"Assessing the impact of closures of the IJtunnel on the demand for public transport in Amsterdam"

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Abstract

This study analysed the impact of closures of the IJtunnel on the demand for public transport in GVB's network in Amsterdam. Based on academic literature the determinants of public transport demand were identified which lead to a conceptual model on public transport demand. This model was applied to a panel of multiple service lines in Amsterdam in order to quantify the effect of the IJtunnel closures. Using fixed effects estimation, this study found an 18,4% decrease of the number of passengers and a 45% reduction of the number of passengerkilometres for the IJtunnel service lines on average per day. Moreover the results suggest a substitution effect from the IJtunnel service lines towards the other service lines in Amsterdam North, where the number of passengers increased by 8,6% and the number of passengerkilometres by 15%. However, this latter effect does not offset the decline of public transport demand on the IJtunnel service lines (both in percentage effects and in absolute terms). In addition, this study found that the IJtunnel closures had a stronger impact during five subsequent weekend closures compared to singular closures. As a consequence of the IJtunnel closures GVB is confronted with extra costs which include a decline of passenger revenues and a subsidy loss. The findings from this study allow GVB to demonstrate the actual effects of the closures of the IJtunnel, which can strengthen their position in the discussion and decision making on future IJtunnel closures.

Keywords: public transport, demand, passenger, Amsterdam, IJtunnel, diversion, closure

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1. Introduction

GVB Amsterdam is the main provider of public transport services in the Dutch capital city and its surroundings, transporting daily commuters, tourists and other travellers to their destinations. Its network operates 24 hours a day and generates approximately 8500 trips a day by means of metro, tram, bus and ferryboat. GVB recognizes the importance of "a quick, reliable, comfortable and safe public transport for the economic and social development of the city" (GVB Amsterdam, 2013). However the public transport network in Amsterdam is often confronted with (un)foreseen circumstances and events, which require adjustments in the service schedule and will thus affect the passengers. Unforeseen circumstances, for example road accidents, temporary road congestion, passenger violence or even weather conditions demand immediate adjustments which cannot be planned in advance. Though, adjustments can be planned for foreseen circumstances such as diversions for maintenance activities of the transport network, or large events in the city like the Amsterdam Marathon. For these latter events GVB implements so called "Temporary Traffic Arrangements" (in Dutch: Tijdelijke VerkeersMaatregelen (TVMs)) which involve diversions and adaptions of the service schedule.

Even though GVB aims to minimize the consequences of these temporary traffic arrangements, passengers and their demand for public transport within the transport network will be affected. Consequently, these arrangements can have an impact on passenger revenues. Extensive literature is available on the factors affecting the demand for public transport, but no research has been done on the impact of temporary diversions. This research therefore analyses the impact of the temporary traffic arrangements (due to maintenance activities and events) on the demand for public transport in GVB's network. In particular, the impact of temporary closures of the IJtunnel is analysed. This tunnel for motorized vehicles connects the northern part of Amsterdam above the IJ with the city centre and is closed regularly due to maintenance activities. Temporary traffic arrangements are planned by GVB in the form of diversions for multiple service lines. GVB perceives the consequences of these closures as substantial, but the actual effect is unknown. Therefore, the main research question is: *What is the impact of temporary traffic arrangements for closures of the IJtunnel on the demand for public transport in Amsterdam?*

As the knowledge on the actual impact of the IJtunnel closures is limited, the objective of this thesis is to provide insight into the magnitude of the effects. Therefore this research develops a quantitative model based on the literature which captures these effects by means of estimated elasticities. The model will be applied to a panel dataset, which allows to control for unobserved (time-invariant) characteristics and can facilitate causal inference. Next to this contribution to the academic literature, the results from this model provide valuable information for GVB as it quantifies the actual effects of the IJtunnel closures on public transport demand in their network. Since GVB can impose a claim for the incurred costs associated with the IJtunnel closures, the results from this research were used to estimate the incurred revenue- and subsidy loss. Furthermore, the findings from this study allow GVB to improve forecasts on the effects of these temporary traffic arrangements. In addition to the academic relevance and the added value for GVB, the model developed in this thesis provides extra value as the panel dataset used is based on chipcard data. The availability of this data allows a more accurate analysis of the demand for public transport compared to former measurement methods of passenger flows.

The remainder of this thesis is organized as follows. Chapter 2 elaborates on public transport and temporary traffic arrangements in Amsterdam. More specifically the closures of the IJtunnel and the associated diversions will be discussed. The literature review in Chapter 3 identifies multiple factors that affect the demand for public transport and summarizes the findings from the available quantitative models on this subject. Based on the findings from literature a model is developed which analyses the effect of IJtunnel closures in Chapter 4. Accordingly, the data and methodology used for this analysis will be discussed. The results of the analysis are presented in Chapter 5 and will be discussed in Chapter 6. Moreover, the latter chapter presents the limitations and implications of the research. Chapter 7 will conclude on the main findings of this study and finally Chapter 8 will present recommendations for further research.

2. Public Transport and Temporary Traffic Arrangements in Amsterdam

As a result of rapid urbanization, population growth and modern (economic) life styles, public transport has become one of the most commonly used transport modes. Public transport is defined as "*a collective form of transport other than private car or taxi, which comprises all transport systems in which passengers do not travel in their own vehicles*" (Polat, 2012, p. 1212). A public transport system transports members of the general public and facilitates mobility within a city. This chapter will first discuss the development and the role of public transport in Amsterdam. Second, the theoretical impact of temporary traffic arrangements will be discussed. Finally, the temporary traffic arrangements for the specific case of the IJtunnel closures will be introduced.

2.1 Public Transport in Amsterdam

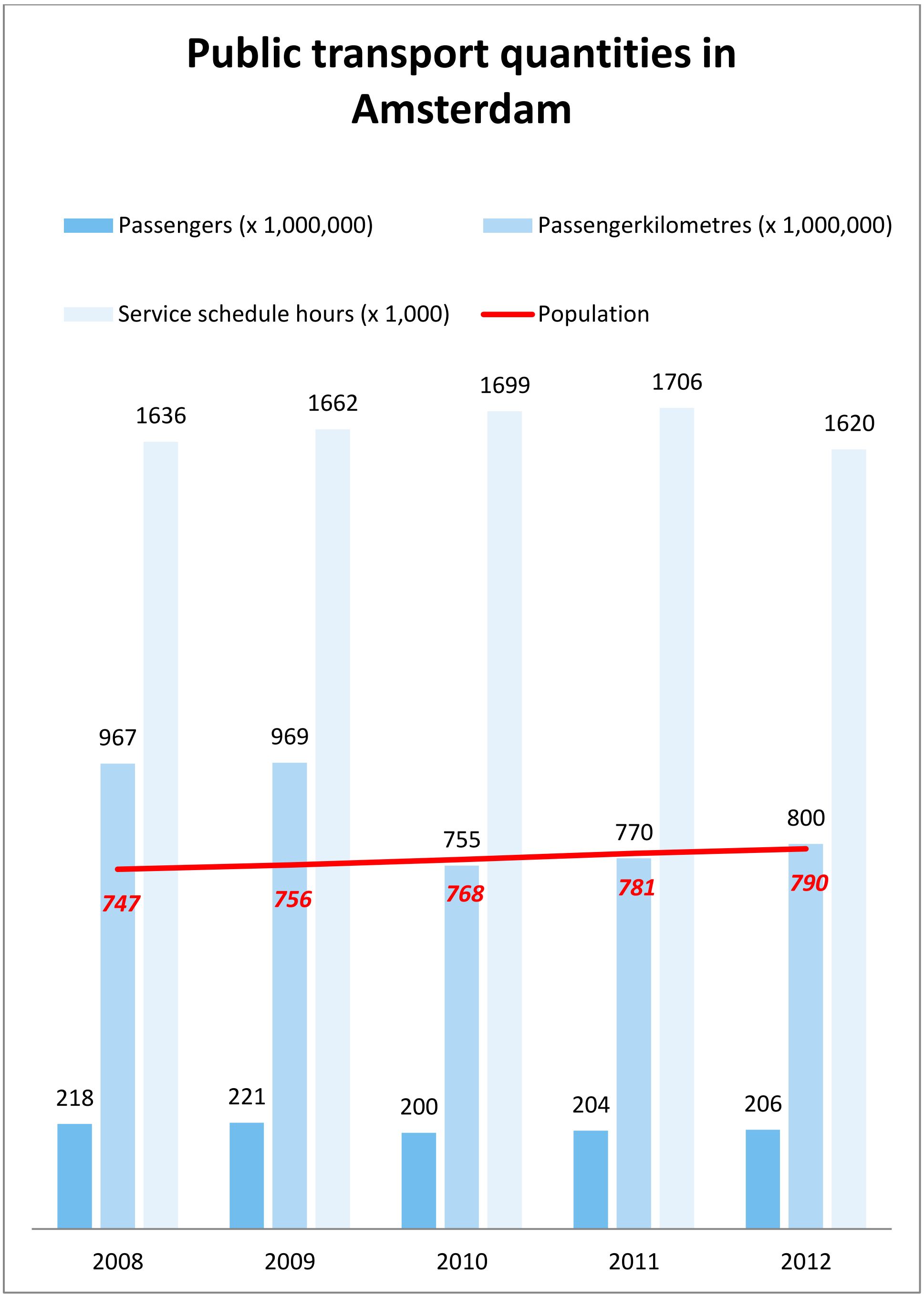
People's mobility is becoming an increasingly important aspect of city life. A growing city population and increasing mobility of the city's inhabitants is associated with an increase in the demand for mobility and therefore the demand for transport (Polat, 2012). Over time a significant increase in the population's mobility and the use of public transport was observed. It is even argued that the increase of public transport demand before 2010 was higher compared to demographic growth (EMTA, 2010). However this appears not to be true for the last five years in Amsterdam, where population grew but the use of public transport declined. Graph 1 (on the following page) illustrates this observation.

The red line in Graph 1 shows population growth over time. On January 1st 2013 the Amsterdam population consisted of 799,442 inhabitants, which implies an increase of 7% compared to 2008. The bars in Graph 1 illustrate the public transport quantities for the last five years in Amsterdam by means of the number of passengers, passengerkilometres and service schedule hours per year[1]. The number of passengers decreased over time from 218 million passengers in 2008 to 206 million in 2012. The number of passengerkilometres in 2012 was 176 million kilometres lower compared to 2008. In addition, the number of service schedule hours decreased over time from 1,636,000 hours in 2008 to 1,620,000 hours in 2012. Though, the service schedule hours follow a different pattern than the number of passenger(kilometre)s. For both the number of passengers and passengerkilometres the sharpest drop can be seen from 2009 to 2010 whereas the service schedule hours increase in this time period. This can be explained as the service schedule hours are planned based on the public transport volumes in the preceding year(s)[2]. Based on Graph 1 it can be concluded that public transport volumes decreased in the time-period from 2008 to 2012 while population grew, which implies that the positive relation found between population growth and public transport demand does not hold for the last few years in Amsterdam.

[1] Note that the magnitude of the numbers is different for service schedule, this number is expressed in thousands while the number of passenger(kilometre)s is expressed in millions.

[2] In 2011 a high number of service schedule hours is observed while the number of passenger(kilometre)s decreased further in the preceding years. This implies that the planning of service schedule hours was not well adapted to the changes in demand.

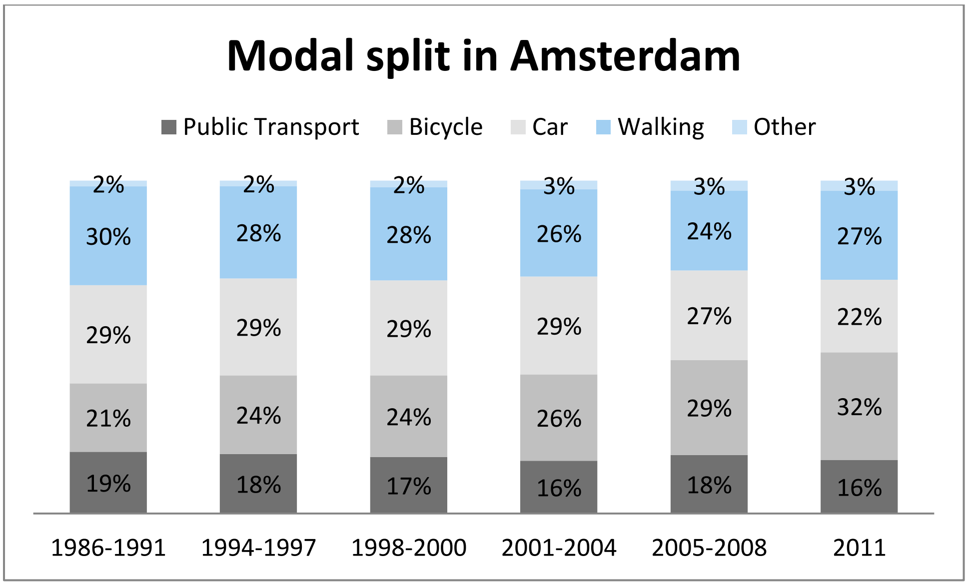
Graph 1: Population growth and public transport quantities in Amsterdam for the period 2008-2012



Source: O+S Amsterdam (2013).

Population growth may be associated with an increase in the demand for transport in general (Polat, 2012). Multiple transport modes can be used to meet this demand which can change the role of public transport within a city. On the one hand the role of public transport in a city may become more important as population grows, since car ownership and car use may be relatively problematic in cities due to lack a of parking space or congestion. On the other hand, other transport modes such as the bicycle or walking are viable alternatives for transport in the city as the travelled distance within the city is relatively small. Graph 2 shows the modal split in Amsterdam.

Graph 2: Modal split in Amsterdam based on the average number of movements per day



Source: O+S Amsterdam (2013).

Graph 2 shows that walking and cycling are important ways to move within the city of Amsterdam. On average, these travel modes were respectively responsible for 27% and 32% of the travel movements per day in 2011. The largest share of transport movements was therefore made by bicycle. Also a substantial share of travel movements was made by public transport. As shown in Graph 2, in 2011 on average 16% of the movements per day in Amsterdam were made by means of public transport. The share of car transport was relatively high compared to public transport; on average the car was used for 22% of the movements per day. In addition, Graph 2 shows that the share of transport by car has decreased from 29% in the period 1986-1991 to 22% in 2011, while transport by bicycle increased from 21% to 32% in these periods. Based on Graph 1 and Graph 2 it can be concluded that even though population grew and public transport volumes fell over time in Amsterdam, the proportion of public transport use compared to total transport appears to be relatively stable and has changed relatively little over time.

Based on the transport volumes and share of public transport in the modal split, it is clear that public transport is an important mode of transport within the city of Amsterdam. Therefore, temporary traffic arrangements due to maintenance activities or events can affect passenger travel within the city. The next section will discuss temporary traffic arrangements and their impact in more detail.

2.2 Temporary traffic arrangements in the GVB network

The road- and rail infrastructure used by GVB requires maintenance work regularly. Accordingly, some (parts of) routes cannot be utilised during the execution of these maintenance activities. Moreover, the city of Amsterdam hosts multiple events during the year (such as the Amsterdam Marathon) for which certain parts of the city are inaccessible for public transport. For these situations GVB imposes adjustments in the form of

“Temporary Traffic Arrangements” (in Dutch: TVM’s, Tijdelijke VerkeersMaatregelen). These include for example the implementation of temporary diversions, shortened or lengthened routes of service lines, adjustments of the timetable, stops which are temporarily suspended and the establishment of temporary new stops. These arrangements will have an impact on GVB’s passengers, the workload of the GVB’s staff and the firm’s finances (GVB, 2011).

2.2.1 Impact of temporary traffic arrangements on passengers

Even though GVB’s objective is to minimize deviations from the standard timetable and therefore to minimize the impact of temporary traffic arrangements, the impact severity differs per situation. The temporary traffic arrangements are categorized on a scale from 0 to 3, where higher levels are associated with a more severe impact on GVB’s passengers. These categories are shown in Table 1.

Table 1: Categories of temporary traffic arrangements

Category	Description
0	No impact on the passenger, only a service announcement
1	Alteration within the currently scheduled driving time and intervals
2	New service schedule, minor impact/short time period/limited number of service lines affected
3	New service schedule, large impact/long time period/ large number of service lines affected

Source: GVB (2011).

Depending on the category of the temporary traffic arrangement, passengers are confronted with changes in timetables, routes and travel duration. Temporary traffic arrangements of category 0 do not affect the passengers and include service announcements such as temporary speed limits or warnings for bad conditions of infrastructure. Category 1 arrangements involve for example temporary displacements of stops and do not require a change in driving time, so that the impact on passengers is only minor. Arrangements of category 2 or 3 include (large scale) events and diversions which require a change in the service schedule. This implies route changes, temporary changes/closures of stops, the need for extra vehicles and changes in time tables. Public transport passengers should therefore adapt their journey in the sense that they should take into account longer travel times or a longer distance to/from the stops. As this may be perceived by passengers as inconvenient, passengers can choose alternative modes of transport or can decide to travel less. The reduction of the number of passengers will in turn lead to a loss of passenger revenues. The impact on passengers and passenger revenues however depends on the duration of the arrangement and the service lines affected.

2.2.2 Impact within GVB

Next to the impact on passengers, the temporary traffic arrangements also demand adjustments within GVB. The process of planning these arrangements takes time and is organized in different steps. The planning process involves among others consultation with multiple external parties[3], the planning of adjusted routes and timetables, adjustments of transport systems[4], adjustments and/or displacements of stops and travel information at the stops, and communication towards the passengers (GVB, 2012). Furthermore, extra personnel are employed to inform passengers at the route and at stops, and extra teams are on stand-by in case of emergencies, irregularities or other disturbances. As multiple departments within the firm are responsible for the execution of these tasks involved, temporary traffic arrangements lead to a higher workload on GVB's staff.

2.2.3 Impact on finances

The costs associated with temporary traffic arrangements derive among others from the preparation process and the need for extra personnel and vehicles. Other costs are related to a loss of the number of passengers and thus passenger revenues. Moreover, since GVB receives a subsidy from Stadsregio Amsterdam based on the number of vehicle kilometres, a diversion which shortens route length of the service lines may reduce the subsidy granted. Considering these costs, relatively small temporary traffic arrangements will be financed by GVB from a previously determined budget. The larger arrangements are not financed from the regular budget but require separate agreements. Since GVB became an independent business on January 1st 2007 (RTV Noord-Holland, 2006), the firm is able to file a claim for the involved costs of temporary traffic agreements at the responsible external parties (municipality of Amsterdam) in order to compensate for the additional costs involved. However, the subsidy loss cannot be included in this claim as separate arrangements are made with respect to subsidies between GVB and Stadsregio Amsterdam.

2.3 Temporary traffic arrangements for the IJtunnel closures

This research estimates the impact of temporary traffic arrangements for one specific case in particular, the temporary closures of the IJtunnel. The IJtunnel directly connects the northern part of Amsterdam with the city centre, and provides a fast and short route for motorized vehicles (including GVB's busses) to cross the IJ. Alternative routes to cross the IJ by road are via the Coentunnel, Zuiderzeeweg or the ringroad A10, but these routes imply a large detour and no direct connection to the city centre. Furthermore, ferryboats provide a frequent service to cross the IJ, though these can only be used by pedestrians and bicyclists. As the IJtunnel is used by multiple public transport operators[5] and provides the most important direct connection between Amsterdam North to the city centre, the closure of the IJtunnel is expected to have a substantial impact on the demand for public transport.

