passengers who have at least one type 1 trip;
- Select all passengers who have at least one trip over the affected line

Determining if a passenger uses a certain route is computationally expensive. Therefore, that filtering step is the latest in the pre-processing. The first filtering step is to select only passengers in the desired area. The (general) filtering steps that are described in Subsection 3.1.2 are performed after the steps listed above. For completion, they are repeated below:

- Select all passengers whose share of trips over another possessed line in the pre-possession period is at most 10%;
- Select all passengers who travel at least eight times over the affected line, distributed over at least four weeks, in the pre-possession period;
- Select all passengers whose share of trips between the same two main zones in the pre-possession period is at least 50%;
- Select all passengers whose trips between their two main zones are affected by the possession.

4.3.2. Computation passenger-dependent possession characteristics and handling missing variables

Subsection 3.3.2 introduced the general method to compute the passenger-dependent possession characteristics. This subsection gives the detailed methodology that is followed to compute these characteristics for the case study in this thesis, for NS in the Netherlands.

For the Netherlands, the travel time by other public transport is calculated with the NS route planner, with the option 'train' disabled, for a regular working day. It is only computed for origin-destination pairs with more than 250 unique passengers in 2025 (approximately 25,000 of the approximately 160,000 OD-pairs), to reduce computational demand. The travel time by other public transport can be undefined, if no route is found. In that case, a travel time of 20 hours is used, which is two hours more than the highest travel time that is found by the NS Reisplanner. The day and time of day are not considered; each OD-pair only has one travel time.

The travel time by other public transport is missing for OD (or zone) pairs with very low traffic volume (less than 250 unique passengers in 2025). This corresponds to trips that presumably have a high travel time, hence the low demand. Therefore, the variable is not missing at random (MNAR: Missing Not At Random), so using, for example, mean value imputation leads to biased results. However, listwise deleting (i.e. deleting the entire row (passenger) if there is one missing variable in the data) also leads to biased results (Hyun, 2013) and unnecessary data loss. The missing values are imputed with higher values than the maximum observed travel time, to incorporate the MNAR mechanism of missing values corresponding to very unattractive travel times. Two hours is added to the maximum observed travel time by other public transport (17.8 hours). This is rounded to a travel time of 20 hours for missing values.

The travel time with an NS-option during a possession is computed with realised trip data. The minimum travel time in minutes (realised by any passenger) between each combination of origin and destination station, during the possession is taken. These data also includes the mode of that trip, which is used for the variables BUS, $METRO$ and $MISSING$. However, the travel time is only known for each OD-pair during a possession if at least one passenger made the trip between those stations. It is not possible to determine the travel time between any combination of origin and destination during a specific possession in any other way. If the travel time and mode are not known for the specific OD-pair, but they are known for the main zones, the average value of the travel time between the stations in the main zones is used instead. In that case, the modes could differ (i.e. from one station of the origin main

the affected stations ('s Hertogenbosch, Zaltbommel, Geldermalsen, Culemborg, Houten Castellum) or one of the larger stations down the line (Utrecht Centraal) are selected. 's Hertogenbosch is the larger station at the other end in this case. This is done purely for computational efficiency.

zone to one station of the destination main zone, the mode could be different than to another station of the destination main zones). Then, the most frequently occurring mode (train, bus or metro) is used. The same holds for when a passengers does not have a distinct OD-pair, as stated before.

The travel time of the NS-provided option is missing for some passengers. It is likely missing for those OD (or zone) pairs that have a high travel time or are unattractive for another reason, because the variable is missing in case no one made the trip between those zones during the relevant possession. A similar approach is used for imputing this variable as for the travel time by other public transport. However, since these data are based on realised trips, and thus potentially based on individual passengers who make unrealistically long trips between OD pairs (while being the only one making that trip during the possession), the additional two hours is not used here. Instead, the maximum value that occurs at least 100 times in the observed data is used as the imputed value for the missing values. Requiring a value that is observed at least 100 times ensures that no artificially long trips are used to impute the missing values.[3]

Subsection 3.1.2 described main zones in which all stations in the same city (and surrounding towns) are grouped. For this thesis, an internal NS-overview of main zones is used as basis and is developed further to become consistent. The overview is included in Appendix E.

4.3.3. Selected passengers and passenger-dependent possession characteristics

Subsection 4.3.1 described the (additional) filtering steps to obtain the passengers for the analysis in the case study. This subsection first describes the data loses due to these filtering steps and then gives and overview of the final data set of selected passengers.

Data loss in filtering

As described in Subsection 4.3.1, only passengers with an OV-chipkaart, OV-pas or debit card are used in the analysis. In addition, only type 1 trips are included. For each possession, all passengers having at least one trip over the impacted line in the pre-possession period are first selected from the data. This is the base population for a possession.

In the next step, only passengers who travel at least in four out of the eight weeks before a possession, at least eight times in total and at least 50% between the same two main zones are included.

It is tested for five cases throughout the country in different periods how much unique passengers (pseudonomysed smartcard IDs) are removed in this filtering step. Filtering from the base population on passengers who travel at least twice over the impacted line already removes 23% to 53% of the passengers from the base population. The first selected filtering step (at least four active weeks and at lest eight trips) leaves 13% to 20% of the original passengers. Together, they make 30% to 35% of the total trips of the base population. The final filtering step (requiring 50% of the trips between the same two main zones) removes approximately 20% from the filtered data.

An example of the data loss, for one case, per filtering step is included in Appendix G.

Final data set and passenger-dependent characteristics

In total, approximately 400,000 passengers affected by a possession are included in the analysis. Appendix A includes the number of selected passengers per case.

Figure 4.6 shows the distribution of passenger groups (of the affected passengers) in all selected cases. The low-medium-frequent business group (on average two tours per week) is the largest, while the high-frequent business group (four or more tours per week) is the smallest. The distribution over the frequency categories is similar for student and business passengers, although the total number of students in the data is lower. The consumer passengers do not have the same distribution.

The three low-frequency groups do not meet the criteria in Equation 3.7 in Subsection 3.4.1 regarding the similarity of the distribution of the pre-possession number of trips of the investigated group and the reference group for most cases (possessions). Therefore, these three groups are not included in the subsequent analyses, and approximately 75% of the originally selected passengers is used in the

[3]There are individuals who travel for fun the entire day, which leads to very high travel times. These should not be considered for imputing the missing variables.

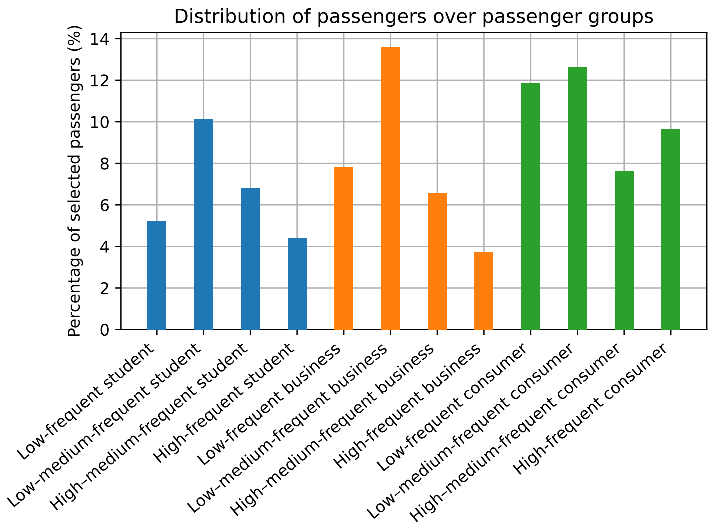
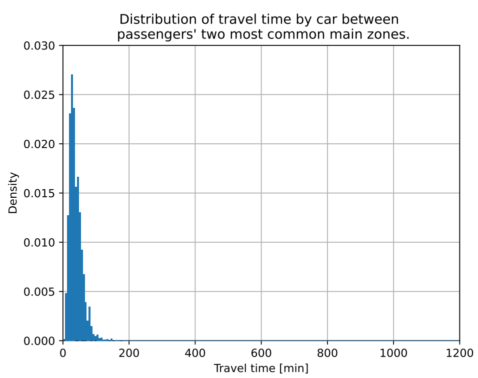


Figure 4.6: Share of passengers used in the analysis per passenger group

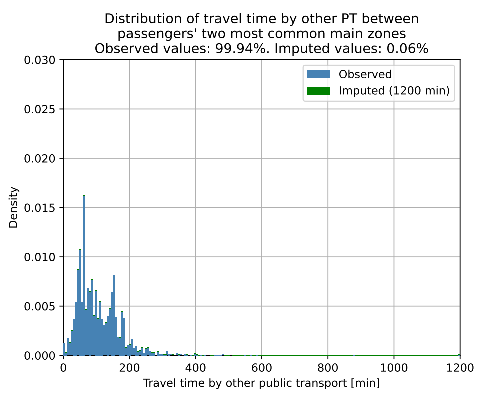
analysis. There are also a few other groups in specific cases that do not satisfy Equation 3.7, but there is not systematic difference between the investigated group and the reference group for the remaining nine passenger groups.

Figure 4.7a and Figure 4.7b shows the distribution of the travel time between passenger's most common OD-pairs (or zones) by car and by other public transport respectively. Figure 4.8 shows the same for the travel time during the possession by an NS-provided option. The travel time by other public transport or with an NS-option during a possession is not known for all passengers. The imputed values, according to Subsection 4.3.2 are added in green. There are only a few imputed values for the travel time by other public transport (0.06%), but 11% of the travel time by NS-provided option is imputed. These are imputed for unattractive OD-pairs (zones), for which no one made the trip during the possession.

In general, the travel time by car between passengers' two most common main zones is shorter than the travel time by public transport (excluding the train). This is expected, since there are often no direct, fast bus routes between two stations, as the train offers that service. The travel time between passengers' two most common main zones using an NS-provided alternative option during a possession is centred around 70 to 90 minutes, for the zones for which an alternative NS-option is known. Since the alternative NS-option between two stations or main zones is only known if at least one person has made the trip, it can be assumed that the travel time for other zone-pairs is even higher.



(a) Distribution of travel time between passenger's most common OD-pair (or zone) by car



(b) Distribution of travel time between passenger's most common OD-pair (or zone) by other public transport

Figure 4.7: Distributions of travel time between passenger's most common OD-pair (or zones)

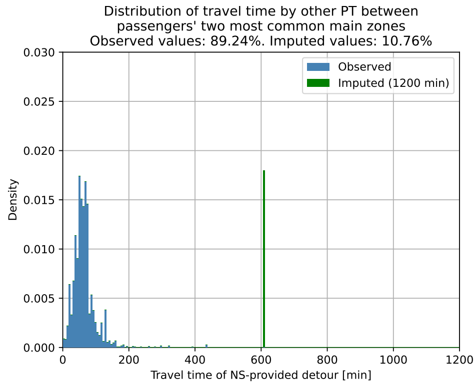


Figure 4.8: Distribution of travel time between passenger's most common OD-pair (or zone) with an NS-provided option during the possession

Table 4.6 shows the distribution of the alternative option provided by NS during the possession. For most passengers, the alternative during the possession is the train, followed by the bus. The metro is only (sometimes) an alternative option when there is a possession near Amsterdam or Rotterdam / The Hague, which explains the relatively low share of this mode as alternative. The alternative NS-option is not known for 11% of the selected passengers. Nobody travelled between these passengers' most common origin and destination zones during the relevant time period, so data on the travel time and travel option are missing.

Table 4.6: Distribution of alternative NS option during possession

Travel option	**Share of passengers**
Bus	33%
Metro	12%
Train	44%
Missing	11%

In conclusion, there is sufficient variation in the passenger-dependent possession characteristics to develop the regression model as introduced in Section 3.4. The extent of missing variables for the public transport by other public transport is limited, but the travel time by the NS-provided option is missing for a higher share. The imputed values ensure that the regression model can be developed.

Correlation matrix possession characteristics

Finally, Figure 4.9 shows the correlation matrix of all the possession characteristics (general and passenger-dependent). Pearson's r measures the linear correlation between two continuous variables (Chee, 2013; Schober et al., 2018). However, some of the possession characteristics are dichotomous (binary), for example the three duration categories. The point biserial correlation (r_{pb}) is used to compute the correlation between a continuous and a dichotomous variable. It is mathematically equivalent to Pearson's r (Chee, 2013; Kornbrot, 2014). Therefore, using regular (software) packages that compute Pearson's r results in the correct values of the point biserial correlation between a continuous and a dichotomous variable (Kornbrot, 2014). For two dichotomous variables, the ϕ-coefficient is used to measure the linear correlation, assuming two discrete univariate distributions (Ekström, 2011), and ranges from -1 to +1 (Wiedmaier, 2017). The ϕ-coefficient is also mathematically equivalent to Pearson's r (Calkins, 2005; Newsom, 2025). However, p-values must be determined with the χ^2-test (Wiedmaier, 2017) instead of the t-test that is used for Pearson's r. The interpretation of this coefficient is similar to the interpretation of Pearson's r (Wiedmaier, 2017). The correlation between all variables, regardless of their type (continuous or dichotomous), is thus quantified with a mathematically equivalent measure, allowing a direct comparison of correlations between different types of variables.

The correlations between mutually exclusive variables are not indicated in Figure 4.9, because they do not provide relevant information. The correlation between *long duration* and *short duration* is, for example, not shown, because a possession is by definition not long if it is short.

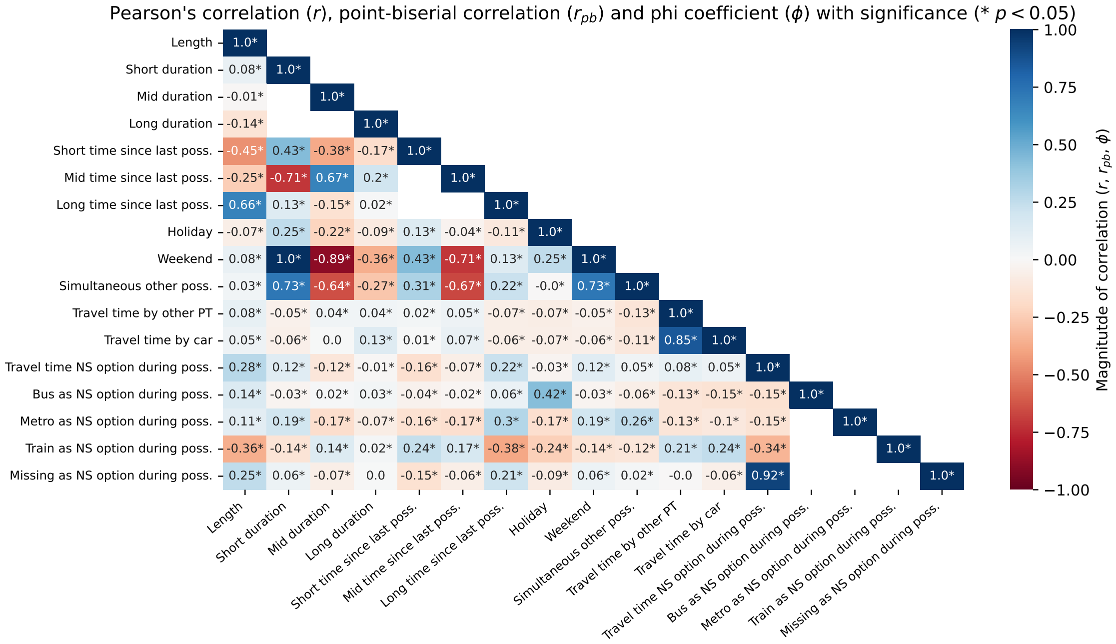


Figure 4.9: Correlation matrix (Pearson's r for continuous variables, point biserial correlation for one continuous and one dichotomous variable, ϕ-coefficient for two dichotomous variables) of the possession characteristics.

The properties *weekend* and *short duration* are perfectly correlated ($\phi = 1$). Short duration possessions are at most two days, as defined by Equation 3.11 in Subsection 3.3.1. There are no selected possessions with a short duration that took place during the week, hence the perfect correlation. The correlation between the travel time of the NS-option and the *missing* variable is 0.92. This is due to the imputed high values for that travel time if the travel time itself (and thus the option as well) is missing.

Next, the *mid duration* property is highly correlated ($\phi = -0.89$) with the *weekend* characteristic. This is due to the definition of these variables: a *mid-duration* possession does by definition not occur fully during the weekend.

Interestingly, the travel time by car and the travel time by other public transport (PT) between passenger's most common origin and destination (zones) are also highly positively correlated ($r = 0.85$). The mode of the other public transport (than the train) is often the bus, which approximately follows the same roads and has approximately the same speed as cars.

Moreover, the property *simultaneous other possession* has a high, positive correlation with the *short duration* and *weekend* characteristic. As explained above, these two properties are perfectly correlated themselves. Evidently, there are often (partial) station closures, with multiple possessed lines from the same station, during the weekend.

In contrast, the *simultaneous other possession* characteristic is negatively correlated ($\phi = -0.64$) with *mid duration* possessions. Apparently, possessions of three to seven days are not scheduled simultaneously with other possessions in the same area. The *simultaneous other possession* property is also negatively correlated ($\phi = -0.67$) with the characteristic *mid time since last possession* (six to twelve months).

Finally, the holiday characteristic is relatively closely correlated with the bus characteristic ($\phi = 0.42$). Evidently, the bus is often used as the alternative mode provided by NS for possessions during a holiday.

These insights in the correlations between the variables are used in the development and the interpretation of the regression models in Section 5.2. As explained in Subsection 3.4.3, the correlation among variables is used to select the order of elimination of insignificant variables in the model development strategy. Figure 4.9 already shows that the weekend and short-duration characteristics should not be included in the final model due to their perfect correlation. Moreover, it shows that the weekend characteristics is correlated with many other general possession characteristics. This also holds with the *simultaneous other possession* property. These expectations will be tested with the VIG and aGVIF (Equation 3.27 and Equation 3.31 in Subsection 3.4.3).

4.4. Selection of reference group

For a fair comparison between the affected passengers and the reference group, only passengers travelling in the same holiday region as the possession are included in the reference group for each case. As stated before, there are three holiday regions in the Netherlands, in which the holidays are not scheduled fully simultaneously, see Appendix F. This section explains additional steps that are taken to obtain the reference group for the case study in the Netherlands.

The reference group consists of passengers whose origin and/or destination is for at least 80% of the passenger's trip in the same holiday region as the possession during the pre-possession period. A trip is defined as within a holiday region if at least one of the origin and destination stations is in the relevant holiday region. The 80% criterion is a first filter, to select only relevant passengers and reduce computational time. Subsequent filtering steps ensure that the passengers in the reference group travel regularly between distinct main zone pairs, within that region. If one end of the possession is in another holiday region than the other, the reference group consists of passengers from both regions.

To obtain the passengers in the reference group for computing this correction factor, the same filtering steps are taken as for selecting the relevant passengers for a possession, except for the filtering on a specific rail line. Instead, only passengers who have a distinct main zones pair (i.e. passengers who often travel between the same two main zones) and whose number of trips is at least 80% in the same holiday region as the possession are selected.

First, the relevant time period is selected (i.e. the two months before a possession). Then, only trips paid for by an OV-chipkaart, OV-pas or debit or credit card are selected. Next, only type 1 trips are selected (i.e. trips for which all information is known). Then, only passengers who have travelled in at least four out of the eight weeks, and at least eight times in total, and have at least 50% of their trips between the same main zones (see Section 4.3) are selected for the reference group, for a specific possession.

In short, the additional filtering steps in the Dutch-specific case ensure that the only difference between the investigated group of passengers and the reference group the possession is. Specifically, the use of the three holiday regions prevents differences between the investigated group and the reference group due to differences in holiday schedules. Therefore, the reference group can be used to account for the seasonality effect, which allows for a accurate investigation of the rail possessions on permanent changes in passenger patterns.

The methods described in Chapter 3 are applied to the cases introduced in this chapter. The results of the analyses of these case studies are presented in Chapter 5.

5
Results

This chapter gives the results of the analyses explained in Chapter 3 for the cases described in Chapter 4. Section 5.1 describes the changes in passenger patterns after a possession. Next, Section 5.2 introduces the regression models that test whether the possession characteristics have an effect on the post-possession number of trips, and if there is a long-term effect of the investigated maintenance works.

5.1. Changes in passenger patterns

This section describes the changes in passenger patterns from the pre-possession period to the post-possession periods. Subsection 5.1.1 first gives the differences between the observed and the expected change in the number of trips in the post-possession periods. It also covers the first indicator introduced in Chapter 3, which is the difference between the observed change and the expected change relative to the pre-possession number of trips. Moreover, it discusses the effect of the passenger groups on that indicator. Thereafter, Subsection 5.1.2 gives the results for the second indicator on changes in route or station choice for all post-possession periods.

5.1.1. Changes in number of trips

This subsection first shows the changes in the number of trips after possessions of different duration categories. Next, the effect of passenger groups on these changes is explained.

Result per possession duration category

The main distinction between cases with and without an observable effect on post-possession passenger patterns is the duration. Therefore, results are presented on an aggregated level per duration category. Appendix B shows the results per case separately.

Figure 5.1 presents the difference between the observed change and the expected change in number of trips for the three possession duration categories (short, mid and long) for all three post-possession periods. This is the numerator of the indicator introduced in Equation 3.2 in Subsection 3.1.3. There are 14 investigated cases with a short duration (one to two days), seven with a mid duration (three to seven days) and two with a long duration (eight or more days). Appendix A includes an overview of the cases and their general characteristics.

The two post-possession periods that can identify long-term changes (i.e. the third and fourth month, and the fifth and sixth month after the maintenance) are shown in blue and yellow respectively, while the first two (short-term) months are shown in grey. This allows for the identification of a potential return process, as Eltved et al. (2021) and Nazem et al. (2018) found.

A value of zero in Figure 5.1 indicates that a passenger does not change his or her number of trips from the pre-possession period to the post-possession period more strongly than the unaffected reference group on average does. In other words, the passenger follows the general trend exactly and is thus not affected by the possession. In practice, without the effect of the possession, some passengers will have positive values, whereas others will have negative values, due to the variability in travel patterns.

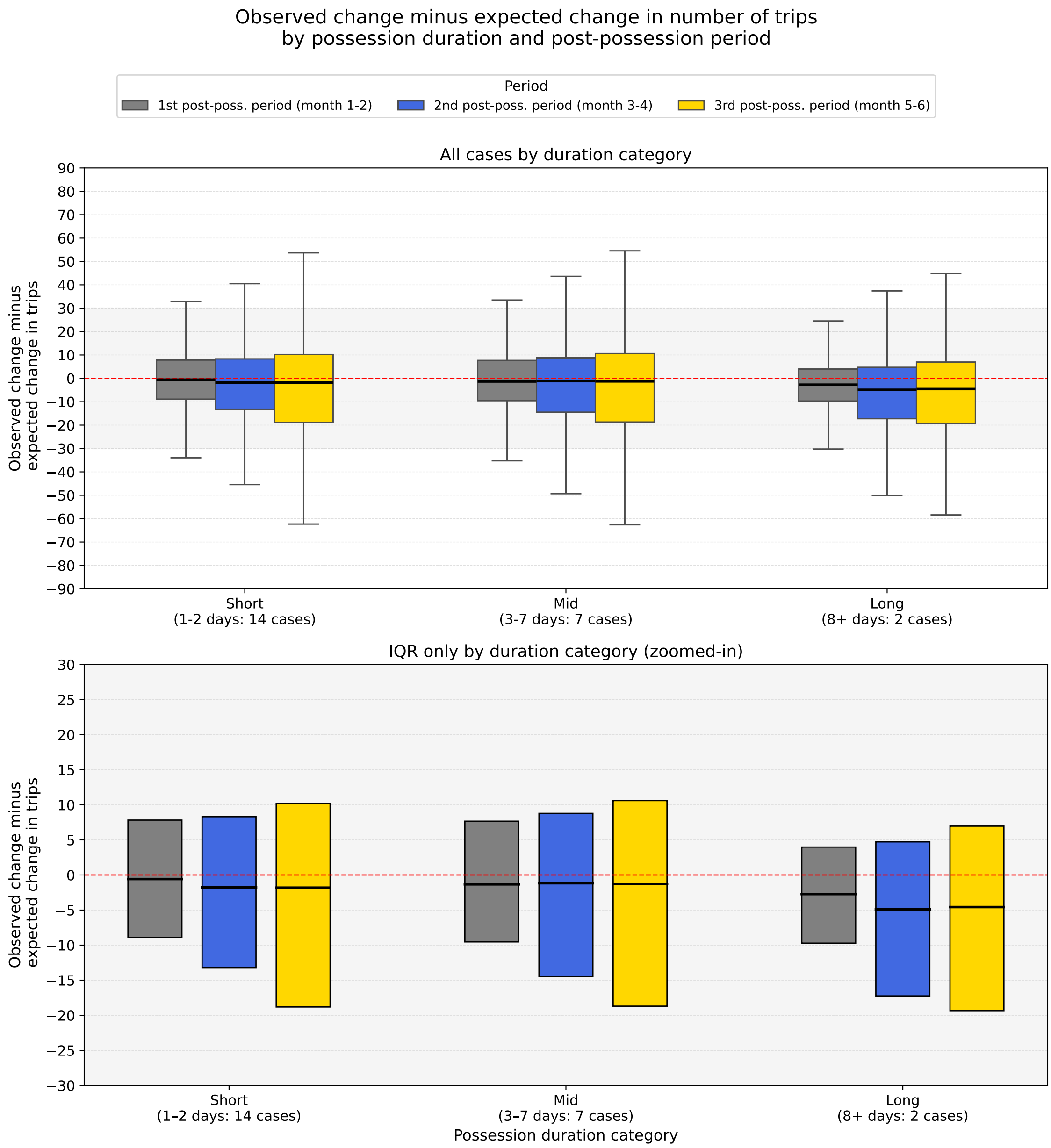


Figure 5.1: Difference between the observed and the expected change in number of trips (i.e. change in trips due to possession), aggregated per duration category. Bottom figure is a zoomed-in version of the top figure, only showing the interquartile range (IQR). Outliers are not shown for readability, but included in Figure B.1

Indeed, Figure 5.1 shows that there are passengers who travel more than expected and passengers who travel less than expected for all three duration categories. This results in the boxes in Figure 5.1, which are, as expected, approximately centred around the zero line for all passenger groups. The boxes represent the interquartile range (IQR): the box spans from the first quartile (the 25th percentile) to the third quartile (the 75th percentile), and thus represents the middle 50% of the data and, therefore, the general trend. The larger the width of the box, the more variation in the difference between the observed and the expected change in the number of trips among the investigated passengers. The bottom of Figure 5.1 contains a zoomed-in version of the top figure, for better readability of the IQR. The median value (the second quartile), indicated by the black line in the boxes in Figure 5.1, is more robust to outliers than the mean value, making it an appropriate measure of the overall behaviour of the passengers.

The whiskers in Figure 5.1 represent the minima and maxima, which are 1.5 times the length of the IQR higher or lower than the first and third quartile. Other observations are outliers and are not shown in Figure 5.1. Instead, they are included in Appendix B.

Counter-intuitively, a negative value does not necessarily correspond to a decrease in number of trips. For example, a passenger increases his or her number of trips by 10, but the expected increase (based on the reference group) is 20. In that case, the difference between the observed and expected number of trips is -10, a negative value, while the passenger increased his or her number of trips. Similarly, a positive value does not necessarily correspond to an increase in the number of trips.

The length of the boxes and the whiskers both increase with the time since the maintenance has ended (i.e. from the first, to the second and third post-possession period), for all possession duration categories. This indicates that the variation in the difference between the observed change and the expected change in trips increases over time, but this is unrelated to the possessions. Instead, the longer time interval since the pre-possession period allows more external effects to influence passenger patterns, leading to a lower ability to predict passenger's number of trip in the post-possession period based on their pre-possession passenger patterns.

Short- and mid-duration possessions show similar results and are discussed first. The distributions of the difference between the observed and the expected changes in the number of trips are slightly shifted towards negative values, especially for the third post-possession period. For example, the IQR of the short duration possessions in the third post-possession period ranges from -18.82 to +10.19, which correspond to 18.82 trips less and 10.19 trips more than expected. This means that the magnitude of the negative values is larger than that of the positive values. All fourteen short-duration possessions show similar results to the aggregated result in Figure 5.1. The same holds for the seven mid-duration cases, see Figure B.3.

However, the number of negative and positive values is approximately equal, since the median is close to zero. The medians for these two duration categories and three periods range between -0.58 and -1.81. The reduction of, on average, at most 1.81 trips per passenger (in the third post-possession period, after short-duration possessions) is too small to be considered a direct effect of the possession. So, on an aggregated level, the number of trips of individual passengers does not change due to short- and mid-duration possessions. However, the distribution is not exactly centred around zero. Passengers who change their number of trips more negatively than expected do so more prominently than those who change their number of trips more positively than expected. This is caused by the asymmetry in the behaviour of individual passengers. A large decrease in the number of trips occurs more frequently than a similarly large increase in trips. The large decreases are (partly) caused by passengers who completely stop travelling (and thus do not occur in the data any more after a possession), which is due to major changes in travel patterns or an expired smart card. However, the stored data do not include expiration dates, so this could not be investigated. Moreover, for high-frequent passengers, large increases are not reasonable, due to the limited amount of days in each period (56 days per period), whereas large decreases are possible[1] The expected change in number of trips is computed with the mean change of the reference, per passenger group. This mean is affected by a relatively small group of passengers who decrease their number of trips largely. Therefore, the average change is lower than experienced by most passengers in the reference group. This is subsequently applied to all the investigated passengers, many of whom exhibit (relatively) small changes in trips. This results in a slightly negatively skewed distribution of the difference between the observed and expected change in the number of trips, as shown in Figure 5.1.

So, the negatively shifted distributions for the fourteen short-duration possessions and the seven mid-duration possessions are not considered to be caused by the possession, but rather by the asymmetry in passenger behaviour. Moreover, the first (short-term) two months show an almost symmetrical distribution around zero (e.g. IQR from -8.90 to +7.83 in the first post-possession period for short-duration possessions), for the short- and mid-duration possessions. This indicates that the number of passengers who make more trips than expected and the number of passengers who make less trips than

[1] For example, a passenger with 50 trips in the pre-possession period (0.9 trips per day, or 25 of the 56 days with a tour) cannot (reasonably) increase his or her number of trips by 50 (1.8 trips per day, or 50 days with a tour), while a decrease of 50 is possible (for example due to an expired card). This negative skewness of the changes in number of trips is observed for high-frequent passengers for all cases.

expected are almost equal, leading to a negligible total effect in the first post-possession period. Therefore, the short- and mid-duration possessions do not have an effect on passenger patterns in the first two months after the maintenance has been completed. This suggests that these possessions also do not have a long-term effect, since that would reveal immediate changes in passenger patterns. This is reinforced by the median values being close to zero for the short- and mid-duration possessions.

In conclusion, the investigated short- and mid-duration possessions are not found to have a lasting effect on passenger patterns. The medians are close to zero, meaning that these possessions do not have a permanent effect on passenger's travel frequency. The negative skewness is not caused by these possessions, but by the asymmetry in travel behaviour.

The long duration cases, on the right in Figure 5.1, show different results. The negative skewness in the distribution is larger. This is mainly observable from a lower third quartile (i.e. the top of the boxes) than for the short- and mid- duration possessions. For the third post-possession period, the third quartile is +10.19 and +10.61 for short- and mid-duration possessions respectively, while it is +6.97 for the long-duration possessions. These numbers indicate the difference in the observed and the expected change in the number of trips, and thus the unexpected change in travel frequency. Approximately 75% of the IQR is below zero in the second and third post-possession period for long-duration possessions, meaning that many affected passengers make less trips than they were expected to make in case there was no long possession.

Moreover, the median value for long-duration possessions, indicating the centre of the distribution, is -4.90 and -4.57 for the second and third post-possession period respectively. This is considered substantial enough to be attributed to the maintenance. It indicates that passengers permanently decrease their travel frequency, on average, by almost five trips (i.e. they make five trips less than expected in an eight week post-possession period). In practice, some passengers stop travelling at all while others only decrease their travel frequency. There are also people who increased their travel frequency, but they are in the minority. Moreover, the medians are much larger, in absolute terms, than for mid-duration possessions (which are -1.17 and -1.28 for the two long-term post-possession periods respectively). In addition, the maxima of the unexpected changes in trips (i.e. the difference between the observed and the expected change in number of trips) are approximately 10 lower for long-duration possessions than for the short- and mid-duration possessions. The minima are approximately equal for all duration categories, as seen in Figure 5.1.

Therefore, the large negative shift in the distribution of long-duration possession indicates that long-duration possessions have a negative effect on passenger patterns. In general, passengers decrease their number of trips more negatively than expected. Moreover, there are clearly more passengers with negative indicator-values than passengers with positive ones, especially compared to the short- and mid-duration possessions. This means that, on an aggregated level, the long-duration possessions lead to lower ridership in the post-possession periods than expected.

Section 5.2 gives the regression model results, and will discuss whether duration is indeed one of the possession characteristics with an effect on permanent changes in passenger patterns.

The indicator on the change in number of trips includes a normalisation with a passenger's pre-possession number of trips (see Equation 3.2 in Subsection 3.1.3). This normalisation quantifies the relative effect of changes in travel frequency, as explained in Subsection 3.1.3. This indicator has similar results as shown in Figure 5.1: the short- and mid-duration possessions do not result in permanent effects of possessions, while long-duration possessions do. However, the differences between the two become more apparent. The median in the second post-possession period of this indicator is -0.03 for mid-duration possessions, while it is -0.17 for long-duration possessions. These are -0.04 and -0.16 for the third post-possession period. The medians are thus five and four times as high for long-duration possessions, indicating a clear difference between the duration categories. Section B.2 includes the distributions of this indicator, per duration category and separately for all cases.

In short, it is concluded that the long-duration possessions have a negative long-term effect on passenger patterns. Passengers make, on average, 4.90 and 4.57 trips less than expected in the second and third post-possession period respectively (of eight weeks each) after being faced with a maintenance period of at least nine days. This effect is not observed for possessions of shorter duration.

Long-duration possessions in more detail

Now, the effects of the long-duration possessions are discussed in more detail. As previously stated, long-duration possessions are the only ones with an observable long-term effect on passenger patterns.

Figure 5.2 shows the difference between the observed and the expected change in the number of trips for the two long-duration possessions. These are the Groningen Europapark-Groningen and Deventer-Zwolle cases, which have a duration of 64 and nine days respectively. There is a large difference in the durations, and their amount of investigated passengers is not equal so both are shown separately to investigate the long-duration possessions more precisely.

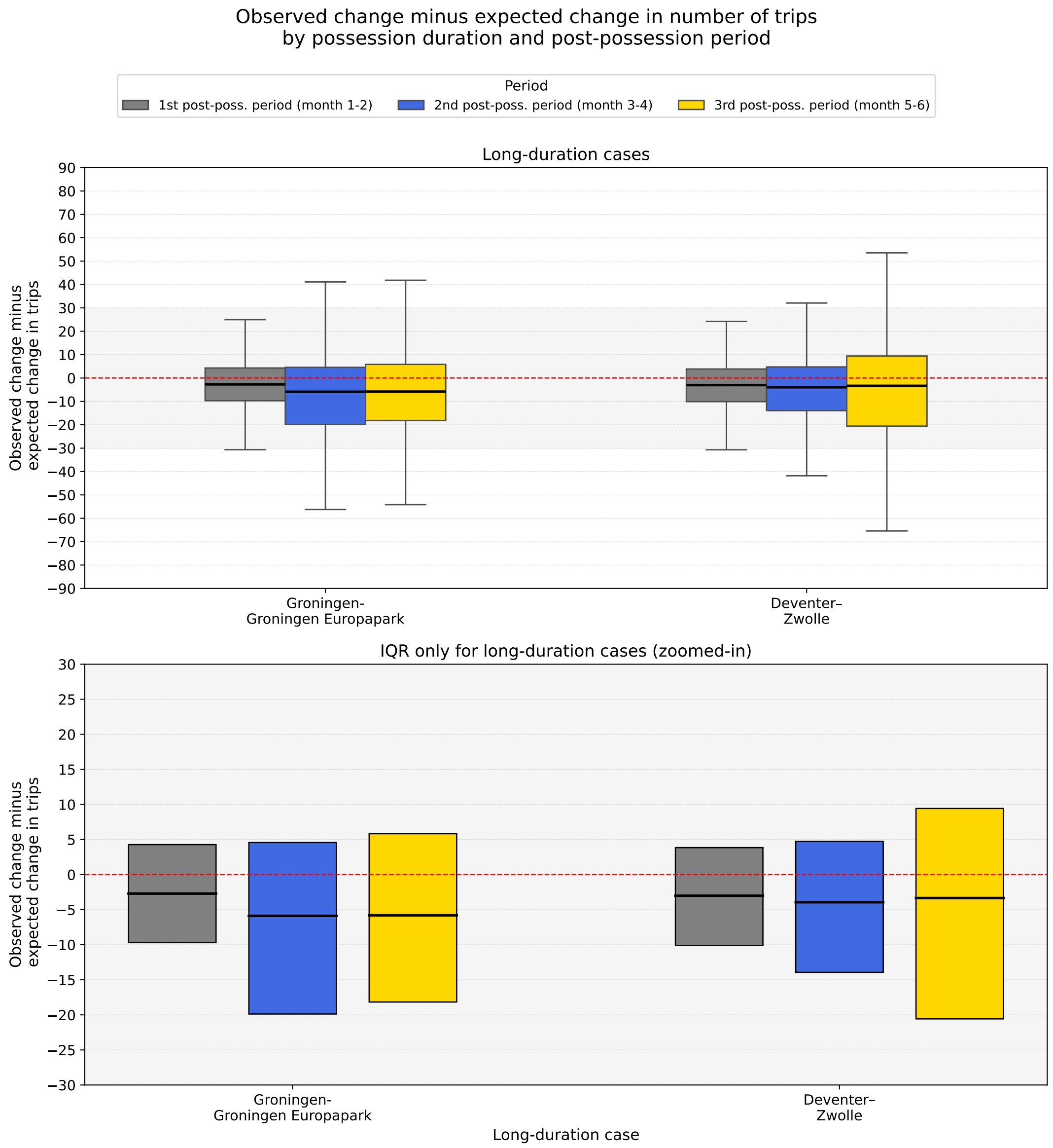


Figure 5.2: Difference between the observed and the expected change in the number of trips, for the two long-duration possessions.

The distributions of the unexpected changes in travel frequency clearly show more negative values for the Groningen Europapark-Groningen possession than for the Deventer-Zwolle case. For the Groningen-possession, the IQR ranges from -19.88 to +4.58 for the second post-possession period, and from -18.17 to +5.83 for the third post-possession period. The median value of the difference between the observed and expected change in the number of trips is also more negative than for all other cases: -5.88 and -5.80 for the second and third post-possession period respectively. When multiplied by the total number of investigated passengers for this case, the reduced travel frequency per person corresponds to a substantial amount of lost trips[2]. However, this number should be very carefully interpreted, because small differences in the median (due to, for example, a not exactly equivalent reference group) lead to major differences in the total number of lost trips given the large investigated population. Moreover, for cases with no observable effect (i.e. cases with a short- or mid-duration), there are also 'lost' trips, due to the median not being exactly zero, although those possessions are not considered to have an effect on passenger patterns.

The above implies that the Groningen-possession has a permanent, negative effect on passenger patterns. In general, passengers decrease their number of trips more negatively than expected. Moreover, there are far more passengers with negative indicator-values than passengers with positive ones. This means that the possession led to a lower ridership in the post-possession periods than expected.

However, the first two (short-term) months of the Groningen-case, in grey in Figure 5.2 result in less negatively shifted boxes. The IQR only ranges from -9.70 to +4.28, and the median is -2.72. However, the short- and mid-duration cases in Figure 5.1 also have a lower median value in the first two months than in the following two post-possession periods. This is thus likely caused by the previously mentioned asymmetry in individual travel behaviour that is partially caused by expiring cards, since more cards expire as time progresses.

In addition, the boxes of the Deventer-Zwolle possession (see Figure 5.2) also show more negative values in both long-term post-possession periods, but especially for the second post-possession period. The medians of both long-term post-possession periods (-3.93 and -3.34 for the second and third post-possession period respectively) are lower compared to all other cases, except the Groningen-possession. The effect of this possession is undoubtedly smaller than that of the Groningen-case, but, in general, the passengers do not follow the trend of the reference group.

The distribution of the Groningen case does not move much from the second to the third post-possession period. The median is approximately equal in both periods (-5.88 and -5.80), indicating that, in general, the difference between the observed and the expected number of trips does not change between both periods. However, the entire distribution (the IQR and the whiskers) moves slightly towards more positive values from the second to the third post-possession period. This means that some people move towards their pre-possession travel pattern in the third post-possession period, and thus that the negative effect of the possession fades away. However, this effect is very small. Moreover, it is not observed in the Deventer-Zwolle case, for which the distribution in the third post-possession period is wider, but centred around approximately the same point, compared to the second post-possession period.

Effect of passenger groups

This thesis also investigates what the effect of passenger groups is on potential permanent changes in passenger patterns due to a possession. The ANOVA-test, as explained in Subsection 3.4.1, found a statistically significant effect of the pre-defined passenger groups. Figure 5.3 shows the overarching passenger groups that are formed based on the Games-Howell test. Appendix C includes more information on how these groups are established.

The overarching passenger group A consists of, presumably, commuters: passengers who travel for work. All three business-passenger categories are included in this group, as is the high-frequent consumer group. This last group also likely consists of commuters, who travel with a personal card rather than a work-issued business card. These four passenger groups behave similarly in terms of the (change in the) number of trips in the investigated period. Group A consists of the most passengers (45% of the investigated passengers), and could, therefore, be considered as the most important group regarding permanent changes in their travel behaviour. It is also the group with the largest financial impacts on passenger revenues for railway operators.

Next, group C consists of medium-low-frequent consumers and students (one to two tours per week). These passengers travel the least of all investigated people, and thus have the least direct negative effects of a possession (i.e. they make the fewest trips, so they also need to find an alternative for the fewest trips).

[2] *The numbers are omitted for confidentiality reasons.*

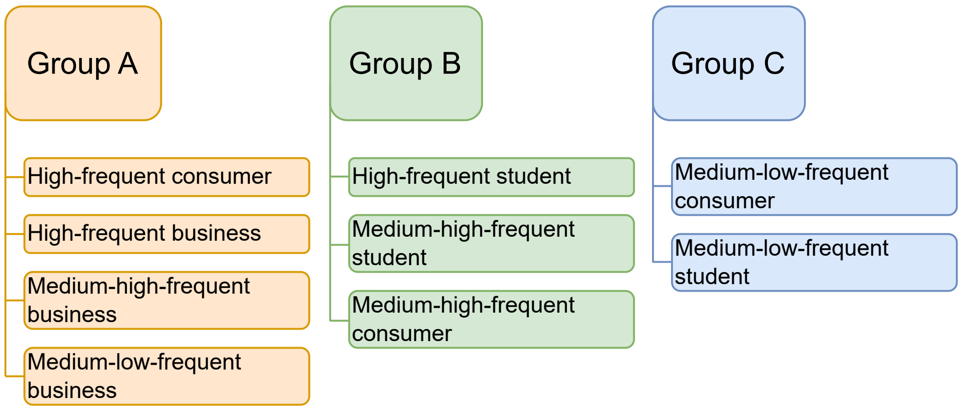


Figure 5.3: Overarching passenger groups based on Games-Howell test, including the number of passengers per group

Finally, group B consists of the fewest passengers and includes the remaining three pre-defined passenger groups: the (medium-)high-frequent students and medium-high-frequent consumers. A part of the students might be public transport captives, i.e. they do not have another option available for their travel needs (Beimborn et al., 2003). If so, the (negative) permanent effects on this group to might be less strong than that of other groups.

Figure 5.4 shows the difference between the observed change and the expected change in number of trips per overarching passenger group, separately for short/mid-duration and long-duration possessions. In other words, how the overarching passenger groups respond differently to possessions of different duration categories. Similarly to Figure 5.1, the top figure shows the IQR and whiskers, while the bottom is a zoomed-in version with only the IQR. Figure B.2 includes the outliers, that are not shown in Figure 5.4.

First, the response of passenger group A is discussed. Figure 5.4 shows, for short- and mid-duration possessions (left), a relatively symmetrically centred distribution around zero for the first two months and the second post-possession period. The minima and maxima are also symmetrical around zero. The third post-possession period shows a negatively shifted distribution, partially caused by large decreases in trip frequency due to expiring smart cards, leading to a negative expected change in trips, as explained before. The medians are approximately zero for all periods (-0.3, -0.3 and +0.5 respectively). This indicates that the overarching passenger group A, consisting of business passengers, has a consistent travel pattern that does not change when affected with a short- or mid-duration possession.

In contrast, the right of Figure 5.4 shows the difference in the observed and expected change in the number of trips for long-duration possessions. The distribution of the overarching passenger group A is shifted towards negative values, and the medians are lower as well compared to those of the short- and mid-duration possessions. For long-duration possessions, the median is -4.2, -3.9 and -1.0 for the three post-periods respectively. This indicates that passengers in group A travel less often than expected after a long-duration possession and are thus negatively affected by it. It also suggests that group A passengers return towards their pre-possession pattern as time progresses after the long-duration possession, indicated with the increasing median value. This effect was also found, but less prominently, for the Groningen Europapark-Groningen possession in Figure 5.2 that showed the aggregated response of all passenger groups. Passenger groups B and C do not show a similar return to pre-possession travel patterns after long-duration possessions, which explains why the return effect is less prominent in Figure 5.2.

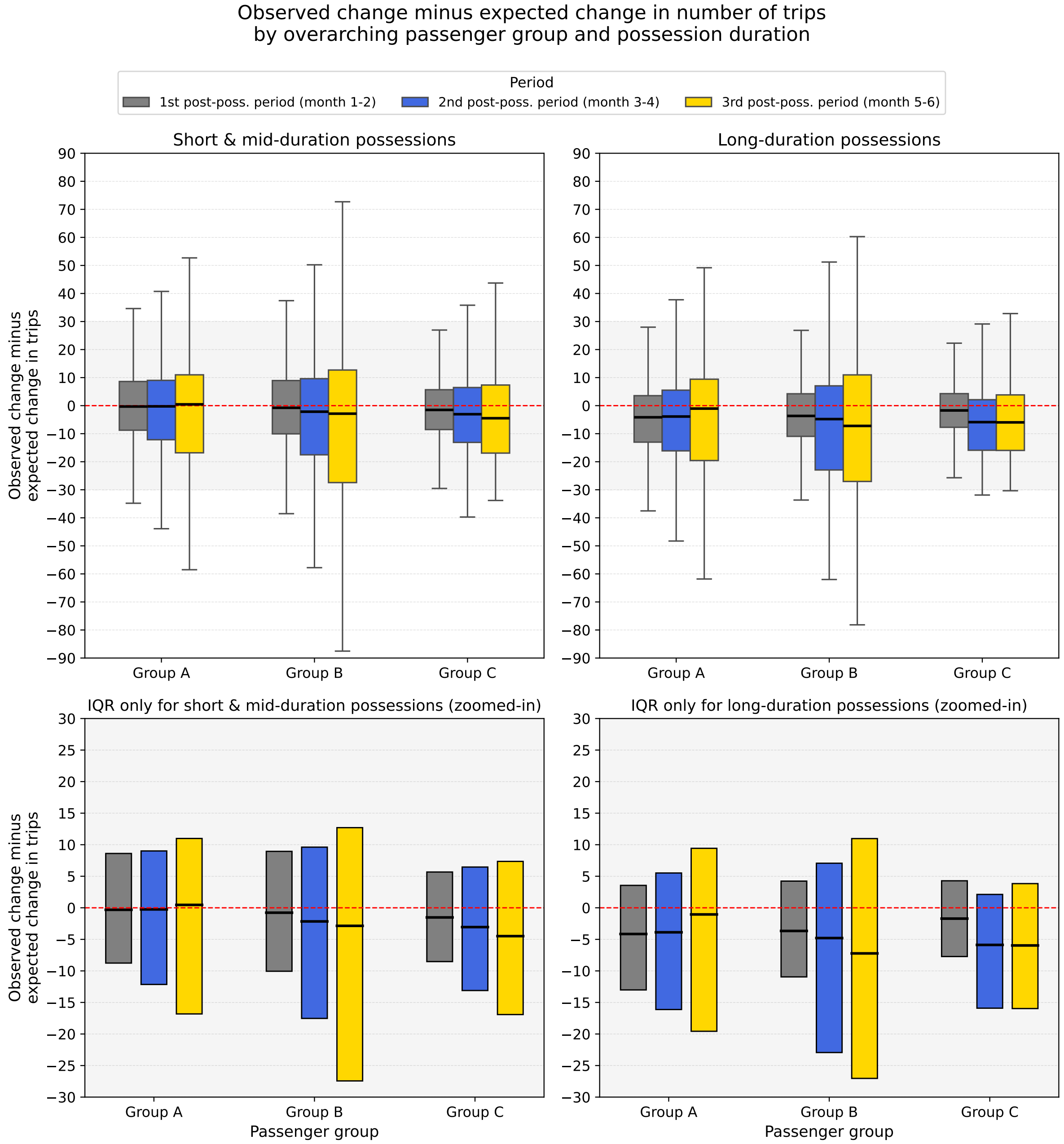


Figure 5.4: Difference between the observed change and the expected change in number of trips, per overarching passenger group (A, B, C) and separately for short/mid-duration (left) and long-duration (right) possessions. Outliers are not shown, but included in Figure B.2

Next, passenger group B shows a negatively shifted box for long-duration possessions compared to short- and mid-duration possessions, for all post-possession periods. For example, the IQR ranges from -17.5 to +9.6 for mid-duration possessions in the second post-possession period, while it ranges from -22.9 to +7.1 for long-duration possessions. Therefore, group B is also negatively affected by long-duration possessions. However, the box of the third post-possession period for long-duration cases is more similar to that of short- and mid-duration possessions, than the boxes of the second and first post-possession period are. This suggests that passengers from group B also return to their pre-possession patterns, after initially decreasing their travel frequency after long-duration possessions. However, the median value of group B decreases as time progresses, for all possession duration categories. This is in line with the general findings in Figure 5.1, but contradicts the suggestion that passengers return to their original travel patterns. In short, group B also travels less frequently than expected after long-duration possessions, indicating that they are permanently negatively affected by those maintenance works. However, the negative effects seem to fade away, but there is no conclusive evidence for this.

In general, passenger group B shows the most variation in differences between the observed and the expected change in the number of trips, as shown by the minima and maxima in Figure 5.4 for all periods. Apparently, the travel patterns of the individuals in this group can change largely, making it more difficult to estimate their post-possession travel pattern based on their pre-possession travel pattern.

Finally, group C shows the narrowest boxes, and thus the least variation in responses, for all duration categories. Notable are the relatively low minima for the difference between the observed change and expected change in trips (at most -40, excluding outliers). This is caused by the relatively low number of trips in the pre-possession period of these passengers (at most 32, or two tours per week on average). The metric can be lower than 32 due to the correction with the expected change in trips. Group C passengers cannot decrease their number of trips largely, because they are bounded by their pre-possession number of trips.

For group C, the boxes are shifted towards negative values for long-duration possessions compared to short- and mid-duration possessions. This is mainly observed from the lower value of the third quartile. In the second post-possession period, the third quartile is +6.5 for short- and mid-duration possessions, while it is +2.1 for long-duration possessions. These numbers are +7.4 and +3.8 in the third post-possession period. Therefore, group C is also negatively affected by long-duration possessions. However, group C has the least negative response of the three overarching groups, as the first quartiles (the bottom of the box in Figure 5.4) are the least negative for this group. This is, however, also caused by the lower travel frequency in the pre-possession period of this group.

Indeed, the relative effect of the possessions is more equal among the passenger groups, due to the normalisation by the number of trips in the pre-possession period. Section B.2 includes more details on the relative effect of the possession on passenger patterns.

In conclusion, all three overarching passenger groups are negatively affected by possessions of long duration. However, group C, consisting of the medium-low-frequent students and consumers is less negatively affected than group A and B. Passengers of group A gradually return to the pre-possession travel pattern as time progresses. None of the overarching groups is negatively affected by short- or mid-duration possessions.

5.1.2. Changes in route or station choice

Now, changes in route or station choice after the possession are described using the indicator defined in Subsection 3.1.3. For most investigated cases, no changes in route or station choice are observed.

Figure 5.5 shows the distribution of the second indicator (on the route or station choice) for the three investigated post-possession periods, for the few cases for which the indicator is not exactly zero. This indicator expresses the change in the share of trips over the affected line among all trips between a passenger's main zones. The median value for these cases is approximately zero, indicating that there are, in general, no major changes in route choice due to possessions. However, the changes in route choice are large compared to the other (non-included) cases.

The change in the share of trips over the affected line among all trips between a passenger's main zones is exactly zero, without any spread in the distribution apart from outliers, for almost all cases and passenger groups. These cases are not included in Figure 5.5, but are included in Figure B.19.

The zero value indicates that passengers do not change their route choice after a possession. This is expected since there is often only one suitable train route for most origin-destination pairs (stations or zones) for the investigated possessions (with a long-term effect). Another route often has a longer travel time, or is not even possible. This could be different when investigating other (long) possessions, for example in the Randstad-region.

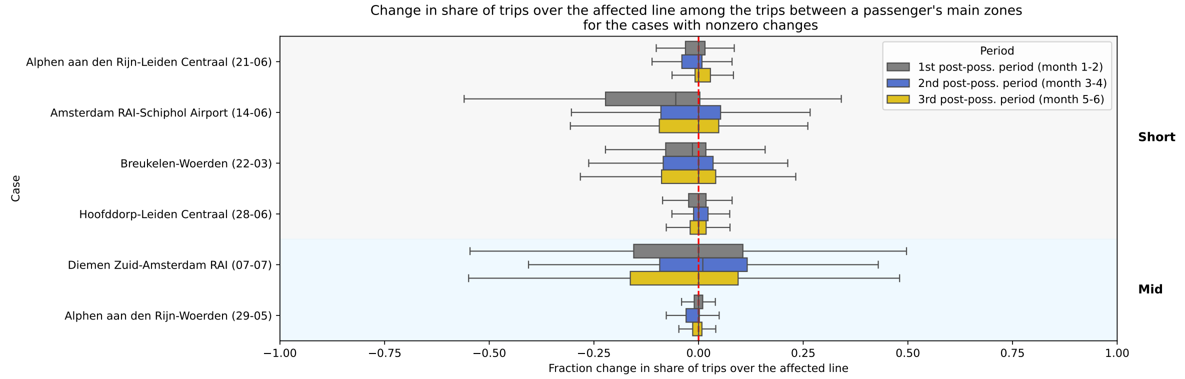


Figure 5.5: Distribution of percentage change of share of trips over the affected line among a the trips between a passenger's main zones, for cases with non-zero changes. Duration categories are indicated on the right. Outliers are not shown, but included in Section B.3.

However, this indicator also captures the changes in station choice in specific situations, where the possession occurred between two stations within the same main zone. The Groningen Europapark-Groningen possession, which resulted in changes in the number of trips as presented in Section 5.1, is such a case. During the possession between Groningen Europapark and Groningen, people who normally use Groningen as station, likely used the more southern Groningen Europapark as access station for their trips towards the southern direction. Since these stations are in the same main zone, a permanent shift in station choice would become apparent from this indicator. This, however, does not occur for this specific example, because the median, 25th and 75th percentiles are all zero, see Appendix B. This specific possession has, therefore, not led to permanent shifts in station choice. Passengers presumably return to Groningen station, because Groningen Europapark is not an intercity station (which it was during the possession), while Groningen main station is.

Three of the six cases in Figure 5.5 have very narrow boxes and are centred around zero. These cases are Alphen aan den Rijn-Leiden Centraal, Alphen aan den Rijn-Woerden and Hoofddorp-Leiden Centraal. The change for these cases is at most 5%. The rail network is dense around these three cases. There are multiple route options, with approximately equal travel time, especially for through-going passengers. For example, passengers between Amsterdam Centraal and Den Haag Centraal can use the Hoofddorp-Leiden line, but can also travel via Haarlem. Therefore, it is unlikely that the possession resulted in these minor changes in route choice. Presumably, changes in the timetable or crowding on one route led to the changes in route choice.