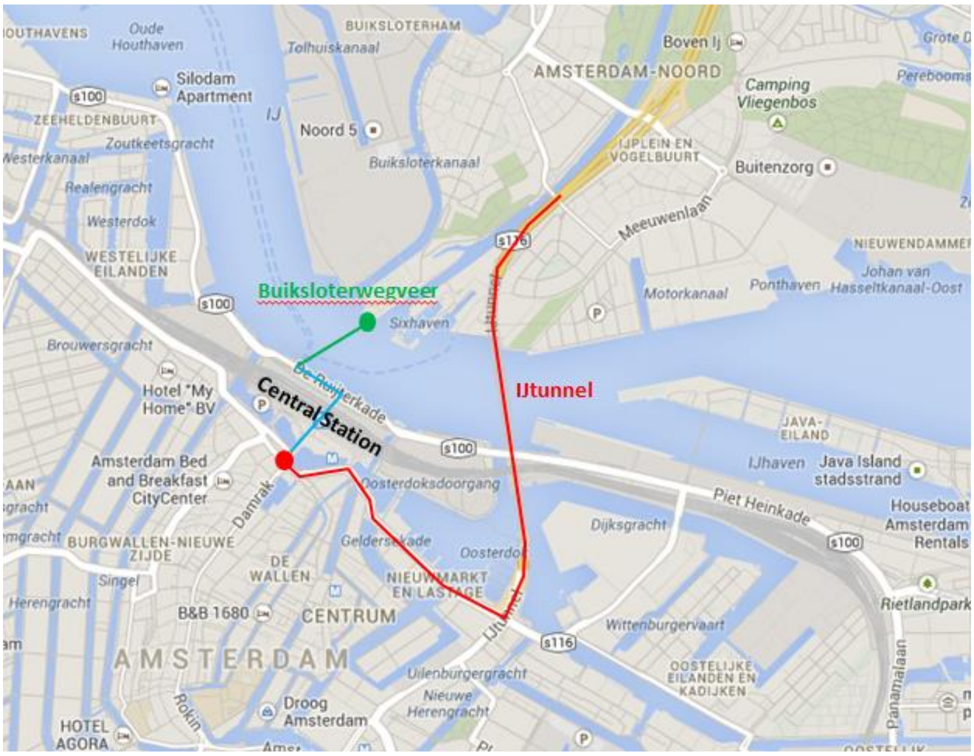
[3] External parties include among others road managers, managers of traffic systems, fire-brigade, police and project engineers.

[4] Adjustments of routes and timetables should be adjusted in transport systems (such as EBS) in order to provide the right travel information for the passengers. In addition, these adjustments are necessary to correctly register check ins and check outs with the public transport chipcard. The latter provides travel information of passengers to GVB, but is moreover it is crucial to calculate the right trip tariff for passengers.

[5] Other public transport operators which use the IJtunnel are Connexxion and EBS.

The IJtunnel is closed regularly due to maintenance activities, mostly during the night or in weekends. As a consequence of these temporary closures, diversions are implemented for the four “IJtunnel service lines”[6]. As Amsterdam Central Station cannot be reached by these bus lines, they are diverted towards the Buiksloterwegveer from which passengers can take the ferryboat across the IJ towards the backside of the Central Station. From this point passengers should walk through the station (which takes approximately 5 minutes) to reach the front of the station were the IJtunnel service lines would otherwise stop. The diversion is illustrated in Figure 1.

Figure 1: Regular route through IJtunnel (red) and diverted route via the Buiksloterwegveer (green)



Next to the IJtunnel service lines, the closure of the IJtunnel is also expected to affect the remaining lines in Amsterdam North. These provide alternative (but longer) routes to the city centre which involve interchanges. Considering the duration and number of affected service lines[7], these IJtunnel closures are categorized as temporary traffic arrangements of category 2. The diversion can cause inconvenience for passengers as it involves extra travel time, interchanges between the bus and ferry boat and walking distance at the Central Station. Therefore passengers may find an alternative mode of transport or alternative routes. Moreover, they can decide to postpone their travel or not to travel at all.

[6] GVB’s service lines 32, 33, 34 and 35 use the IJtunnel in the regular timetable and are diverted during the IJtunnel closures. Next to the service lines of GVB, an additional ten service lines of EBS and five service lines of Connexxion are affected by the IJtunnel closure, though these will not be included in this research.

[7] In addition to the IJtunnel service lines, the nightlines (service lines 391, 392 and 394) will also be affected by the temporary traffic arrangements. Though, for this analysis there is no chipcard data available for these lines as separate nightbus tickets were sold in the time period used.

In 2012 the IJtunnel was closed in multiple weekends during the year. However, in March 2013 the tunnel was closed for five subsequent weekends from Saturday morning to Monday morning. As the nature of these closures differs with respect to the sequence, the effect of the closures in March 2013 may differ from the effect of other (single) IJtunnel closures. On the one hand, the effect on the demand for public transport may be stronger for the closures in March 2013 compared to other closures. Passengers are more likely to be informed about the five subsequent closures compared to a single weekend closure, so that they can adapt their travel plans, find alternative modes of transport, postpone their journey or may decide not to travel at all. For short single weekend closures, passengers are less well informed and are more likely to continue their (diverted) journey as they notice the diversion along the way. On the other hand, the effect of the closures in March 2013 can be less severe compared to other closures. Passengers may be less likely to postpone their trip for five weekends compared to one weekend (though this depends on the travel purpose, importance and urgency of the trip, where more urgent trips will be made despite the closures). Moreover as passengers are more likely to be informed they can prepare themselves for their diverted route. It is unclear whether the effect on the demand for public transport of subsequent closures differs from random closures. This study will therefore analyse the effect of the IJtunnel closures for March 2013 and for other IJtunnel closures in more detail. The announcement of the temporary traffic arrangement for the specific IJtunnel closures in March 2013 is added in Appendix A.

Concluding, this chapter discussed the characteristics of public transport in Amsterdam. Moreover, the organization and the consequences of temporary traffic arrangements for GVB were presented. The specific case of closures of the IJtunnel was introduced, for which the impact on the demand for public transport will be analysed in this study. The next chapter will identify multiple factors that affect public transport demand based on the scientific literature.

3. Literature review

The demand for public transport is extensively discussed in academic and professional papers, as well as in government and consulting reports. Most of these studies focused on price as the main determinant for the demand for transport, and accordingly estimated own-price elasticities. Other studies identified and estimated elasticities of multiple other factors which affect the demand for public transport. Differences in research techniques, country selection, research period and transport mode are the main causes for varying results. The literature on the demand for public transport also includes meta-analyses. These compared and summarized the results from multiple quantitative analyses on this topic in order to derive more accurate effects (and magnitudes of these effects). This chapter defines the demand for public transport and provides an overview of the factors that affect this demand according to the academic literature. In addition, quantitative findings from previous studies on this subject will be discussed.

3.1 Public transport demand

Many different models have been developed on the demand for public transport in the scientific literature, in which this demand is expressed in multiple ways. In economics, demand reflects the amount of a good or service that people are willing to buy for a certain price. The demand for public transport could therefore be defined as the amount of public transport services that people are willing to make use of for a specific price. According to Balcombe et al. (2004) the demand for transport reflects the choice of travellers among different alternatives of trips which maximizes their utility, considering all the constraints specific to their choice. These constraints include time and money available to the traveller to spend on travelling, and the supply of transport which is determined by the service timetable and is thus beyond the traveller's choice. The demand function therefore reflects the number of trips demanded in a given time period in terms of multiple explanatory variables.

The most commonly used indicator for the demand for public transport is the number of trips within a specific time period. An alternative and often used measure is the number of passengerkilometers, which is a function of the number of passengers and their distance travelled (FitzRoy and Smith, 1998). The number of trips and the number of passengerkilometres were also used by Nijkamp and Pepping (1998) in their meta-analysis on the variance of the public transport demand elasticities in Europe. In addition to these measures, Balcombe et al. (2004) used passenger revenues to reflect the demand for public transport.

Public transport services have some specific characteristics which should be taken into account in the analysis of demand. First, public transport is dynamic and interactive as it involves multiple transport modes, passenger types, travel purposes, travel frequencies and travel times. Second, time is an important dimension in public transport. During morning and evening peak hours demand is higher and more concentrated as mainly workers and students demand transport, but demand is more evenly spread during the rest of the day when leisure- or other types of travellers mainly use public transport. Third, the expectations from public transport services differ per type of traveller; the time and purpose of travel shape expectations differently. For example, workers travelling during rush hour have lower expectations of service quality and comfort than leisure travellers. Fourth, the availability of alternative travel modes influences the demand for public transport (Polat, 2012). These characteristics imply that not one explicit demand function exists as the demand for public transport is different for each person, transport mode, time, place etcetera.

3.2 Factors affecting the demand for public transport

As mentioned above, the academic literature has identified multiple factors which affect the demand for public transport. One often cited paper on this subject is the so called TRL-report by Balcombe et al. (2004), which analysed and quantified the determinants for public transport demand in Great-Britain. Quantitative models were developed by Matas (2004) and Wang (2011) who respectively modelled the demand for public transport in Madrid and three cities in New Zealand (Auckland, Wellington and Christchurch). Both models include multiple explanatory variables that affect demand. In addition, meta-analyses by Nijkamp and Pepping (1980) and Holmgren (2007) combined results from multiple studies in order to draw some general conclusions on public transport demand (Holmgren, 2007). Each of these papers elaborate on quantifying the effect of factors that influence the demand for transport.

With respect to these factors, a distinction is made between endogenous factors which can directly be influenced by transport operators and exogenous factors which cannot directly be influenced by operators. Endogenous factors include the cost of travel (in terms of fares and travel time), service quality and marketing & promotion activities. Exogenous factors include behavioural factors, travel distance, travel time, availability of alternative modes of transport and transport dependency (which are specific to individuals), but also economic, demographic and social factors, government policy, land use and weather conditions. The next sections will discuss these factors separately and will review the findings on these factors from the above mentioned literature.

3.2.1 Endogenous factors

A first endogenous factor that affects public transport demand is the *cost of travel*, where an increase in the cost of travel is associated with lower demand for public transport. The cost of travel can directly be influenced by the public transport operator and consists of two elements: fares and time. Fares represent the direct costs (sum of fares) charged for a specific trip, while time is a traveller-specific component associated with the traveller's valuation of his/her time (Polat, 2012). These elements will be discussed separately.

The majority of literature focuses on the effect of *fares* and fare changes on the demand for public transport. In general it can be stated that an increase of the fare level is associated with a decline in public transport patronage (Balcombe et al., 2004). This corresponds to the results by Webster and Bly (1980) who found a public transport fare elasticity of -0.3. The elasticity value of -0.3 implies that a 1% increase in the public transport fare would lead to a decrease in the demand for transport of 0.3%. As the relative change in the demand is smaller than the relative change in fare, public transport demand is said to be inelastic. This result was based on international aggregated elasticities for all fares, journey purposes, passenger types and trip lengths (Balcombe et al., 2004) and has been used as a rule of dumb for the 1980s (Bresson et al., 2003). Although this result was based on averages from multiple studies, the different conditions under which the estimates were obtained are not taken into account (Holmgren, 2007). Therefore estimated elasticities for fares and other factors will differ based on the conditions under which they are estimated.

Since the 1980s multiple studies on the demand for public transport found different elasticities. These differences may be addressed to changing elasticities over time, but also because a distinction was made between the effects of fares on public transport demand on the short-, medium- and long term (1-2 years, 5-7 years and 10-12 years respectively) (Balcombe et al., 2004). Additionally elasticities differ between countries, cities and types of areas (rural versus urban areas), but also for area size, transport modes, time periods during the day (peak/off-peak), the type of traveller, journey purpose and the direction and distance of travel. Moreover, the effects of fare changes depend on the fare level, the magnitude and the direction of the fare change. All these dimensions contribute to a wide variety of studies on fare elasticities with differing results.

In Webster and Bly's footsteps, Oum et al. (1992) reviewed multiple other studies and found elasticity values for urban transit mostly ranging within -0.1 to -0.6. Meta-analysis by Holmgren (2007) found an average elasticity of -0.38 based on 81 estimated price-elasticities for public transport. Bresson et al. (2003) reported fare long run price-elasticities of approximately -0.7 for France and England and Wang (2011) found long-run values with respect to bus transport ranging from -0.34 to -0.46. Finally, Goodwin (1992) reported an average elasticity of -0.41 for bus transport based on analysis of 50 studies. In addition Goodwin (1992) stated that there is a reasonably clear pattern for long term elasticities to be between 50 per cent higher and three times higher than the short term. With this respect, the more recent study by Balcombe et al. (2004) distinguished between short-, medium- and long term elasticities and found values of -0.4, -0.56 and -1.0 respectively for bus fares. This implies that the demand for public transport becomes more price-sensitive on the long run. Based on these findings fare elasticities differ significantly depending on time periods, transport modes and other specific factors in which a mode operates.

Next to fares, another determinant for the cost of travel is *travel time*. In general, a longer travel time is associated with higher costs of travel (opportunity costs of time) and is therefore negatively related to the demand for public transport. Travel time includes access time, waiting time, journey time and interchange time. First, access time refers to the time needed to get to a service stop, either walking, cycling or by other modes of transport. A longer access time can be considered as inconvenient and is associated with higher opportunity costs of time and lower public transport demand. Second, related to access time is access coverage, which refers to the span of the area where public transport is offered. A larger access coverage is associated with more potential travellers who can make use of public transport and thus with a higher level of public transport demand. Third, waiting time at the stop is another time component. This depends on the frequency of service offered at a certain stop. A higher frequency reduces waiting time and therefore the cost of travel. After all, waiting time is also considered as inconvenient and is perceived more negatively than journey time and access time (Polat, 2012). Fourth, with respect to journey times, alternative modes of transport might provide a shorter journey time compared to public transport. One source for increasing journey times is (network) congestion, which decreases the service quality provided, increases the cost of travel with respect to time and therefore may lead to preference for other modes of transport. Finally, time spend on interchanges between transport modes also affects the cost of travel. The travel time component is thus positively related with the costs of travel and hence negatively related to the demand for public transport.

A second endogenous factor that is often included in demand models for public transport is *service quality*, which may be more important for passenger transport than price (Oum et al., 1992). Service quality is closely related to the cost of travel and comprises multiple (time and non-time related) aspects. Some time-related aspects were discussed above and regard for example access time to the boarding point and egress time at the alighting point and in-vehicle time. Another time-related service quality aspect is the service interval. Service intervals are often measured by total vehicle kilometres, which is the product of frequency and route length (Fitzroy and Smith, 1998). This implies that the service quantity supplied is actually an important component of service quality supplied.

With respect to vehicle kilometres, Balcombe et al. (2004) summarized average elasticity values for bus demand of 0.4 in the short-run and 0.7 in the long-run based on 27 and 23 measurements respectively, so that a 1% increase of the number of vehicle kilometres is associated with a less than 1% increase in the demand for transport. Wang (2011) found long-run elasticities ranging from 0.62 to 0.73 with respect to (bus) vehicle kilometres. Holmgren's (2007) meta-analysis found an average elasticity with respect to vehicle kilometres of 0.72 based on 58 observations. These elasticity values are higher for Sundays, in the evenings and in rural areas in which the service levels are generally lower compared to weekdays, daytime and urban areas. In addition, Holmgren (2008) emphasized the positive two-way relationship between this service quality and the demand for transport. That is, service quality affects the demand for public transport, and the level of demand in turn affects the quality of service offered.

Considering the two elements of vehicle kilometres in more detail, both frequency and route length are positively related to the demand for public transport. A higher frequency (that is; the more often a service is offered on a specific route within a specific period of time) is associated with shorter waiting times for customers and therefore a higher demand for public transport. Furthermore, route length reflects the area covered for public transport services on a network level. The wider this area, the higher the accessibility and the more passengers can make use of the services. A higher service level (in terms of frequency and route length) can thus increase service quality and can reduce the cost of travel in terms of time, which in turn can lead to an increase of public transport demand. Matas (2004) found a positive relationship between route length and public transport patronage and reported an elasticity value of 0.53 for bus trip demand with respect to the bus route length.

In addition, other service quality factors are related to vehicle specific characteristics, service reliability, the provision of information and interchanges between modes (Balcombe et al., 2004). Vehicle characteristics are important determinants for the comfort a transport mode provides. Even though transport operators can try to maximize comfort within their vehicles, transport by car is perceived as more comfortable with respect to seating, ventilation and storage capacity than public transport. In addition, crowdedness in public transport may reduce travel comfort. Service reliability is the degree of dependability and trust-ability of passengers in a specific transport mode, which includes aspects as accessibility, confidence, frequency, punctuality and service capacity (Polat, 2012). With regard to punctuality, Nordheim & Ruud (2011) found that delays are perceived as extremely inconvenient in the city of Oslo. Delays are associated with irritation by passengers as they have to wait for the delayed public transport service, do not arrive on time for appointments, or have to take an earlier departure because of the unreliable service (Nordheim & Ruud, 2011). In general, vehicles which provide a comfortable travel environment, high service reliability and good information are associated with higher levels of demand. However, more interchanges between modes are associated with lower levels of demand. By (re)developing their public transport network, operators could therefore minimize the need for interchanges.

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A final endogenous factor for public transport demand relates to *marketing and promotion* activities. In combination with quality and price incentives, marketing and promotion by public transport operators can increase the demand for public transport. However, public transport operators tend to rely on conventional forms of communication towards their customers while communication towards non-users of public transport is limited (Balcombe et al., 2004). Though, in the medium/long run, marketing can substantially contribute to the promotion of public transport.

3.2.2 Exogenous factors

The demand for public transport is also affected by exogenous factors, which cannot directly be influenced by transport operators. Some of these factors depend (to a certain degree) on the individual traveller, for example behavioural factors, travel distance, travel time and the availability of other transport modes. Other factors are more associated to the external environment, such as economic, demographic and social factors or government policy. Even though each of these factors affect the demand for public transport, the existing quantitative models on this subject only include a selection of these factors since it is difficult to measure or quantify some of them (Polat, 2012). Varying estimated elasticities for these factors were found in scientific literature.

First, *behavioural factors* are specific to individual travellers and affect public transport demand. For each individual, the demand for transport depends among others on personal characteristics, preferences and goals. Trip behaviour therefore differs per individual and per situation. However, it must be noted that in the short run passenger behaviour is more predictable than in the long run as travel patterns may change over time (also due to socio-economic changes).

Another traveller specific factor is *travel distance*. In general, traveller's willingness to make journeys decreases when travel distance increases. This can be explained by the negative perception of travellers for journey duration, boredom, discomfort and the rising opportunity costs of travel time. Shorter trips are made more frequently. In addition, when travel distance is beyond a certain threshold distance, travellers tend to choose another mode of transport than public transport (Polat, 2012).

The demand for public transport also heavily depends on the *time of travel* during the day. During morning and evening peak times, the demand is high as journeys are made for work and school purposes. Next to the peak hours, journeys for leisure purposes are made outside the peak hours where demand for public transport is more evenly spread. Therefore, the time of travel depends on the journey purpose of the individuals.

The *availability of other transport modes* than public transport, and the costs associated with these modes, also affects public transport demand. In general, when the availability (costs) of alternative modes rises, the demand for public transport expected to decrease (increase). The most important competitor and substitute for public transport is the private car. The car is often preferred for its higher comfort level, more convenient door-to-door transport and shorter travel times. Car ownership and the associated costs (for example in terms of fuel price) therefore affect the demand for public transport.

Another exogenous factor that is specific to individual travellers is the degree of public *transport dependency* which is related to car ownership. When a traveller has a limited number of transport alternatives, demand for public transport is expected to be higher (Polat, 2012). This may especially be the case in low income regions or in cities in which car ownership may be more problematic due to a lack of space.

Furthermore, *economic factors* affect public transport demand. These factors include among others the employment rate and the general level of wealth. In the long run, the employment rate is positively related to the demand for public transport. Matas (2004) found an elasticity value for GDP (as indicator of the level of wealth) of 0.15 with respect to the demand for transport. However, if household income or wealth exceeds a certain threshold, public transport is often substituted for transport by private vehicles (Polat, 2012). Income, car ownership and petrol prices are economic factors which are discussed in more detail.

The effect of *income* on the demand for transport is still unclear. In general, an increase in income is associated with an increase in the demand for transport, assuming that transport is a normal good. Meta-analysis by Holmgren (2007) reported income elasticities for public transport ranging from -0.82 to 1.18, with an average value equal to 0.17. Bresson et al. (2004) found elasticities ranging from -0.02 in France to -0.66 in England. The wide range of values may be explained as income is also related to car ownership. As the car may be seen as a substitute for public transport, there is a negative impact of income on the demand for public transport via car ownership. When interpreting income elasticities it is important to know whether car ownership is included in the estimation. Balcombe et al. (2004) found income elasticities ranging between -1.0 and -0.5 including the car ownership effect. Though, they stated that when car ownership reaches saturation the elasticities are expected to become less negative in the long run.

As mentioned, *car ownership* and the availability of alternative modes of transport affects the demand for public transport. According to Balcombe et al. (2004) a person in a car-owning household is less likely to make a trip by public transport than a person in a non car-owning household. Since car ownership strongly depends on income it is difficult to separate car ownership effects and income effects. However, some studies estimated only the effect of car ownership on the demand for public transport. Holmgren's (2007) meta-analysis showed elasticities ranging from -3.37 to 0 based on 8 observations, with a mean of -0.86. Wang (2011) found a long-run elasticity of car ownership with respect to bus transport in Auckland of -3.10. This indicates that public transport demand is highly sensitive to the level of car ownership.

Petrol prices are another important component of the cost of travel by car. Petrol prices are negatively related to the level of consumption of petrol and therefore car use. Based on 120 observations, Goodwin (1992) found average petrol price elasticity with respect to the consumption of petrol of -0.48, implying that higher petrol prices are associated with less petrol consumption. As the car can be seen as a substitute for public transport, higher petrol prices are associated with lower car use and higher public transport use. Accordingly, Goodwin (1992) found an average elasticity of public transport demand with respect to petrol prices of 0.34. Holmgren (2007) reported elasticity values ranging from 0 to 1.04 with an average of 0.38 and Matas (2004) estimated an elasticity value of 0.155 for petrol price with respect to demand for bus transport in Madrid. Finally, Wang (2011) found long-run elasticity values for petrol prices with respect to bus transport ranging from 0.32 to 0.37. All these values imply that a higher petrol price is indeed associated with a rise in the demand for public transport.

Next to economic factors, *demographic and social factors* affect the demand for public transport. These include among others population growth, the population age structure, gender and child ownership. Groups like young adolescents and elderly people are more likely to use public transport as these groups are associated with low car ownership/use and relatively low incomes. Furthermore, males are more likely to have access to a car so that they are more sensitive to fares compared to females (Balcombe et al., 2004). However, these demographic and social factors change slowly over time and are expected to affect public transport demand in the long run, while they are less likely to affect demand in the short run.

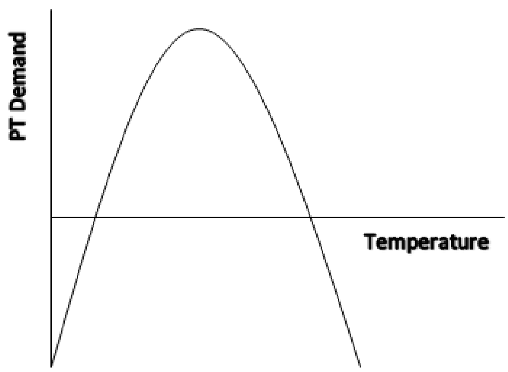
Government policy affects public transport demand since the government or local authorities are often involved in the provision of public transport (infrastructure). In many cities, municipalities consider this as one of their main duties. On the one hand, government policies may stimulate public transport demand for example by means of subsidies. On the other hand, pricing mechanisms may discourage the use of alternative transport modes such as the car, which can relieve congestion and negative environmental impacts in cities but can increase the demand for public transport (Polat, 2012).

The demand for public transport is also influenced by *land-use* characteristics. This is a very broad concept and includes among others population density, where highly populated areas are associated with more public transport use and less car use. Based on 8 studies, Tsai (2013) found elasticities with respect to population density ranging from 0.004 to 2.70, which illustrates the positive relation between density and public transport demand. Another land-use characteristic is reflected by settlement size (in terms of population), which is positively related to public transport use. Settlement size is also positively related to the facilities and services provided in the local area, and it is negatively related to travel distance. Also the layout of land use affects public transport use. Mixed land use, which combines housing, employment and shopping facilities, enables people to carry out their daily activities locally and therefore reduces the need for travel. Concentrated employment provision stimulates public transport demand and reduces car use, partially because of a lack of parking space (Balcombe et al., 2004). Based on 7 studies, Tsai (2013) reported elasticities with respect to land use mix ranging from 0.01 to 0.365, which indicates a positive relationship between land use mix and public transport demand.

Finally with respect to the exogenous factors, *weather conditions* in the form of rainfall, snowfall and temperatures can play a role in the demand for public transport. Transit users are subject to direct physical impact from weather, both on their way to/from public transport as in the public transport vehicles. *Rainfall* and *snowfall* affect public transport demand for multiple reasons. Krygsman, Dijst and Artenze (2004) discussed that environmental conditions such as rainfall and wind affect the accessibility to public transport, which is mostly done by walking or cycling. The disutility of getting wet during access to public transport would imply a reduction of the demand for public transport. Moreover, rain and snow reduce visibility and traffic speed which reduces public transport service quality. Martin et al. (2000) reported traffic speed reductions ranging from 10% during wet conditions to 25% in wet and slushy conditions. This reduction of service quality would be associated with a decline in public transport demand. Gaudry (1975) found a loss in the number of passengers in public transport due to rainfall in the city of Montreal, but found two opposite effects for snowfall. New snowfall was negatively related to public transport demand, whereas accumulated snowfall (old + new snowfall) showed a positive relation. This would imply that travellers are less inclined to use public transport during actual snowfall, while the accumulation of snow increases public transport demand. As Montreal's inhabitants are used to large amounts of rain- and snowfall, the latter does not impede travellers to use public transport.

With regard to *temperatures*, Gaudry (1975) found that a fall in temperature was associated with a loss in the number of passengers for public transport in the city of Montreal. During cold weather travellers may prefer other transport modes (such as private car) which can provide more comfort like heating and shelter. Guo, Wilson and Rahbee (2007) stated that cold (wet) weather may depress outdoor sports and recreation activities as well as social events, so that public transport demand reduces. They find a positive relation between temperature and public transport demand in Chicago, so that warmer weather tends to lead to higher transit ridership. However, opposite cold weather (extreme) heat may also affect public transport demand. On the one hand, demand may increase since hot weather increases recreation activities for example in parks or near water (Guo et al., 2007). On the other hand it could be expected that extremely high temperatures discourages travellers to use public transport, as rising (in-vehicle) temperatures may be associated with less travel comfort. Moreover, extreme heat may cause technical failure of cooling systems which reduces the quality of the public transport service. These findings with regard to temperature suggest that temperature may have an exponential relation with the demand for public transport, so that demand is positively related with public transport demand below a certain threshold temperature, whereas a negative relation occurs for higher temperatures than this threshold (Figure 2). However, a study by a British bus operator found that the effects of weather conditions showed little impact of temperature or hours of sunshine on public transport use, while rainfall was associated with a reduction in public transport use (Balcombe et al., 2004).

Figure 2: Potential exponential function between temperature and demand for public transport



3.3 Summary of findings

The discussed literature identified multiple endogenous and exogenous factors that affect the demand for public transport. These factors are summarized and categorized in Table 2 (on the next page).

Table 2: Endogenous and exogenous factors for the demand for public transport

Endogenous factors	**Exogenous factors**	
	Related to individuals	*Related to external environment*
Cost of travel - Fares - Time	Behavioural factors	Economic factors - Income - Car ownership - Petrol price
Service quality	Travel distance	Demographic and social factors
Marketing and promotion	Travel time	Government policy
	Availability of alternative transport modes	Land use
	Transport dependency	Weather conditions - Rain - Snowfall - Temperatures

As discussed there is an extensive pool of research on the factors influencing the demand for public transport, resulting in different findings and estimations of elasticities. Balcombe et al. (2004) concluded that fare, quality of service and car ownership are the most significant factors for public transport demand. Holmgren (2007) supported these findings and stated that an ideal demand model should incorporate these three factors and additionally fuel price and income. However, it must be noted that some of these relevant factors are more important than others under different circumstances. Modelling the demand for transport as a complex function of these factors remains difficult, but imperfect models are not without value as they may be more useful to planners and policymakers than some random guesses (Balcombe et al., 2004).

In summary, this chapter identified multiple factors that affect the demand for public transport. Based on these findings, a model was developed which captures the effect of the IJtunnel closures on public transport demand. In the next chapter this model will be discussed and the data and methodology used for the analysis will be presented.

4. The model: Data and Methodology

Based on the findings from the literature review, a conceptual model was developed which captures the effect of temporary diversions on the demand for public transport in the GVB network. This chapter describes the data and methods used for this analysis. First the conceptual model for the demand for public transport will be discussed. Second, the variables in the analysis, their source and their expected signs will be discussed. Third, the final models will be presented. Fourth, the methodology used for the analysis and the tests performed on the dataset will be discussed. Finally, the descriptive statistics of the data will be presented.

4.1 Conceptual model

Model development usually starts with specifying in conceptual terms the variables which are to be modelled and the factors which influence these variables (Zureiquat, 2012). As the goal of this thesis was to estimate the impact of temporary diversions on the demand for public transport, a model was developed on public transport demand in which a diversion is the main factor of interest. Other factors on demand which were identified in the literature review were included in the model according to data availability. By controlling for these variables, the specific (net) effect of diversions on the demand for transport could be isolated. Conceptually, the model was composed as follows:

$$y = f(x_1, x_2, x_3)$$

where

y = the demand for transport

x_1 = variable of interest: temporary traffic arrangements

x_2 = endogenous factors (directly influenced by public transport operator)

x_3 = exogenous factors (not directly influenced by public transport operator)

Multiple measures could be used to represent these independent variables in a model on public transport demand. However, not every factor found in the literature review can be quantified. Table 3 (on the next page) shows the quantifiable variables which could potentially be included in the model.

Table 3: Quantifiable variables which could potentially be included in the model

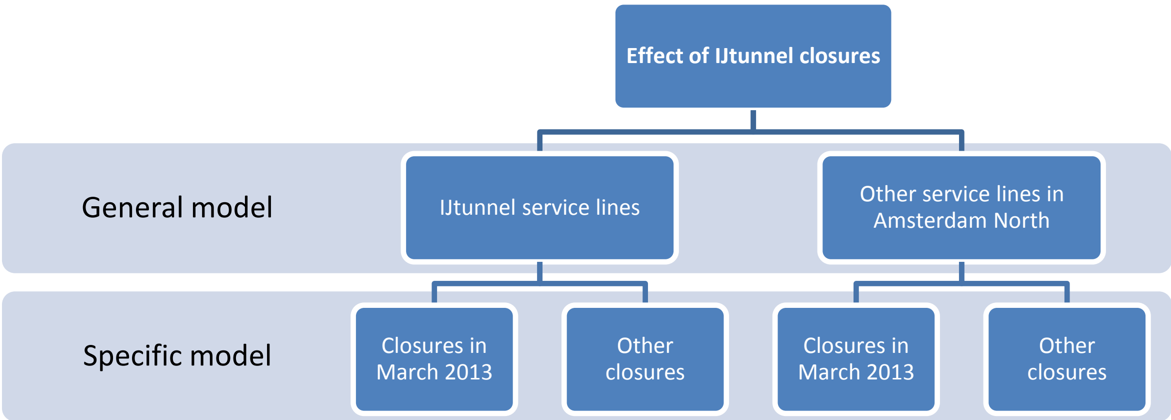
	Potential measures
***y* = the demand for transport**	The number of trips Passenger kilometres Passenger revenues
x_1= variable of interest: temporary traffic arrangements	IJtunnel closures for IJtunnel service lines (lines 32, 33, 34, 35) IJtunnel closures for lines in Amsterdam North (lines 36, 37, 38) Other temporary traffic arrangements
x_2= endogenous factors	Fares: fare level, fare changes Service quality: - Access and egress time - Service intervals: vehicle kilometres operated, frequency, route length, waiting time, schedule delay - Service reliability: (excessive) waiting time, punctuality, (excessive) in-vehicle time - Interchanges between modes: average number of interchanges within trip
x_3= exogenous factors	Petrol price: average fuel price per day Transport dependency: availability of alternative modes of transport, car ownership Economic factors: - Income: income per capita, income per household - Car ownership: number of cars, average number of cars per household - Employment: employment rate - Overall wealth: GDP, household income Demographic/social factors: population growth, average population age, gender, number of children within household. Government policy: level of subsidies/taxes Land use: population density, settlement size, land use density Weather conditions: rainfall, snowfall, temperature

Source: own construction of Balcombe et al. (2004), Bresson et al. (2003), Goodwin (1992), Holmgren (2007), Nijkamp and Pepping (1980), Oum et al. (1992), Polat (2012) and Tsai (2013).

Since many of the previously discussed factors were not quantifiable and many data had constraints, it was not possible to include all of these variables in the analysis. Therefore, a selection of variables was added to the model according to data availability.

The conceptual model was used to analyse the impact of the IJtunnel closures, which was expected to have an effect on both the IJtunnel service lines and the other service lines in Amsterdam North. Moreover, as discussed in Section 2.3 the closures in March 2013 were expected to have a different effect compared to other IJtunnel closures. Therefore two separate models were used to analyse the effect of the IJtunnel closures. First, a general model was used to capture the total effect of all IJtunnel closures. Second, a specific model was used in which the effects are split up for March 2013 and other periods. This is shown schematically in Figure 3.

Figure 3: Schematic representation of the analysis



First these models were used for an analysis per day. Though, Section 3.1 discussed that time is an important dimension of public transport demand. During morning- and afternoon peak hours demand is relatively concentrated whereas demand is more evenly spread during off-peak hours. In order to analyse whether the effect of the IJtunnel closures differ for these different time periods per day, both the general model and specific model were applied for the morning peak, afternoon peak and off-peak hours. In total, this resulted in sixteen estimated models.

4.2 Data and variables

In order to analyse the impact of temporary diversions on the demand for public transport, the conceptual model was applied to a panel dataset. This panel comprised data for twenty service lines (see Appendix B) in the period February 1st 2012 to July 31st 2013. The panel dataset included both the service lines which are affected by the IJtunnel closures and control lines. The IJtunnel service lines (lines 32, 33, 34 and 35) and the remaining lines in Amsterdam North (lines 36, 37 and 38) were included as they are affected by the IJtunnel closures directly. Moreover, thirteen control lines were included which were selected according to multiple criteria. These were either bus or tram lines, which have Amsterdam Central Station as their turning point or which stop at the Central Station on their way to their final destination. Metro lines were excluded as data were not available for each metro line separately. Based on data availability, multiple dependent and independent variables were included in the dataset which will be discussed in the next sections.

4.2.1 Dependent variables

The demand for public transport is a broad concept and is represented by two measurements. One measurement for the demand for transport derived from the literature is the number of trips. As the data on the number of trips were incomplete[8], *the number of boarding passengers* was used as a measure for the demand for public transport. This variable reflects the number of check-ins made with the chipcard and was available on a daily and hourly basis. Though, this measurement may be biased. First, the number of check-ins may be influenced as a consequence of false check-ins (for example when passengers unintentionally check in twice), this would overestimate the number of trips. Additionally, fare dodgers are not counted in this measure (after all, they do not check in). Therefore the actual number of passengers may be underestimated. Finally, trips of which only a check out is registered and transactions in degraded mode[9] are not included in this measurement. This may also imply an underestimation of the actual number of passengers. Data on the number of boarding passengers were extracted from the GVB chipcard database. The number of boarding passengers was derived per day and per hour for each service line separately.

The second dependent variable for the public transport demand is *the number of passenger kilometres*, which reflects the distance travelled by the passengers. Just as the number of boarding passengers, this measure may be biased due to missing check ins and check outs for which no distance can be registered. Data on this variable were derived from the GVB chipcard database per day and per hour for each service line separately.

4.2.2 Independent variables

The independent variables were chosen according to the academic literature on the demand for transport. Two types of independent variables were included in the analysis. First the endogenous variables (which can directly be influenced by the public transport provider) reflected service levels which affect the demand for transport. Second, exogenous factors (which cannot directly be influenced by the public transport provider) were included such as weather conditions and fuel prices.

The endogenous factors included in the model are related to service quality. As discussed in Section 3.2.1 an often used measure for the service level is the number of vehicle kilometres, for which Holmgren (2008) identified a positive two-way relationship with the demand for transport (that is; supply and demand for public transport are mutually dependent). The number of vehicle kilometres supplied is a function of frequency (service intervals) and route length, which were included separately in the conceptual model. *Frequency* is expressed as the number of scheduled trips per hour and was derived from GVB's "Interval overview" for each service line separately. Since service intervals are associated with the supply and quality of public transport, frequency was expected to be positively related to the demand for transport. *Route length* represents the covered distance of the service lines in kilometres and was derived from GVB's "List of service stops" for each service line separately. As discussed in Section 3.2.1, route length as a measure of service quality reflects the area covered by public transport services which would be positively related to public transport demand.

[8] The number of trips based on chipcard data involves linking check-ins and check-outs. However, the data includes missing check-ins or check-outs which cannot be linked and are therefore not counted as a trip. Moreover, data on the number of trips were not available per day and per hour.

[9] When the in-vehicle systems which register the chipcard transactions are in "degraded mode", the vehicle is unable to recognize its location. Transactions in degraded mode will be registered as (partially) unknown, consequently no distance and trip price will be calculated.

Though, it must be noted that this is applicable on a network level but is less applicable for individual service lines. After all the route length may be long when the route covers large distances in a straight line, but also when the route circles through multiple streets in a relatively small area. Therefore, route length in this model does not necessarily reflect service level (the area covered) but was included as a component of supply of public transport. Moreover, it controls the demand for public transport in terms of passengerkilometres for route distance.

A second element of service quality is service reliability, which was represented in the model by the departure *punctuality* measure. Departure punctuality is expressed as the percentage of vehicles in the schedule which depart "on time", that is; the percentage of vehicles which depart exactly on time or within a range of two minutes from the exact departure time. Punctuality was expected to be positively related to the demand for transport so that a more reliable transport service leads to higher demand. Punctuality was measured per day and the data were derived from the GVB Dashboard Line Management (DBLM) which reports among others on punctuality, productivity and absence of employees.

The first exogenous factor is the *price of petrol.* This measure was included to link the demand for transport to the availability of alternative modes of transport. As fuel prices rise, the use of alternative transport modes such as the car may decline which may increase the demand for public transport. Therefore, fuel prices were expected to be positively related to the demand for public transport. The variable was measured by the price of petrol per day in euros per litre, as registered by Travelcard Nederland BV in the CBS Statline database (CBS, 2013).

Second, weather conditions were included as exogenous factors. These were represented by rainfall and temperature as measured by KNMI's weather station at Amsterdam Schiphol Airport. This is the nearest weather station to the city of Amsterdam. *Rainfall* was measured in millimetres of rain per square meter per hour, and was expected to be positively related to the demand for transport. *Temperature* was measured in degrees Celsius on a height of 1.5 meters during the observation and was measured per hour. This variable was expected to exponentially (parabolic function) related to the demand for public transport (see Section 3.2.2). The data on these variables were derived from KNMI's historical weather database (KNMI, 2013).

4.2.3 Overview of included data

The previous sections discussed the dependent and independent variables included in the dataset. Table 4 provides an overview of the available data for the variables used, their source and their extraction level. In addition, the expected sign of their relation to the demand for public transport are shown. These expectations were based on the academic literature.