Only for the possessions between Diemen Zuid and Amsterdam RAI, Amsterdam RAI and Schiphol Airport, and Breukelen and Woerden are larger differences noticeable. Although the medians of the distribution are zero for these cases as well, there are passengers who changed their route choice. For the former two cases, both in Amsterdam, it is most likely that the passengers switched to another access or egress station that is in the same main zone. In Amsterdam, there are many other good public transport options, such as the metro to reach alternative railway stations. Likely, the passengers use these options for the first or last stretch of their trip in the post-possession period, instead of the train. This is not necessarily due to the possession. It could also be caused by an improvement of the service of the local public transport (metro, tram or bus), which makes another access or egress train station the overall better option.

For the Breukelen-Woerden case, there are also changes in the route choice of the passengers, although the median is again zero. However, the size of the box is clearly larger on the negative side. Most of the passengers with a large decrease in the share of trips over the affected line have Amsterdam and one of Gouda, Rotterdam and Woerden as main zones. The pre-possession period for this case is the end of January to the end of March, and the first post-possession period is from the end of May to the end of July. In the 2025 timetable, introduced mid December 2024, the frequency of sprinter trains between Utrecht Centraal and Woerden has doubled to four per hour and the frequency of intercity trains between Utrecht Centraal and Rotterdam Centraal on Friday mornings has also increased to four (Nederlandse Spoorwegen, n.d.-b). These changes make travelling via Utrecht Centraal more attractive for passengers from Amsterdam to Rotterdam, Gouda or Woerden. Passengers may need a few months to adjust their travel pattern to the new timetable. It is therefore considered more likely that the changes in the timetable led to the changes in route choice than the (one-day) possession between Breukelen and Woerden did.

In conclusion, the investigated possessions do not lead to route or station choice changes in the long-term. In most cases, passengers still use the same route in the third to sixth month after the maintenance period as before the possession. Few cases show small changes in route choice. However, these changes are more likely caused by other effects, such as changes in the timetable of the railway operator or of local public transport operators, making other train routes more attractive for certain origin-destination pairs. Interestingly, the Groningen Europapark-Groningen case did not result in changes in station choice, while passengers had to use Groningen Europapark instead of Groningen for a long time. Changes in route or station choice likely only occur in situations in which there is an equivalently good alternative travel option, for example when travel times are equal or when an alternative station that is used during a possession also has an intercity-status. These situations do not occur for the investigated cases with a long-term effect on travel frequency.

5.2. Regression models

This section presents the regression models for the second and third (long-term) post-possession periods. These regression models estimate the number of trips in the post-possession period and capture the effect of the possession characteristics on the passenger patterns, in terms of the number of trips. The models are developed with the strategy described in Subsection 3.4.3.

Subsection 5.2.1 presents the final model for the second post-possession period, including possession characteristics and passenger groups. The base model for the second post-possession period is given in Section D.1. Section D.1 also includes the comparison between the base and advanced model of the second post-possession period. Next, Subsection 5.2.2 presents the final model for the third post-possession period. This is the base model, because the advanced model is not considered to be reliable, as explained in Subsection 5.2.2 and Section D.2. Section D.2 also includes the comparison between the base and the advanced model for the third post-possession period. Finally, Subsection 5.2.3 summarises the findings on the effect of possessions characteristics and passenger groups on permanent changes in passenger patterns.

5.2.1. Model for second post-possession period

Model 5.1 shows the regression model that estimates the number of trips in the second post-possession period based on the number of trips in the pre-possession period, the expected change in number of trips, the possession characteristics and the passenger groups. *The exact amount of observations cannot be listed in the public version of the thesis. It is approximately 300,000.*

Model 5.1: Advanced model for number of trips in second post-possession period (month 3-4)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   n_34   R-squared:                       0.308
Model:                            OLS   Adj. R-squared:                  0.308
Method:                 Least Squares   F-statistic:                 8.151e+04
No. Observations:             ~300000   Prob (F-statistic):           3.65e-46
Df Residuals:                 ~300000   Log-Likelihood:            -1.2194e+06
Df Model:                           5   AIC:                         2.439e+06
Covariance Type:              cluster   BIC:                         2.439e+06

=========================================================================================
                          coef       std err      z         P>|z|       [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept                3.5920       0.368      9.765      0.000       2.871       4.313
n_expected_34            0.8185       0.011     73.272      0.000       0.797       0.840
Long duration           -3.5932       0.616     -5.837      0.000      -4.800      -2.387
Group B                 -1.8886       0.387     -4.874      0.000      -2.648      -1.129
Group C                 -2.4263       0.280     -8.652      0.000      -2.976      -1.877
Long duration : gr C     0.4877       0.154      3.164      0.002       0.186       0.790
=========================================================================================
```

The R^2 of this advanced model is 0.308, compared to 0.305 in the base model for the number of trips in the first investigated post-possession period (Model D.1). Therefore, the ability of the model to estimate the number of trips has increased, although very limitedly. The adjusted R^2, which penalises for adding variables, shows a similar increase. The addition of possession characteristics and passenger groups leads to a slightly higher model performance, but this increase is very limited. The Akaike Information Criterion (AIC) also shows this. The AIC decreased by 1,000 (-0.04%), indicating that the model almost did not improve by adding the extra explanatory variables.

So, the advanced regression model (Model 5.1) confirms what was seen in Section 5.1. The investigated possessions, in general, do not lead to long-term effects on passenger patterns, since the addition of possession characteristics does not lead to a large increase in model performance. This is also explains why the expected number of trips, based on the number of trips in the pre-possession period and the expected change in number of trips due to seasonality, is the best estimator for the number of trips in the post-possession period.

However, the coefficient of the expected number of trips is 0.0352 lower in Model 5.1 than in Model D.1. This indicates that this variable loses some weight when adding the additional variables, meaning that the possession characteristics and passenger groups have a small impact on the post-possession number of trips.

Passenger group B and C are both significant in Model 5.1 as dummy variables. Their coefficients are negative (-1.89 and -2.43 respectively), so passengers from group B and C make fewer trips than expected compared to passengers from (the excluded) group A. This effect is larger for group C. The expected number of trips is a better estimator for passenger group A than for groups B and C. Group A consists of the business passengers and high-frequent consumers (who likely are regular commuters as well). This overarching passenger group apparently has a more consistent travel pattern, that changes less over a long period, and is less impacted by possessions.

In addition, the variable long-duration, representing possessions of eight or more days, has a negative effect (β = -3.5932) on the number of trips in the post-possession period. After possessions with a long duration, the number of trips of the passengers is 3.59 lower than expected in the second post-possession period. This number is on average 15% and 9% of the pre-possession number of trips for the medium-low and medium-high frequency groups respectively. It is lower for the high-frequency passengers, for example 6% for passengers with 60 trips in the pre-possession period. Section 5.1 showed a relatively large negative effect of the Groningen Europapark-Groningen possession on the number of trips. The Deventer-Zwolle case also saw a lower than expected number of trips in the post-possession period. These two cases are the only ones included in the long-duration category, and are the only ones with a negative effect on passenger patterns.

It should be noted, however, that the threshold between mid- and long-duration possessions could be different from the now selected eight days. If the threshold would be higher, the long-duration property will likely also be significant, and maybe even stronger (more negative coefficient), since than only the Groningen case (64 days), with the largest effect, falls in that category.

The intercept and the coefficient of the long-duration characteristic are approximately equal in magnitude, but opposite in sign. Therefore, the intercept for possessions of long duration is actually zero, while it is 3.59 for cases with a short or mid duration.

The negative effect of long-duration possessions is less severe for passengers of group C, indicated by the positive coefficient (+0.49) of the interaction term between the long-duration characteristic and passenger group C, meaning that this group makes 3.10 trips less than expected in the second post-possession period (-3.59+0.49=-3.10). This group, consisting of medium-low-frequent consumers and students, who make on average one to two tours per week, is less sensitive to long maintenance periods, although the difference with the other groups is small. These passengers are less hindered by these long possessions than the other passenger groups, because they travel less often in normal situations. Therefore, they presumably get less annoyed and are less required to find a good alternative during the possession, and return to their normal travel patterns to a larger extent than the other groups do. On average, they make 0.49 trip more in the second post-possession period than the other two overarching passenger groups. This means that, if there is a large share of passengers from group C among all passengers using a rail line, maintenance can be scheduled for a longer continuous period on that line, without leading to as much negative effects on post-possession number of trips as on lines with a low share of group C passengers.

For possessions of long duration, this interaction term makes group C approximately equal to group B. When the positive coefficient of the interaction (0.49) is added to the negative coefficient of passenger group C (-2.43), this results in -1.94, which is close to the coefficient of group B (-1.89).

Other general possession characteristics that are found in Section 2.3 are not significant in estimating the number of trips in the second post-possession period. These are the length, the time since the last possession, the presence of simultaneous possessions with a shared station and the time planning (i.e. during a holiday and/or during the weekend). This is likely caused by the absence of effects for most investigated possessions. The two previously mentioned possessions with long-term effects are similar in most of these characteristics. They are both not only during the weekend, not fully in a holiday, and there is not another simultaneous possession for both. The similarities for these cases in combination with the absence of effects of the other cases result in the non-significance of most general possession characteristics. Moreover, there are also possessions without long-term effects with the same possessions characteristics (e.g. also not during the weekend). However, the time since the last possession and the length of the possession are different for both cases. Since other cases without effects also have variation in the values for these two indicator, but do not have the long-duration characteristic, the model only finds a significant coefficient for the duration. The high duration is the only similar characteristic of the two cases with noticeable long-term effects, that does not correspond to any case without long-term effects.

The absence of most general possession characteristics could also be explained by the correlations between these properties. As seen in Figure 4.9 in Table 4.3.3, the long-duration characteristic has a relatively correlation with the *simultaneous other possession* and *weekend* properties ($\phi = -0.27$ and $\phi = -0.36$ respectively). These characteristics are, in turn, correlated with the *time since the last possession* dummy variables. Therefore, the long-duration being the best explanatory variable for the number of trips in the second post-possession period might prevent other general possession characteristics from being included in the model due to correlations between the variables, for the selected possessions.

The passenger-dependent characteristics are not found to be significant in Model 5.1. These are the travel time by car, travel time by other public transport (non-train), travel time by NS-provided alternative option during the possession, and the travel mode of that option (train, bus or metro), between a passenger's most common origin-destination (main zone) pair. The metro is not an alternative for the two cases with a long-term effect of the possession, because there are no metros in Groningen, Deventer and Zwolle. Moreover, the effect of the alternative travel option and travel time could also be related to the duration of the possession. Passengers might tolerate a long travel time by, for example, a replacement bus for a few days, but do not accept it if they have to use it for a longer period.

The correlations between the passenger-dependent characteristics among themselves and with the general characteristics are mostly low, except for the correlations between the dummy variables for the mode of the alternative option provided by NS during a possession (see Figure 4.9 in Table 4.3.3). However, the correlation between the travel time by car and by other public transport is also high ($r = 0.85$). The absence of both of these variables means that the alternative option does not have an effect on the number of trips in the post-possession periods. Again, this can be caused by the low overall effect of the investigated possessions except for the two long-duration cases, while these two characteristics vary between all passengers of all cases.

In short, the only two investigated possessions with a permanent effect on the number of trips are both long possessions. Other similar possession properties between these cases also have similar variation among the cases without effects. Therefore, the long-duration characteristic is the only significant possession characteristic, with a negative effect on the number of trips in the second post-possession period. This means that for long duration maintenance (≥ 8 days), people permanently change their travel patterns, resulting in lower overall ridership on the train than without the maintenance period.

5.2.2. Model for the third post-possession period

Model 5.2 shows the base regression model for the number of trips in the third investigated post-possession period. The R^2 of this model is 0.186, so this model has less predictive power than the base model for the second post-possession period. This is likely caused by the longer time period between the pre-possession period and this post-possession period. The longer period allows for more factors unrelated to the possession leading to changes in the number of trips, which makes the prediction harder. This also led to the larger variation in the distributions shown in Section 5.1 in the third post-possession period. The coefficients of the intercept and the expected number of trips also show this. The intercept is larger than in Model D.1, while the coefficient for the expected number of trips is lower. The 95% confidence interval of the parameter is also larger compared to Model D.1.

The exact amount of observations cannot be listed in the public version of this thesis. It is approximately 300,000.

Model 5.2: Base model for number of trips in third post-possession period (month 5-6)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   n_56   R-squared:                       0.186
Model:                            OLS   Adj. R-squared:                  0.186
Method:                 Least Squares   F-statistic:                     1942.
No. Observations:             ~300000   Prob (F-statistic):           5.89e-23
Df Residuals:                 ~300000   Log-Likelihood:            -1.2551e+06
Df Model:                           1   AIC:                         2.510e+06
Covariance Type:              cluster   BIC:                         2.510e+06


================================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept       2.6676      0.200     13.362      0.000       2.276       3.059
n_expected_56   0.7795      0.018     44.068      0.000       0.745       0.814
================================================================================
```

Model 5.2 is considered the final model for the third post-possession period. The advanced model (Model D.2) has a larger R^2 and is significantly better (see Section D.2), but includes possession characteristics with illogical parameters. The inclusion of possession characteristics that were not included in the model for the second post-possession period in the model in the third post-possession period is not considered reliable. Moreover, some parameters contradict the literature or the findings from the first post-possession period. Section D.2 explains in more detail why the advanced model is not considered reliable.

5.2.3. Effect of possession characteristics and passenger groups on changes in passenger patterns

The regression models are developed to investigate the effect of possession characteristics and passenger groups on permanent changes in passenger patterns due to maintenance works.

The addition of possession characteristics and passenger groups to the base models led to significantly better models for both post-possession periods. However, the advanced model for the third post-possession period (Model D.2) is not considered to be reliable. Conclusions on the effect of characteristics and passenger groups are, therefore, based on the advanced model of the second post-possession period (Model 5.1).

Subsection 5.2.1 showed that possessions with a long duration have a negative effect on the number of trips a passenger makes in the future, which also followed from Section 5.1. Passengers make 3.59 trips less than expected in the second post-possession period after being faced with a long-duration possession. However, the exact threshold between long and mid or short durations could not be investigated adequately. The effect is slightly less severe for medium-low-frequent students and consumers than for the business passengers and more frequent students and consumers. The medium-low-frequent students and consumers make 3.10 trips less than expected after being faced with a long-duration possession.

Other possession characteristics were not found to be significant in the analysis of the 23 investigated cases. This is caused by the absence of permanent effects on passenger patterns for most of the investigated cases in this thesis. The long duration is the main distinction between cases with and without lasting effects on passenger patterns. Therefore, when investigating more cases with a long duration, the effect of other characteristics will likely become apparent.

5.3. Prediction model

Finally, Subsection 3.5.2 introduced an extension of the method to build a predictive model that estimates the long-term passenger losses due to maintenance works.

This method is applied to an -at the moment of writing- future possession between 's Hertogenbosch and Geldermalsen (August 11th, 2026 to August 21st, 2026). This classifies as a long duration possession. Figure 5.6 shows the distribution of the difference between the predicted change in trips (based on the model) and the expected change in trips (based on the reference), for the second post-possession period. This shows that a slightly negative effect is expected for this possession.

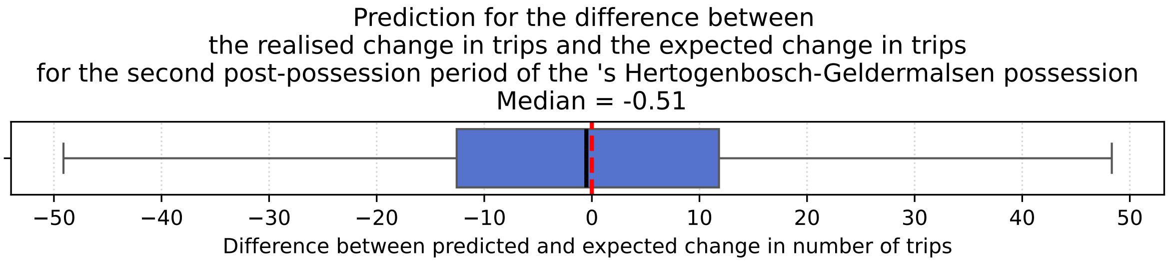


Figure 5.6: Prediction model applied to future 's Hertogenbosch-Geldermalsen possession in August 2026

However, the regression model needs further development to become suitable for reliable prediction. Currently, the coefficients of the long-duration characteristic depend on two cases, that vary largely in duration. Moreover, other characteristics are not found to be significant in the investigated cases, but could play a role.

In conclusion, there is potential for the developed method to be used as a predictive model, but it needs further development (by including more cases) to be reliable enough for prediction purposes.

6
Discussion

This chapter discusses the findings presented in Chapter 5. First, Section 6.1 gives considerations related to the scope and methodological choices that must be considered when interpreting the results. Next, Section 6.2 discusses the findings and the implications of the results. Thereafter, Section 6.3 explains the limitations of the study. Finally, Section 6.4 covers the generalisability of the results and methods.

6.1. Scope and methodological considerations

The results of this thesis should be interpreted considering the underlying methodological choices and within the scope they are found in. Important points related to these aspects are described in this section.

First of all, (very) low-frequent passengers[1] are not considered in the analysis, so the results do not hold for those groups. The overall effect of individual passengers from these groups on the rail network is limited, because they do not travel often. Moreover, it can be argued that a decrease in the number of trips of (very) low-frequent passengers cannot directly be linked to a possession. For example, a decrease from four to two trips in an eight-week period (-50%) is not necessarily caused by a possession, but can also be caused by other effects, especially for (very) low-frequent passengers with generally less consistent travel patterns. The changes are too small -but with a high relative impact- to draw conclusions about them.

Very infrequent passengers are out of the scope of this thesis (see Chapter 1), and the low-frequent passengers as defined in Equation 3.1 in Subsection 3.1.2 are removed during the analysis. For the latter, the reference group cannot be found in a similar way as for the other (higher frequency) groups, as the Kolmogorov-Smirnov test rejected the reference group. Investigation of the effect of possessions on (very) infrequent passengers thus requires a (partially) other method, which is suggested and explained in Section 7.2, but not incorporated in this thesis. There is likely also an effect of (long) possessions on people who do not use the train. These people might hear about the rail maintenance works on the news or from friends, and therefore do not consider using the train, as there are ‘always’ problems.

Moreover, the long-duration category of possessions consists of only two cases and there is a large difference in time span between the two (nine days versus 64 days). Therefore, it could be argued that they cannot be considered to be equal with respect to the duration. Passengers (commuters) only need to adapt their travel pattern for one (working) week for the one case, while they need to adapt for up to seven weeks for the other. So, the threshold between mid and long durations could be higher than the eight days used in this thesis. To test this, an additional regression model is developed with a higher threshold for the long duration category, which places the Deventer-Zwolle case in the mid-duration category instead. In that case, the coefficient of the long-duration characteristic in the regression model is more negative (0.65 lower than in Model 5.1) for the second post-possession period. This indicates a larger effect of long possessions, and thus that the boundary between mid- and long-duration possessions is likely to be higher than the currently used eight day limit. However, there are

[1] Low-frequent passengers make eight to sixteen trips in the pre-possession period, or one to two tours every two weeks. Very low-frequent passengers make less than eight trips in the pre-possession period, or less than one tour every two weeks.

no cases with a duration between ten and 64 days in the period for which data are available for this study and that meet the additional requirements (see Section 3.2) to investigate this further. Therefore, no conclusion can be drawn on the exact boundary between mid- and long-duration possessions.

Nazem et al. (2018) recommended using a longer post-possession period than the four months they used, although it is more difficult to isolate the effect of a single possession for longer post-possession periods. This downside is mitigated in this thesis by only using possessions without new maintenance work in the six months after the possessions, and by excluding passengers faced with maintenance on other rail lines in the post-possession period. However, this criterion largely limits the number of available cases (see Table 4.1). Subsection 6.3.2 discusses how this disadvantage could be overcome. However, the analyses show there is more variation in travel behaviour as time progresses. The expected change in number of trips is less accurate for the third post-possession period than for the first and second post-possession periods, even for short- and mid-duration possessions, which do not lead to long-term effects (see Section 5.1). This led to the advanced model for the third post-possession (Model D.2) period being unreliable. Therefore, Nazem et al. (2018) made a valid point: isolating the effect of a specific possession is difficult when comparing passenger patterns before the maintenance to the patterns six months after, due to a high variability in passenger patterns in general during such a long period.

In addition, the method of this thesis includes two methodological choices with regard to excluding passengers affected by possessions in either the pre- or post-possession period. For the reference group, passengers affected by other possessions in the post-possession period are not excluded. This choice is made in order to use a sufficiently large reference group and to save computational time (determining route choice is computationally very expensive in the NS-system). This decision could lead to an involuntary reduced travel frequency of the reference group in the post-possession period and thus an artificially high (negative) correction factor (i.e. expected change in trips). The effect of possessions could be underestimated due to this methodological choice. However, as stated in Subsection 3.1.4, it is unlikely that the entire reference group (which consists of many passengers), is affected by possessions in the same post-possession period. This mitigates the potential effect of the methodological choice on the results. However, the distribution of the difference between the observed and expected change in the number of trips might have a slight negative bias.

Moreover, passengers who are affected by other maintenance works in the pre-possession period are not removed from the investigated period. This group is very small, because it is rare that nearby rail tracks are possessed shortly after each other, but are not part of the same maintenance project with at least one overlapping day. Therefore, only passengers who (regularly) make long trips could be included in the analysis, and be faced with other maintenance in the pre-possession period of an investigated possession. This would be for example a passenger who travels from Groningen to Haarlem, faced with a possession between Groningen and Assen, and in the pre-possession period with a possession between Amsterdam Sloterdijk and Haarlem. There are few passengers for whom this holds, so the total effect on the results in negligible.

In conclusion, the results of this thesis do not hold for low-frequent passengers, due to methodological choices. Moreover, the exact threshold between mid- and long-duration possessions (without and with a long-term effect) could not be determined exactly, due to the absence of possessions with a duration between ten and 64 days, that also meet the additional requirements. Finally, methodological choices regarding the exclusion of passengers can have a limited effect of the results.

6.2. Implications of the results

Chapter 5 presented the results of the analyses. This section examines the implications of these results for practice, society and science.

The findings of this study are based on an analysis of individual passenger patterns. This has not been done before in the Netherlands. Previously, the long-term effects of an unplanned (three-month) possession were found with aggregated AFC data (Verhoof et al., 2023), and comparing the total passenger numbers with a reference period to account for autonomous growth and seasonality. This thesis provides an alternative approach to identify such long-term effects, while also giving more insights into which passengers and which trips are affected. Moreover, the newly developed method allows for proving that previously frequent passengers decrease their travel frequency (or leave the rail network), while the aggregated approach assumes that the autonomous growth on the affected line would be equal to a reference line or area, which cannot be validated. In addition, the method enables investigating the effect of different possession characteristic on long-term effects of rail maintenance, and therefore fills that gap in the literature.

The Groningen Europapark-Groningen case has an effect on passenger patterns. Passengers are negatively impacted by this maintenance project. They make on average 5.88 trips less than expected in the second post-possession period. Moreover, the 25th and 75th percentiles -of the unexpected change in number of trips in second post-possession period- are -19.88 and +4.58, which clearly indicates that there are more passengers who make less trips than expected than passengers who travel more frequently than expected. The third post-possession period has similar results, although slightly less negative. This possession has the longest duration of all investigated cases (64 days). The negative impact of such a major maintenance project -in terms of duration- is in line with the findings of the literature. Eltved et al. (2021) and Nazem et al. (2018) investigated major rail possessions in Copenhagen (13 weeks) and Montreal (four months) and found permanently lower passenger volumes, indicating that passengers travel less frequently after the possession, and thus that there is a lasting effect on passenger patterns. The Groningen possession investigated in this thesis adds evidence to the existing body of literature on the permanent effects of long-duration possessions on passenger patterns. This thesis strengthens the previous findings, emphasising that the structural impact on passenger patterns should be considered when scheduling such large maintenance projects, which could alter the current scheduling process. Currently, in the Netherlands, the direct negative impacts of rail maintenance on passengers are considered -although not quantitatively-, and alternative options are scheduled for the duration of the possession (e.g. replacement buses, rerouted trains), but changes in travel behaviour in the long-term are not taken into account in the scheduling process.

However, in this thesis, the Groningen possession is the only one with a large negative effect. Therefore, special attention should be paid when interpreting these results. The Deventer-Zwolle case also led to permanent changes in passenger patterns, but its effect is less prominent than for the Groningen case. Nevertheless, in combination with the results of Eltved et al. (2021) and Nazem et al. (2018), there is growing evidence of the permanent effect of possessions on passenger patterns.

This long-term impact of possessions on individual passenger patterns, and thus on total ridership, could lead to calls for financial compensation of railway operators. Railway operators operate under a concession in most countries and lose ridership (and revenue) due to the maintenance and its permanent effects, which are factors outside their control. One could argue that the infrastructure manager, who closes the rail track for a (long) period, should compensate the railway operator. However, one could also argue that the infrastructure manager facilitates the railway operator to operate safely and to improve its services, by possessing the track for maintenance, which enables the railway operator to make (more) revenue in the future. The increasing knowledge on permanent effects of possessions might start discussions about these financial aspects between the operator and infrastructure manager. However, there is often misalignment of (financial) incentives between the infrastructure manager and railway operators, which is the cause of higher system costs in a vertically separated rail system (Nash et al., 2014). The costs of long-term impacts of rail possessions on passenger patterns are an example of financial costs for the one (railway operator), indirectly caused by the other (infrastructure manager). Alignment of incentives can help to reduce these costs and to find a system-optimum. Apart from the financial interests of both entities, the insight in the long-term effect of possessions could lead to more dialogue between railway operators and infrastructure managers, aiming to minimise the negative (permanent) impact of possessions on passenger patterns, for the passenger, the railway operator and society.

The developed method cannot be directly used to compute the lost revenue of the railway operator due to the long-term effects of a possession. However, the fare per trip and per passenger is known for the trips between a passenger's two main zones. The lost revenue is easily computed when only considering trips between a passenger's main zones, by multiplying this fare with the computed number of 'lost' trips. However, people might switch subscription type, likely to a cheaper one if they reduce their travel frequency. This complicates computing the exact lost revenue due to the long-term effects of a possession.

As stated in Subsection 3.5.2, the developed post-hoc analysis can also be inversely applied to predict the permanent passenger losses due to a planned rail possession. This can be used to find a maintenance strategy that minimises these losses, but it can also be used to estimate the lost revenue. In combination with the predictive model of Yap et al. (2018) on the direct negative effects of a rail disruption (albeit in an urban network), this gives a complete overview of the financial consequences of maintenance for railway operators. However, the predictive model needs to be further developed before being able to do so.

In contrast, this thesis provides evidence from 21 cases in the Netherlands that short- and mid-duration possessions (i.e. seven days at most) do not have a lasting effect on passenger patterns. These possessions have a direct, temporary impact on passenger levels (Mo et al., 2022), as long possessions also have. However, passengers return to their pre-possession passenger pattern within two months after the possession. This means that long-term impacts on passenger numbers do not have to be considered when scheduling single short- or mid-duration possessions. As far as the author knows, there are no other studies on the long-term effect of short or mid duration possessions on passenger patterns. This thesis does not give any motive for others to investigate this further. However, frequently occurring short possessions on the same route could lead to long-term impacts, but this is not investigated in this thesis.

In the Netherlands, NS is required to offer alternative travel options during maintenance (Ministerie van Infrastructuur en Waterstaat, 2023), as explained in Section 2.3. The absence of long-term effects for the short- and mid-duration possessions could imply that these alternative options are good, and that passengers use and appreciate them during the maintenance period. Guis et al. (2024) indeed found that approximately half of the passengers continue to travel during maintenance, using one of the alternative options. However, Guis et al. (2024) also found that 63% of the passengers experienced hindrance and 27% experienced had a very bad experience during rail maintenance. Both groups indicate that they were faced with a lot of additional travel time, a lower-than-expected quality of the alternative travel option and experienced stress and uncertainty. In addition, they state that they had to adjust their planning. Therefore, the alternative travel option provided by NS is likely not the reason for the absence of long-term effects of short- and mid-duration possessions, as most passengers do not experience it positively.

However, the alternative travel option provided by the railway operator can be relatively good in some cases. The Groningen Europapark-Groningen possession can be seen as an example. During the maintenance period, intercity trains to the south (i.e. all NS-trains serving Groningen) turned at Groningen Europapark (Nederlandse Spoorwegen, 2025a), which is only 1.5 km from Groningen. Replacement buses operated between Groningen and Groningen Europapark (Nederlandse Spoorwegen, 2025a). However, considering the short distance between the stations, it is more than likely that passengers from or to Groningen city did not use these, but used a private mode to reach Groningen Europapark as access or egress station. Moreover, NS placed 300 additional *OV-fietsen* (shared bicycles) at Groningen Europapark station during the maintenance, to travel between the two stations, specifically due to the small distance (Nederlandse Spoorwegen, 2025c). This raises the question whether the permanent negative impacts on travel patterns would be larger if the length of the possession would be larger, i.e. if the alternative travel option would be worse. This can be investigated when more long-duration possessions are investigated, for which an approach is suggested in Section 7.2. In addition, the shared bicycle is apparently in specific situations also an alternative option provided by the railway operator, which could be included in the regression model that estimates the number of trips in the post-possession period as passenger-dependent possession characteristic.

The duration of a possession is the only characteristic that is found to have an effect on permanent changes in passenger patterns. Specifically, only the two possessions in the long-duration category, Deventer-Zwolle and Groningen Europapark-Groningen, are found to have a lasting effect. This finding implies that, for those types of possession, with habits being broken for a long time, frequent train passengers find a suitable alternative during the possession (e.g. other public transport, the car, an active mode, teleworking, etc.) and continue to regularly use that after the possession ends. The findings of this thesis suggest that the new, initially temporary, travel pattern needs to be executed for a sufficiently long time for the new pattern to become a new habit, as also suggested by Eltved et al. (2021). However, the exact time frame cannot be determined with the investigated cases.

Other general possession characteristics are not found to have an impact on the permanent changes in passenger patterns. This suggests that these properties do not have to be considered when scheduling large maintenance projects and when trying to minimise the negative impact of these projects on passenger patterns. However, these findings are not in line with the literature, in which the characteristics were found to have an effect. Nazem et al. (2018), for example, suggest that the geographical size (i.e. the length) of the possession and the time planning do have an effect on structural changes. Therefore, the results of this thesis should be carefully examined. As explained in Section 5.1, the characteristics do not vary greatly between the two investigated possessions for which a long-term effect is found. Consequently, these possession characteristics could not be adequately investigated in this thesis and no conclusions are drawn about the influence of the general possession characteristics on long-term changes in passenger patterns.

Moreover, passenger-dependent characteristics are also found not to have an effect on permanent changes in passenger patterns. However, these characteristics could again not be investigated well, because of the absence of long-term effects for most (21 of the 23) investigated cases. Therefore, no general conclusions can be drawn regarding the effect of the passenger-dependent characteristics.

In addition, the passenger type is found to have an effect on permanent changes in passenger patterns, as also found by Eltved et al. (2021). In this thesis, the medium-low-frequent students and consumers were found to be the least sensitive to long possessions. This is in line with the finding of Eltved et al. (2021), in a study about a long possession, that daily commuters (i.e. similar to the high-frequent business and consumer passengers in this thesis) change their travel patterns the most. However, the analysis of the Groningen-possession also showed that these business passengers return to their pre-possession pattern as time progresses, which was not found by Eltved et al. (2021).

The lower effect of the long duration possessions on passenger group C (medium-low-frequent students and consumers) suggests that on lines with a relatively high share of this group, longer possessions can be scheduled without losing as much passenger trips in the long-term as on other lines. However, it should always be considered whether the relatively minor reduction in travel frequency of this group compensates for the losses in frequency of the more frequent passengers who also use that line.

Moreover, this thesis also found that possessions do not lead to changes in route choice. This suggests that the investigated possessions do not have a large enough negative impact for regular routes (habits) to change, or that frequent passengers already use their optimal or only possible route. Both explanations likely play a role. Since the total number of trips does not change unexpectedly in most investigated cases, it is unlikely that route or station choices change due to the possessions. In addition, the rail network in the Netherlands is dense in the Randstad-area, but less dense in regional areas. In those regional areas, train passengers do not have many route options, so they are captured by a certain route if they decide to continue using the train. Other routes are available in other situations, but often involve a higher generalised travel costs (a combination of travel time and number of transfers[2]). It is unlikely that passengers who still use the train after the maintenance, continue to use the worse route, because they are aware of a better option.

Besides, the investigated possessions also did not lead to changes in station choice. Again, this is partially explained by the limited impact of most cases (the short- and mid-duration cases). However, the long-duration possessions also did not lead to changes in station choice. For the Deventer-Zwolle case, this is explained by the local context. Both cities do not have other stations in the same main zone (e.g. there is only one main station in both cities). For the Groningen Europapark-Groningen possessions, this is caused by the non-intercity status of Groningen Europapark, as explained in Subsection 5.1.2.

During a possession on the most optimal route, (some) people will use an alternative route. This means that trains should be added or lengthened on that line during the possession, to facilitate the additional demand. However, the findings in this thesis show that these measures do not need to become permanent after the possession, because people do not continue to use the alternative route.

In short, this thesis found permanent changes in travel patterns for long-duration maintenance works, placing it next to the studies of Eltved et al. (2021) and Nazem et al. (2018) in the literature. How-

[2]Financial costs are usually also included in the generalised travel costs, but the fare only depends on the origin and destination for a given subscription type and travel class in the Dutch main rail system, regardless of the route.

ever, this thesis went beyond their work and developed a method to determine the effect of different possession characteristics on these changes by investigating multiple possessions. Unfortunately, this could not be adequately performed due to the absence of long-term effect for most investigated possessions. Moreover, this thesis did not find changes in route or station choice, likely due to the local context of the investigated cases. The permanently reduced travel frequency of individual passengers after a long-duration possession could lead to calls for financial compensation of the railway operators and suggests that this long-term effect should be considered when scheduling such maintenance, see Section 7.2.

6.3. Limitations

Although this thesis has been performed with great care, it has some limitations that need to be considered when interpreting the results. The limitations related to the data are first discussed in Subsection 6.3.1, followed by limitations due to methodological choices in Subsection 6.3.2.

6.3.1. Data availability

The largest limitation is caused by limited data availability. The analyses are performed on an individual passenger level, using pseudonymous smart card data. Data are provided by NS. NS is allowed to store these data for a duration of 18 months, according to Dutch privacy law. However, data were only made available for a duration of 15 months for this study. In combination with the required time period of two months before and six months after the possession, which was found in Section 2.4, this limits the number of available cases to a large extent. Only cases between March 2025 and August 2025 could be used. Further filtering steps in the cases (Section 3.2) reduced the number of cases even more. Most investigated possessions are short. There are only two cases in the category *long duration*, of which only one is extremely long. In the regression models, the duration was found to be the only relevant possession characteristic for estimating the number of trips in the post-possession period. However, if more long-duration possessions were included in the analysis, the effect of other characteristics could have been investigated better.

Another limitation related to data availability is the absence of expiration dates of the smart cards in the data. A Dutch *OV-chipkaart* (smart card) expires after five years (OV-chipkaart, n.d.). The same holds for the OV-pas (OV Pay, n.d.) and for most debit cards. The owner of a card that suddenly stops appearing in the data has not necessarily stopped using the train. One could also have obtained a new card and continue with the same travel pattern. This effect could not be included in the analysis. However, this effect also occurs in the reference group, likely at a similar rate. However, the correction factor (the mean change in number of trips of the reference group) does not fully account for the expiring cards, which leads to a slightly negative skew of the indicator on the changes in the number of trips, as explained in Subsection 5.1.1.

Moreover, the effect of changes in the timetable is not considered. Changes in timetables often lead to improved services for train passengers, which would lead to an underestimation of the long-term effect of possessions on passenger patterns. However, since long-term effects are not observed for most cases, this likely does not occur. The Groningen-case, however, does lead to long-term changes, and the timetable of the local train operator (Arriva) with feeder lines to Groningen main station has changed after the maintenance period. The timetable of the line between Veendam and Delfzijl is shifted by 15 minutes (Groningen Bereikbaar, 2025). For some specific OD-pairs, mainly between stations on the line Veendam and Delfzijl and stations south of Zwolle, the travel time increases by approximately 10 minutes. This might also decrease the ridership of the selected passengers of the Groningen-case. These are, however, OD-pairs with a high travel time, and thus likely few passengers, leading to a small overall effect.

The last limitation due to data availability is related to the selected passengers. This thesis only considers passengers who travel with an OV-chipkaart, OV-pas or debit card. Other tickets, like QR-codes, paper tickets or combi-deals can only be used once, and the passengers who use them cannot be followed over time, so their potential changes in travel pattern after a possession cannot be identified. The number of passengers who are excluded by this limitation is high, but this group only makes a small fraction of the total trips. These people do not travel often, so the effect of potential changes in their travel patterns on the overall rail network, the revenue of the railway operator and the positive externalities of train travel compared to car travel is low. Nevertheless, these passengers would have been filtered out of the investigated group by the threshold for the minimum number of trips in the pre-possession period (Subsection 3.1.2). On an aggregated level, the number of single-use tickets before and after a possession could be compared to make an estimate of the effect of a possession on these passengers. However, this requires a correction for seasonality and autonomic growth.

6.3.2. Methodological choices and assumptions

There are also limitations related to methodological choices. First of all, in the analysis, it is assumed that passengers on a specific (affected) line follow the average seasonality pattern of all other passengers in the same region in the same passenger group. The travel patterns in the pre-possession period of the investigated groups and reference groups, in terms of the number of trips per passenger group, are equivalent, as is ensured with the Kolomogrov-Smirnov test (see Subsection 3.1.4). However, it cannot be verified if the investigated group would have followed the reference group perfectly in case there was no possession.

In addition, highway maintenance projects are not considered in this thesis, but could have an effect on the seasonality correction factor (i.e. the expected change in the number of trips) if a part of the reference group makes a (temporary) modal shift from car to train. In theory, this could occur if the highway maintenance is in a pre-possession period of a rail possession, because the temporary train-users could satisfy the threshold on the minimum number of trips. In that case, the average number of trips of the reference group would be artificially high in the pre-possession period, compared to the post-possession period. However, this only occurs for a relatively small group of the reference, since the reference group consists of passengers from a much larger geographical area than the area around the highway maintenance. So, although Von der Thüsen et al. (2026) found an increased train ridership during long highway maintenance projects, the overall effect on the seasonality correction factor used in this thesis is limited.

Moreover, unplanned incidents are not considered in the pre-possession and post-possession period of both the investigated group and the reference group. There is no effect of this choice if the frequency of occurrence and the duration of these incidents is equally divided among both groups. However, this is not necessarily true. The affected line can have many more unplanned incidents than other lines in the same (school holiday) region. In that case, the potential negative effect of possessions on passenger patterns is over-estimated. The number of trips is by default lower than expected, because there is no possibility for the passengers to make their trip. In addition, the effect of the possession characteristics might be wrongly determined if passengers consider the many unplanned incidents as the last straw which makes them stop travelling altogether. However, since there is not a clearly identifiable effect of possessions for most investigated cases, it seems that the effect of this limitation is also limited, unless the investigated lines all had lower-than-average number of incidents in the post-possession period.

Next, only cases without any new possessions of at least a day on the same route are considered in this thesis. This isolates the effect of a single possession, and prevents needing to correct the number of trips for days that no train traffic was possible on a certain route. However, this also limits the number of available cases largely (see Table 4.1). Therefore, finding a method to account for these aspects would increase the number of suitable cases, and thus strengthen the results and implications of the study. The direct effect of new possessions is easily accounted for by removing the relevant days from the reference group as well. However, there is also an indirect effect of new possessions. They might cause a build-up effect of increasing annoyance for passengers (e.g. a passenger stops travelling after the third time of maintenance on the same route within a few months). This can be accounted for in the regression model, by including the number of days that the route is again possessed in the post-possession period of the possession under investigation. That also allows for investigating this build-up effect, but investigating the effect of a single possession is not possible with this approach. Applying this approach and the method followed in this thesis to a selection of cases might give more insight into the effect of relaxing the requirement on no new possessions in the post-possession period.

In addition, some people stop travelling by train (on a specific line) due to life events, such as moving houses or changing jobs, as was found in Section 2.3. The effect of this phenomenon is negligible, because it also occurs in the reference group. Moreover, it cannot be taken into account in any way using only AFC data only and would require the use of surveys.

Lastly, it is assumed that each smart card is used by only one passenger. Most smart cards are indeed personalised, which means that only one person can travel with it. However, an individual could, in theory, travel with somebody else's debit card. This effect is likely small, and cannot be mitigated.

In short, the methodological choices have a limited impact on the final result. However, the limitations due to data availability lead to partially inconclusive results. The effects of some possession characteristics could not be investigated adequately, because the long-term effect of most selected possessions is limited.

6.4. Generalisability of results and methods

This thesis uses case studies from the rail network of the Netherlands. The Netherlands is a relatively small country, and one of the most densely populated in Europe (Eurostat, 2026). Moreover, it has the busiest rail network in Europe (Autoriteit Consument & Markt, 2019). The train is used for commuter traffic by a large share of the country's inhabitants. The Dutch are accustomed to the train, which might cause them to tolerate a longer period of hindrance in the rail network than other country's citizens, with a less extensive, dense and used rail network. The findings of Eltved et al. (2021) and Nazem et al. (2018) were also in dense (urban) areas (Copenhagen and Montreal). There have been no studies in less dense areas with less used rail lines. The findings of this and the two mentioned studies likely hold only for western, dense areas, and do not hold in other areas with other cultures.

The methodology of this thesis can be used in other countries that collect AFC data in their public transport (train) system. The Netherlands has a closed system, while most countries only require checking in with a smart card. A tap-in-only system makes route inferring more challenging, because the destination is unknown. However, methods are available to infer destinations (e.g. Zhao et al., 2007; Cheng et al., 2021), which allows the methodology of this study to be applied in all countries with AFC data and AVL data. As stated in Chapter 1, major rail possessions are also scheduled in other European countries. It is therefore interesting to apply the methodology and investigate long-term effects of rail maintenance in those countries as well.

Moreover, as discussed in Subsection 3.1.2, passenger groups are partly based on subscription types. These types differ per country, but the method can be used regardless of which passenger groups are used. However, the passenger groups must be partly based on travel frequency in the pre-possession period, especially for computing a correct expected change in number of trips with the reference group, consisting of people with the same passenger type.

Besides, the method of this thesis is also applicable to possessions in urban rail networks (tram, metro or light rail). These modes often require tapping in and out in the vehicle (in the Netherlands), which makes route inferring easier. Moreover, the method is also applicable to maintenance projects on bus routes. However, buses are not bound to physical infrastructure (rails), so a detour around the maintenance often leads to limited increased travel time. Limited permanent effects are expected for possessions on bus networks, but the method is applicable to them.

In addition, unplanned, but long disruptions are beyond the scope of this thesis (Section 1.4). These are situations in which an accident requires major repair works, for example the train derailment in Voorschoten in April 2023 (ProRail, 2023) and the fire in a cable trough in Rotterdam in July 2026 (NOS, 2026). However, these situations are relatively similar to planned possessions, and might have similar effects. The method in this thesis is directly applicable to these type of unplanned, long disruptions. In order to investigate whether these situations indeed have similar effects, an additional characteristic (planned $\in (0, 1)$) should be included in the regression model.

In conclusion, the method developed for this thesis is not only applicable to the main rail network of the Netherlands. The method also works for other countries or operators, with a few changes or additional steps. Therefore, the method of this thesis is a contribution to the field of public transport travel behaviour analyses. It provides an alternative to aggregated ridership analyses (without pseudonymous smart card IDs). Moreover, it can be used to show that previously frequent passengers decrease their travel frequency (or totally stop travelling) after a specific event, which is not necessarily a possession. This is not possible to prove with an analysis on an aggregated level.

Moreover, the methodology used to establish an overview of past possessions in the Netherlands (see

Subsection 4.1.1) is a contribution to NS. It provides an accurate overview of all rail maintenance works in the past, which was not available yet. This method can also be used for other projects within the company. This also holds for the method that links possessed routes to affected passengers and OD-pairs, which was not yet directly available in the systems of NS.

The methodology of identifying possessions is likely not directly applicable to other railway operators, because the data is structured in another way. However, if another railway operator also works with multiple timetables (i.e. timetables comparable to the BDu and SD of NS) and record all realised train movements (i.e. the realised trips of NS), the logic of the method to identify maintenance works can be used in other countries as well.

7 Conclusion & Recommendations

This chapter gives the conclusions and recommendations of this study. First, Section 7.1 answers the research questions. Next, Section 7.2 gives recommendations for practice and science, and suggests future research.

7.1. Conclusions

Chapter 5 gave the results of the study, and Chapter 6 discussed its implications and limitations. This section answers the research questions and summarises the most important findings. Chapter 1 defined the following research question.

- Which rail possession characteristics have the greatest impact on structural changes in passenger patterns on a specific line given the passenger group composition on that line?

To answer the main research question, the answers to the following four sub-questions are first discussed.

1. What characteristics of a planned rail possession influence passengers' post-possession travel patterns?
2. What time period before and after a rail possession should be considered when determining its long-term impact on passenger patterns?
3. How do passenger patterns of different passenger groups structurally change after a planned rail possession for selected rail possessions in the Dutch main rail network?
4. How do different passenger groups respond to different characteristics of a rail possession in the Dutch main rail network?

The first research question is initially answered through a literature review, and later with the data analyses. The literature review found two categories of possession characteristics. These are the general possession characteristics and the passenger-dependent characteristics. General possession characteristics include the duration, spatial scale (length), the time planning (i.e. during the weekend or a holiday), the time since the last possession on the same route, and the presence of simultaneous possessions in the vicinity. Passenger-dependent characteristics are related to the quality of alternative travel options. These are expressed as the travel time by car or other public transport, and the travel time and travel option of the alternative provided by the railway operator during the possession. However, in the data analyses, only the duration of a possession is found to have an effect on passenger's post-possession travel patterns, for the investigated possessions in this thesis. A long-duration possession has a negative effect on the future number of trips, as explained in the answer to the fourth research question below.

The second research question is also answered with the literature. Previous studies showed a transition period of two months after a (long) possession before passenger patterns (e.g. the number of trips per passenger or total ridership) stabilise. Patterns in these two months are, therefore, not permanent. Therefore, in this thesis, only changes in passenger patterns that are observed after two months after the end of a possession are considered lasting. The post-possession period ends six months after the maintenance has been completed, based on the recommendations of previous studies. These previous studies used a post-possession period that ended at most four months after the end of the possession, but the authors suggested that a longer period should be investigated to determine if effects remain in place. The post-possession period in this thesis is divided into three periods of two months each, to investigate if the passenger patterns change (return to the original patterns) with progressing time and after the four-month point, which has not been investigated before. The pre-possession period, that is used to compare the (new) passenger patterns to, is defined as the two months before the maintenance starts. An equal duration of the pre-possession period and post-possession periods allows for a fair comparison between them.

Next, the third research question on permanent changes in passenger patterns is answered through data analyses. The results show limited to no changes in passenger patterns after the possession for 21 of the 23 investigated cases. These are the 21 short- or mid-duration cases. The change in the number of trips of the investigated passengers between the pre-possession period and the post-possession periods is, in general, equal to that of the unaffected reference group for most cases. Some people travel more than expected, compared to the reference, while others travel less. These effects cancel each other out, and, therefore, the overall effects are, negligible. This holds for both investigated long-term post-possession periods (i.e. month 3-4 and month 5-6 after the possession has ended) and implies that these short- and mid-duration possessions do not have a permanent effect on passenger patterns.

However, there is a clear, negative effect of the Groningen Europapark-Groningen possession, which lasted 64 days. The investigated passengers of this possession make, in general, 5.88 and 5.80 trips less than expected in the second and third post-possession periods respectively. Moreover, the distribution of the difference between the observed and expected change in the number of trips is much shifted towards negative values: the middle 50% of the observations are between -19.88 and +4.58 for the second post-possession period. This means that there are (far) more people who change their number of trips more negatively than expected than people who make more trips than expected. This phenomenon also occurs for the other case with a long duration (Deventer-Zwolle), but to a lesser extent. For this case, the medians are -3.94 and -3.34 for the second and third post-possession periods respectively. The results of these cases mean that there is a long-term, negative effect of the long-duration possessions.

The negative effect of the Groningen Europapark-Groningen possession decreases minimally from the second to the third post-possession period. There are passengers who move towards their pre-possession travel pattern in the third post-possession period, but the effect is mostly the same in the second and third post-possession period. However, this observation is only based on one case, and is not observed for the Deventer-Zwolle case. However, all duration categories have decreasing median values from the first to the last post-possession period, which is likely caused by expiring smart cards. Therefore, the fact that this does not occur for the Groningen Europapark-Groningen case suggests that passengers indeed return to their pre-possession pattern as time progresses.

Passenger patterns are also described by the route or station choice. For most cases, the passengers do not change route after the possession. There are six cases with (very) minor changes in route or station choice for certain passenger groups, but these are most likely not caused by the possession, but by improvement of the quality of (local) public transport near these rail lines or improvements in the train timetable, although this is not investigated. The possession Groningen Europapark-Groningen also has not led to changes in the share of trips over the affected line, which means that the possession did not lead to a permanent shift in station choice from Groningen to Groningen Europapark. This is due to the non-intercity-status of Groningen Europapark compared to the intercity-status of Groningen.

The fourth research question on the effect of different possession characteristics and the passenger groups is answered with linear regression models that estimate the number of trips in a post-possession period. The addition of the possession characteristics to the models does not lead to a large increase in model performance for both post-possession periods, meaning that the possessions do not largely influence the number of trips in the post-possession period, regardless of the passenger group. This corresponds to the answers to the third research question. The estimation of the number of trips in the third post-possession period is less accurate than for the second post-possession period. This is caused by the longer time span since the pre-possession period.

Most of the possession characteristics from the literature are not found to have a significant effect on the change in passenger patterns for the investigated possessions in this thesis. Only the duration of the possessions is found to have an effect in the second post-possession period. For long possessions (i.e. eight or more days), the number of trips in the post-possession period is found to be lower than expected. Only two investigated possessions fall into this duration category, and those are the two previously mentioned cases with a long-term effect of the possession (Groningen Europapark-Groningen and Deventer-Zwolle). The effect of the other possession properties could not be adequately investigated, since permanent effects were found only for two cases. The characteristics that are not found to be significant vary among all cases, including the two with a permanent effect, while the long-duration characteristic is only observed for those two. This leads to the duration property being the distinction between the cases with and without permanent effects, which prevents the potential effect of other possession properties to be identified. Therefore, no conclusions are drawn about the effect of the other possession characteristics.

More possession characteristics were found to have a significant effect on the number of trips in the third post-possession period. However, these results are not considered valid. Likely, the lower predictive power of the expected number of trips on the observed number of trips causes the characteristics to be significant, while they actually capture some of the noise. As stated in Section 5.2, the coefficients of the possession characteristics are illogical or in contrast to the literature. Therefore, the model of the second post-possession period is considered to be more accurate, and no conclusions on the effect of possession characteristics are drawn based on the regression model of the third post-possession period.

The investigated business passengers and high-frequent consumer passengers follow the trend of the reference group more closely than the other passenger groups, since the expected number of trips is a better estimator for the observed number of trips for those passengers than for passengers of other groups. However, the effect of the possession characteristics differs only limitedly between passenger groups. Only passenger group C, the medium-low-frequent consumers and students (one to two tours per week on average) respond differently to the duration of a possession than the other groups. These passenger groups are less severely affected by possessions of a long duration. If a possession has a long duration, passenger group C makes 0.49 trip more, on average, than the other passenger groups, but still less than expected (-3.10). So, although there is a statistically significant difference between the groups, the effect is small.

Finally, the main research question asks which rail possession characteristics have the greatest impact on permanent changes in passenger patterns on a specific line, given the passenger group composition. As follows from the above, the duration is the only possession characteristic that has an effect on structural changes in passenger patterns. Therefore, the answer to the main research question is that the long-duration characteristic has the largest impact on permanent changes in passenger patterns. This does not depend on the composition of the passenger groups on the line, because there are no other properties that have an effect. However, the effect is slightly less severe on lines with a large share of medium-low-frequent students and consumers.

7.2. Recommendations and future research

Although this thesis provides valuable knowledge about the (lack of) long-term effects of possessions on passenger patterns, further research is required to gain more insight in especially the effects of different characteristics on these effects. Subsection 7.2.1 gives recommendations for future work to science, and Subsection 7.2.2 gives recommendations to railway operators and infrastructure managers , i.e. for practice.

7.2.1. Science

More possessions with a long duration should be investigated. This serves three purposes: (1) it should confirm (or question) the findings of this thesis and previous studies that possessions with a long duration have a permanent effect on passenger patterns; (2) the additional cases will likely have more variation in the other possession characteristics, which allows for the investigation of the effect of those characteristics on the permanent changes in passenger patterns; (3) the additional cases will likely have more variation in the duration, this will give more insight in the exact boundary between mid-duration and long-duration possessions, which helps finding the turning point between maintenance with and without long-term effects.

However, these cases with a long duration are relatively rare, especially since they also have to meet the additional requirements of Subsection 4.1.2. For example, there may not be days with another possession on the same line in the two month pre-possession period and the six month post-possession period. Subsection 6.3.2 discussed how this requirement can be relaxed and which additional methodological steps must be taken to do so. There are interesting, large rail maintenance projects to come in the Netherlands. The rail track between Alphen aan den Rijn and Bodegraven will be possessed from October 2026 to July 2027 (Nederlandse Spoorwegen, n.d.-f). This is very long, much longer than the Groningen Europapark-Groningen case, and therefore interesting to investigate. Unfortunately, long-term impacts can be observed in the end of 2027 at the earliest. Similarly, the high speed rail line between Rotterdam Centraal and Hoofddorp will be possessed for at least 82 days in 2028. Finally, a four month possession is scheduled in Zeeland (Vlissingen-Goes) to test ERTMS in 2029 (Provincie Zeeland, 2024). NS is recommended to investigate the long-term effect of these possessions on passenger patterns by using the methodology of this thesis, potentially extended with additional steps to account for new maintenance in the six month post-possession period.

The methodology that is developed in this thesis is directly applicable to these cases, once the post-possession period has ended. Only the input needs to be changed, which consists of the affected stations, the affected track segments, the start and end date, and the other track segments with maintenance in the post-possession period. The latter are easily identified in the Netherlands with the method of obtaining an overview of all possessions that is also developed in this thesis (see Subsection 4.1.1). For that method, the last step still needs to be automated. This is the step that finds the separate possessed routes in case there are multiple route segments possessed that share a train-basis-series (e.g. the output is *Goes-Haarlem-Leiden-Roosendaal*, which means that Goes-Roosendaal and Haarlem-Leiden are possessed). It is recommended to find these separate segments based on the arrival times of specific trains (which is already included in the data), with which the sequence of stations can be found. Alternatively, the sequence of stations on each corridor can be constructed by hand, and given as input to the model.

Moreover, another approach to include more long-duration possessions in the analysis is to set up a European collaboration between railway operators interested in this topic. The method developed in this thesis is applicable in other countries that use AFC and AVL data, as explained in Section 6.4. Although the local (cultural) context might play a role in long-term effects, the general phenomenon of reducing train travel after a long period of maintenance is likely equivalent in (western) European countries.

In addition, it is recommended to railway operators, and to NS specifically, to include the expiration dates of smart cards in the data set for longitudinal analyses on individual passengers. This is currently missing in the data, which prevents determining if a passenger stops travelling due to specific events (such as a possession) or due to his or her card being expired. Separating these two explanations increases the quality of passenger analyses. However, compliance with privacy regulations needs to be confirmed before including the expiration dates in the data set for travel analyses.