Table 4: Variables included in the dataset

	Variable (name)	Description	Source	Level	Sign
Demand for public transport	Boarding passengers *(lnpassengers)*	Number of check ins	GVB Chipcard database[10]	Per service line per hour/per day	
Demand for public transport	Passenger kilometres *(lnpassengerkms)*	Number of passenger kilometres	GVB Chipcard database[10]	Per service line per hour/per day	
Service level (intervals)	Frequency *(lnfrequency)*	Number of scheduled trips per hour	GVB Interval Overview 2012/2013[10]	Per service line Per hour/per day	+
Service level	Route length *(Dlnroutelength)*	Route length (sum of both directions) in kilometres	GVB List of service stops 2012/2013[10]	Per service line Per hour/per day	+
Service level (reliability)	Departure punctuality *(punctuality)*	% of departures on time (0=>x<2 minutes)	GVB Dashboard Line Management (DBLM)[10]	Per service line Per hour/per day	+
Alternative mode of transport	Petrol price *(Dlnpetrolprice)*	Price of petrol per litre in euros	CBS Statline	Per hour/per day	+
Weather conditions	Rainfall *(lnrainfall)*	Rainfall in millimetres per hour	KNMI weather historical database	Per hour/per day	-
Weather conditions	Snowfall *(lnsnowfall)*	Number of hours snowfall per day	KNMI weather historical database	Per day	-
Weather conditions	Temperature *(temperature(2))*	Temperature in degrees Celsius	KNMI weather historical database	Per hour/per day	-[11]

Next to independent variables in Table 4, multiple dummy variables were used in order to capture the effect of the IJtunnel closures on the demand for public transport. In the general model (see Section 4.1) two dummies were included to capture the total effect of closures of the IJtunnel; one for the effect on the IJtunnel service lines and one for the remaining service lines in Amsterdam North. In the specific model four dummies were included which isolate the effect of the IJtunnel closures for March 2013 and other periods for both the IJtunnel lines and other lines in Amsterdam North. In both the general and the specific models a dummy was added to control for the effect of other temporary traffic arrangements for all service lines in the dataset (for a list of all temporary traffic arrangements, see Appendix C)[12]. Finally, time dummies were included to control for time effects as unexpected variation or special events may affect the outcome variable (Torres-Reyna, 2013). That is, time dummies capture the effects for reasons which are not captured in the other independent variables (Wooldridge, 2002, p. 410). Table 5 provides an overview of the included dummy variables.

[10] Internal documentation at GVB Amsterdam.

[11] Note that the demand for public transport with respect to temperature was expected to be a parabolic function which opens downwards. For this relation the estimated coefficient for the quadratic function of temperature requires to be negative. Hence, the negative expected sign does not imply that a negative relation between temperature and demand for public transport is expected.

[12] These other temporary traffic arrangements include only the arrangements of category 2 and 3, as they are expected to affect public transport demand (see Section 2.2.1). Arrangements in lower categories are often only service announcements and do not include changes in timetables. Their effect on passengers is perceived as minimal.

Table 5: Dummy variables included in the models

Dummy type	*Dummy name*	Dummy for	For service lines	Sign
General model				
IJtunnel closure dummy	*dijLtunnel*[13]	All IJtunnel closures	IJtunnellines	-
IJtunnel closure dummy	*dijLadamN*[13]	All IJtunnel closures	Lines in Amsterdam North	+
Specific model for March 2013				
IJtunnel closure dummy	*dijLtunnelm13*[13]	IJtunnel closures March 2013	IJtunnellines	-
IJtunnel closure dummy	*dijLtunnelother*[13]	Other IJtunnel closures	IJtunnellines	-
IJtunnel closure dummy	*dijLadamNm13*[13]	IJtunnel closures March 2013	Lines in Amsterdam North	+
IJtunnel closure dummy	*dijLadamNother*[13]	Other IJtunnel closures	Lines in Amsterdam North	+
All models				
Temporary traffic arrangements dummy	*dttaother*	Other temporary traffic arrangements	All service lines	-
Time dummy	*dyear12*	Yearly variation		
Time dummy	*djan, dfeb, dmar, dapr, dmay, djun, djul, daug, dsep, doct, dnov, ddec*	Monthly variation		
Time dummy	*dmonday, dtuesday, dwednesday, dthursday, dfriday, dsaturday, dsunday*	Daily variation		

4.3 Final models

The demand for public transport was modelled based on the variables described in the previous section. However, in order to specify the final models the functional form of the models should be addressed. According to Balcombe et al. (2004) there is no consensus among researchers to either the functional form of the model or the variables which should be included to obtain the best explanation of demand. Empirical analysis and testing different model specifications should lead to the optimal model specification.

One argument to use a log-linear model is the ease of interpretation, as the estimated parameters can be interpreted as constant elasticities. With respect to modelling the demand for public transport, the use of arc-elasticities is commonly preferred over linear elasticities. The former assumes the demand function to be convex, while the latter assumes it to be linear. According to Balcombe et al. (2004) there is empirical evidence that the demand functions are indeed convex, so that linear elasticities are likely to give unrealistic predictions. Second, log transforming data is useful when there are large differences in the magnitudes of the numbers the

[13] With respect to the dummy names, *d* refers to dummy, *ij* refers to IJtunnelclosure, *L* refers to type of line (*tunnel*: IJtunnel service lines or *adamN*: lines in Amsterdam North), *m13* refers to the specific IJtunnelclosures in March 2013, other refers to other IJtunnel closures than in March 2013.

data takes on (University of Maryland, 2010). Third, log transformations lead to constant variances of variables so that potential heteroskedasticity problems are reduced (University of Southern California, 2013). Another advantage is that the difference in logs approximates the growth rate. For these reasons, the dependent variables in this research were expressed in the form of a natural logarithm. The independent variables were also log transformed, except for variables which took on negative values (the logarithm of a negative number does not exist) or variables which were expressed as ratios.

Considering the functional form and the discussed variables, the final (general) model estimated was:

$$
\begin{aligned}
&lnpassengers_{it}\, and\ lnpassengerkms_{it} \\
&\quad = \hat{\beta}_0 + \hat{\beta}_1 lnfrequency_{it} + \hat{\beta}_2 Dlnroutelength_{it} + \hat{\beta}_3 punctuality_{it} + \hat{\beta}_4 Dlnpetrolprice_{it} \\
&\quad + \hat{\beta}_5 lnrainfall_{it} + \hat{\beta}_6 lnsnowfall_{it} + \hat{\beta}_7 temperature_{it} + \hat{\beta}_8 temperature_{it}^2 \\
&\quad + \hat{\beta}_9 dijLtunnel_{it} + \hat{\beta}_{10} dijLadamN_{it} + \hat{\beta}_{11} dothertta_{it} + \delta_t timedummies + \alpha_i + u_{it}
\end{aligned}
$$

The specific model which isolated the effect of the IJtunnel closures in March 2013 from other IJtunnel closures was reflected by:

$$
\begin{aligned}
&lnpassengers_{it}\, and\ lnpassengerkms_{it} \\
&\quad = \hat{\beta}_0 + \hat{\beta}_1 lnfrequency_{it} + \hat{\beta}_2 Dlnroutelength_{it} + \hat{\beta}_3 punctuality_{it} + \hat{\beta}_4 Dlnpetrolprice_{it} \\
&\quad + \hat{\beta}_5 lnrainfall_{it} + \hat{\beta}_6 lnsnowfall_{it} + \hat{\beta}_7 temperature_{it} + \hat{\beta}_8 temperature_{it}^2 \\
&\quad + \hat{\beta}_9 dijLtunnelm13_{it} + \hat{\beta}_{10} dijLtunnelother_{it} + \hat{\beta}_{11} dijLadamNm13_{it} \\
&\quad + \hat{\beta}_{12} dijLadamNother_{it} + \hat{\beta}_{13} dothertta_{it} + \delta_t timedummies + \alpha_i + u_{it}
\end{aligned}
$$

In these formulas, *ln* indicates a log-transformed variable, *Dln* indicates the first difference of a log-transformed variable (the reason for this is explained in Section 4.4.2) and *d* indicates dummy variables. In addition, the subscript *i* represents the individual (service line) dimension of the panel data and subscript *t* indicates the time dimension. Since *i* denotes the different service lines, α_i reflects the unobserved service line effect. That is, it represents all factors affecting the number of passenger(kilometre)s that do not change over time. u_{it} is the often called idiosyncratic error (time-varying error) as it represents the unobserved factors that change over time and affect the number of passenger(kilometre)s (Wooldridge, 2002, p.420).

4.4 Methodology

As discussed this research used panel data in order to capture the impact of the IJtunnel closures on the demand for public transport. The use of panel data has multiple advantages. Panel data contains multiple observations over time for the same units (service lines). This allows to control for unobserved characteristics of these service lines that affect the outcome variables (that is, it can control for omitted variables). In addition, panel data can facilitate causal inference and can be used to study the results of policy making (Wooldridge, 2002, p.13). Panel data analysis provides the possibility to observe dynamic behaviour as it includes a temporal effect which is crucial for accurate forecasts of demand (Zureiqat, 2008). Finally, panel data increases the sample size compared to single cross-sectional data or time-series data, which leads to more precise estimates and test statistics with more power (Wooldridge, 2002, p.409).

4.4.1 Model estimation technique

Although panel data provides multiple advantages, Ordinary Least Squares estimation leads to incorrect results as it ignores the panel structure of the data. Two alternative estimation techniques can be applied to panel data, the fixed effects estimation technique and the random effects technique. The fixed effects estimation explores the relation between predictor and outcome variables within an entity or individual (Torres-Reyna, 2013). In this research, the entity dimension was reflected by the service lines so that fixed effects estimation concentrates on differences "within" service lines over time. Fixed effects assumes that the individual (service line) unobserved effects are correlated with the independent variables. Time-invariant variables are constant and perfectly collinear with the service line, so that time-invariant variables are eliminated by the within transformation: its impact will be subsumed by the fixed effects (Verbeek, 2008). Random effects estimation combines variation within and between service lines, so that the variation across service lines is assumed to be random and uncorrelated with the predictor or independent variables included in the model (Torres-Reyna, 2013). That is, the random effects estimator is appropriate when the individual (service line) unobserved effect is thought to be uncorrelated with all the explanatory variables (Wooldridge, 2002, p. 455). Contrary to fixed effects estimation, random effects do allow time-invariant variables to be included in the model. The most important difference between fixed effects and random effects estimation is thus that fixed effects allow for correlation between the unobserved effect and the explanatory variables, whereas random effects does not.

As this research mainly focused on changes over time within service lines, it was expected that fixed effect estimation was more appropriate in this research. Moreover the time period available for this analysis was only 18 months, so that some variables were likely to be time-invariant. Fixed effects estimation would capture these time invariant factors. A Hausman test was performed to determine whether fixed effects were indeed more appropriate (see Appendix D). Except for one model, fixed effects estimation was preferred for all models. Therefore this research followed a more conservative approach in which it was assumed that the unobserved effect is correlated with the explanatory variables (ANU, 2009), so that fixed effects estimation was used for all models. This also allowed for a more consistent comparison of the models. The assumptions for fixed effects estimation are discussed in Appendix E.

4.4.2 Tests on the dataset

Missing values

Before quantifying the model, the dataset was analysed for missing values. For departure punctuality, 1.83% of the observations (7,483 out of 409,667) were missing. This may be due to the fact that the EBS system (from which the data was derived) did not register punctuality as a consequence of technical errors. For example, when a failure in the vehicle's GPS system occurs or when EBS' servers do not function properly, punctuality is not registered. Next to technical errors, non-registered punctuality may also occur during temporary diversions. This occurs when the adapted route and service schedule is not loaded properly onto the bus/tram's registration systems. For the panel data analysis this implies that when no observations for punctuality were present, these observations were not used in the estimated models. As punctuality is an important factor for the demand for public transport, missing data were corrected by mean imputation. For this panel dataset, this implies that the mean value of punctuality was calculated per month for each service line separately. Mean punctuality was imputed for all missing observations, except for days on which special events occurred such as Queensday 2012 and 2013 or during the Amsterdam Marathon 2012. Data on punctuality for these latter events are likely to be outliers, as the crowdedness in the city is expected to (negatively) affect punctuality.

With respect to the number of passengerkilometres, registration errors in the data occurred during two days of the IJtunnel closures. As the registered number of passengerkilometres had a value equal to zero, this would imply an overestimation of the actual effect of the IJtunnel closure. In order to avoid this bias, these specific observations were eliminated from the dataset.

Test for multicollinearity

The included variables in the dataset were tested for perfect multicollinearity, which refers to an exact linear relationship between independent variables (Wooldridge, 2002). As a consequence of multicollinearity, standard errors may be large and t-statistics tend to be small, which may lead to wrong inference of results. In addition, multicollinearity may result in incorrect signs or insignificance for theoretically important variables.

The correlation table in Appendix F shows that there was no perfect collinearity (that is; none of the correlation coefficients in the table was equal to 1) between any of the included variables in the dataset. Though, some variables showed a relatively high correlation, which implies that the variables share (to some extent) similar information and have the same explanatory power. This forms a risk for multicollinearity problems. The correlation coefficient between the number of boarding passengers and passenger kilometres was equal to 0.9173. This is not surprising, as the number of passenger kilometres is a function of the number of boarding passengers. However, this did not cause any problems as these variables were not included in the same model, after all they are dependent variables which were used in separate models. The variable frequency was highly correlated to both the number of boarding passengers (0.8274) and the number of passenger kilometres (0.8625). As frequency is a measure of the supply of transport, this high correlation can be explained by the two-way relationship between the demand for transport and the supply of transport (see Section 3.2.1 under service quality). Even though frequency may cause multicollinearity problems, the variable was included in the models as it is an important determinant for the demand for transport.

Test for non-stationarity

Since panel data includes a time dimension, the data were tested for non-stationarity. A non-stationary time series is one whose statistical properties such as mean, variance and autocorrelation are not constant over time (Duke University, 2005). Using non-stationary time series in a regression model leads to the problem of spurious results. This implies that a significant relationship may be obtained between variables which actually are unrelated (Humboldt University Berlin, no date). Using non-stationary data for modelling or forecasting purposes can lead to spurious results. An often used solution for this problem is to transform the data into stationary data by first-differencing (Duke University, no date). The first-difference of the process is often stationary (Wooldridge, 2002, p.363).

An Augmented Dickey-Fuller unit-root test was performed on each panel within the dataset. This test includes a number of lags and the option of a time trend. As no lag length selection criteria for daily data was available in the literature, the test was performed for both one and two lags. In addition, the test can include a linear time trend in the model which describes the process by which the time series develops. All variables were tested both with and without a time trend. The results from these test specifications were similar and are shown in Appendix G. The variables *petrol price* and *route length* had non-stationary properties (contained a unit root) in all tests. In order to eliminate potential spurious regression problems, the data on these variables were transformed into stationary data by taking first differences. In the final model formulas in Section 4.3 this is indicated by the letter D.

Test for heteroskedasticity and autocorrelation

The estimated models were tested for heteroskedasticity and serial (auto)correlation. Heteroskedasticity implies that the variance of the error term is the not the same regardless of the values of the independent variables. Serial correlation occurs in time-series when the error terms are correlated to the error terms of the previous period. As a consequence of heteroskedasticity and serial correlation the standard errors of the estimated parameters are incorrect, so that t-statistics and confidence intervals are no longer valid. This may lead to wrong inference. As it appears from the Wald test for groupwise heteroskedasticty in Appendix H, heteroskedasticity was apparent in the estimated models. In order to check for serial correlation the Wooldridge test for autocorrelation in panel data was performed (see Appendix H). This test showed that there was serial correlation in the error terms. As both heteroskedasticity and serial correlation were apparent, serial correlation robust standard errors were used to correct for both these problems.

4.5 Descriptive statistics

The dependent variables in the original dataset contained 409,667 half-hourly observations for twenty service lines (N=20). These observations were aggregated to a daily level, which leaves 10,887 observations daily observations in the dataset. On average the dataset contained 544 observations per service line. As the number of service lines *N* was smaller than the number of time periods *T* (*N < T),* the dataset had the form of a long panel (Kim, 2012). However the dataset was unbalanced as each service line had a different number of observations over time. Table 6 shows the descriptive statistics of the daily dataset, after which these observations will be discussed for each variable separately.

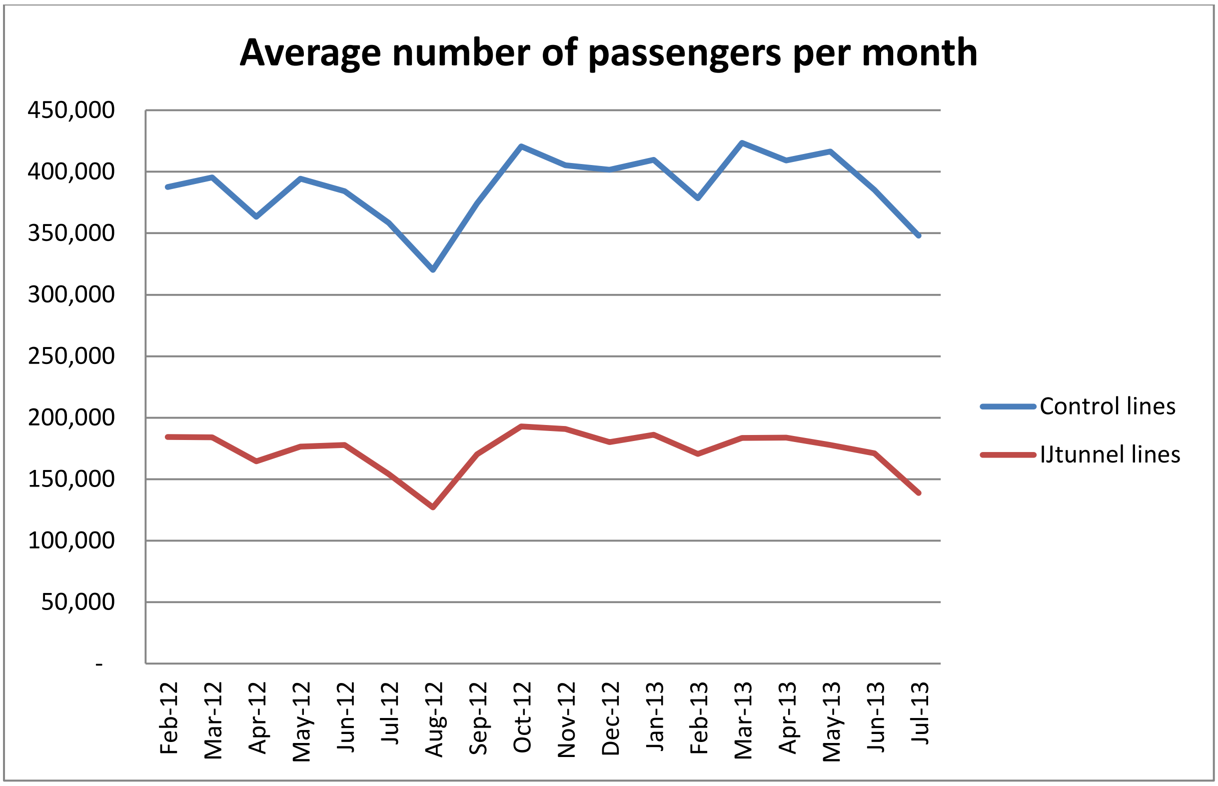
Table 6: Descriptive statistics of the dataset

Variable		**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
Passengers	overall	11396.69	7923.767	53	39933	N = 10887
	between		7502.195	1495.55	28840.85	n = 20
	within		3046.434	-7381.16	22488.84	T-bar = 544.35
Passengerkilometers	overall	33749.66	22100.27	0	108807	N = 10887
	between		20664.62	6173.746	79413.58	n = 20
	within		9101.854	-25524.5	63143.68	T-bar = 544.35
Frequency	overall	5.667135	1.610809	1.878788	10.8	N = 10887
	between		1.501194	3.142362	9.339713	n = 20
	within		0.675217	3.127423	7.127423	T-bar = 544.35
Route length	overall	19.68789	5.710265	11.936	39.289	N = 10887
	between		5.851148	12.52929	39.27495	n = 20
	within		0.241595	18.53218	20.42018	T-bar = 544.35
Punctuality	overall	0.844977	0.087737	0	1	N = 10874
	between		0.037977	0.76357	0.911277	n = 20
	within		0.07955	-0.03692	1.081407	T-bar = 543.7
Petrol price	overall	1.75841	0.0349	1.695	1.83	N = 10887
	between		5.61E-05	1.758368	1.758622	n = 20
	within		0.0349	1.694788	1.830042	T-bar = 544.35
Rainfall	overall	3.323569	6.849571	0	54.4	N = 10887
	between		0.065502	3.208624	3.475229	n = 20
	within		6.849273	-0.15166	54.51495	T-bar = 544.35
Snowfall	overall	0.516212	2.203143	0	19	N = 10887
	between		0.001082	0.515596	0.519409	n = 20
	within		2.203143	-0.0032	19.00062	T-bar = 544.35
Temperature	overall	10.56175	6.845665	-10.1421	27	N = 10887
	between		0.104782	10.13641	10.63941	n = 20
	within		6.844902	-10.1637	26.96599	T-bar = 544.35