Moreover, railway operators, such as NS, should thoroughly investigate the exact effect of these long and impactful possessions. As stated in Section 6.2, it could lead to arguments to opt for different maintenance strategies, if those lead to a lower extent of travel frequency reduction among frequent passengers. This is in the first place beneficial for the railway operator themselves, since they lose less passengers trips and thus less revenue. It is, however, also beneficial for society, if it leads to less people shifting from the train to the car for (inter-)regional trips. It is unlikely that people change their work or living location due to a long period of maintenance on the rail track, so passengers who leave the rail system likely switch to the car, which has a more negative impact on the environment than the train.

In addition, this study only considered regular train passengers, with on average at least one to two tours (two to four trips) per week (after removing the low-frequent groups based on the KS-test). These frequent passengers have the largest impact on the overall rail network, because they make the most trips. However, there is also a large group of passengers with few trips, who, as a group, also have a relatively large impact. It is more difficult to identify changes in the passenger patterns of these passenger groups, because they travel less regularly. These groups are probably more sensitive to disruptions, for the same reason. Therefore, the chance of losing these passengers permanently due to possessions is larger, which makes it interesting to investigate their responses to maintenance work. However, the travel patterns of individual people in these groups are likely too inconsistent to establish a travel patterns that might or might not change due to possessions. Instead, an aggregated approach could be used, i.e. comparing the total number of infrequent passengers before and after the possession. However, this approach does not allow for investigating the actual effect of possessions on individual passengers, nor for investigating the effect of passenger-dependent possession characteristics on these groups.

Moreover, this thesis only investigated single possessions. The effect of repeated maintenance on the same line is included as one of the possession characteristics. However, unplanned disruptions are not considered in the study, while frequently occurring unplanned disruptions on a specific line (i.e. the investigated group is faced with substantially more unplanned disruptions than the reference group) might also have an effect on changes in passenger patterns, as discussed in Section 6.3. This combination of planned and unplanned disruptions and the effect thereof on passenger behaviour is the logical next step in this line of research.

Besides, for the cases with long-term effects on passenger patterns, it would be interesting to combine the AFC data with, for example, traffic counts on parallel highways and AFC data from local public transport operators. This would allow for determining to which modes people switch (or shift to teleworking). This could also be realised by using surveys. Insights in these modal shifts can be used to determine if the lower passenger patterns are a problem from a societal point of view, and thus if a political intervention has to be made.

In short, more long-duration possessions should be investigated to determine the boundary between mid- and long-duration possessions, and to determine the effect of other possession characteristics on permanent changes in passenger patterns. Investigating more long maintenance periods requires the relaxation of one of the selection criteria used in this thesis (no new maintenance in the post-possession period), which involves some changes to the method, as explained in Subsection 6.3.2. Moreover, the inclusion of smart card expiry dates to the data would increase the quality of the method. In addition, a different method, on an aggregated level, is recommended to investigate the effect of possessions on low-frequent passengers. Finally, combining the method of this thesis with other data sources allows for investigating to which alternatives passengers switch if they permanently decrease their train travel frequency.

7.2.2. Practice

The identified long-term impact of the Groningen Europapark-Groningen and -to a lesser extent- Deventer-Zwolle cases on passenger patterns, in combination with similar findings in the literature, raise the desire for considering these effects when scheduling maintenance with a long duration. This requires dialogue between the infrastructure manager and the railway operator, who need to collaborate and share knowledge to decrease the negative, long-term effects of major rail maintenance works for train passengers.

Once a more robust turning point between short/mid and long possessions is found, after investigating more cases, this information could be used to change the maintenance strategy. Maintenance will always be required on the track, and shortening its duration is usually not possible (i.e. the work needs to be done, which takes time). However, the findings of this thesis, in combination with the findings of Eltved et al. (2021), Nazem et al. (2018), and Verhoof et al. (2023), and (likely) in combination with results from future work give reason to divide a long maintenance period into two or multiple shorter (mid-duration) possessions with a sufficiently long time between them. These mid-duration periods do not have a lasting effect on passenger patterns, and are thus more beneficial for both railway operators and passengers. However, there needs to be a sufficiently long period between the maintenance periods, otherwise the passenger might value it even worse than one long possession. In this thesis, only possessions are investigated if there has not been a new possession on the same route within six months. Therefore, a six-month intermediate period between two possessions does not result in the phenomenon mentioned before. However, a shorter intermediate period (e.g. two to three months) might be sufficient, but this needs to be investigated. For mid-duration possessions, there is reduced necessity to find a suitable, permanent alternative, since the hindrance is relatively short. Of course, this maintenance strategy leads to higher financial costs, which need to be paid for by the infrastructure manager. Therefore, close collaboration with the infrastructure manager (ProRail in the Netherlands) is required. However, if it indeed leads to less train travel reduction, it also leads to less societal costs in terms of the environment. In the end, it is a political choice if this is desirable, but further studies are required to be able to make this choice.

Moreover, it is recommended to railway operators to launch promotion strategies targeted at long-term travel patterns for long-duration maintenance works. Currently, most information that is given to the passengers by NS is related to the alternative options during a possession. It is of course good to inform the passengers well on how they can travel during the maintenance, but it places the focus on the (direct) negative effects. Promotion of the benefits of the maintenance (e.g. a track that needs no maintenance in the coming months, increased safety, higher capacity) might decrease the long-term negative effects, since passengers know that the maintenance also benefits them. They might feel less inclined to find a suitable alternative (that they continue to use after the maintenance) if they are informed about these benefits. The infrastructure manager in the Netherlands, ProRail, already uses these types of promotion strategies (Treinenweb, 2026), but NS does not on a large scale. For example, the Groningen-possession information campaigns focused on alternative travel options (Nederlandse Spoorwegen, 2025a, 2025c).

Once more possessions are investigated, the effect of other characteristics is also known. This could then also be used to adjust the maintenance strategy. If it is, for example, found that possessions during a holiday have a similar long-term impact as possessions during non-holidays, the wish for scheduling maintenance as much as possible during holidays might decrease, although the direct negative effects are larger during non-holidays. However, these other characteristics could not be adequately investigated in this thesis, so giving recommendations about them is only speculation.

Finally, the predictive model shows potential to be used in the scheduling of (long) maintenance in the future. A simulation of different combinations of possession characteristics will give insight in the long-term effects of different maintenance strategies. It can be used by railway operators and infrastructure managers to find an optimal maintenance strategy regarding the long-term effects on passenger patterns. However, it needs to be developed further, by investigating more cases, before being suitable for practice. This predictive model could be combined with other models that infrastructure managers currently use to schedule maintenance, which are primarily focused on the direct financial costs of the maintenance. This will help aligning the incentives of railway operators and infrastructure managers, and find a system-optimum regarding the costs of rail maintenance.

To summarise, the long-term effects of long-duration possessions on passenger patterns gives reason to consider it when scheduling large maintenance projects. Dividing the maintenance into multiple shorter possessions is expected to lead to reduced long-term impact, but involves higher financial costs. Considering the long-term effect of maintenance works on passenger patterns in the scheduling process requires collaboration between the railway operator and the infrastructure manager. Moreover, information campaigns of the railway operator should not only focus on the alternative travel options during a possession, but also on the (long-term) benefits of the maintenance for the passengers, because this likely decreases the long-term impacts. Finally, the predictive model of this thesis can be used, once further developed, in the scheduling process of maintenance, to find an optimal combination of possession characteristics, that reduces the long-term effects as much as possible.

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A

Overview of selected possessions

Table A.1 provides an overview of the selected possessions (after filtering) that are used in the analysis. The general possession characteristics are indicated per case.

The number of investigated passengers per case is not included in the public version of this thesis for confidentiality reasons.

Table A.1: Selected possessions for analysis with general possession characteristics

Start date	End date	Possessed line	No. of selected passengers	Duration (days)	Distance (km)	Weekend	Holiday	Simultaneous poss. nearby	Days since last poss.
15-03-2025	16-03-2025	Amersfoort Centraal - Apeldoorn		2	43.85	1	0	0	419
18-03-2025	23-03-2025	Hoorn - Heerhugowaard		6	16.68	0	0	1	98
22-03-2025	22-03-2025	Breukelen - Woerden		1	12.59	1	0	0	14
29-03-2025	30-03-2025	Almelo - Deventer		2	38.27	1	0	0	49
05-04-2025	06-04-2025	Beverwijk - Uitgeest		2	6.59	1	0	0	34
03-05-2025	04-05-2025	’s Hertogenbosch - Houten Castellum		2	38.44	1	1	1	657
10-05-2025	12-07-2025	Groningen - Groningen Europapark		64	1.59	0	0	0	280
16-05-2025	18-05-2025	Anna Paulowna - Den Helder		3	11.33	0	0	0	59
17-05-2025	19-05-2025	Alphen aan den Rijn - Gouda		3	17.55	0	0	0	358
24-05-2025	01-06-2025	Deventer - Zwolle		9	29.92	0	0	0	390
24-05-2025	25-05-2025	Delft Campus - Zwijndrecht		2	30.26	1	0	1	1154
29-05-2025	01-06-2025	Alphen aan den Rijn - Woerden		4	19.10	0	0	0	291
07-06-2025	09-06-2025	Amersfoort Vathorst - ’t Harde		3	42.69	0	0	0	203
14-06-2025	15-06-2025	Amsterdam RAI - Schiphol Airport		2	10.32	1	0	1	16
21-06-2025	22-06-2025	Alphen aan den Rijn - Leiden Centraal		2	14.99	1	0	1	70
21-06-2025	22-06-2025	Goes - Roosendaal		2	50.11	1	0	0	70
27-06-2025	29-06-2025	’s Hertogenbosch - Nijmegen		3	43.57	0	0	0	1426
28-06-2025	29-06-2025	Hoofddorp - Leiden Centraal		2	24.37	1	0	1	70
07-07-2025	11-07-2025	Diemen Zuid - Amsterdam RAI		5	5.40	0	0	0	254
12-07-2025	13-07-2025	Alkmaar - Heerhugowaard		2	6.87	1	1	0	116
12-07-2025	13-07-2025	Almere Centrum - Weesp		2	15.14	1	1	1	56
26-07-2025	27-07-2025	Arnhem - Nijmegen		2	17.02	1	1	0	315
26-07-2025	27-07-2025	Geldermalsen - Tiel		2	11.88	1	1	0	84

B

Detailed results on changes in passenger patterns

Section 5.1 showed the results of the two indicators on changes in number of trips and changes in route or station choice. This appendix presents more detailed results that are the foundation of Section 5.1. Section B.1 shows additional figures showing the difference between the observed and the expected change in the number of trips, explained in Section 5.1. Section B.2 covers additional figures on the first indicator, that includes the normalisation by the number of trips in the pre-possession period. Next, Section B.3 shows additional figures for the change in route or station choice.

B.1. Change in number of trips

Figure B.1 is equivalent to Figure 5.1, but includes the outliers. It shows the difference between the observed and expected change in number of trips, aggregated over the three duration categories. Figure B.2 is equivalent to Figure 5.4, but includes the outliers. It shows the difference between the observed and expected change in trips as well, but now aggregated per overarching passenger group. The outliers are relatively symmetrically centred around zero. Notable are the outliers below -300 for the long-duration possessions. These are from one individual passenger in each of the three post-possession periods. The individual who decreased his or her travel frequency much is part of the overarching group A (all business passengers and high-frequent consumers), see Figure 5.4. It is also notable that group C (medium-low-frequent students and consumers) does not have negative outliers for the two long-term post-possession periods, caused by the maximum decrease of number of trips of 32 (the upper limit of trips in the pre-possession period) for this passenger group.

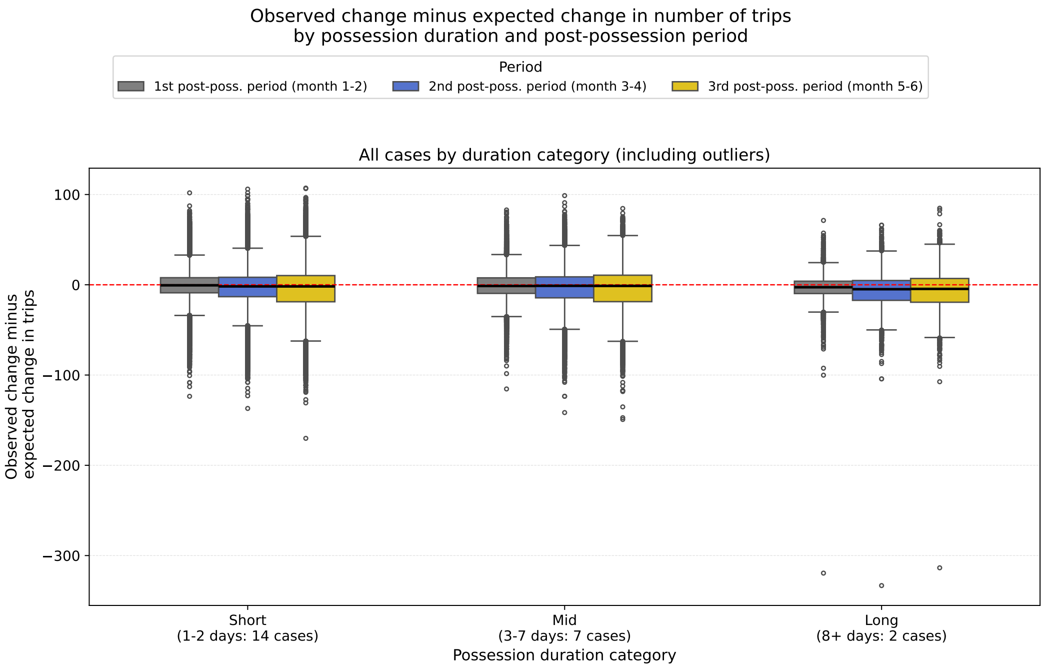

Figure B.1: Difference between the observed change and the expected change, per duration category, including outliers

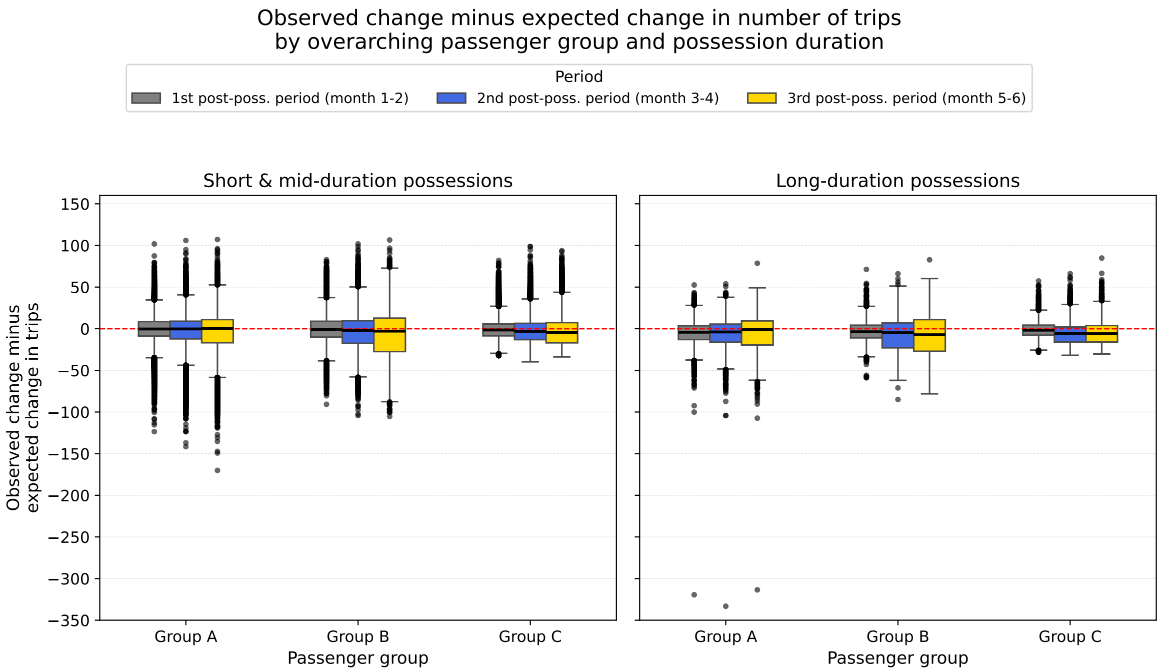

Figure B.2: Difference between the observed change and the expected change, per overarching passenger group and duration category, including outliers

Figure B.3 and Figure B.4 show the difference between the observed and expected change in number of trips per case, with and without outliers. The order of cases, from top to bottom- is based on (1) the duration (short, mid, long) and (2) the median of the first investigated post-possession period. These figures support what was found in Figure 5.1: only possessions with a long duration negatively affect individual passenger patterns.

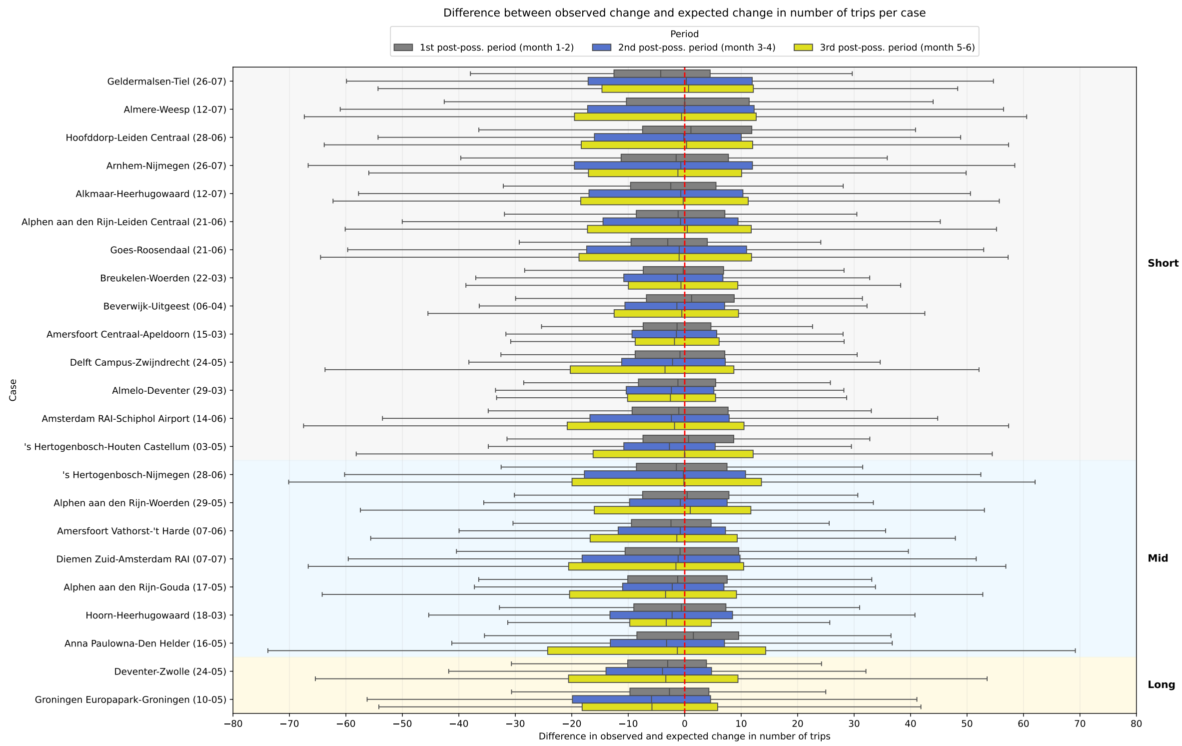

Figure B.3: Difference between the observed and the expected change in number of trips, per case. Order is based on duration category (indicated on the right). Outliers are excluded, but included in Figure B.4.

For the short- and mid-duration cases, the boxes in all post-possession periods are approximately symmetrically centred around zero, but slightly shifted towards negative values. The median values are also around zero, but mostly slightly negative, as already discussed in Section 5.1.

In the second investigated post-possession period, the median is between -1 and +1 for nine of the 23 cases (of which six are short-duration and three are mid-duration), and between -2.5 and +2.5 for 21 cases. Only the two long-duration cases (Groningen Europapark-Groningen and Deventer-Zwolle) have a median value below -2.5. Similar numbers are found for the third investigated post-possession period (11 and 6 for the former and the later ranges respectively). Therefore, in most cases, the investigated group follows the reference group relatively well, indicating that most possessions have no effect on the passenger patterns.

For example, the Geldermalsen-Tiel and Almere-Weesp cases, shown at the top of Figure B.3, show symmetrically centred boxes around the zero line for both post-possession periods. There are as many passengers with more trips than expected as passengers with less trips than expected. Therefore, there is no effect of these possessions on the post-possession passenger patterns.

However, the boxes are clearly shifted towards more negative values for a few cases. This is most evident for the Groningen Europapark-Groningen possession, at the bottom of Figure B.3. This case results in an IQR from -19.88 to +4.58 in the second post-possession period, and -18.17 to +5.83 in the second. As explained in Section 5.1, this is also the case for the Deventer-Zwolle possession, but to a lesser extent (i.e. IQR from -13.94 to +4.74 and -20.57 to +9.43 in the second and third post-possession respectively). These findings indicate that long-duration possessions lead to permanently reduced ridership on an individual passenger level, and thus 'lost' passengers for the railway operator.

Some other possessions also have negative median values, as seen in Figure B.3. Six cases have a median value lower than -2.5 in at least one post-possession period, in addition to the Groningen Europapark-Groningen and Deventer-Zwolle cases. These are the 's Hertogenbosch-Houten Castellum and Anna Paulowna-Den Helder cases for the second investigated post-possession period, and the

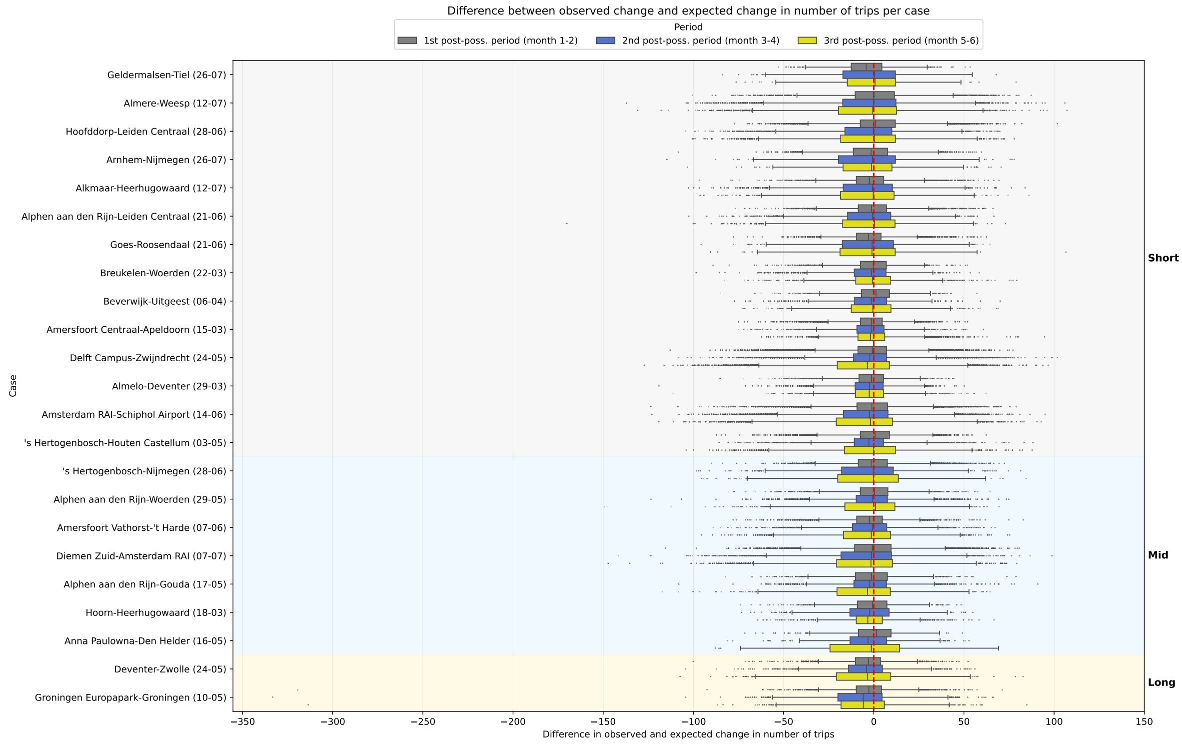

Figure B.4: Difference between the observed and the expected change in number of trips, per case. Order is based on duration category (indicated on the right).

Almelo-Deventer, Alphen aan den Rijn-Gouda, Delft Campus-Zwijndrecht and Hoorn-Heerhugowaard cases for the third period. However, the distribution is approximately symmetrically centred around zero for these cases, especially compared to the Groningen case. Therefore, there are no clear long-term effects of the possession for these cases.

Notable is that the former two cases ('s Hertogenbosch-Houten Castellum and Anna Paulowna-Den Helder) have a median close to zero in the third investigated post-possession period (-0.01 and -1.30 respectively). This indicates either that affected passengers return to their original travel patterns in the third period, or that their number of trips was reduced in the second period due to another, generally applicable reason. This could, for example, be a high number of unplanned incidents on the line (more than the reference group was faced with) or disruptions on the local public network that is used for access and egress to the rail network. However, both are not investigated in this thesis. Anyway, the long-term effect of these cases is negligible, given the distribution of the difference between the observed and expected change in the number of trips for the third period, and the approximately symmetrical distribution around zero in both post-possession periods. Moreover, the first two (short-term) months after the possession show symmetrically centred distributions around zero for both cases, strengthening the conclusion that there are no long-term effects of these possessions.

These relatively large changes between the medians in the two long-term post-possession periods are not visible for the latter four cases with low medians. However, for these cases, the median is more negative in the third post-possession period than in the second. This is unlikely caused by the possession, because the opposite change would be expected, i.e. passengers returning to their pre-possession patterns, and thus distributions that are more close to the zero line in Figure B.3. Therefore, these lower-than-expected number of trips in the second post-possession periods are, as stated before, likely caused by other factors, such as a higher share of unplanned disruptions on the rail network or disruptions in the local public transport network.

In short, for most cases, the investigated passengers closely follow the general trend of the reference group, observed by the symmetrical distributions centred around zero, with a median of approximately zero. This means that there are no long-term effects for most investigated possessions. However, for the two long-duration possessions, especially the Groningen Europapark-Groningen case and to a lesser extent the Deventer-Zwolle case, long-term effects are observed by the negatively shifted distributions and negative median values.

Next, the long-term effect per pre-defined passenger group is discussed in more detail. Figure B.5 shows the distribution of the difference between the observed and the expected change in the number of trips, per pre-defined passenger group, for all post-possession periods. Figure B.5 includes the investigated passengers of all cases. The number of investigated passengers is not equal for all cases, as shown in Table A.1, so cases with many investigated passengers have relatively much influence in this figure. Figure B.6 is a zoomed-in version of Figure B.5, only showing the IQRs.