4.5.1 Dependent variables

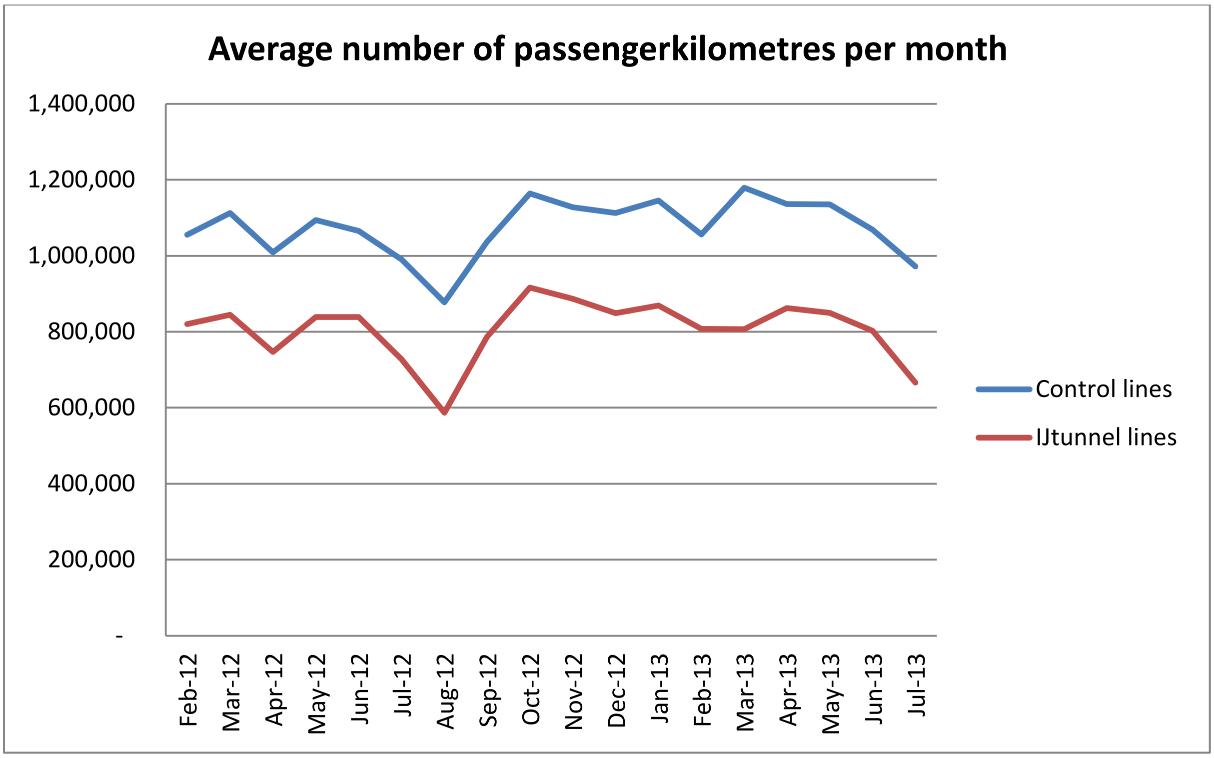
Table 6 showed the descriptive statistics for among others the dependent variables in this research. From the table it can be derived that on average, the service lines in the dataset had an average number of 11,396 boarding passengers and 33,750 passenger kilometres per line per day. In order for the dataset to be a representative sample, the included service lines should provide a good reflection of the public transport network. With respect to the dependent variables, Graph 3 and 4 show the development of the average number of boarding passengers and passengerkilometres per month over time for both the control lines and the IJtunnel service lines included in the dataset.

Graph 3: Development of the average number of passengers per month over time



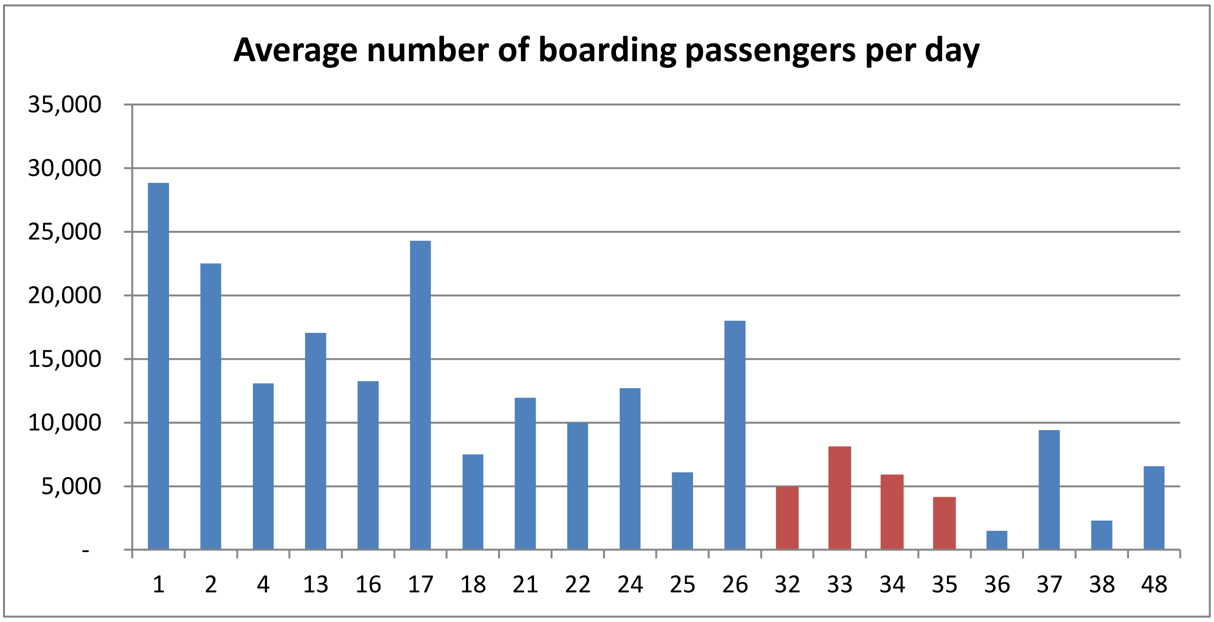
In both Graph 3 and 4 the number of passenger(kilometre)s follow a similar pattern for the IJtunnel service lines and the control lines. However, the average values of the passenger(kilometre)s were higher for the control lines than for the IJtunnel service lines. This occurs as the control lines include service lines with higher levels of public transport patronage (this will be discussed later, see Graph 5 and 6). When Graph 3 and 4 are compared, a similar pattern can be observed over time for the number of boarding passengers and the number of passenger kilometres. This is not surprising as the number of passenger kilometres is a function of the number of passengers. Therefore the absolute values of the number of passenger kilometres were higher than the number of passengers. As the graphs show, the number of passenger(kilometre)s fluctuates per month. For example, October 2012 and March 2013 show the highest values and August 2012 the lowest values. The latter can be explained by the summer holidays, in which an adjusted summer timetable was implemented.

Graph 4: Development of the average number of passenger kilometres per month over time



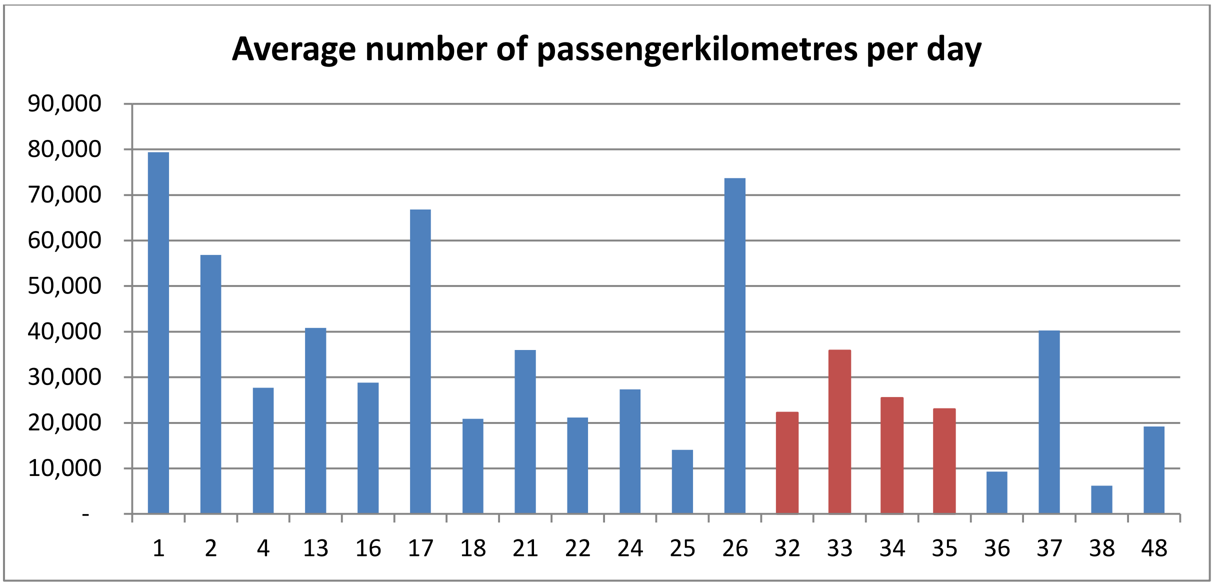
Next to variation over time, the passenger(kilometre)s differ between service lines. Graph 5 and Graph 6 show the average number of boarding passengers and passenger kilometres respectively per day for each service line separately, where the four IJtunnel servicelines are shown in red. As the average number of passengers and passengerkilometres for the IJtunnel service lines per day were 5,715 and 26,617 respectively, the passenger flows on these lines were below the average of the complete sample[14].

Graph 5: Average number of passengers per day for each service line in the dataset



[14] For the descriptive statistics of the IJtunnel service lines in particular, see Appendix I.

Graph 6: Average number of passengerkilometres per day for each service line in the dataset



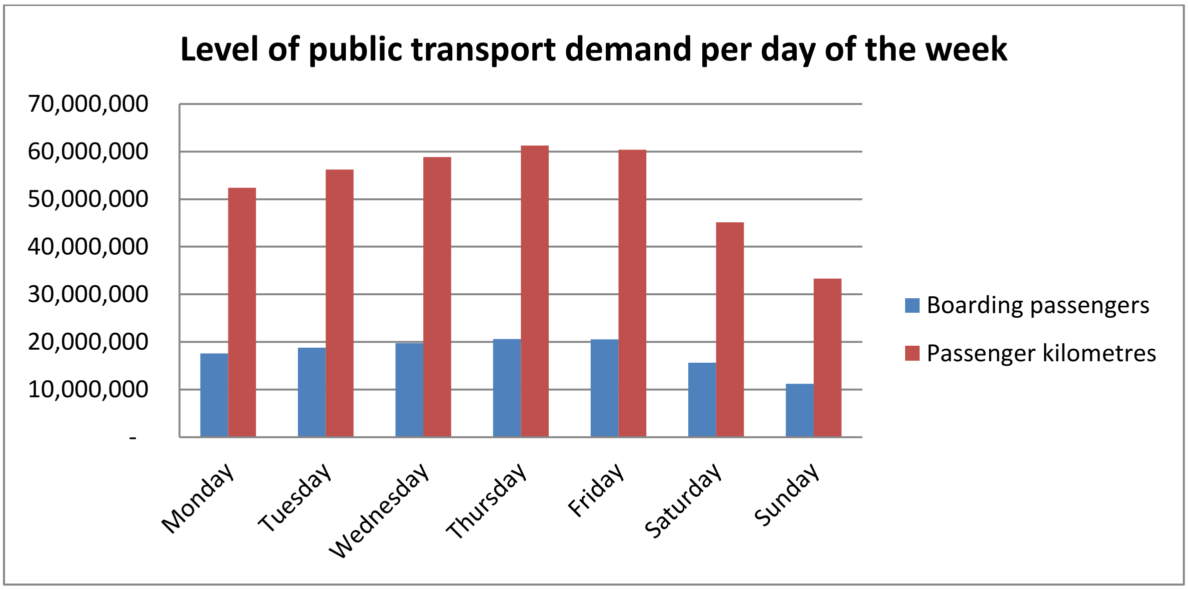
Graph 5 and 6 show the two measures for the demand for transport for each service line separately[15]. Line 1, 17 and 26 appear to transport the largest passenger flows. The absolute number of passenger(kilometre)s for these lines were relatively high compared to the IJtunnel service lines and could therefore be seen as outliers. Even though the presence of outliers can lead to inflated errors and distorted parameter estimates, there is no conformity on whether outliers should be removed from the sample. When the data points are legitimate the data are more likely to be a representative of the population (GVB's public transport network) as a whole if outliers are not removed (Osborne and Overbay, 2004). For this reason, and for the fact that removal of these three service lines leads to a substantial loss of observations, the data for these lines were preserved in the dataset. Graph 5 and 6 also show that the service lines 36 and 38 (two out of the three remaining service lines in Amsterdam North) transport the smallest passenger flows. These differences in passenger(kilometre)s between lines are also shown in Table 6, where the between variation was equal to 7,502 boarding passengers and 20,664 passenger kilometres per day. The variation within service lines was smaller than the between variation, and was equal to 3,046 passengers and 9,100 passenger kilometres per day.

Distinction between days of the week

Next to differences in the demand for transport per month as shown in Graph 3 and 4, there is also a difference in the demand for transport per day of the week. These differences are visualized in Graph 7 (on the next page), which shows the number of boarding passengers per day of the week. From the graph it can be derived that both the number of passenger(kilometre)s were highest on Wednesdays, Thursdays and Fridays. The lowest levels of public transport occurred on Saturdays and Sundays, so that the passenger flows were larger during the weekdays compared to the weekends.

[15] For a description of origins and destinations of these lines, see Appendix B.

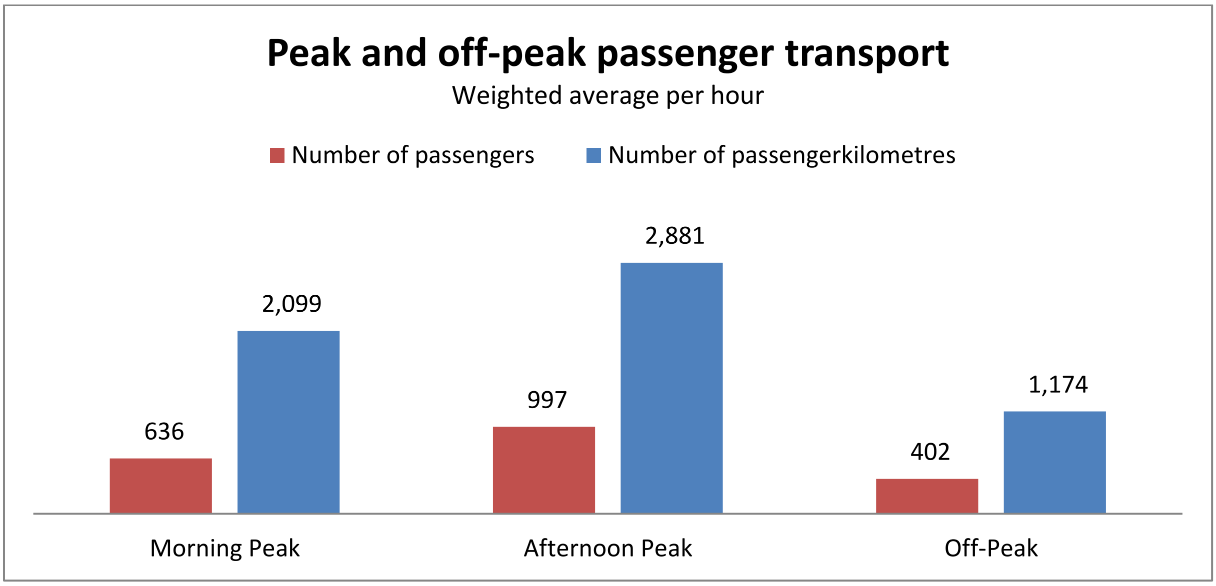
Graph 7: Level of public transport per day of the week



Distinction between Peak and Off-Peak hours

Next to the analysis per day, the models were estimated separately for peak and off-peak hours. The morning peak was defined as the period between 7 am and 9 am, whereas the afternoon peak hours were defined between 4.30 pm and 6 pm. The remaining time period was then defined as off-peak hours. Graph 8 shows the proportions of passengers in peak and off-peak hours on average per day. As the duration of the peak and off-peak hours differ this is shown as a weighted average per hour.

Graph 8: Passenger transport in peak and off-peak hours, weighted average per hour



Graph 8 shows that passenger transport per hour was most concentrated in the afternoon peak. On average per hour 997 passengers were transported, compared to 636 passenger per hour in the morning peak and 402 passengers per hour in off-peak periods. This implies that passenger transport per hour in the afternoon peak was more than twice the size of passenger transport in off-peak periods. The number of passengerkilometres showed similar proportions. On average 2,881 passengerkilometres per hour were covered in the afternoon peak, whereas the number of passengerkilometres per hour was lowest during off-peak hours. A possible explanation for the observed proportions of passenger transport in peak and off-peak hours may be derived from the types of travellers and travel purposes. During the morning peak public transport is mostly used by passengers going to school or work, whereas travellers for leisure purposes usually travel later during the day in the off-peak hours. In the afternoon peak both types of passengers may be combined as workers and leisure travellers both return to their homes, so that passenger transport per hour is more concentrated during the afternoon peak.

4.5.2 Independent variables

Next to information on the dependent variables, Table 6 (on page 37) shows the descriptive statistics for the explanatory variables on the network level. When these descriptive statistics on the network level are compared to the descriptive statistics of the IJtunnel service lines in particular (as shown in Appendix I) it can be concluded that the average punctuality of the IJtunnel lines was lower compared to punctuality on the network level. The average punctuality of the IJtunnel service lines shows that on average 80,7% of the departures were on time, whereas the average punctuality on the network level was 84,49%. The overall variation of punctuality was relatively small so that the fluctuation of average from the mean was only minimal. The variation over time (within service lines) was 7,95% on the network level whereas the variation between service lines was only 3,79%.