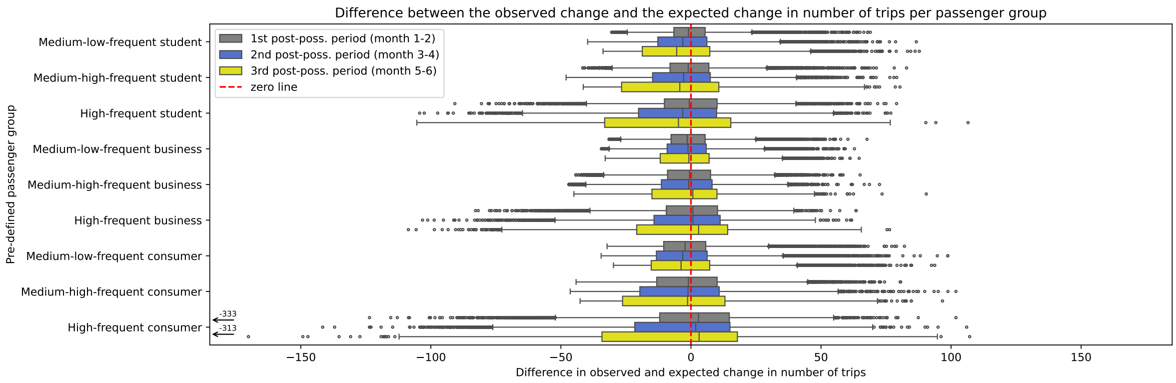

Figure B.5: Difference between the observed and expected change in number of trips, per post-possession period and per pre-defined passenger group

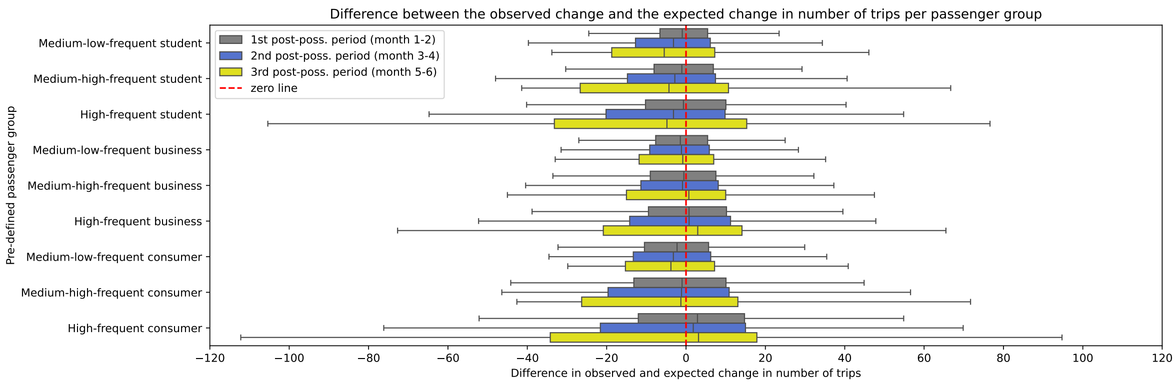

Figure B.6: Difference between the observed and expected change in number of trips, per post-possession period and per pre-defined passenger group. Zoomed-in on the IQR only.

The median of all passenger groups is close to zero. For the second investigated post-possession period (i.e. the first long-term period), the lowest median is -3.19 for the medium-low-frequent consumers, while the largest median value is +1.83 for the high-frequent consumers.

For each of the base passenger groups (student, business, consumer), the lowest frequency groups have the most negative differences in the observed and the expected change in the number of trips, although the differences between groups are small.

For the third post-possession period, the lowest median value is -5.49 for the medium-low-frequent students and the highest median value is +3.15 for the high-frequent consumers. In general, the median values in the third post-possession period have larger absolute values than in the second post-possession period. This can be caused by the longer period between the pre-possession period and the third post-possession period, which allows for more external effects on passenger patterns, and lower ability to predict passenger's number of trip based on their pre-possession passenger patterns.

The boxes in Figure B.5 are not symmetrically centred around zero for most passenger groups. In general, the boxes are (slightly) leaning towards negative values. However, the median values of all passenger groups are close to zero, as mentioned above. This means that the magnitude of the negative values is larger than that of the positive values, while the number of negative and positive values is approximately equal. So, on an aggregated level, the number of trips does not change much, indicated by the median. However, passengers who change their number of trips more negatively than expected do so more prominently than those who change their number of trips more positively than expected. The negatively shifted distribution is likely caused by few possessions with a negative effect on passenger patterns, and the asymmetric behaviour of individual passengers (due to, for example, the expiry date of smart cards).

Interestingly, the width of the boxes increases with increasing frequency category, for all three base passenger groups (student, business and consumer), for all post-possession periods. Therefore, the higher the trip frequency in the pre-possession period, the less closely the investigated passengers follow the average of the reference. The passengers from these higher frequency groups have more variation over time in their travel patterns.

The boxes in the third post-possession period are wider than those in the second post-possession period. As for the median values, this is likely caused by the longer time span between the pre-possession period and third post-possession period.

Notable is the distribution of the high-frequent consumers, at the bottom of Figure B.5. This group's box clearly points to negative values, while the median value is positive. Most passengers are not negatively affected by the possessions, but the passengers who are, decrease their number of trips drastically. However, this can also be caused by the higher probability that high-frequent passengers decrease their number of trips largely due to their high number of trips in the pre-possession period.

The distance between the minimum and maximum values increases for increasing frequency groups, similar to the width of the boxes. The higher frequency groups can have more extreme negative values for the difference between the observed and expected number of trips, due to their higher number of trips in the pre-possession period. A passenger with 100 trips in the pre-possession period can have, for example, only 20 trips in the post-possession period, a decrease of 80. The average change in number of trips of the reference is not as extreme, which leads to a very low value for the difference between the observed and expected change in number of trips. For passengers with a lower number of trips in the pre-possession period, such a high decrease in number of trips is not possible, because they have at most 48 trips in the pre-possession period (passengers who are not in a high-frequency group). Similarly, these high-frequency passengers are more likely to increase their number of trips largely. It is more likely that somebody with many trips (i.e. more than 48) increases his or her number of trips largely than that somebody with relatively few trips does so to the same extent, because lower-frequent likely use another mode for most of their trips.

Finally, Figure B.8, Figure B.7 and Figure B.9 include more details. They show the difference between the observed and expected change in number of trips per case and per pre-defined passenger group, for the first, second and third post-possession period respectively.

Figure B.7: Difference between observed and expected number of trips in the first post-possession period (1-2 months after end of possession) per case per passenger group

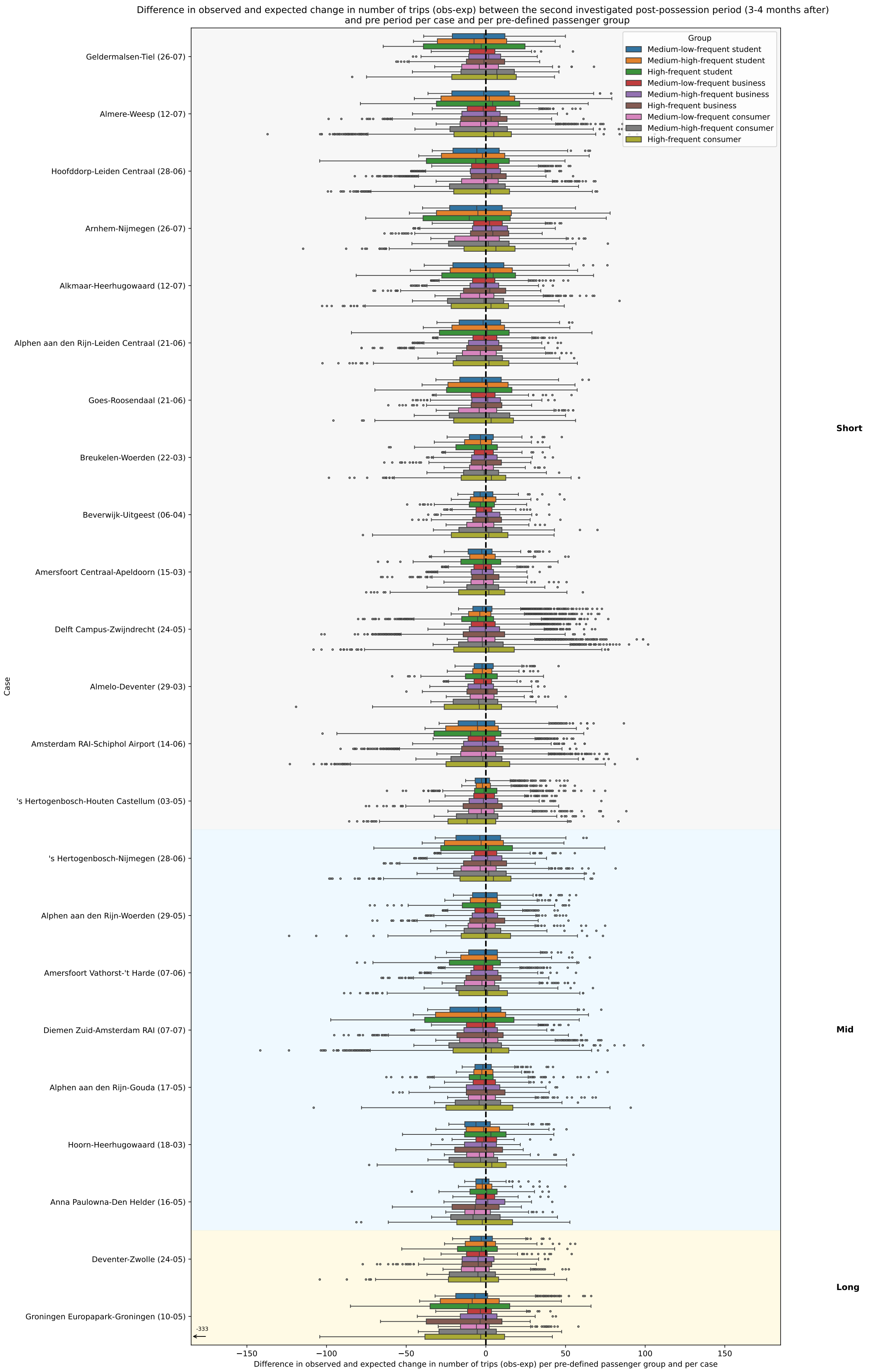

Figure B.8: Difference between observed and expected number of trips in the second post-possession period (3-4 months after end of possession) per case per passenger group

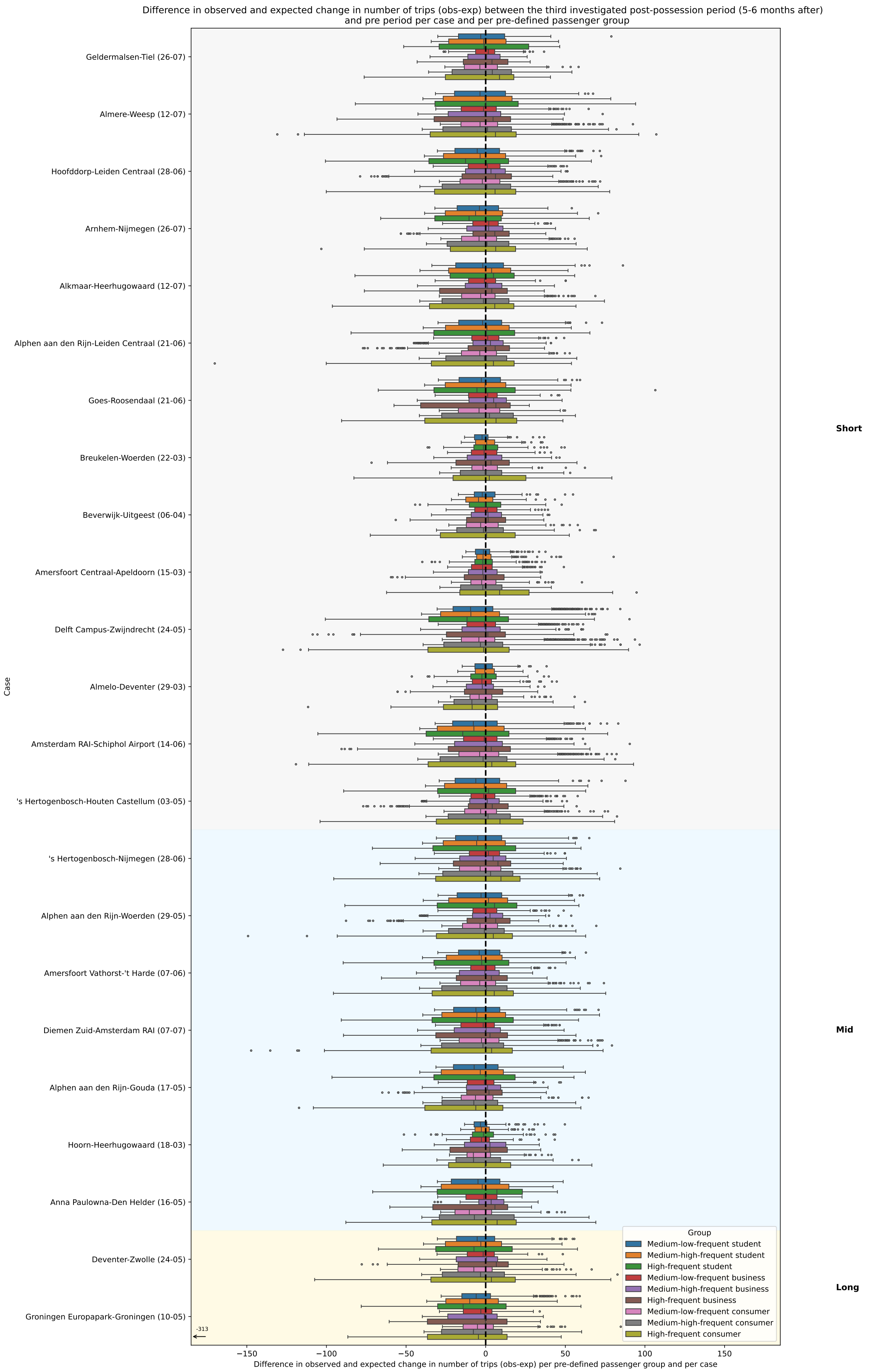

Figure B.9: Difference between observed and expected number of trips in the third post-possession period (5-6 months after end of possession) per case per passenger group

B.2. Relative change in number of trips

Figure B.10 shows the difference between the observed change and expected change in number of trips (Equation 3.2 in Subsection 3.1.3), per duration category and per post-possession periods. The figures on the right of Figure B.10 show the two long-duration cases separately. Next, Figure B.11 presents the indicator per overarching passenger group, as defined with the Games-Howell test. The results are similar to the ones in Section B.1. The investigated long-duration possessions have a permanent negative effect on travel frequency, while the short- and mid-duration cases do not. Moreover, as explained in Subsection 5.1.1, passenger group A shows a return process to pre-possession passenger patterns after being faced with long maintenance, while group B and C do not. However, the effect of long-duration possessions is less severe for group C.

The normalisation quantifies the relative effect of a possession, based on the pre-possession number of trips. Group B shows the largest variation in the difference between the observed and the expected change in number of trips, as seen in Section 5.1. However, group C has the most variation after applying the normalisation, which supports the importance of considering a person's pre-possession number of trips.

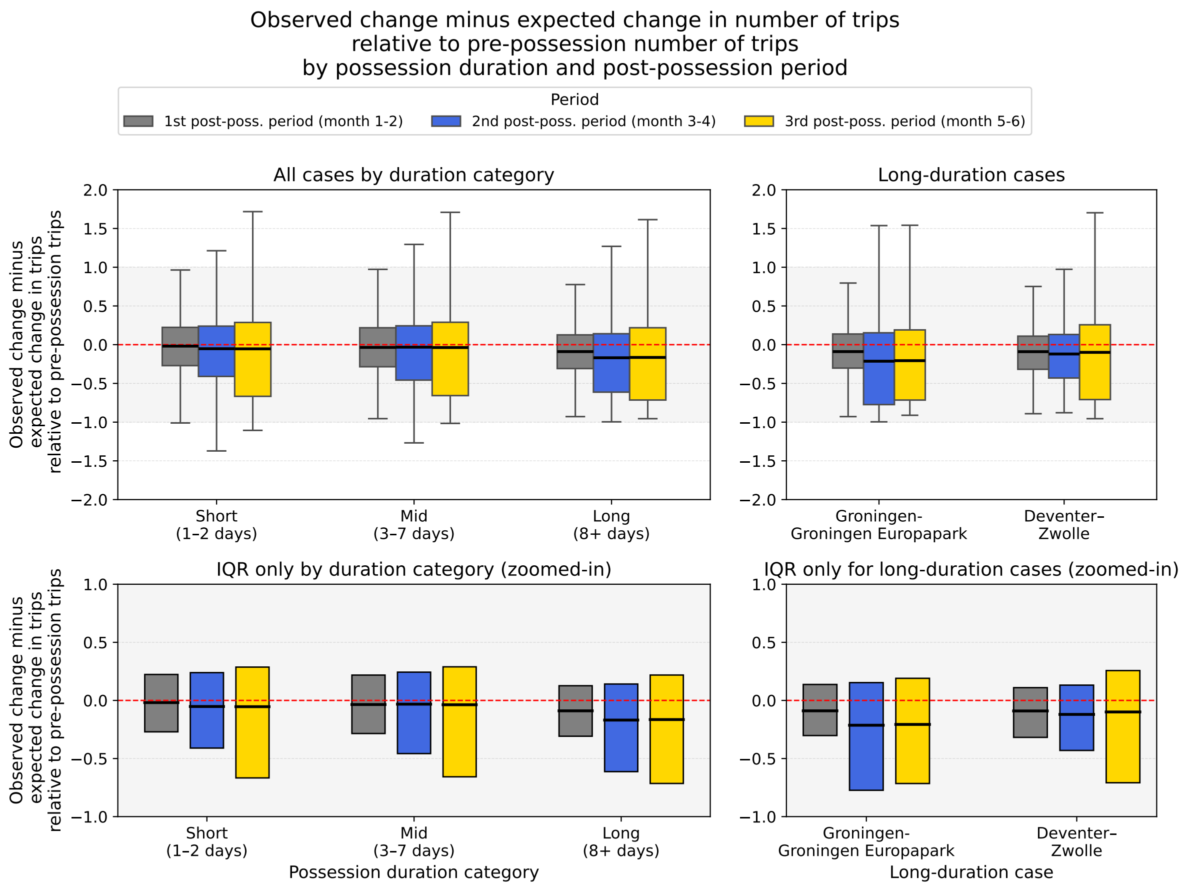

Figure B.10: Relative change in number of trips, per duration category and post-possession period.

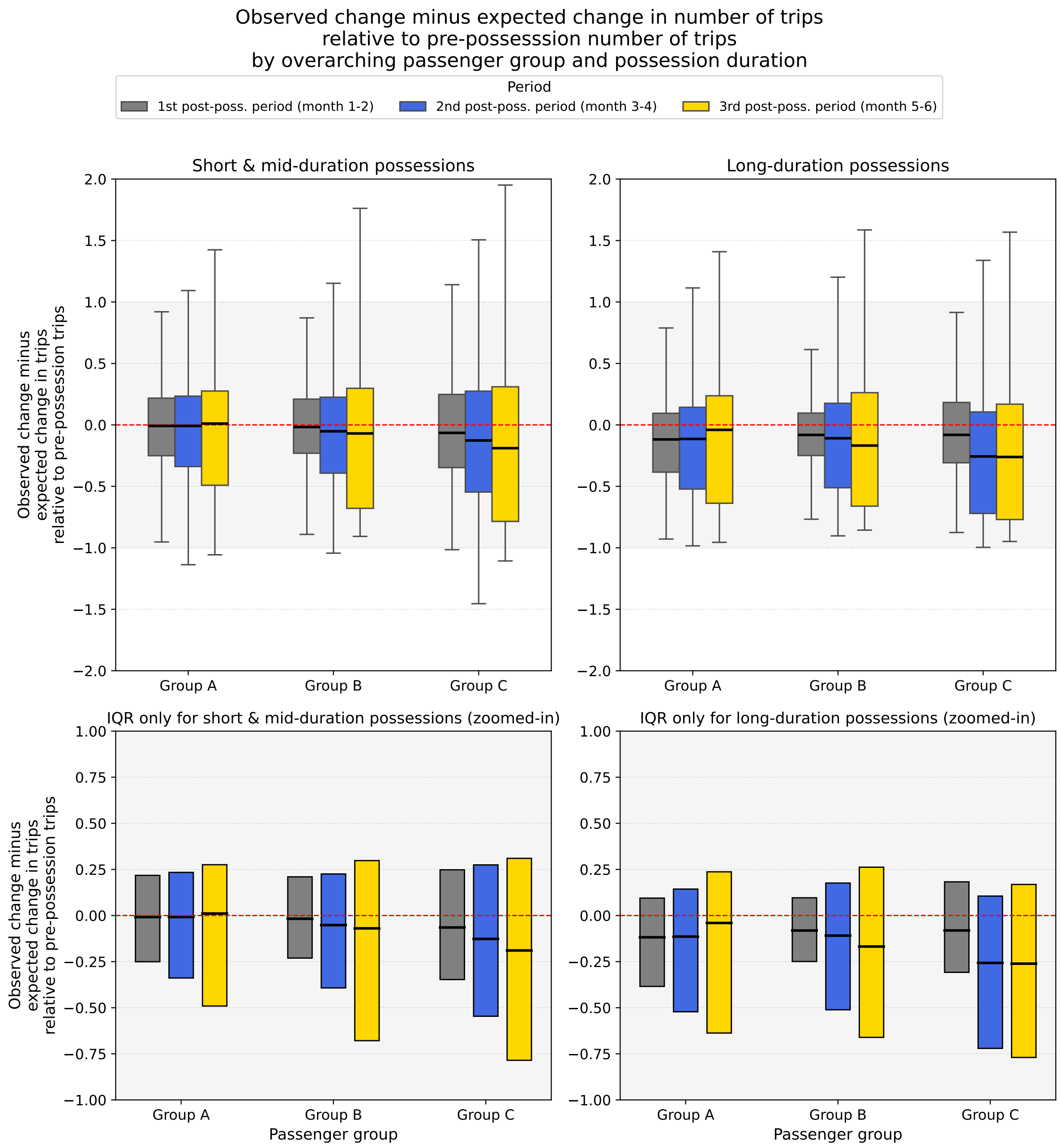

Figure B.11: Relative change in number of trips, per overarching passenger group and post-possession period.

Figure B.12 and Figure B.13 show the distribution of the first indicator per case, without and with outliers respectively.

Next, Figure B.14 and Figure B.15 show the same indicator, but separately for each pre-defined passenger group. These show that the relative impact of small (unexpected) changes in the number of trips of medium-low-frequent passengers is large compared to the other passenger groups.

Finally, Figure B.16, Figure B.17 and Figure B.18 show box plots of the first indicator on the difference between observed and expected change in number of trips, relative the a passenger's pre-possession number of trips, for all investigated possessions, split out per pre-defined passenger group, for the first, second and third post-possession period respectively.

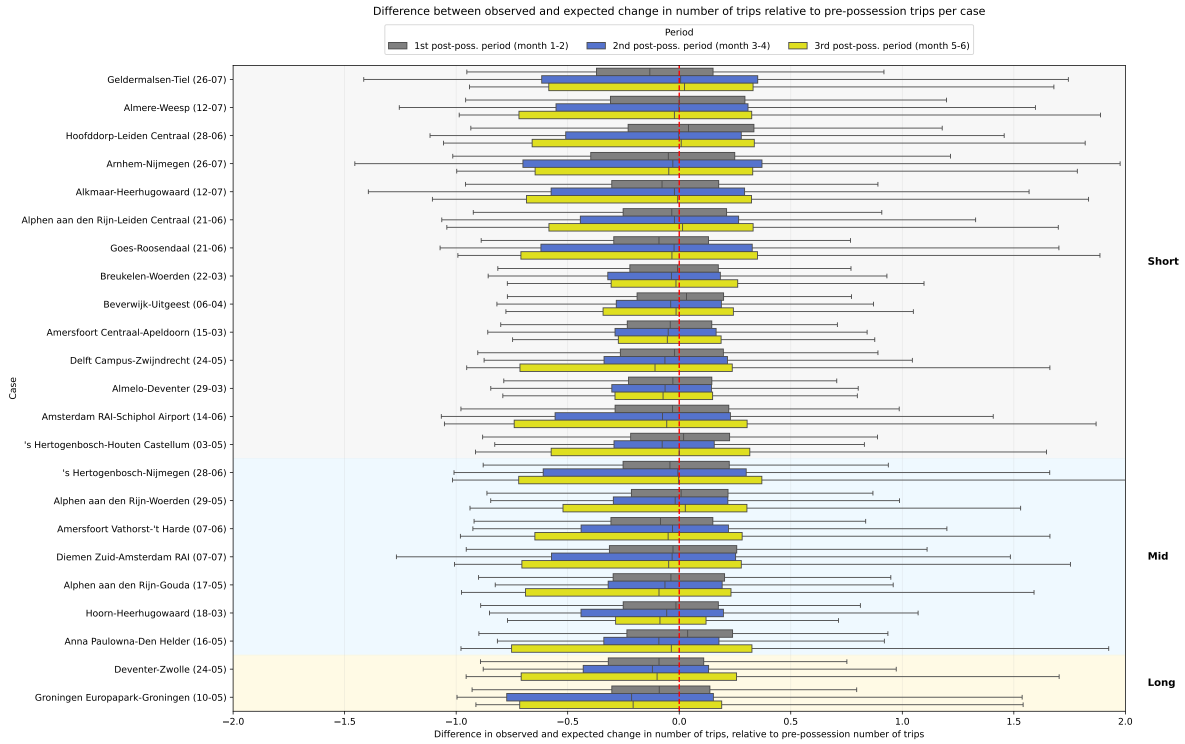

Figure B.12: Difference between the observed and expected change in number of trips, relative to pre-possession number of trips, per post-possession period and per pre-defined passenger group. Zoomed-in on the IQR only.

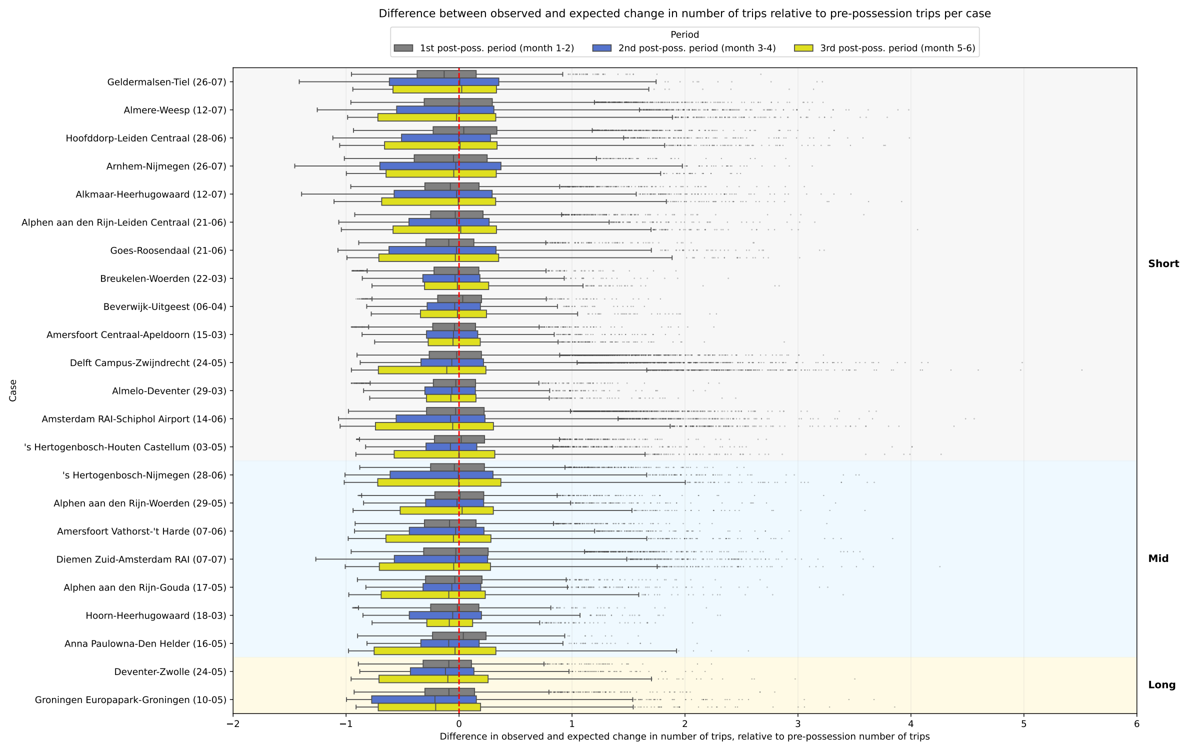

Figure B.13: Difference between the observed and expected change in number of trips, relative to pre-possession number of trips, per post-possession period and per pre-defined passenger group.