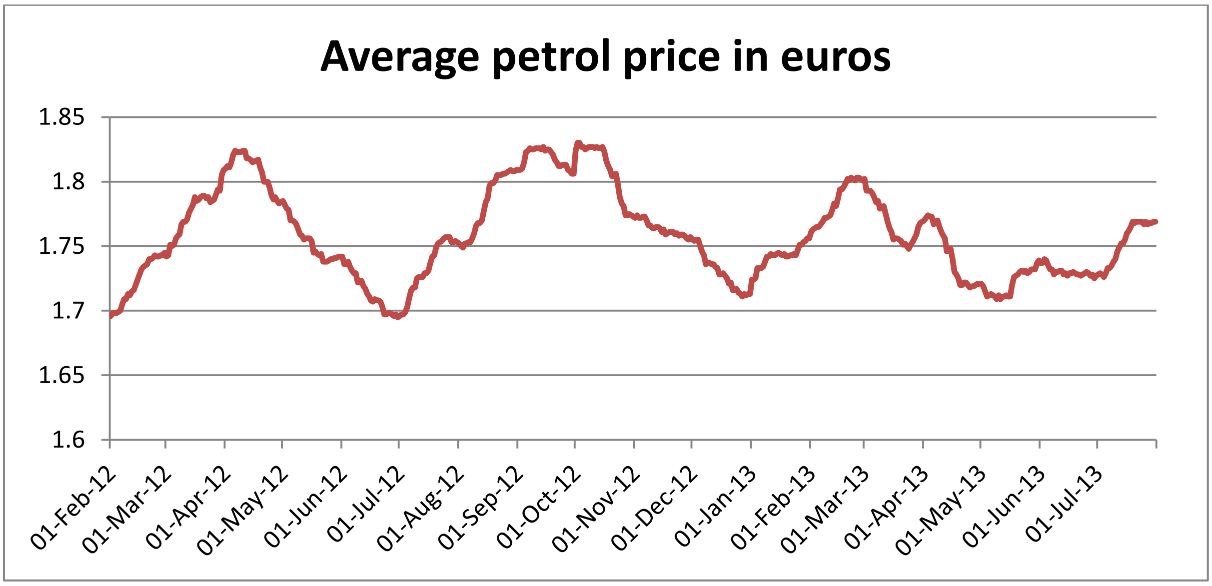
With respect to frequency, Table 6 (on page 37) shows that the average frequency for all the service lines in the dataset was equal to 5.6 scheduled trips per hour, which is exactly equal to the average frequency of the IJtunnel service lines (see Appendix I). However, frequency depends on the time of day (peak/off-peak hours), day of the week and even per month (during summer vacations the frequencies on some service lines are adjusted downwards). Next to the variation over time, frequency differs between service lines as passenger flows (and therefore the required frequencies) are larger on one line compared to the other. According to the descriptive statistics this between variation on the network level was equal to 1.5 scheduled trips per hour. Within service lines frequency changes as peak-hours require a higher frequency compared to off-peak hours and early mornings and late evenings require fewer trips per hour than time periods during the day. This within variation was equal to 0.676 trips per hour on average for all service lines (see Table 6 on page 37).

The average route length of the service lines in the dataset was equal to 19.68 kilometres. From the descriptive statistics it can be derived that the variation of route length between service lines in the dataset was larger compared to the within variation. The small within variation could be explained as the route length of a service line only changes once a year when the new timetable is implemented. Though there was a large difference of route lengths between the service lines in the dataset. The average route length of the IJtunnel service lines was equal to 18.7 kilometres, which is a little lower compared to the total average of the dataset (see Appendix I).

The described descriptive statistics for the dependent and endogenous variables thus vary for different service lines. In summary, the level of public transport on the IJtunnel service lines was relatively small compared to other GVB service lines included in the dataset. Though, the pattern of the number of passenger(kilometre)s over time appeared to be similar for these lines compared to the control lines. Punctuality and the average route length for the IJtunnel service lines were lower compared to the average of the sample whereas frequency of the IJtunnel lines was exactly equal to the dataset's average.

Finally with respect to the exogenous variables, the average temperature at the weather station of Amsterdam Schiphol Airport was equal to 10.5 degrees Celsius, whereas the average rainfall per hour was 3.32 millimetres. Snow was expected to affect the demand for public transport as well. On 45 out of the 547 days in the dataset snowfall was observed, with a maximum of 19 hours a day. In particular, snow fell during two of the five weekends in March 2013 in which the IJtunnel was closed. More specifically, on March 10th 2013 and March 30th 2013 snowfall was relatively intense as it was observed for 10 and 9 hours a day respectively. The final explanatory variable which cannot be influenced by the transport operator is the price of petrol. The average price of petrol between February 1st 2012 and July 31st 2013 was equal to 1,758 euros per litre. Graph 9 shows the development of the petrol price over time.

Graph 9: Average petrol price per litre in euros



Graph 9 shows that the price of petrol fluctuates over time around its mean. As discussed in Section 4.4.2 this variable had non-stationary properties so that this variable could cause problems of spurious regression. Therefore this variable was included by using the first-difference.

In summary, this chapter presented the models used to analyse the effect of the IJtunnel closures on the demand for public transport. Moreover, the data and methodology used for this analysis were discussed and descriptive statistics of the data were described. In the next chapter the results of the analysis will be reported.

5. Results

In order to estimate the impact of the temporary traffic arrangements for the IJtunnel closures, the conceptual model on the demand for transport was applied to the dataset as described in Chapter 4. The models were estimated on a daily basis and for the morning peak, afternoon peak and off-peak periods in particular. In this chapter the results from the analysis will be presented. It is important to note that these results are all addressed under the Ceteris Paribus assumption (that is, “other (relevant) factors being equal” (Wooldridge, 2002, p.13)). The results of the models estimated for the number of passengers will be discussed in Section 5.1 and for the number of passengerkilometres in Section 5.2. The findings will be summarized in Section 5.3.

5.1 Models on the number of passengers

The results of the analysis are presented in Table 7 (on the next page). The total effect of the IJtunnel closures on the number of passengers estimated by the general model are shown in the four columns on the left side of the table. The specific model which isolates the specific effect of the IJtunnel closures in March 2013 from other IJtunnel closures are shown in the four columns on the right side of the table. Each model was estimated for an average day and for peak- and off-peak hours in particular. The bold figures in the table indicate significant effects at the 5% significance level.

The effect of the IJtunnel closures were captured by the included dummies which are listed at the bottom of Table 7. The closures were associated with a significant decline of the number of passengers on the IJtunnel service lines, except for during the morning peak hours. The percentage effects of the IJtunnel closures are presented in Table 8. Based on the analysis per day, the IJtunnel closures were associated with an 18,4% decline in the number of passengers on the IJtunnel service lines. This effect was larger during off-peak periods (19,4% less passengers) compared to the afternoon peak hours (13,6% less passengers). In addition to the effect on the IJtunnel service lines, the closures had a positive effect on the number of passengers on the service lines in Amsterdam North (except for in the morning peak), though this effect was not significant.

Table 8: Percentage effect of the IJtunnel closures on the number of passengers[16]

Effect of IJtunnel closure on:	**Analysis per day**	**Morning peak**	**Afternoon peak**	**Off-peak**
IJtunnel service lines (total)	**-18.37 %**	-5.26 %	**-13.58 %**	**-19.35 %**
- for IJtunnel closures in March 2013	**-21.10 %**	-12.54 %	**-15.80 %**	**-22.04 %**
- for other closures	**-14.87 %**	4.39 %	**-10.86 %**	**-15.80 %**
Other service lines in Amsterdam North (total)	8.55 %	-6.57 %	2.53 %	9.64 %
- for IJtunnel closures in March 2013	12.98 %	-9.88 %	1.31 %	14.68 %
- for other closures	2.63 %	-2.27 %	3.98 %	3.05 %

Printed in **bold** = significant at a 5% significance level

[16] Note: these percentages were calculated by the formula: $100 * [\exp(\hat{\beta}) - 1]$ (Wooldridge, 2002, p. 219).

Table 7: Models on the number of passengers

	Analysis per day	Morning peak	Afternoon peak	Off-peak	Analysis per day	Morning peak	Afternoon peak	Off-peak
log Frequency *(departures per hour)*	**1.317 (0.131)**	**0.733 (0.153)**	**0.776 (0.144)**	**1.212 (0.110)**	**1.319 (0.132)**	**0.731 (0.153)**	**0.776 (0.145)**	**1.215 (0.111)**
Δ log Route length *(in kilometres)*	**7.309 (0.810)**	**25.895 (2.745)**	**5.938 (0.944)**	**6.052 (0.614)**	**7.309 (0.808)**	**25.883 (2.743)**	**5.934 (0.943)**	**6.052 (0.613)**
Punctuality *(% departures on time)*	**0.143 (0.036)**	**0.350 (0.058)**	**0.161 (0.044)**	**0.130 (0.035)**	**0.143 (0.036)**	**0.352 (0.059)**	**0.162 (0.044)**	**0.129 (0.036)**
Δ log Petrol price *(in euros per litre)*	0.685 (0.609)	-0.619 (1.099)	-1.254 (1.114)	0.673 (0.606)	0.688 (0.605)	-0.744 (1.109)	-1.290 (1.109)	0.679 (0.607)
log Rainfall *(in millimetres)*	**0.008 (0.002)**	**0.088 (0.006)**	**-0.024 (0.008)**	**0.007 (0.002)**	**0.008 (0.002)**	**0.088 (0.006)**	**-0.024 (0.008)**	**0.007 (0.002)**
log Snowfall *(number of hours per day)*	0.005 (0.002)	**0.051 (0.004)**	-0.001 (0.003)	0.001 (0.002)	0.005 (0.002)	**0.052 (0.004)**	-0.001 (0.003)	0.001 (0.002)
Temperature *(in degrees Celsius)*	**-0.007 (0.001)**	**-0.013 (0.001)**	**-0.003 (0.001)**	**-0.006 (0.001)**	**-0.007 (0.001)**	**-0.013 (0.001)**	**-0.004 (0.001)**	**-0.006 (0.001)**
Temperature^2 *(in degrees Celsius)*	0.000 (0.000)	**0.000 (0.000)**	**-0.000 (0.000)**	0.000 (0.000)	0.000 (0.000)	**0.000 (0.000)**	**-0.000 (0.000)**	0.000 (0.000)
dummy Year12	-0.023 (0.015)	0.021 (0.015)	-0.003 (0.014)	-0.029 (0.015)	-0.023 (0.015)	0.020 (0.015)	-0.003 (0.014)	-0.029 (0.015)
dummy February	**0.055 (0.004)**	**0.089 (0.010)**	**0.025 (0.007)**	**0.056 (0.004)**	**0.055 (0.004)**	**0.090 (0.010)**	**0.025 (0.007)**	**0.056 (0.004)**
dummy March	**0.078 (0.007)**	**0.153 (0.013)**	**0.020 (0.010)**	**0.076 (0.008)**	**0.078 (0.007)**	**0.157 (0.014)**	**0.022 (0.011)**	**0.076 (0.008)**
dummy April	**0.110 (0.010)**	**0.106 (0.010)**	**0.032 (0.011)**	**0.120 (0.010)**	**0.110 (0.010)**	**0.107 (0.010)**	**0.032 (0.011)**	**0.120 (0.010)**
dummy May	**0.076 (0.013)**	**0.050 (0.018)**	0.014 (0.013)	**0.089 (0.014)**	**0.076 (0.013)**	**0.051 (0.018)**	0.014 (0.013)	**0.089 (0.014)**
dummy June	**0.122 (0.011)**	**0.219 (0.015)**	**0.050 (0.012)**	**0.120 (0.011)**	**0.122 (0.011)**	**0.220 (0.015)**	**0.050 (0.012)**	**0.120 (0.011)**
dummy July	**0.123 (0.025)**	0.040 (0.037)	0.034 (0.034)	**0.119 (0.022)**	**0.123 (0.025)**	0.040 (0.037)	0.035 (0.033)	**0.119 (0.022)**
dummy August	0.074 (0.040)	-0.052 (0.052)	0.017 (0.047)	0.067 (0.037)	0.075 (0.040)	-0.053 (0.052)	0.016 (0.047)	0.067 (0.037)
dummy September	**0.072 (0.033)**	**0.232 (0.020)**	-0.009 (0.051)	0.054 (0.038)	**0.072 (0.033)**	**0.232 (0.020)**	-0.009 (0.051)	0.055 (0.038)
dummy October	**0.102 (0.027)**	**0.184 (0.019)**	0.048 (0.042)	**0.097 (0.031)**	**0.103 (0.028)**	**0.186 (0.019)**	0.048 (0.042)	**0.097 (0.031)**
dummy November	**0.111 (0.014)**	**0.235 (0.020)**	**0.070 (0.019)**	**0.098 (0.014)**	**0.111 (0.015)**	**0.235 (0.020)**	**0.070 (0.019)**	**0.099 (0.014)**
dummy December	0.031 (0.017)	**-0.146 (0.016)**	0.011 (0.021)	**0.053 (0.017)**	0.032 (0.017)	**-0.145 (0.016)**	0.012 (0.021)	**0.054 (0.017)**
dummy monday	**0.221 (0.028)**	**1.615 (0.095)**	**0.388 (0.034)**	**0.167 (0.028)**	**0.220 (0.028)**	**1.617 (0.095)**	**0.388 (0.035)**	**0.166 (0.028)**
dummy tuesday	**0.297 (0.030)**	**1.729 (0.096)**	**0.425 (0.034)**	**0.240 (0.030)**	**0.297 (0.030)**	**1.730 (0.096)**	**0.425 (0.034)**	**0.239 (0.030)**
dummy wednesday	**0.324 (0.030)**	**1.725 (0.098)**	**0.441 (0.033)**	**0.277 (0.029)**	**0.324 (0.030)**	**1.727 (0.098)**	**0.441 (0.033)**	**0.277 (0.029)**
dummy thursday	**0.364 (0.029)**	**1.746 (0.097)**	**0.474 (0.034)**	**0.323 (0.027)**	**0.364 (0.030)**	**1.747 (0.097)**	**0.474 (0.034)**	**0.323 (0.028)**
dummy friday	**0.353 (0.030)**	**1.643 (0.098)**	**0.408 (0.035)**	**0.337 (0.026)**	**0.352 (0.031)**	**1.644 (0.098)**	**0.408 (0.035)**	**0.337 (0.027)**
dummy saturday	**0.209 (0.022)**	**0.625 (0.032)**	**0.158 (0.037)**	**0.213 (0.020)**	**0.209 (0.022)**	**0.625 (0.032)**	**0.158 (0.037)**	**0.213 (0.021)**
dummy other temporary traffic arrangements	-0.015 (0.032)	-0.056 (0.042)	-0.022 (0.036)	-0.007 (0.031)	-0.015 (0.032)	-0.057 (0.042)	-0.022 (0.036)	-0.008 (0.031)
dummy IJtunnel service lines (total)	**-0.203 (0.038)**	-0.054 (0.051)	**-0.146 (0.046)**	**-0.215 (0.043)**				
dummy service lines Amsterdam North (total)	0.082 (0.072)	-0.068 (0.112)	0.025 (0.071)	0.092 (0.084)				
dummy IJtunnel service lines (March 2013)					**-0.237 (0.044)**	-0.134 (0.066)	**-0.172 (0.050)**	**-0.249 (0.052)**
dummy IJtunnel service lines (other)					**-0.161 (0.040)**	0.043 (0.062)	**-0.115 (0.047)**	**-0.172 (0.042)**
dummy service lines Amsterdam North (March 2013)					0.122 (0.079)	-0.104 (0.104)	0.013 (0.058)	0.137 (0.094)
dummy service lines Amsterdam North (other)					0.026 (0.071)	-0.023 (0.125)	0.039 (0.096)	0.030 (0.075)
constant	**6.450 (0.210)**	**3.691 (0.238)**	**5.143 (0.272)**	**6.431 (0.179)**	**6.448 (0.212)**	**3.692 (0.238)**	**5.144 (0.273)**	**6.427 (0.180)**
Number of observations	*10823*	*10779*	*10816*	*10823*	*10823*	*10779*	*10816*	*10823*
R^2-within	*0.678*	*0.8319*	*0.6277*	*0.6057*	*0.6782*	*0.832*	*0.6278*	*0.606*

Printed in **bold** = significant at a 5% significance level (Standard errors in parentheses)

The specific IJtunnel closures in March 2013 also showed a significant negative effect on the number of passengers on the IJtunnel service lines, except for the morning peak hours. Based on the analysis per day, Table 8 shows that these specific IJtunnel closures were associated with 21% less passengers on the IJtunnel service lines whereas the other closures were associated with 15% less passengers compared to regular situations. For the other service lines in Amsterdam North the effect was also stronger during the five subsequent closures in March 2013 compared to other closures, though neither of these effects were significant. A test was performed to investigate whether the effect on the number of passengers in March 2013 was significantly different from the effect of other closures (see Appendix J). This test showed that the effect on the number of passengers on the IJtunnel service lines was not significantly different from other closures, whereas the effect on the service lines in Amsterdam North was different. With respect to the other temporary traffic arrangements for other service lines in the public transport network, Table 7 shows no significant effect on the number of passengers.

Comparing the effects during peak and off-peak hours, no significant effects of the IJtunnel closures on the number of passengers were found during the morning peak. Though, for the IJtunnel service lines the effect was less strong during the afternoon-peak compared to off-peak hours.

Considering the endogenous variables in the model, the three service level variables (*frequency, route length* and *punctuality*) had a significant positive effect on the number of passengers. That is, an increase in the service level (and therefore service quality) was associated with an increase of the demand for public transport. The effect of frequency was smaller during the peak hours, however the interpretation of the estimated effect for *frequency* could be incriminating because of causality issues (this will be explained in the Discussion (Chapter 6)). The effect of route length and punctuality was larger in the morning peak compared to other time-periods during the day.

With respect to the exogenous variables, *petrol price* had no significant effect on the number of passengers. The weather conditions did affect the number of passengers, though the effects were only small. *Rainfall* had a significant effect, but the signs were inconsistent as a negative effect was found during the afternoon peak but a positive effect was found in the remaining models. *Snowfall* only appeared to have a significant effect during the morning peak, where snowfall was associated with an increase of the number of passengers. The effect of rainfall appeared to be stronger than the effect of snowfall. With respect to *temperature* the effect was very small and unclear. The relation between temperature and public transport demand was expected to be a parabolic function which opens downwards (captured by the quadratic variable *temperature*^{2}), but this only appeared to be significant during peak hours. The shape of the parabola is unclear as both positive and negative estimates were found. Moreover, the very small estimates (coefficients are almost equal to zero) indicate very wide parabolas[17]. This implies that the number of passengers grows and declines relatively slowly with temperature. The linear term of temperature would indicate a negative relation with the number of

[17] When $\hat{\beta}_2$ is the estimated coefficient for the quadratic term of temperature (*temperature2*), the parabola opens downwards when $|\hat{\beta}_2| < 0$ while the parabola opens upwards when $|\hat{\beta}_2| > 0$. A smaller (larger) value for $\hat{\beta}_2$ indicates a wider (smaller) the parabola.

passengers, so that higher temperatures are associated with lower public transport demand. Even though the temperature variables are jointly significant, no clear relation with the number of passengers was found.

Finally, dummies were included to control for general trends over time. The number of passengers in 2013 did not significantly differ from the number of passengers in 2012 (*dyear12).* Regarding monthly effects, the analysis per day showed that the number of passengers was significantly higher in all months compared to January (reference situation). Especially in April, June, July, October and November the number of passengers was higher compared to January. However, the monthly effects differ for the peak and off-peak models. In the morning peak June, September and November showed a significantly higher number of passengers, while the number of passengers was significantly lower in December compared to January. The model for the afternoon peak showed little monthly variation in the number of passengers, while the off-peak model showed significantly more passengers in April, June and July. The dummies included for each day of the week showed that the number of passengers was higher for each day compared to Sundays (the reference situation). The number of passengers was highest on Wednesdays, Thursdays and Fridays and this effect was significantly larger in the morning peak hours compared to other models. Also the number of passengers in the morning peak was higher during weekdays compared to days in the weekend.

5.2 Models for the number of passengerkilometres

Next to the number of passengers, the number of passengerkilometres was used as a measure for the demand for public transport. Table 9 (on the next page) shows the results for the models estimated for this dependent variable for the analysis per day, the morning peak, afternoon peak and off-peak hours. The general model in the four columns on the left side of the table again estimate the total effect of the IJtunnel closures, whereas the specific model in the columns on the right side isolate the effect of the specific closures in March 2013.

With regard to the variables of interest, the IJtunnel closures show large and significant effects on the number of passengerkilometres. The percentage effects are shown in Table 10.