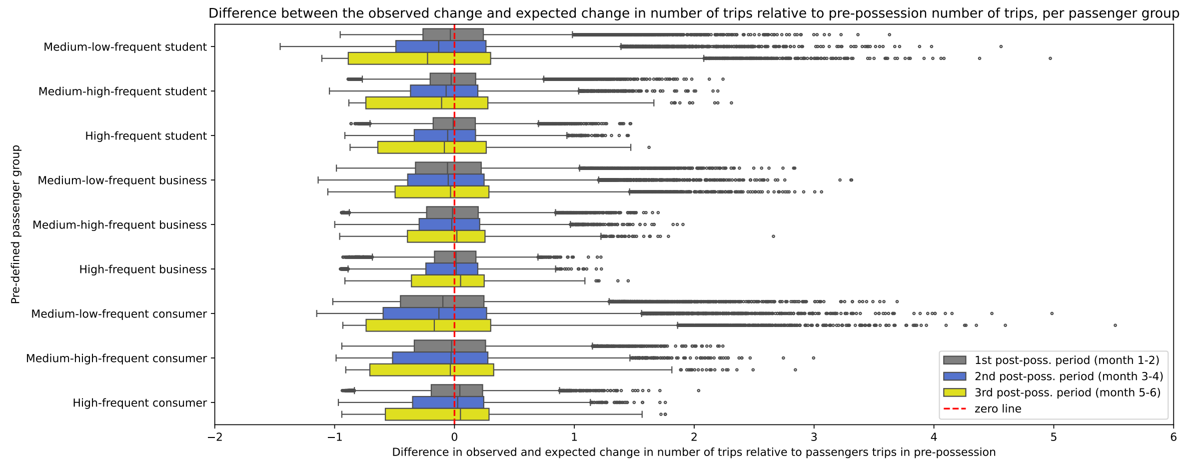

Figure B.14: Difference between the observed change and the expected change in number of trips, relative to a passenger's pre-possession number of trips, per pre-defined passenger group

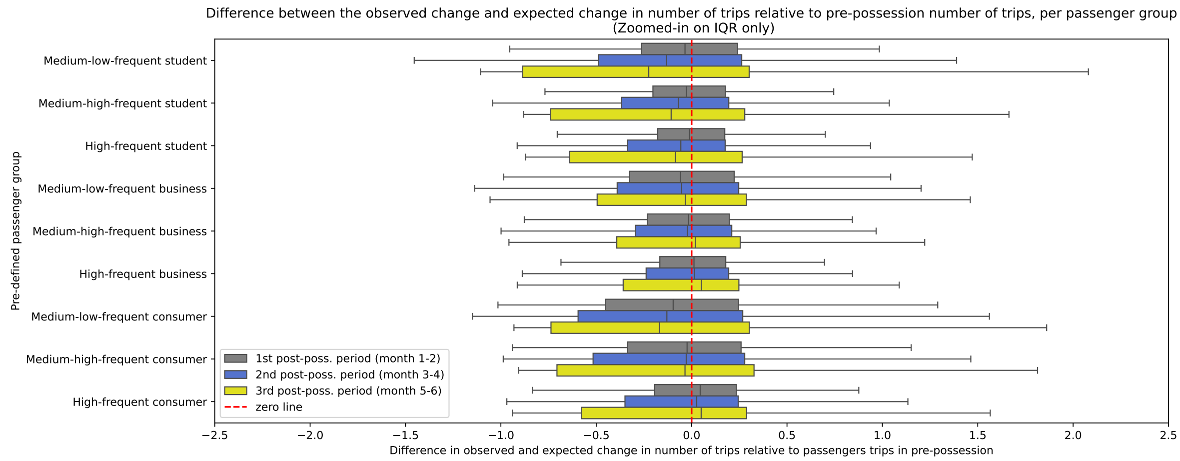

Figure B.15: Difference between the observed change and the expected change in number of trips, relative to a passenger's pre-possession number of trips, per pre-defined passenger group. Zoomed-in on IQR only for readability.

B.3. Change in route or station choice

Next, the additional figures on the changes in route or station choice are presented. Figure B.19 shows the distribution of the percentage change in trips over the affected line among a passenger's trips between his or her two main zones. For most cases, there are no changes, so the box plot is just a line. The outliers are removed from Figure B.19, to increase interpretability of the indicator by zooming in on the domain from -1 to +1. Note that the x-axis represents the fractional change, i.e. a value of +1 indicates a 100% increase. Figure B.20 shows all outliers between -1 and +20. Figure B.21 shows all outliers, so the x-axis is unlimited. There are some cases with extreme outliers. Therefore, it is chosen to show the results in multiple figures.

Figure B.16: Difference between observed and expected number of trips in the first post-possession period (1-2 months after end of possession) relative to passenger's pre-possession number of trips per case per passenger group

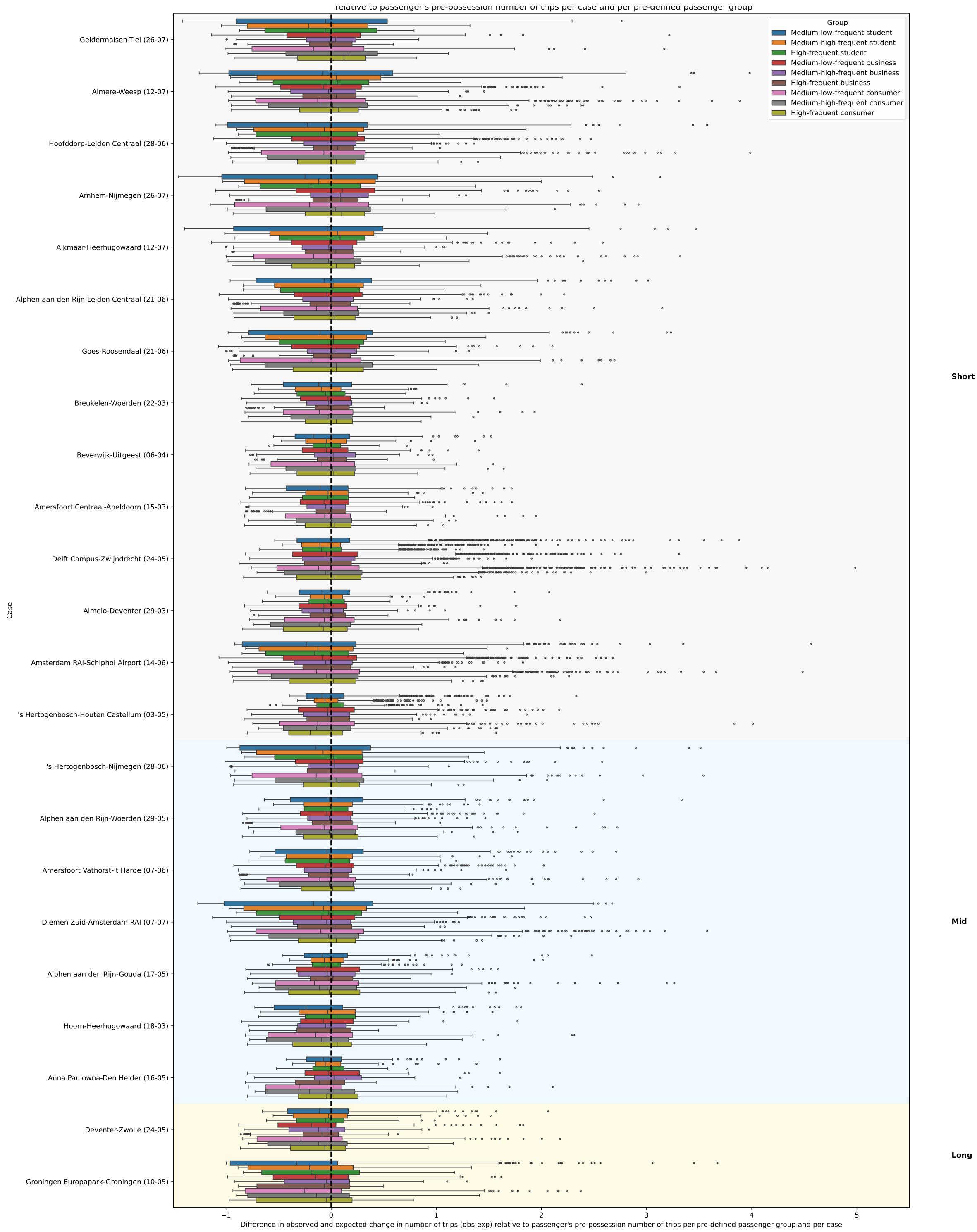

Figure B.17: Difference between observed and expected number of trips in the second post-possession period (3-4 months after end of possession) relative to passenger's pre-possession number of trips per case per passenger group

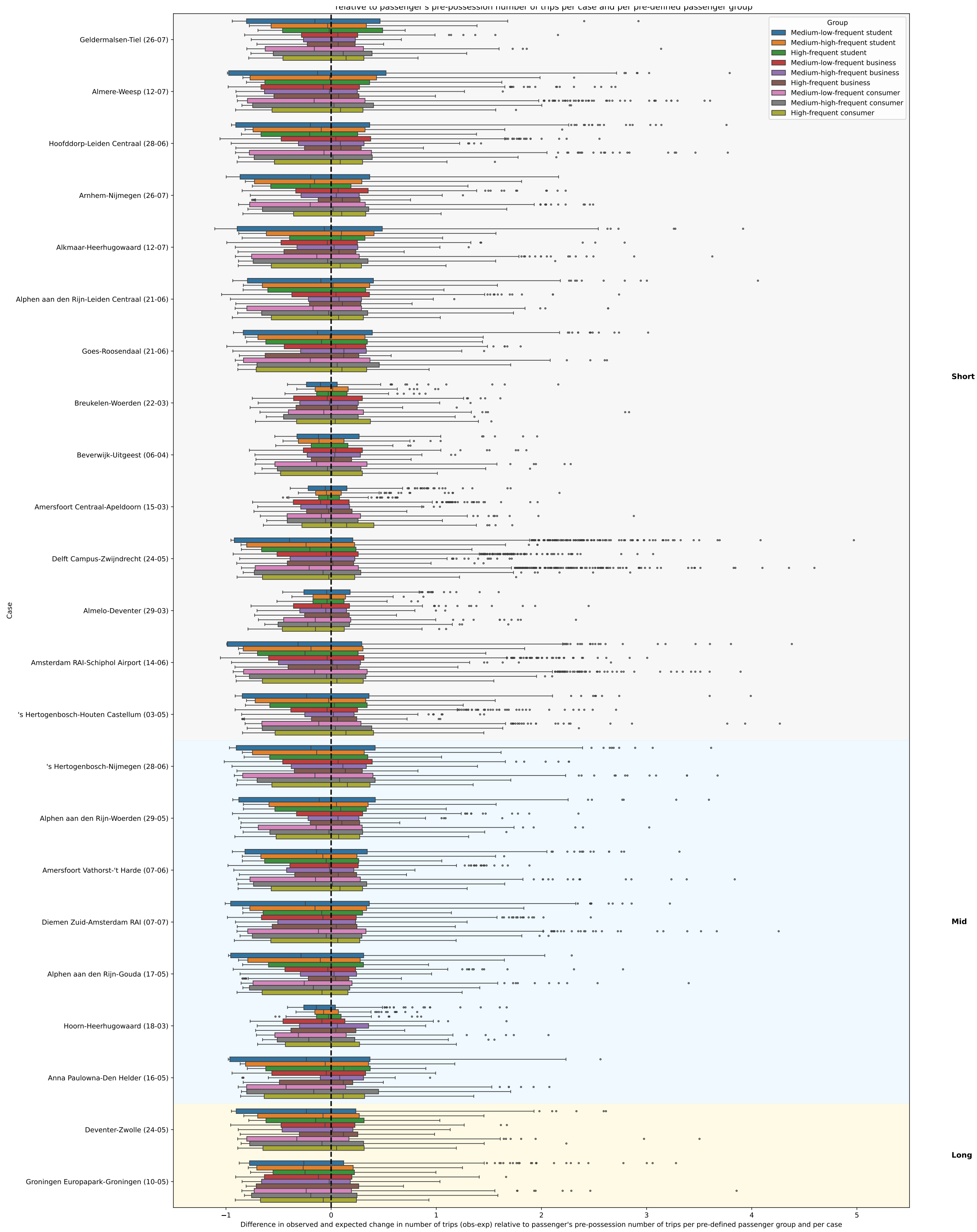

Figure B.18: Difference between observed and expected number of trips in the third post-possession period (5-6 months after end of possession) relative to passenger's pre-possession number of trips per case per passenger group

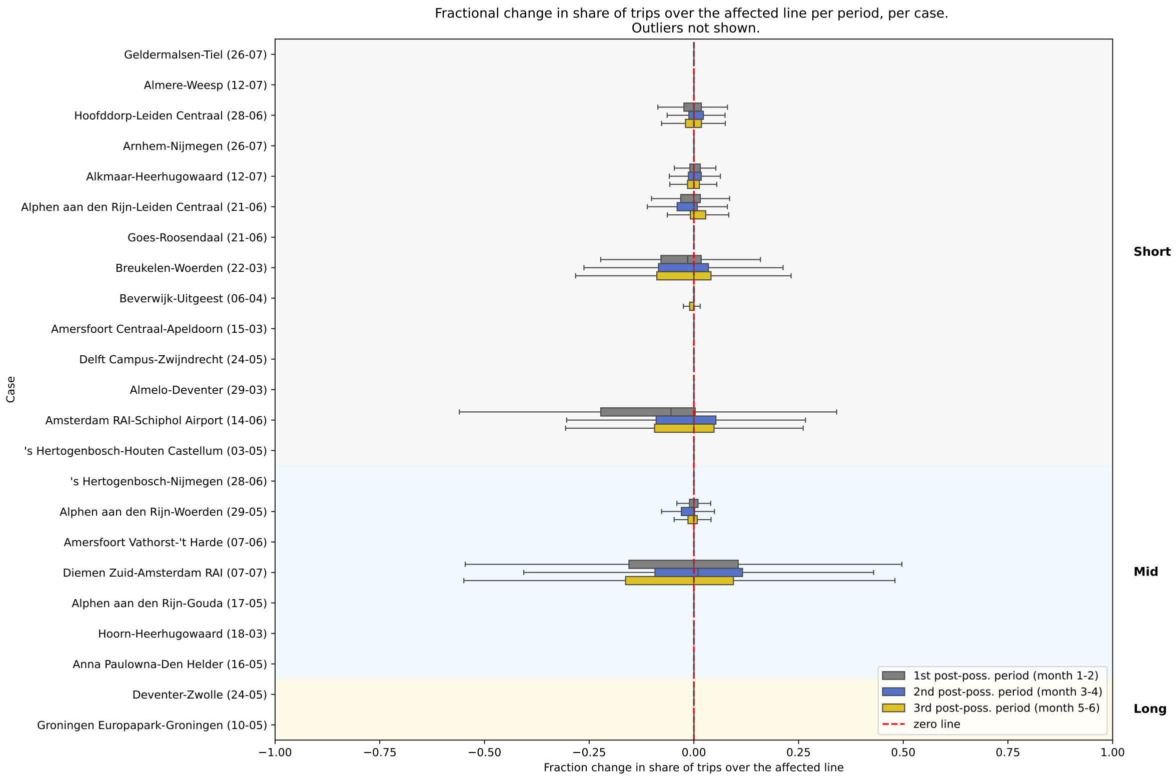

Figure B.19: Box plots of the change in share of trips over the affected line among the trips between a passenger's main zones. Excluding outliers.

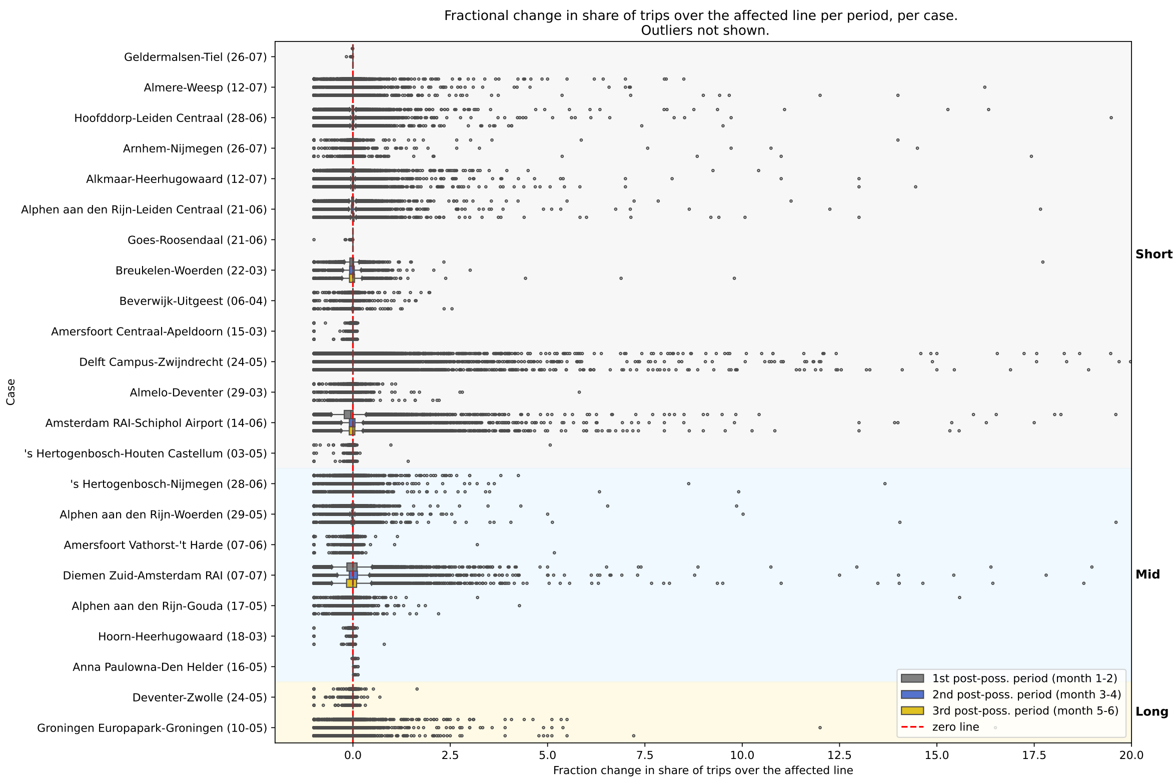

Figure B.20: Box plots of the change in share of trips over the affected line among the trips between a passenger's main zones, including outliers, limited from -1 to +20

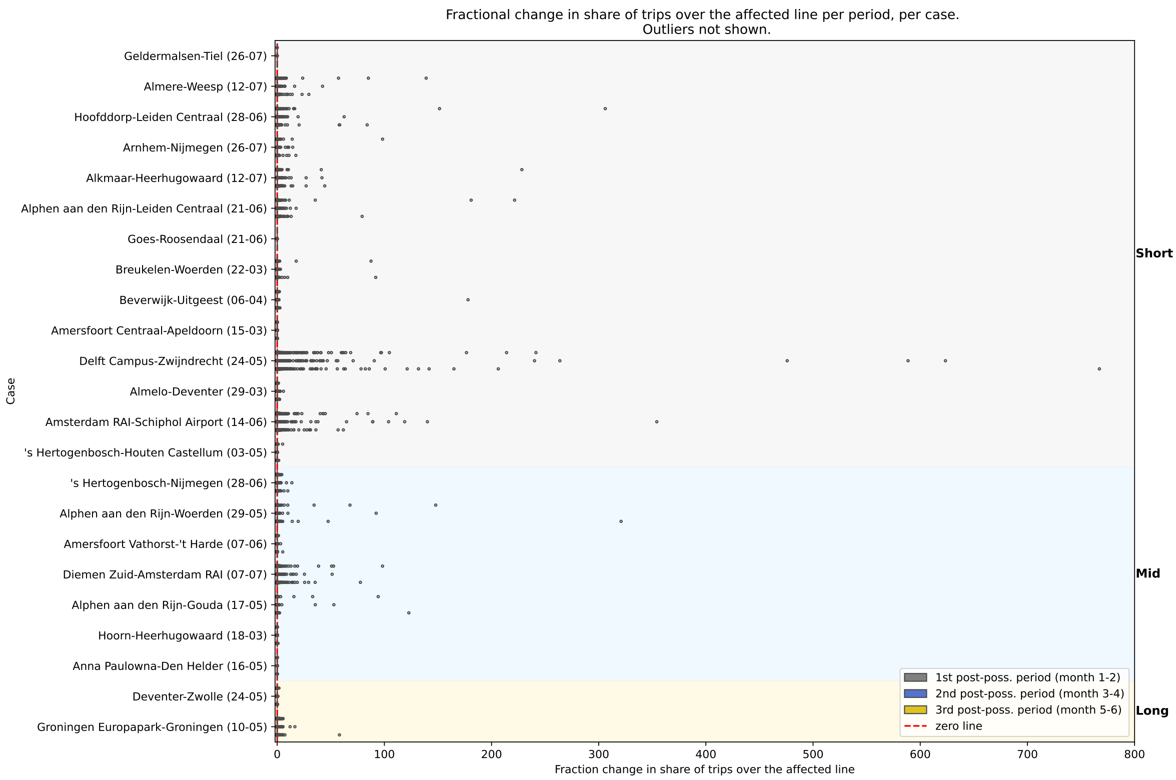

Figure B.21: Box plots of the change in share of trips over the affected line among the trips between a passenger's main zones, including all outliers

C Overarching passenger groups

Section 5.1 showed that there are limited long-term effects for most investigated possessions, except for the two long-duration cases. It also presented the overarching passenger groups identified with the Games-Howell test.

This appendix gives the results of the ANOVA-test that found that the pre-defined passenger groups have a significant effect on the first indicator on changes in the number of trips. Next, the results of the Games-Howell test that are used to determine which pre-defined passenger groups behave similarly and can be grouped together in an overarching passenger group are presented.

Figure B.5 and Figure B.14 show differences in the response to possessions among passenger groups (without and with the normalisation respectively). The three business groups have similar median values and box widths. These boxes are smaller than for the other groups. The medium-high-frequent and high-frequent students have almost the same boxes in Figure B.14, but the box of the high-frequent students is wider in Figure B.5 for both post-possession periods. The same holds for the extent of the whiskers: they are longer for the high-frequent students than the medium-high-frequent students in Figure B.5, but more similar in length in Figure B.14. This shows the importance of the normalisation by the pre-possession number of trips, since that shows similar behaviour for the groups, while there are differences without the normalisation. The boxes of the medium-high-frequent consumers are similar to the boxes of the two mentioned student groups.

The difference in response between passenger groups also follows from the ANOVA-test, presented in Table C.1 for the second investigated post-possession period and in Table C.2[1] for the third post-possession period. In the second post-possession period, the sum of squares (SS) of the passenger groups is 54.85, but the residual sum of squares is 77,399.27. This indicates that only a very small part of the variance is explained by the passenger groups. However, the variance within groups is smaller than the variance between groups, indicated by the lower mean square (MS) within groups (0.27) than between groups (6.86). The F-statistic is significant, indicating that there are statistically significant differences between passenger groups. This is at least partially due to the high degrees of freedom (df) of the residuals, due to the large sample size. This effect size is quantified with the η-statistic, which is 0.001 and 0.002 for the first and second investigated post-possession period respectively. Therefore, passenger groups have an effect on changes in passenger patterns when considering all cases at once, although the influence is very limited. However, the results of the separate cases (see for example Figure B.17) show differences per passenger group. The η-statistic of only the Groningen Europapark-Groningen case is, for example, 0.008. For the Deventer-Zwolle case, it is even 0.020. This shows that the effect of passenger groups is higher for separate cases, especially for those with an effect on passenger patterns.

Table C.2 shows similar findings as Table C.1. There is also a statistically significant difference between passenger groups in the third post-possession period, indicated by the significant F-statistic ($p \leq 0.05$). However, the mean square (MS) is in this post-possession period much higher than in the previous period (27.48 compared to 6.86). This indicates that the differences between groups are larger in the

[1]The residual in these tables can be used to infer the total of investigated passengers, which is confidential. It is approximately 300,000

Table C.1: ANOVA table first indicator ($N^{\text{total}}_{i;\text{pre-post34}}$) for the second post-possession period (month 3-4).

	df	SS	MS	F	p-value
Passenger group	8	54.85	6.86	24.96	7.83e-39
Residual	*confidential*	77,399.27	0.27		

third post-possession period than in the second.

Table C.2: ANOVA table first indicator ($N^{\text{total}}_{i;\text{pre-post56}}$) for the third post-possession period (month 5-6.)

	df	SS	MS	F	p-value
Passenger group	8	219.83	27.48	80.73	4.58e-134
Residual	*confidential*	95,895.86	0.34		

Table C.3 shows, per pre-defined passenger group, the groups that do not have a statistically different indicator in the second investigated post-possession period based on the Games-Howell test. Those passenger groups are said to respond similarly to the investigated possessions.

Table C.3: Passenger groups that have no statistical difference in difference between indicator-values for the second investigated post-possession period (month 3-4) based on the Games-Howell test

Pre-defined passenger group	Pre-defined passenger groups with similar indicator-values (p > 0.05)
High-frequent consumer	HF business, MHF business, MLF business
Medium-high-frequent consumer	HF student, MHF student, MHF business, MLF business
Medium-low-frequent consumer	MHF student, MLF student
High-frequent business	HF consumer, MHF business, MLF business
Medium-high-frequent business	HF consumer, HF student, HF business, MHF consumer, MLF business
Medium-low-frequent business	HF consumer, HF business, MHF consumer, MHF business
High-frequent student	MHF consumer, MHF student, MHF business
Medium-high-frequent student	HF student, MHF consumer, MLF consumer, MLF student
Medium-low-frequent student	MHF student, MLF consumer

HF = High-frequent, MHF = Medium-high-frequent, MLF = Medium-low-frequent

All passenger groups without statistically different distributions of the indicator in the first post-possession period are combined as an overarching group. These overarching groups are listed below. All three business groups have similar responses, and the high-frequent consumers follow the behaviour of this overarching group (A) as well. The lowest frequency consumers and students that are included in the study behave similarly (group C). Finally, group B consists of the two highest frequency categories for students and the medium-high frequent consumers.

- Group A
  - High-frequent consumer
  - High-frequent business
  - Medium-high-frequent business
  - Medium-low-frequent business
- Group B
  - High-frequent student
  - Medium-high-frequent student
  - Medium-high frequent consumer
- Group C
  - Medium-low-frequent consumer
  - Medium-low-frequent student

The three categories of business passengers behave similarly, as was apparent from Figure B.5. The high-frequent consumers are likely also people who commute regularly, as the business passengers do, but with a private (non-company) card. This explains the similarity of this group with the business passengers.

The other two groups are mainly formed based on the trip frequency. The medium-low-frequent consumers and students travel between 16 and 32 times in the pre-possession period, corresponding to one to two tours per week (two to four trips). Their number of trips changes similarly between the pre-possession period and the second post-possession period. The same holds for the last overarching group, consisting of the (medium-) high-frequent students and medium-high-frequent consumers. These passengers make at least four trips per week, on average.

The Games-Howell test is also applied to the third post-possession period. There is again no statistical evidence that the passenger groups of Group A have different indicator-values (for the indicator on the change in number of trips), meaning that this overarching group is also valid in the second period. This does not hold for Group B and C. However, for the sake of simplicity and to facilitate the interpretation of the results, the previously defined overarching passenger groups are used in both post-possession periods. Moreover, although the differences between the mean values of the indicator on changes in number of trips are significantly different for the passengers in group C (i.e. these groups do not behave similarly between the pre-possession period and the third post-possession period), the mean values are close to each other ($\Delta = 0.047$). For group B, the differences in mean values are even lower ($\Delta_{\text{max}} = 0.022$). These differences are similar to the ones for group A, which were not significant. Therefore, although groups B and C do not follow from the Games-Howell test for the second post-possession period, the behaviour of their pre-defined passenger groups is relatively similar, and can be used in the second post-possession period as well.

The overarching groups formed with the Games-Howell test are used in the regression analysis, for which the results are presented in Section 5.2.

D

Intermediate regression models

This appendix includes the base model for the second post-possession period (Section D.1) and the advanced model for the third post-possession period (Section D.2). It also includes the quantitive comparison between the base and advanced models for both long-term post-possession periods. The advanced model for the second post-possession period and the base model for the third post-possession period are presented in Section 5.2, and are considered the final models.

D.1. Second post-possession period

Model D.1 shows the base regression model for the number of trips in the second investigated post-possession period. The 95% confidence interval of the coefficient for the expected number of trips is small, suggesting a precise estimator. However, the R^2 of this model is only 0.305, so the model does not explain all variation. The coefficient of the expected number of trips is 0.8537, so there is not a one-on-one relationship between the observed and expected number of trips.

The exact amount of observations cannot be listed in the public version of this thesis for confidentiality reasons. It is approximately 300,000.

Model D.1: Base model for number of trips in second post-possession period (month 3-4)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   n_34   R-squared:                       0.305
Model:                            OLS   Adj. R-squared:                  0.305
Method:                 Least Squares   F-statistic:                 1.036e+04
No. Observations:             ~300000   Prob (F-statistic):           6.51e-31
Df Residuals:                 ~300000   Log-Likelihood:            -1.2200e+06
Df Model:                           1   AIC:                         2.440e+06
Covariance Type:              cluster   BIC:                         2.440e+06
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept         1.2222      0.153      7.980      0.000       0.922       1.522
n_expected_34     0.8537      0.008    101.788      0.000       0.837       0.870
=================================================================================
```

Table D.1 shows the ANOVA model comparison between the base and advanced model (Model 5.1, which is discussed in Section 5.2) for the second investigated post-possession period. The degrees of freedom (df) of the advanced model is four lower than that of the base model. The sum of squared residuals (SSR) is 410,180.69 (ΔSS) lower for the advanced model. This results in a significant F-statistic, indicated by the p-value of approximately zero, meaning that including the four additional variables results in a statistically better model. However, the statistical increase in model performance can also be caused by the high degrees of freedom, which make small changes (improvements) significant. In short, the advanced model statistically improves model performance, but to a low extent. This is likely due to the absence of long-term effects for most investigated cases.

Table D.1: Result comparison between base and advanced model for second post-possession period

Model	df	SSR	Δdf	ΔSS	F	p-value
Base	*confidential*	9.515659e07	0.0			
Advanced	*confidential*	9.474641e07	4.0	410,180.69	304.94	3.06e-262

D.2. Third post-possession period

Model D.2 shows the final regression model for the third post-possession period. The R^2 and adjusted R^2 of this model is 0.192, compared to 0.186 for the base Model 5.2. The increase in model performance from the base to the advanced model is larger than the increase in the second post-possession period. However, the increase is still very limited, meaning that the possessions do not have a large permanent effect on passenger patterns. The overall model performance is lower than for the first post-possession period.

Model D.2: Advanced model for number of trips in third post-possession period (month 5-6)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   n_56   R-squared:                       0.192
Model:                            OLS   Adj. R-squared:                  0.192
Method:                 Least Squares   F-statistic:                     1941.
No. Observations:             ~300000   Prob (F-statistic):           8.95e-30
Df Residuals:                 ~300000   Log-Likelihood:            -1.2541e+06
Df Model:                           9   AIC:                         2.508e+06
Covariance Type:              cluster   BIC:                         2.508e+06


=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept             5.1736      0.635      8.141      0.000       3.928       6.419
n_expected_56         0.7230      0.020     36.330      0.000       0.684       0.762
dagen_vorige_kort     1.2294      0.370      3.319      0.001       0.503       1.955
dagen_mid             1.2161      0.452      2.693      0.007       0.331       2.101
vakantie              1.1837      0.493      2.403      0.016       0.218       2.149
metro                -0.8780      0.305     -2.874      0.004      -1.477      -0.279
gr_B                 -2.8067      0.202    -13.868      0.000      -3.203      -2.410
gr_C                 -3.6345      0.335    -10.835      0.000      -4.292      -2.977
gr_B:dagen_mid        1.0128      0.327      3.100      0.002       0.373       1.653
gr_B:vakantie         2.1156      0.438      4.833      0.000       1.258       2.973
=====================================================================================
```

Table D.2 shows the ANOVA comparison between Model 5.2 and Model D.2. The addition of the possession characteristics leads to a significantly better model, as seen by the p-value. Note that the sum of squared residuals (SSR) of both models is a factor 10 larger than in the second post-possession period, see Table D.1. This corresponds to the lower quality of this model, as already seen with the R^2.

Table D.2: Result comparison between base and advanced model for third post-possession period

Model	df	SSR	Δdf	ΔSS	F	p-value
Base	*confidential*	1.220574e08	0			
Advanced	*confidential*	1.211712e08	8	886,226.94	257.58	0.0

The intercept of Model D.2 is higher than that of Model 5.1 for the second post-possession period (5.17 compared to 2.66). Moreover, the coefficient for the expected number of trips is lower (0.7230 compared to 0.8185). This implies that estimating the number of trips in the third post-possession period based on the pre-possession number of trips and the average change of the same passenger group in the reference group is less accurate than for the second post-possession period.

Similarly to Model 5.1 (the advanced model for the second post-possession period), the dummy variables for passenger groups B and C are included in the model with negative coefficients. However, the magnitude of these coefficients is in Model D.2 approximately 1.0 larger than in Model 5.1. Therefore, the expected number of trips, based on the pre-possession travel frequency and average change of the reference group, is over-estimated for a larger extent in the third investigated post-possession period than for the second post-possession period for these groups.

The most noticeable difference between Model D.2 and Model 5.1 is the inclusion of more (and other) possession characteristics. However, it is unlikely that possession characteristics that do not have an effect on the number of trips in the second post-possession, start having an effect in the third post-possession period. Train users follow their pre-possession travel patterns in the third and fourth month after the end of the maintenance, for most cases, as concluded in Section 5.1. There are also no major differences between the travel patterns in the second and third post-possession period; see for example Figure B.5 and Figure B.12.

Therefore, it is considered more likely that the additional possession characteristics are included in Model D.2 due to the lower predictive power of the expected number of trips in combination with the high number of observations. As stated above, the sum of squared residuals is a factor 10 higher for Model D.2 than Model D.1. This allows for other variables (possession characteristics) to 'estimate' part of the noise in the observations. This makes these variables significant, but not practically relevant or necessarily correct.

Moreover, the characteristic mid-duration is included in Model D.2. This suggests that possessions of short and long durations result in the same effect on the number of trips, while Model 5.1 clearly showed otherwise. There, the long-duration characteristic is the only included possession characteristic. Moreover, Figure B.5 and Figure B.12 both only show negative effects of the possessions for possessions of long duration.

The positive coefficient for the holiday characteristic makes sense, as possessions during a holiday affect passengers to a lesser extent, since they might not need to travel during that period. However, if this characteristic really has an effect on permanent changes in passenger patterns, it would also be included in Model 5.1. This is not the case, which makes the influence of this variable questionable.

Moreover, the variable metro is included in Model D.2. It has a negative coefficient, meaning that the number of trips in the third post-possession period is lower if the alternative option provided by NS was by metro. As before, if these characteristics really have an effect on the passenger pattern in the second post-possession period, they would also have an effect in the second post-possession period, which is not the case. Moreover, the metro was not an alternative travel option in the two long-duration cases that were found to have a long-term effect, which makes the inclusion of this characteristic in the regression model more questionable.

Finally, interaction terms between passenger group B and the mid-duration and holiday characteristic are significant in Model D.2. The effect of these characteristics on the number of trips is larger for group B, consisting of (medium-)high-frequent students and medium-high-frequent consumers, than for passengers of group A and C. However, the effect of these interaction terms is questionable, since the effect of these characteristics themselves is doubtful as explained before.

In short, the inclusion of these possession characteristics in Model D.2 is not considered reliable. Rather, Model 5.1 is deemed to present an accurate view of the influence (or lack thereof) of the possession characteristics and passenger types on permanent changes in passenger patterns after a possession.

E

Overview of stations per main zone

Table E.1 shows the overview of the stations per main zone. Stations that are not included in the overview are not part of a defined main zone. They are considered as separate zones in this thesis. Note that stations that are not in the main rail network (where NS does not operate) are also included.

Table E.1: Stations per main zone (including stations that NS does not serve

Main zone	Stations
Alkmaar	Alkmaar, Alkmaar Noord, Heerhugowaard
Almelo	Almelo, Almelo de Riet
Almere	Almere Buiten, Almere Centrum, Almere Muziekwijk, Almere Oostvaarders, Almere Parkwijk, Almere Poort
Amersfoort	Amersfoort Centraal, Amersfoort Schothorst, Amersfoort Vathorst
Amsterdam	Amsterdam Amstel, Amsterdam Arena, Amsterdam Bijlmer ArenA, Amsterdam Centraal, Amsterdam Holendrecht, Amsterdam Lelylaan, Amsterdam Muiderpoort, Amsterdam RAI, Amsterdam Sciencepark, Amsterdam Sloterdijk, Amsterdam Zuid, Diemen, Diemen Zuid, Duivendrecht
Apeldoorn	Apeldoorn, Apeldoorn De Maten, Apeldoorn Osseveld
Arnhem	Arnhem Centraal, Arnhem Presikhaaf, Arnhem Velperpoort, Arnhem Zuid, Oosterbeek, Velp
Barneveld	Barneveld Centrum, Barneveld Noord, Barneveld Zuid
Beverwijk	Beverwijk, Heemskerk
Boskoop	Boskoop, Boskoop Snijdelwijk, Boven Hardinxveld
Breda	Breda, Breda Prinsenbeek
Delft	Delft, Delft Campus
Delfzijl	Delfzijl, Delfzijl West
Den Bosch	’s Hertogenbosch, ’s Hertogenbosch Oost, Vught
Den Haag	Den Haag Centraal, Den Haag HS, Den Haag Laan van NOI, Den Haag Mariahoeve, Den Haag Moerwijk, Den Haag Ypenburg, Rijswijk, Voorburg
Den Helder	Den Helder, Den Helder Zuid
Deventer	Deventer, Deventer Colmschate
Doetinchem	Doetinchem, Doetinchem De Huet
Dordrecht	Dordrecht, Dordrecht Stadspolders, Dordrecht Zuid, Zwijndrecht
Ede	Ede Centrum, Ede-Wageningen
Eindhoven	Eindhoven Centraal, Eindhoven Stadion, Eindhoven Strijp-S, Geldrop
Emmen	Emmen, Emmen Zuid
Enkhuizen	Bovenkarspel Flora, Bovenkarspel-Grootebroek, Boxmeer, Enkhuizen, Hoogkarspel
Enschede	Enschede, Enschede De Eschmarke, Enschede Kennispark
Eygelshoven	Eygelshoven, Eygelshoven Markt
Geleen	Geleen Oost, Geleen-Lutterade

(Continues on next page)

(Continuation of Table E.1)

Main zone	Stations
Gouda	Gouda, Gouda Goverwelle
Groningen	Groningen, Groningen Europapark, Groningen Noord, Haren
Haarlem	Bloemendaal, Driehuis, Haarlem, Haarlem Spaarnwoude, Heemstede-Aerdenhout, Overveen, Santpoort Noord, Santpoort Zuid
Hardinxveld	Hardinxveld Blauwe Zoom, Hardinxveld-Giessendam
Harlingen	Harlingen, Harlingen Haven
Heerenveen	Heerenveen, Heerenveen IJsstadion
Heerlen	Heerlen, Heerlen Woonboulevard
Helmond	Helmond, Helmond Brandevoort, Helmond Brouwhuis, Helmond 't Hout
Hengelo	Hengelo, Hengelo Gezondheidspark, Hengelo Oost
Hilversum	Hilversum, Hilversum Media Park, Hilversum Sportpark, Naarden-Bussum
Hoorn	Hoorn, Hoorn Kersenboogerd
Houten	Houten, Houten Castellum
Kampen	Kampen, Kampen Zuid
Leeuwarden	Leeuwarden, Leeuwarden Camminghaburen
Leiden	De Vink, Leiden Centraal, Leiden Lammenschans, Voorschoten
Maastricht	Maastricht, Maastricht Noord, Maastricht Randwyck
Nijmegen	Nijmegen, Nijmegen Dukenburg, Nijmegen Goffert, Nijmegen Heyendaal, Nijmegen Lent, Wijchen
Oss	Oss, Oss West
Purmerend	Purmerend, Purmerend Overwhere, Purmerend Weidevenne
Rotterdam	Barendrecht, Capelle Schollevaar, Rotterdam Alexander, Rotterdam Blaak, Rotterdam Centraal, Rotterdam Lombardijen, Rotterdam Noord, Rotterdam Stadion, Rotterdam Zuid, Schiedam Centrum
Sliedrecht	Sliedrecht, Sliedrecht Baanhoek
Sneek	Sneek, Sneek Noord
Soest	Soest, Soest Zuid, Soestdijk
Tiel	Tiel, Tiel Passewaaij
Tilburg	Tilburg, Tilburg Reeshof, Tilburg Universiteit
Utrecht	Utrecht Centraal, Utrecht Leidsche Rijn, Utrecht Lunetten, Utrecht Maliebaan, Utrecht Overvecht, Utrecht Terwijde, Utrecht Vaartsche Rijn, Utrecht Zuilen, Vleuten
Veenendaal	Veenendaal Centrum, Veenendaal West, Veenendaal-de Klomp
Venlo	Blerick, Venlo
Vlissingen	Vlissingen, Vlissingen Souburg
Waddinxveen	Waddinxveen, Waddinxveen Noord, Waddinxveen Triangel
Zaandam	Koog aan de Zaan, Krommenie-Assendelft, Wormerveer, Zaandam, Zaandam Kogerveld, Zaandijk Zaanse Schans
Zoetermeer	Zoetermeer, Zoetermeer Oost
Zwolle	Zwolle, Zwolle Stadshagen

End of Table E.1

F

Stations per school holiday region in the Netherlands

Figure F.1 shows the school holiday regions (North, Centre and South) of the Netherlands, which are used for selecting the passengers in the reference groups for all cases and for one of the possession characteristics. Table F.1 gives per holiday region the stations. Note that stations that are not part of the main rail network (where NS does not operate) are also included.

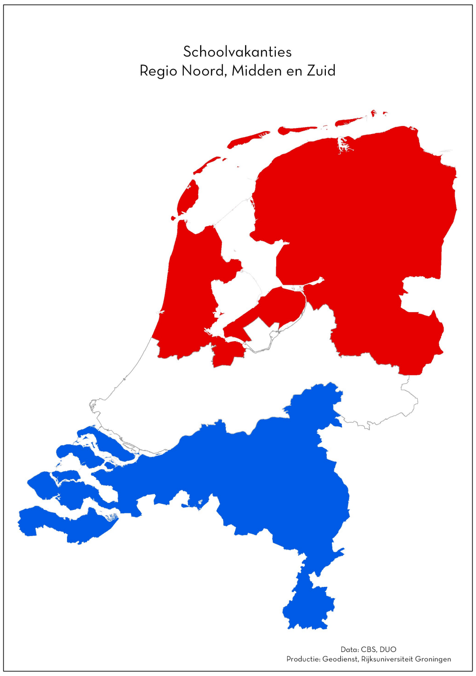

Figure F.1: School holiday regions in the Netherlands: North, Centre and South (indicated with red, white and blue) (Geodienst Rijksuniversiteit Groningen, 2017)

The following list consists of all days and periods that are considered as a holiday by NS:

- Christmas break
- Spring/Carnival holiday
- May holiday
- Summer holiday
- Autumn holiday
- Good Friday
- Easter
- Ascension day and the day after
- Whit Monday
- Liberation day
- Kingsday
- New Year's Eve and New Year's day

Note that some of the bank holidays usually overlap with one of the holiday periods. The first five holiday periods on the list are in different periods in the different holiday regions.

Table F.1: Stations per holiday regions (including stations that NS does not serve)

Region	Stations
North	Abcoude, Akkrum, Alkmaar, Alkmaar Noord, Almelo, Almelo de Riet, Almere Buiten, Almere Centrum, Almere Muziekwijk, Almere Oostvaarders, Almere Parkwijk, Almere Poort, Amsterdam Amstel, Amsterdam Bijlmer ArenA, Amsterdam Centraal, Amsterdam Holendrecht, Amsterdam Lelylaan, Amsterdam Muiderpoort, Amsterdam RAI, Amsterdam Science Park, Amsterdam Sloterdijk, Amsterdam Zuid, Anna Paulowna, Appingedam, Assen, Bad Nieuweschans, Baflo, Bedum, Beilen, Beverwijk, Bloemendaal, Borne, Bovenkarspel Flora, Bovenkarspel-Grootebroek, Buitenpost, Bussum Zuid, Castricum, Coevorden, Daarlerveen, Dalen, Dalfsen, De Westereen, Deinum, Delden, Delfzijl, Delfzijl West, Den Helder, Den Helder Zuid, Deventer, Deventer Colmschate, Diemen, Diemen Zuid, Driehuis, Dronryp, Dronten, Duivendrecht, Emmen, Emmen Zuid, Enkhuizen, Enschede, Enschede Kennispark, Feanwâlden, Franeker, Glanerbrug, Goor, Gramsbergen, Grijpskerk, Groningen, Groningen Europapark, Groningen Noord, Grou-Jirnsum, Haarlem, Haarlem Spaarnwoude, Halfweg-Zwanenburg, Hardenberg, Haren, Harlingen, Harlingen Haven, Heemskerk, Heemstede-Aerdenhout, Heerenveen, Heerenveen IJsstadion, Heerhugowaard, Heiloo, Heino, Hengelo, Hengelo Gezondheidspark, Hengelo Oost, Hilversum, Hilversum Media Park, Hilversum Sportpark, Hindeloopen, Holten, Hoofddorp, Hoogeveen, Hoogezand-Sappemeer, Hoogkarspel, Hoorn, Hoorn Kersenboogerd, Hurdegaryp, Kampen, Kampen Zuid, Koog aan de Zaan, Koudum-Molkwerum, Krommenie-Assendelft, Kropswolde, Leeuwarden, Leeuwarden Camminghaburen, Lelystad Centrum, Loppersum, Mantgum, Mariënberg, Martenshoek, Meppel, Naarden-Bussum, Nieuw Amsterdam, Nieuw Vennep, Nijverdal, Obdam, Oldenzaal, Olst, Ommen, Overveen, Purmerend, Purmerend Overwhere, Purmerend Weidevenne, Raalte, Rijssen, Roodeschool, Santpoort Noord, Santpoort Zuid, Sauwerd, Schagen, Scheemda, Schiphol Airport, Sneek, Sneek Noord, Stavoren, Stedum, Steenwijk, Uitgeest, Uithuizen, Uithuizermeeden, Usquert, Veendam, Vriezenveen, Vroomshoop, Warffum, Weesp, Wierden, Wijhe, Winschoten, Winsum, Wolvega, Workum, Wormerveer, Zaandam, Zaandam Kogerveld, Zaandijk Zaanse Schans, Zandvoort aan Zee, Zuidbroek, Zuidhorn, Zwolle, Zwolle Stadshagen
Centre	Aalten, Alphen aan den Rijn, Amersfoort, Amersfoort Schothorst, Amersfoort Vathorst, Apeldoorn, Apeldoorn De Maten, Apeldoorn Osseveld, Arkel, Baarn, Barendrecht, Barneveld Centrum, Barneveld Noord, Barneveld Zuid, Beesd, Bilthoven, Bodegraven, Boskoop, Boskoop Snijdelwijk, Boven Hardinxveld, Breukelen, Brummen, Bunnik, Capelle Schollevaar, Culemborg, De Vink, Delft, Delft Campus, Den Dolder, Den Haag Centraal, Den Haag HS, Den Haag Laan van NOI, Den Haag Mariahoeve, Den Haag Moerwijk, Den Haag Ypenburg, Doetinchem, Doetinchem De Huet, Dordrecht, Dordrecht Stadspolders, Dordrecht Zuid, Driebergen-Zeist, Ede Centrum, Ede-Wageningen, Ermelo, Gaanderen, Geldermalsen, Gorinchem, Gouda, Gouda Goverwelle, Harde ‘t, Harderwijk, Hardinxveld-Giessendam, Hillegom, Hoevelaken, Hollandsche Rading, Houten, Houten Castellum, Kesteren, Klarenbeek, Lansingerland-Zoetermeer, Leerdam, Leiden Centraal, Leiden Lammenschans, Lichtenvoorde-Groenlo, Lochem, Lunteren, Maarn, Maarssen, Nieuwerkerk a/d IJssel, Nijkerk, Nunspeet, Oosterbeek, Opheusden, Putten, Rhenen, Rijswijk, Rotterdam Alexander, Rotterdam Blaak, Rotterdam Centraal, Rotterdam Lombardijen, Rotterdam Noord, Rotterdam Stadion, Rotterdam Zuid, Ruurlo, Sassenheim, Schiedam Centrum, Sliedrecht, Sliedrecht Baanhoek, Soest, Soest Zuid, Soestdijk, Terborg, Tiel, Tiel Passewaaij, Twello, Utrecht Centraal, Utrecht Leidsche Rijn, Utrecht Lunetten, Utrecht Maliebaan, Utrecht Overvecht, Utrecht Terwijde, Utrecht Vaartsche Rijn, Utrecht Zuilen, Varsseveld, Veenendaal Centrum, Veenendaal West, Veenendaal-De Klomp, Vleuten, Voorburg, Voorhout, Voorschoten, Voorst-Empe, Vorden, Waddinxveen, Waddinxveen Noord, Waddinxveen Triangel, Wehl, Wezep, Winterswijk, Winterswijk West, Woerden, Zoetermeer, Zoetermeer Oost, Zutphen, Zwijndrecht
South	Arnemuiden, Arnhem Centraal, Arnhem Presikhaaf, Arnhem Velperpoort, Arnhem Zuid, Beek-Elsloo, Bergen op Zoom, Best, Blerick, Boxmeer, Boxtel, Breda, Breda Prinsenbeek, Bunde, Chevremont, Cuijk, Deurne, Didam, Dieren, Duiven, Echt, Eijsden, Eindhoven, Eindhoven Strijp-S, Elst, Etten-Leur, Eygelshoven, Eygelshoven Markt, Geldrop, Geleen Oost, Geleen-Lutterade, Gilze-Rijen, Goes, Heerlen, Heerlen Woonboulevard, Heeze, Helmond, Helmond ’t Hout, Helmond Brandevoort, Helmond Brouwhuis, Hemmen-Dodewaard, Hertogenbosch ’s, Hertogenbosch ’s Oost, Hoensbroek, Horst-Sevenum, Houthem-St.Gerlach, Kapelle-Biezelinge, Kerkrade Centrum, Klimmen-Ransdaal, Krabbendijke, Kruiningen-Yerseke, Lage Zwaluwe, Landgraaf, Maarheeze, Maastricht, Maastricht Noord, Maastricht Randwyck, Meerssen, Middelburg, Mook-Molenhoek, Nijmegen, Nijmegen Dukenburg, Nijmegen Goffert, Nijmegen Heyendaal, Nijmegen Lent, Nuth, Oisterwijk, Oss, Oss West, Oudenbosch, Ravenstein, Reuver, Rheden, Rilland-Bath, Roermond, Roosendaal, Rosmalen, Schin op Geul, Schinnen, Sittard, Spaubeek, Susteren, Swalmen, Tegelen, Tilburg, Tilburg Reeshof, Tilburg Universiteit, Valkenburg, Velp, Venlo, Venray, Vierlingsbeek, Vlissingen, Vlissingen Souburg, Voerendaal, Vught, Weert, Westervoort, Wijchen, Wolfheze, Zaltbommel, Zetten-Andelst, Zevenaar, Zevenbergen

G

Data loss in passenger filtering

Figure G.1 shows the filtering steps (see Figure 3.4 in Subsection 3.1.2), including the share of passengers per step and the percentage of the size of the original data set, for the Groningen Europapark-Groningen case. Other cases have similar data losses due to these filtering steps. Note that filtering on the passenger groups (business, consumer, student) does not lead to data loss. This filtering step occurs implicitly in the filtering step on OV-chipaart, OV-pas or debit card.

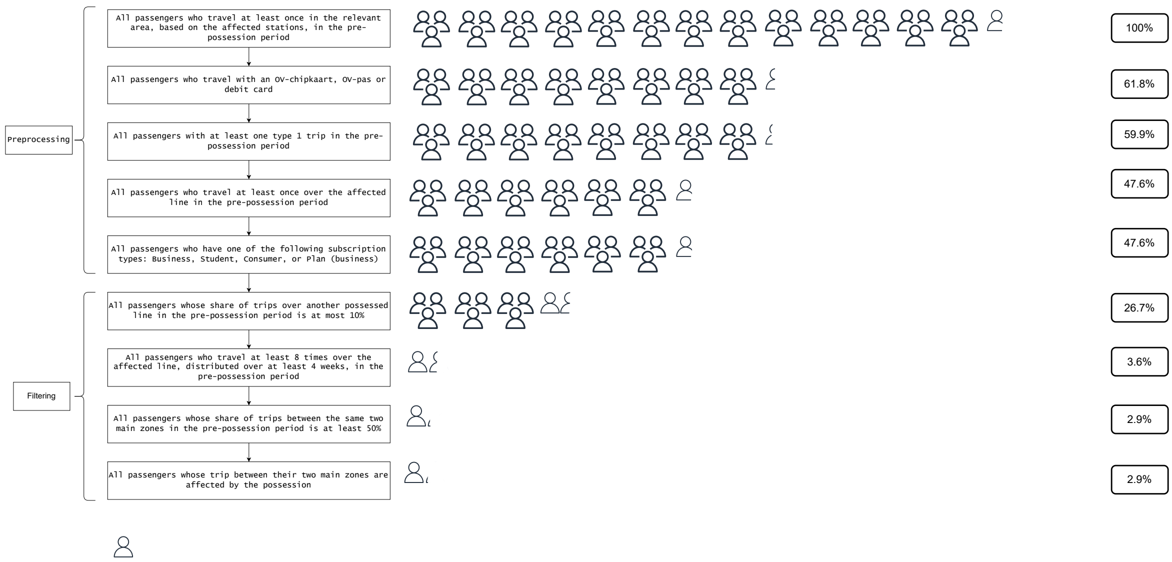

Figure G.1: Filtering steps for passenger selection, including number of passengers per step. Example for the Groningen Europapark-Groningen case. Share of passengers per filtering step indicated at the right side of the figure.

H Code

The code used for this thesis is available on a Github repository. Access can be requested.

Link to repository (only available when access is granted): https://github.com/thijskvs/MSc_Thesis

I

AI statement

Introduction
This thesis has been written in a time in which Artificial Intelligence (AI) is increasingly being used. This statement explains how AI has been used for this thesis. The author takes full responsibility for the content of the entire thesis.

Report
AI has not been used to generate or improve any text in this thesis.

AI (Copilot, Microsoft) has been used in the formatting of tables and models in Overleaf (the text editor in which this thesis is written). AI has not been used in any way regarding the content of tables and models.

Coding
AI has been used to improve the code. The AI tools that are used are ChatNS (the AI tool of NS) and Copilot.

Coding is mostly done in Snowflake, an online environment. Python is used in this environment, but Snowflake uses different packages than the author was familiar with. At the start of the project, ChatNS is used to learn how these packages work (e.g. how to add a column to a dataframe, how to join two dataframes, how to filter, etc.). Later, AI is used to solve code errors. When AI is used, the result of each code step is always printed, to see whether the correct computations are being done (also done for self-written code).

AI has been used to find the exact required syntax in the code for the regression models (OLS), ANOVA test and Games-Howell test, which are performed with the stats.models package in Python. AI is not used for the interpretation of these models and tests.

AI has been used to improve the graphics of the figures in Python. Examples are the inclusion of the desired labels and colours and the inclusion of extreme outliers with an arrow (e.g. Figure B.5). AI has not been used to brainstorm or generate ideas on how to visualise results, only to help with the production of the visuals that the author wanted to make.

AI has not been used to generate whole code sections (e.g. 'write code to compute the number of trips per passenger in a given time period' is not used as prompt).

Travel time by car between stations with OSRM
The only exception to this is the code to compute the travel time by car between all combinations of stations with OSRM. AI has been used to determine the travel time by car between any combination of stations. Copilot is used to generate the code for this. Random checks are performed by the author to verify the results.

Cover image
The cover image was initially generated with AI (Google Gemini), after which it is further enhanced by Rona Jak.