Table 10: Percentage effect of the IJtunnel closures on the number of passengerskilometres[18]

Effect of IJtunnel closure on:	Analysis per day	Morning peak	Afternoon peak	Off-peak
IJtunnel service lines (total)	**-45.01 %**	**-37.06 %**	**-41.26 %**	**-45.88 %**
- for IJtunnel closures in March 2013	**-46.37 %**	**-42.07 %**	**-42.54 %**	**-47.11 %**
- for other closures	**-42.59 %**	**-28.11 %**	**-39.16 %**	**-43.67 %**
Other service lines in Amsterdam North (total)	**15.03 %**	-1.09 %	11.07 %	**16.30 %**
- for IJtunnel closures in March 2013	**21.65 %**	-2.08 %	13.54 %	**23.37 %**
- for other closures	6.29 %	-0.10 %	7.68 %	7.14 %

Printed in **bold** = significant at a 5% significance level

[18] Note: these percentages were calculated by the formula: $100 * [\exp(\hat{\beta}) - 1]$ (Wooldridge, 2002, p. 219).

Table 9: Models on the number of passengerkilometres

	Analysis per day	Morning peak	Afternoon peak	Off-peak	Analysis per day	Morning peak	Afternoon peak	Off-peak
log Frequency *(departures per hour)*	**1.282 (0.167)**	**0.608 (0.157)**	**0.742 (0.158)**	**1.184 (0.134)**	**1.285 (0.168)**	**0.607 (0.157)**	**0.742 (0.158)**	**1.188 (0.135)**
Δ log Route length *(in kilometres)*	**7.561 (0.769)**	**27.670 (2.978)**	**6.507 (0.828)**	**6.145 (0.550)**	**7.563 (0.768)**	**27.657 (2.976)**	**6.506 (0.828)**	**6.148 (0.549)**
Punctuality *(% departures on time)*	**0.150 (0.032)**	**0.374 (0.067)**	**0.194 (0.052)**	**0.131 (0.032)**	**0.149 (0.032)**	**0.376 (0.067)**	**0.195 (0.052)**	**0.131 (0.033)**
Δ log Petrol price *(in euros per litre)*	0.179 (0.585)	-0.928 (1.268)	-0.943 (1.113)	0.005 (0.602)	0.192 (0.584)	-1.073 (1.273)	-0.957 (1.111)	0.024 (0.601)
log Rainfall *(in millimetres)*	0.005 (0.003)	**0.083 (0.005)**	**-0.034 (0.010)**	0.004 (0.003)	**0.005 (0.003)**	**0.083 (0.005)**	**-0.034 (0.010)**	0.004 (0.003)
log Snowfall *(number of hours per day)*	0.004 (0.002)	**0.053 (0.004)**	-0.000 (0.003)	-0.000 (0.002)	0.004 (0.002)	**0.054 (0.004)**	-0.000 (0.003)	-0.000 (0.002)
Temperature *(in degrees Celsius)*	**-0.005 (0.001)**	**-0.012 (0.001)**	-0.002 (0.001)	**-0.004 (0.001)**	**-0.005 (0.001)**	**-0.012 (0.001)**	-0.002 (0.001)	**-0.004 (0.001)**
Temperature^2 *(in degrees Celsius)*	-0.000 (0.000)	**0.000 (0.000)**	**-0.000 (0.000)**	-0.000 (0.000)	-0.000 (0.000)	**0.000 (0.000)**	**-0.000 (0.000)**	-0.000 (0.000)
dummy Year12	**-0.034 (0.016)**	0.016 (0.014)	-0.016 (0.014)	**-0.042 (0.016)**	**-0.034 (0.016)**	0.016 (0.014)	-0.016 (0.014)	**-0.042 (0.016)**
dummy February	**0.045 (0.005)**	**0.081 (0.010)**	0.011 (0.009)	**0.047 (0.005)**	**0.045 (0.005)**	**0.082 (0.010)**	0.011 (0.009)	**0.047 (0.005)**
dummy March	**0.078 (0.010)**	**0.152 (0.015)**	0.018 (0.012)	**0.076 (0.010)**	**0.077 (0.010)**	**0.156 (0.015)**	0.018 (0.012)	**0.075 (0.010)**
dummy April	**0.102 (0.012)**	**0.100 (0.013)**	0.023 (0.015)	**0.113 (0.012)**	**0.102 (0.012)**	**0.101 (0.013)**	0.023 (0.015)	**0.112 (0.012)**
dummy May	**0.065 (0.013)**	**0.039 (0.016)**	-0.002 (0.014)	**0.079 (0.013)**	**0.065 (0.013)**	**0.040 (0.016)**	-0.002 (0.014)	**0.079 (0.013)**
dummy June	**0.113 (0.015)**	**0.202 (0.020)**	**0.037 (0.016)**	**0.111 (0.015)**	**0.113 (0.015)**	**0.203 (0.020)**	**0.038 (0.016)**	**0.110 (0.015)**
dummy July	**0.121 (0.027)**	0.012 (0.037)	0.028 (0.036)	**0.120 (0.024)**	**0.121 (0.027)**	0.013 (0.037)	0.029 (0.036)	**0.120 (0.024)**
dummy August	0.070 (0.045)	-0.093 (0.053)	0.008 (0.052)	0.067 (0.039)	0.071 (0.045)	-0.094 (0.053)	0.008 (0.052)	0.068 (0.039)
dummy September	**0.062 (0.029)**	**0.188 (0.026)**	-0.027 (0.057)	0.043 (0.035)	0.061 (0.029)	**0.187 (0.026)**	-0.027 (0.057)	0.043 (0.035)
dummy October	**0.105 (0.025)**	**0.178 (0.019)**	0.044 (0.045)	**0.100 (0.029)**	**0.105 (0.025)**	**0.179 (0.019)**	0.045 (0.045)	**0.100 (0.029)**
dummy November	**0.110 (0.022)**	**0.232 (0.025)**	**0.073 (0.027)**	**0.097 (0.021)**	**0.110 (0.022)**	**0.231 (0.025)**	**0.073 (0.027)**	**0.097 (0.021)**
dummy December	0.035 (0.018)	**-0.143 (0.018)**	0.013 (0.021)	**0.060 (0.019)**	0.035 (0.018)	**-0.142 (0.018)**	0.013 (0.021)	**0.060 (0.019)**
dummy monday	**0.197 (0.034)**	**1.654 (0.096)**	**0.371 (0.035)**	**0.130 (0.029)**	**0.196 (0.034)**	**1.654 (0.096)**	**0.371 (0.035)**	**0.129 (0.029)**
dummy tuesday	**0.277 (0.035)**	**1.772 (0.096)**	**0.410 (0.035)**	**0.205 (0.031)**	**0.276 (0.036)**	**1.773 (0.096)**	**0.410 (0.035)**	**0.204 (0.031)**
dummy wednesday	**0.304 (0.036)**	**1.766 (0.098)**	**0.429 (0.033)**	**0.244 (0.030)**	**0.303 (0.036)**	**1.767 (0.098)**	**0.429 (0.033)**	**0.243 (0.030)**
dummy thursday	**0.344 (0.036)**	**1.792 (0.097)**	**0.464 (0.035)**	**0.289 (0.030)**	**0.343 (0.036)**	**1.793 (0.097)**	**0.464 (0.035)**	**0.288 (0.030)**
dummy friday	**0.326 (0.037)**	**1.689 (0.098)**	**0.383 (0.036)**	**0.299 (0.029)**	**0.325 (0.038)**	**1.690 (0.099)**	**0.383 (0.037)**	**0.298 (0.030)**
dummy saturday	**0.180 (0.026)**	**0.619 (0.032)**	**0.129 (0.041)**	**0.181 (0.024)**	**0.179 (0.027)**	**0.619 (0.032)**	**0.129 (0.041)**	**0.181 (0.024)**
dummy other temporary traffic arrangements	0.001 (0.050)	-0.075 (0.068)	0.004 (0.050)	0.008 (0.049)	0.001 (0.050)	-0.076 (0.068)	0.004 (0.050)	0.008 (0.049)
dummy IJtunnel service lines (total)	**-0.598 (0.035)**	**-0.463 (0.052)**	**-0.532 (0.055)**	**-0.614 (0.030)**				
dummy service lines Amsterdam North (total)	**0.140 (0.063)**	-0.011 (0.134)	0.105 (0.073)	**0.151 (0.071)**				
dummy IJtunnel service lines (March 2013)					**-0.623 (0.030)**	**-0.546 (0.048)**	**-0.554 (0.045)**	**-0.637 (0.028)**
dummy IJtunnel service lines (other)					**-0.555 (0.050)**	**-0.330 (0.073)**	**-0.497 (0.073)**	**-0.574 (0.042)**
dummy service lines Amsterdam North (March 2013)					**0.196 (0.074)**	-0.021 (0.129)	0.127 (0.073)	**0.210 (0.086)**
dummy service lines Amsterdam North (other)					0.061 (0.054)	-0.001 (0.143)	0.074 (0.076)	0.069 (0.055)
constant	**7.667 (0.265)**	**5.084 (0.252)**	**6.322 (0.303)**	**7.642 (0.212)**	**7.663 (0.267)**	**5.083 (0.252)**	**6.321 (0.304)**	**7.637 (0.213)**
Number of observations	*10815*	*10771*	*10808*	*10815*	*10815*	*10771*	*10808*	*10815*
R^2-within	*0.6541*	*0.8161*	*0.5786*	*0.5724*	*0.6543*	*0.8162*	*0.5787*	*0.5727*

Printed in **bold** = significant at a 5% significance level (Standard errors in parentheses)

Based on the analysis per day, the IJtunnel closures showed a decline in the number of passengerkilometres of 45% on the IJtunnel service lines compared to regular situations. Furthermore, the results showed a significant 15% increase of the number of passengerkilometres on the service lines in Amsterdam North.

The five subsequent weekend closures in March 2013 were associated with a 46,4% decrease in the number of passengerkilometres on the IJtunnel service lines, whereas the number of passengerkilometres declined by 42,6% during other IJtunnel closures. This shows that there was a stronger decline of the number of passengerkilometres during the five subsequent closures in March 2013 compared to other closures, though the difference was relatively small. With respect to the service lines in Amsterdam North, the results showed a 21,7% increase in the number of passengerkilometres during the closures in March 2013 but no significant effect was found for other closures. Again a test was performed to check whether the effects of the closures in March 2013 are significantly different from the effect of other closures (see Appendix J). This test showed that the effect on the number of passengerkilometres on both the IJtunnel service lines and the lines in Amsterdam North was significantly different in March 2013 compared to other closures of the IJtunnel. Other temporary traffic arrangements for other service lines in the public transport network had no significant effect on the number of passengers, as shown in Table 9.

The effect of the IJtunnel closures on the IJtunnel service lines appeared to be significant for all time-periods. This effect was stronger during off-peak hours compared to peak hours. Moreover, the effect in the morning peak was smaller compared to the afternoon peak. Considering the service lines in Amsterdam North, the effect of the IJtunnel closures was only significant during the off-peak periods.

Regarding the endogenous variables, *frequency, route length* and *punctuality* showed a positive and significant effect on the number of passengerkilometres. The effects for *route length* and *punctuality* were stronger in the morning peak model compared to the other time periods. Considering the exogenous variables, *petrol price* had no significant effect on the number of passengerkilometres. Moreover, the models showed limited effects of weather conditions. The effect of *rainfall* on passengerkilometres was small and was significant during the morning- and afternoon peak, but the direction of the effect differed[19]. During the morning peak rainfall was associated with an increase in the number of passengerkilometres, while the opposite effect occured during the afternoon peak. *Snowfall* had a positive significant effect on the number of passengerkilometres during the morning peak. Even though the linear and quadratic term of the *temperature* variables were jointly significant the effect of temperature was ambiguous and very small, as the directions and significance for the quadratic term (and thus the form of the parabola) differed among the models.

The included time dummies indicate that the number of passengerkilometres differed significantly in 2013 from 2012 in the analysis per day and the off-peak model. Based on the analysis per day, the number of

[19] Considering the analyses per day, the effect of rainfall was found to be significant in the specific model but not in the general model. The p-value of this variable was very close to -0.05, so that rainfall is perceived as significant in one model but not in the other.

passengerkilometers in 2012 was approximately 3,4% lower than 2013[20]. The monthly dummies show that in the analysis per day and off-peak model the number of passengerkilometres was significantly higher in April, June, July, October and November compared to January (reference situation). In the morning peak model the largest difference was shown between November and January. Also, June showed a significantly higher number of passengerkilometres in the morning peak, while the number of passengerkilometres in December was significantly lower compared to January. The monthly variation in the model for the afternoon peak was small. On Wednesdays, Thursdays and Fridays the highest number of passengerkilometres occurred compared to Sundays. The daily effect was significantly larger in the morning peak hours compared to other models.

5.3 Goodness of fit

The goodness of fit of the estimated models is reported in Table 8 and Table 10 by the within R-squared. This measure shows the explained variance of the demeaned data, and can be interpreted as the amount of time variation in the dependent variable that is explained by the time variation in the independent variables (Wooldridge, 2002, p.444). In the estimated models per day, approximately 66% of the time variation in both then number of passengers and passengerkilometres could be explained by the time variation in the included explanatory variables (see Table 8 and Table 10). The within-R^2 was higher for the models in the morning peak. This implies that the time variance of the explanatory variables explained a larger proportion of the variance of the number of passenger(kilometre)s in the morning peak compared to the other models. In the morning peak approximately 82% of the variance over time of the number of passenger(kilometre)s could be explained by the time variation in the explanatory variables. The estimates of the morning peak models therefore provide more accurate predictions.

5.4 Summary of findings

The conceptual model was applied to two measures of the demand for transport (the number of passengers and the number of passengerkilometres). The results show that the directions of the effects of the independent variables were very similar for both the number of passengers and passengerkilometres. However, the sizes of the effects differed per variable and per time period. The model was also estimated for peak- and off-peak hours, where the effects of the included variables appeared to be stronger for the morning peak periods compared to other time periods.

The size of the effect of the IJtunnel closures on the explained variables differed. For example, based on the analysis per day the IJtunnel closures were associated with 18,4% less passengers but 45% less passengerkilometres on the IJtunnel service lines. The decline in the demand for public transport on the IJtunnel service lines was stronger during the five subsequent closures in March 2013 compared to other IJtunnel closures. The number of passenger(kilometre)s increased for the service lines in Amsterdam North during these closures but this effect was only significant for the number of passengerkilometres in March 2013 (in the analysis per day and off-peak hours).

[20] This percentage was calculated by the formula: $100 * [\exp(\hat{\beta}) - 1]$ (Wooldridge, 2002, p. 219).

Considering the control variables, the size of the effects on both the number of passengers and passengerkilometres were very similar. The service quality variables were positively associated with both the number of passengers and the number of passengerkilometres whereas petrol price had no significant effect on either of these explained variables. The effect of weather conditions on both measures was inconsistent and very small in all models. The endogenous variables thus had significant positive effects on the demand for public transport, but the significance and size of the effects of the exogenous factors was limited.

This chapter presented the results of the analysis on the impact of the IJtunnel closures on the demand for public transport. In the next chapter these findings will be discussed in more detail and possible explanations for the results will be provided.

6. Discussion

This study analysed the effect of the temporary traffic arrangements for closures of the IJtunnel on the demand for public transport in Amsterdam. In this chapter the results of the analysis will be discussed and will be put into perspective by relating the results to previous findings from the literature. Furthermore the limitations of this research will be discussed. Taking these limitations into account, this chapter will conclude with the implications which can be derived from this study.

6.1 Discussion of the results

6.1.1 Results for variables of interest

The temporary traffic arrangements for the IJtunnel closures were expected to have a negative effect on the demand for public transport on the IJtunnel service lines. The results of the analysis confirm this expectation as the closures of the IJtunnel are associated with a significant decline of both the number of passengers and passengerkilometres for these lines. Based on the analysis per day, closing the IJtunnel would reduce the number of passengers on the IJtunnel lines by 18,4% and the number of passengerkilometres by 45%. The reduction of the number of passengerkilometres is stronger compared to the reduction of the number of passengers since both the number of passengers and the travelled distance are reduced (the route is shortened). Moreover, a relatively long and highly occupied distance of the route is eliminated from the original route distance, as the IJtunnel service lines cannot drive the regular route through the IJtunnel to Amsterdam Central Station. On this particular part of the route the highest degree of occupation is reached during regular circumstances, as the number of passengers on these lines grows (declines) towards (from) the Central Station). Therefore, the reduction of the number of passengerkilometres may be even stronger compared to the number of passengers.

Contrary to the IJtunnel service lines, the temporary traffic arrangements for the IJtunnel closures were also expected to affect the demand for public transport on the other three service lines in Amsterdam North. These service lines offer an alternative but longer route (both in terms of travel time and distance) between Amsterdam North and the city centre and could thus be seen as substitutes for the IJtunnel service lines. Based on the analysis per day a significant increase of the number of passengerkilometres (15%) was found, whereas the effect on the number of passengers was smaller (8,5%) and not significant. Since the number of passengerkilometres is a function of the number of passengers and the route distance of these service lines is relatively long, the change in the number of passengerkilometres was again stronger compared to the number of passengers. However it must be noted that the decline of public transport demand on the IJtunnel service lines is not offset by the increase of public transport demand on the service lines in Amsterdam North, both in percentage effects and in absolute terms. After all, the absolute number of passenger(kilometre)s on the service lines in Amsterdam North is relatively small compared to the absolute number of passenger(kilometre)s on the IJtunnel service lines (as discussed in Section 4.5; shown in Graph 5 and Graph 6 on page 39/40).

The effect of the IJtunnel closures for the five subsequent weekends in March 2013 was isolated from other single weekend closures in separate models. Regarding the magnitude of these effect, the results show that the decline of the number of passengers on the IJtunnel service lines in March 2013 (-21,1%) was stronger compared to other IJtunnel closures (-14,9%). Also the decline of the number of passengerkilometres on these service lines was stronger for the IJtunnel closures in March 2013 (-46,4%) compared to other IJtunnel closures (-42,6%). With respect to the service lines in Amsterdam North the closures in March 2013 were associated with an increase in the number of passengers of 13%, whereas the increase was only 2,6% for other closures. Also the effect on the number of passengerkilometres on these service lines was stronger for the closures in March 2013 (+21,7%) compared to other closures (+6,3%). This might imply that the IJtunnel lines are more likely to be substituted for the other lines in Amsterdam North, as passengers are willing to try these alternative routes of public transport in case of multiple subsequent closures of the IJtunnel (but to a less extent during singular IJtunnel closures). Passengers are likely to be better informed on the subsequent closures so that they can plan their alternative route in advance, whereas passengers are less well informed on single closures. In the latter case they find out about the temporary traffic arrangements during their trip, and are more likely to continue this journey.

A test was performed to investigate whether these effects in March 2013 were indeed significantly different from the other closures (see Appendix J). The results of this test indicate that the effect on both the number of passengers and passengerkilometres of the IJtunnel closures in March 2013 were significantly different, except for the effect on the number of passengers on the IJtunnel service lines. However, this latter exception does not necessarily imply that the decline of the number of passengers for the IJtunnel service lines is similar for all IJtunnel closures. Rather this test result may occur since (the effect of the IJtunnel closures on) the number of passengers is relatively small so that the test does not find a significant difference for the included data, whereas more data over a longer time period might result in significant test results. Overall, the results indicate that the effect of the subsequent closures in March 2013 were different compared to the effect of other (single) IJtunnel closures.

The effect of the IJtunnel closures on the demand for transport appeared to be stronger during off-peak periods compared to peak periods per day. The closures are planned during weekends in which the peak and off-peak periods are less distinctive, after all passengers in the weekends mostly travel for leisure purposes and are less restricted by time. The closures will thus affect the passengers in off-peak periods more compared to peak periods. This can be explained by the fact that almost 90% of time per day is considered as off-peak period is, whereas the remaining 10% is considered as morning- and afternoon peak.

The effect of the temporary traffic arrangements for the IJtunnel closures differed from the effect of other temporary traffic arrangements on other service lines. The latter did not show a significant effect on the demand for public transport. The nature of the IJtunnel closures is different from the nature of other temporary traffic arrangements since the water (the IJ) forms a major obstacle between Amsterdam North and the city centre. For other temporary traffic arrangements in the city, more alternative routes are available which deviate less from the original route, whereas alternative routes for the IJtunnel have a substantial longer route length. The IJtunnel closures can thus be perceived as more radical and have a substantial effect on the demand for public transport within Amsterdam.

In summary, the temporary traffic arrangements for the IJtunnel closures lead to a significant decline in the demand for transport on the IJtunnel service lines (especially during off-peak hours) and a small increase of public transport demand on the service lines in Amsterdam North. The five subsequent weekend closures of the IJtunnel in March 2013 had a stronger effect on both the IJtunnel service lines and the lines in Amsterdam North compared to other IJtunnel closures. This may suggest that substitute travel from the IJtunnel service lines to the lines in Amsterdam North is more likely during multiple subsequent closures.

6.1.2 Results for endogenous and exogenous variables in the model

With respect to the endogenous variables in the model, the service level variables had a significant positive effect on the demand for public transport. Though, interpreting the effect for *frequency* could be incriminating because of causality issues. On the one hand an increase of frequency may lead to an increase in the demand for public transport. On the other hand, due to an increase in the demand for public transport the public transport operator may increase frequency in order to fulfill transport demand. Even though the effect of frequency appeared to be highly significant, the causality of the effect is ambiguous. However, the variable was included in the model to control for time table characteristics.

Another variable related to the supply of public transport is *route length*, which was positively associated with the demand for public transport. On a network level, this would correspond to the findings from the literature where longer route lengths are associated with a wider area covered by public transport services. A wider area covered increases public transport accessibility so that more passengers can make use of the services. This effect was especially strong in the morning peak, which would imply that a wider area covered could increase the number of potential commuters by public transport. However, it must be noted that route length is less applicable as a measure of service level for the individual service lines (as discussed in Section 4.2.2). Though the variable was included in the model in order to control for route distance.

Finally with respect to the endogenous variables, *punctuality* appeared to be positively related to public transport demand. An improvement of departure punctuality could lead to an increase of public transport demand since passengers are less displeased by waiting time for delayed vehicles. Moreover, service reliability is improved so that passengers do not have to take an earlier departure in order to be sure to arrive on time. The effect of punctuality was especially strong in the morning peak, in which passengers are mostly commuters to work and school for whom it is important to arrive on time. Overall these results are in line with the findings from the literature, where an improvement of service quality is associated with higher public transport demand.

Regarding the exogenous variables only the weather conditions appeared to have some significant effect on the demand for public transport, though the effects were only small. Rainfall and snowfall were expected to be negatively related to the demand for public transport as they reduce public transport accessibility and traffic speed. Moreover, heavy snowfall may obstruct the public transport network so that the supply of public transport falls and consequently demand. Contrary to these expectations, the results showed that rainfall was associated with an increase in the demand for public transport (except for in the afternoon-peak). This may be explained by the fact that the bicycle is an important mode of transport in the city of Amsterdam. As travellers do not prefer to get wet, bicyclist may be more inclined to substitute their bike for public transport when rain occurs. This would imply that this effect outweighs the possible negative effect caused by reduced traffic speed or access to public transport. However one exception occurred during the afternoon peak hours, where rainfall was negatively related to the demand for transport. A possible explanation for this observation is that travellers postpone their journey when it rains during the afternoon peak. Especially commuters from work who are planning to go home may decide to stay at work a little longer. Also snowfall showed an opposite effect from what was expected based on the literature, as snowfall was positively related to public transport demand. Though, this effect was only significant for the morning peak. The slipperiness caused by snow adds to the disutility of getting wet during travel, so that bicyclist may be more inclined to use public transport instead.

With respect to temperature, a parabolic relation with the demand for public transport was expected which opens downwards. That is, below a certain threshold temperature public transport demand was expected to decrease with declining temperatures as cold weather depresses outdoor activities. Above this threshold, rising temperatures were expected to depress public transport demand as (in-vehicle) heat reduces service quality and travel comfort. However, this research did not find significant results for this type of relation for the city of Amsterdam. Moreover, the effect of temperature on the public transport demand was very small. This may be explained by the moderate climate in Amsterdam, in which extreme temperatures are rather exceptional and temperature varies within a relatively small range. Temperature may have a larger effect on public transport demand in cities where temperatures extremes are more common and varies within a larger range.

Finally, the number of passengerkilometres has grown in 2013 compared to 2012 but no significant growth of the number of passengers was found. This can again be explained by the fact that absolute values of the number of passengers are relatively small compared to the number of passengerkilometres. Next to the yearly effects, the levels of demand for public transport appeared to be higher in April, June, July, October and November compared to January, whereas the number of passengers is relatively low in January, August and December. The results also showed that the demand for transport was larger on Wednesdays, Thursdays and Fridays whereas demand was relatively low on Saturdays and Sundays. Commuter travel during the weekdays is responsible for a large part of public transport demand, whereas leisure travel during the weekends reflects a smaller part of public transport demand.

Summarizing the effects of the control variables, service quality appeared an important determinant on the demand for public transport. This would imply that GVB can increase patronage on their network by improving their service level. The effects of exogenous factors appear to be limited for public transport demand in Amsterdam.

6.2 Limitations

The results of this study showed a significant impact of the IJtunnel closures on public transport demand. Though, multiple limitations should be taken into account in the interpretation of the results. These limitations derive among others from the data used, the model and the used methodology.

First, the analysis in this thesis was based on chipcard data. This chipcard data may be imperfect or biased for multiple reasons. Travelers may accidentally check in or check out multiple times as they are for example inexperienced with chipcard use, keep their card for the reader too long or too often, do not see or hear the transaction properly or may simply forget to check in/out. This leads to “missing check ins” and “missing check outs” or incorrect registration of trips or interchanges. The latter also occurs when vehicles are in so-called “degraded mode”. That is, when vehicles end up outside the range of their scheduled route or when the vehicles chipcard registration systems or do not function properly for another reason, the systems cannot determine the vehicles’ location so that check ins/outs are registered at an unknown location. Next to the loss of chipcard travel information for the transport provider, this implies that the travelled distance and travel fare cannot be calculated properly. Though, it should be noted that the bias due to technical failure may differ per day. Finally, GVB’s chipcard data does not include all public transport demand within the network in Amsterdam, as non-chipcard travel products still exist. For example, passengers may travel with combined paper tickets for theaters and concerts. In addition fare dodgers are not registered, however this is no different compared to former counting methods of passengers. As the majority of passengers in Amsterdam’s public transport network travels by chipcard and the degree of missing/incorrect check ins and check outs are only limited, the chipcard data are assumed to be a good reflection of public transport travel.

A second limitation of the used dataset is related to chipcard data, as the used data contains personal details of travelers. Due to privacy consideration this data is only allowed to be stored for 18 months by the transport provider, so that the data used for this analysis were available only for this limited time period. This implies that the estimates reflect effects in the short term, and cannot be used to conclude on long-term effects. Additionally, the dataset only includes bus and tram services. Night busses were not included as there was no possibility to use the chipcard on these busses, so that no chipcard data was available. Data on metro services were not readily available and metro as a transport mode has characteristics different from bus and tram services (for example, metro lines are not affected by road traffic and road diversions whereas busses and trams are). However the metro is one of the most important transport modes in Amsterdam, so that the dataset may not be a perfect representation of public transport within the city and no inferences can be made for metro services. These data limitations should be kept in mind when analyzing the results.

Third, the model used to estimate the impact of temporary traffic arrangements was based on findings from the academic literature. However, due to data availability issues some determinants of the demand for transport could not be included in the model. For example, fares and fare changes have been identified as important explanatory variables in modeling the demand for transport. Since fares depend on a boarding fare and a fare per travelled kilometer, the price of each trip differs. Fares are also different for certain passenger groups; for example elderly, children and students travel against a reduced tariff. Moreover, fares are a complicated variable to add to the model as interchanges within a trip may take place. The boarding fare is charged only once so that in case of interchanges within 30 minutes of a journey, travelers only pay for the extra traveled kilometres after the interchange. Though, interchanges could not be derived from the chipcard data so that the number of check ins could overestimate the number of passenger and their fares paid. Note that the latter can also lead to an overestimation of the calculated revenue loss, as this was based on the decline of the number of passengers and an average revenue per trip.

One possibility to incorporate fares would be to include the average fare paid based on for example travelled kilometres per service line. However this factor would be time-invariant for the time-period included in the dataset, so that the variable would have been eliminated from the model. For the above reasons, and the fact that fares are difficult to reflect on a service line level, fares were not included in the model as an explanatory variable. Also fare changes could not be included in the model as the yearly indexation of fares differs per ticket type. This yearly change would then also be perfectly correlated to the included year dummy, so that also this variable would be eliminated from the model.

Next to fares other determinants of the demand for transport derived from the literature could not be included in the model due to data availability. For example the time of travel could not be included as this differs per trip, per service line and per person (including transport to- and from the public transport stop). Other behavioral, social, economic and demographic factors were not included due to measurement problems or time invariance. Some factors do not differ per service line and can be perceived as time invariant for the time period in the model so that they are not included in the model. After all, time invariant variables are perfectly correlated to the unit dimension of the data so that they cannot be estimated when fixed effects are used: time invariant variables are eliminated from the model. It would be too difficult to measure and quantify all the relevant factors in the complex public transport modeling, though imperfect models may be more valuable to planners and policymakers than some random guesses (Balcombe et al., 2004). Though it should be taken into account that the factors which cannot be included in the model do affect the demand for transport.

Finally, limitations derive from the used methodology, more specifically the used estimation technique. All models in this research were estimated by means of fixed effects estimation. This estimator is limited in the sense that it ignores the between-variation (so the variation between service lines). Also fixed effects estimation cannot be used to analyse time-invariant causes of the dependent variable, after all time-invariant variables cannot be added to the model as the effects are subsumed by the fixed effects. Though, this also provides an advantage as the fixed effects estimator cannot be biased because of omitted time-invariant characteristics, as it controls for all time-invariant differences between the units (service lines) (Torres-Reyna, 2013). However, fixed effects estimation does not allow to generalize inferences beyond the sample used in the model, whereas random effects estimation does.

6.3 Implications of the IJtunnel closures

Taking the discussed limitations into account, multiple implications can be derived from the results of this study. First, the closures of the IJtunnel have important financial implications for GVB. The public transport operator will experience a loss of passenger revenue as a consequence of the decline of the number of passenger(kilometre)s on the IJtunnel service lines during the IJtunnel closures. The elasticities quantified by this study allow to estimate the loss of passengers and revenue more accurately. Based on the estimates derived by the analysis per day, a weekend closure of the IJtunnel would lead to a decline of passengers on the IJtunnel lines and an increase of passengers on the other service lines in Amsterdam North. However the decline of passengers on the IJtunnel service lines is not offset by the increase of passengers on the lines in Amsterdam North, as both the percentage effects and the absolute number of passengers are smaller on the service lines in Amsterdam North. This implies that GVB incurs a net loss of passengers and passenger revenues as a consequence of the IJtunnel closures. The loss of passenger revenues was calculated based on the net loss of passengers per weekend day and an average revenue per trip (see Appendix K)[21].

In addition to the revenue loss, the closures of the IJtunnel will affect the subsidy that GVB receives for the exploitation of Amsterdam's public transport network. This subsidy is granted by Stadsregio Amsterdam and is based on a certain amount per kilometre that differs per transport mode. Since the route distance is shortened for the IJtunnel service lines during the closures of the IJtunnel, the amount of subsidy for GVB will be reduced. The actual loss of subsidy was calculated based on the reduction of route distance for the IJtunnel service and the amount of subsidy per kilometre (see Appendix K)[21]. Note that the route distance for the other service lines in Amsterdam North does not change, so that the subsidy received for these lines remains unaffected.

Next to the revenue- and subsidy loss, GVB is confronted with additional costs for the closures of the IJtunnel. These involve for example costs for communication of the diversions towards the passengers and the extra utilization of the ferry boats across the IJ. Moreover, additional costs are involved with the extra personnel employed to inform passengers and to monitor and preserve safety during the closures. Except for the subsidy loss[22], GVB can impose a claim for these costs involved at the municipality of Amsterdam (which is the responsible party for these closures). This study enables GVB to make a more accurate estimate of this claim.

Second, this study analysed the specific effects of the IJtunnel closures for public transport demand in GVB's network. As a substantial effect was found for GVB, one can argue that the closures will also affect other public transport operators which use the IJtunnel. Therefore, the total effect of the IJtunnel closures on the demand for public transport may be even larger. Moreover, the estimated effects in this study only focused on the short-term impact of the IJtunnel closures but the demand for public transport may also be affected in the long run. Considering the inconvenience of the closures for public transport passengers, regular and subsequent closures may lead to a structural loss of GVB's customers. As this research showed that the effects of the

[21] As the calculation of the revenue- and subsidy loss involves confidential information specific to GVB, the actual numbers used in the calculations and the outcomes are not allowed to be published in this thesis.
[22] For subsidies separate arrangements are made with Stadsregio Amsterdam, see Section 2.2.3.

IJtunnel closures appear to be stronger during multiple subsequent closures, the long term impact should be taken into account as a serious threat.

Third, this research allows to make some inferences with respect to policy on future closures of the IJtunnel. As the impact of multiple subsequent closures appears to be stronger, the loss of passenger revenues could be reduced by avoiding a sequence of IJtunnel closures within a limited time period. With respect to the time period in which the closures are planned, the months January, August and December are associated with relatively low public transport demand. Considering the days of the week, public transport demand is relatively low on Saturdays and Sundays compared to other days of the week. In order to minimize the number of passengers affected by the IJtunnel closures and therefore the loss of passenger revenues, the best time to plan IJtunnel closures is during weekends in January or during summer (August). Even though public transport demand is relatively low in December, this month may be less appropriate for IJtunnel closures as the weekends are characterized by high shopping activity for the holidays.

Concluding, this study allows GVB to demonstrate the magnitude of the impact of the IJtunnel closures. This implies that GVB's position (and the position of other public transport providers which use the IJtunnel) may be strengthened in the discussions and decision making for future closures of the IJtunnel. Moreover, this research allows for a more accurate estimation of net revenue loss and thus the claim involved for the municipality. The results of this study can therefore be especially valuable with respect to the negotiations on the days and time at which the IJtunnel is to be closed, the duration of the closures and the associated compensation.

7. Conclusion

This study analysed the impact of temporary traffic arrangements for closures of the IJtunnel on the demand for public transport in Amsterdam. Multiple public transport service lines use the IJtunnel as the main direct connection between Amsterdam North and the city centre, so that closures of the tunnel will lead to temporary diversions for the IJtunnel service lines. During these diversions public transport passengers are confronted with longer travel durations and more interchanges between transport modes. This will affect the demand for public transport and hence passenger revenues. Additionally, GVB is confronted with additional costs for organizing the temporary diversions and receives less subsidy. Since the knowledge on the actual effect of the IJtunnel closures was limited, this research provides useful insights as it quantifies the effect on the demand for public transport and the accompanying costs.

The results of this study showed that closures of the IJtunnel result in a significant decline in the demand for transport on the IJtunnel service lines, especially during the off-peak hours. Based on the analysis per day, closing the IJtunnel is associated with an 18,4% reduction of the number of passengers and a 45% decline in the number of passengerkilometres. Though these effects are partially offset by an increase of public transport demand on the remaining service lines in Amsterdam North, which provide an alternative (but longer) connection with the city centre. Taking into account these opposite effects, the closure of the IJtunnel is associated with a decline of public transport demand and consequently a net revenue loss. Moreover, GVB would receive less subsidy from Stadsregio Amsterdam as a consequence of the shortened routes of the IJtunnel service lines during the IJtunnel closures.

In addition, this research found that the effects on public transport demand were different for the IJtunnel closures in the five subsequent weekends in March 2013 compared to other (single) closures. The decline of passengers on the IJtunnel service lines and the increase on the lines in Amsterdam North were both stronger during the closures in March 2013, which suggests a stronger substitution effect from the IJtunnel service lines to the other lines in Amsterdam North when the IJtunnel is closed for multiple subsequent weekends.

Taking the limitations of this research into account, this study enables GVB to demonstrate the magnitude of the impact of the IJtunnel closures in discussions and decision making processes for prospective closures of the IJtunnel. This could strengthen GVB's position (and the position of other public transport providers which use the IJtunnel) in the negotiations with respect to the days and time at which the IJtunnel is to be closed, the duration of the closures and the associated compensation.

As a final note with respect to the future, this research has made a first step in analysing the effect of temporary traffic arrangements for maintenance activities and events. As this type of research can provide valuable information for public transport operators, this study may encourage other public transport operators to analyse the effects of similar issues in their specific network.

8. Recommendations for further research

The discussed limitations in Chapter 6 provide opportunities for further research. The performed analysis could be improved or elaborated in multiple ways.

First the dataset used for the analysis could be improved. The limited time period used in this research could be expanded into a longer time series, which would improve the accuracy of the model. A longer time period also allows to include more explanatory variables which were considered as time invariant for this analysis, but which may be time variant over a longer time period. Additionally the dataset may be expanded by inclusion of more service lines so that the dataset embodies an improved reflection of the network. This may strengthen the model specification and its estimates. More specifically, the effect of the IJtunnel closures on the night busses may be estimated in future research. On August 20th 2013 a nightbus ticket for the chipcard was introduced by GVB, which allows passengers to use the chipcard for these bus lines. This provides additional data for future use.

Second, the analysis can be expanded to deepen the understanding of the effect of the IJtunnel closures. For example one might analyse whether the effect of a single day closure may be different from weekend closures (multiple days in a row), or one might isolate the effect for the specific bus lines separately. Furthermore, the revenue loss may be calculated in more detail according to the boarding fare and fare per travelled kilometre. This requires more specific information on the trip length, number of interchanges[23] and ticket type per individual.

Third, the conceptual model and methodology used in this research can be used to quantify the impact of other specific temporary traffic arrangements which are expected to have a substantial impact on the demand for public transport. As this application can provide useful and valuable information not only on public transport in Amsterdam but also for other cities, this research may encourage other public transport operators to analyse the effects for their specific network.

[23] The number of interchanges was not available for the time period analysed in this research. On September 1st 2013 a new tool was introduced in GVB's chipcard database which allows to extract this information. This can provide more accurate estimates on the loss of passenger(revenue)s.

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Appendix A: Announcement for the IJtunnel closures in March 2013

Tijdelijke maatregel

GVB

Nummer	13036 AH	**Afdeling**	Tijdelijke Verkeersmaatregelen en Evenementen
Ophangdatum	22 februari 2013	**Telefoon**	020 460 6421
Verwijderen	1 april 2013	**Fax**	020 460 6439
Datum	21 februari 2013	**Aantal pagina's**	2

Lijnen 32, 33, 34, 35, 48, 110, 118, 124, 125, 225, 301, 304, 306, 307, 308, 311, 312, 314, 315, 316, 317, 361, 362, 391, 392, 394, N01, N04, N10, N14, N92 en N94

Weekend afsluitingen IJtunnel

Hiermee vervalt Geeltje 13022 EW

Voor werkzaamheden zal de IJtunnel **alle weekenden in maart 2013, van zaterdagmorgen 00.30 uur tot maandagmorgen 06.00 uur,** afgesloten zijn voor al het verkeer.

De **lijnen 32, 33, 34, 35, 391, 392 en 394,** en de **R-net lijnen 301, 304, 306, 307, 308, 311, 312, 314, 315 en 316, van EBS,** rijden tussen bovenstaande tijden naar het Buiksloterwegveer, en krijgen hiervoor de volgende omleiding:

Lijn 32 en 33;
- Johan van Hasseltweg - Meeuwenei - Johan van Hasseltweg - la. Mosplein - Van der Pekstraat - Ranonkelkade - Buiksloterweg en keren bij de pont, vice versa.

Lijn 34, 35, 391 en 394;
- Mosplein - Van der Pekstraat - Ranonkelkade - Buiksloterweg en keren bij de pont, vice versa.

Lijn 392;
- Nieuwe Leeuwarderweg - ra. afrit naar Johan van Hasseltweg - ra. Johan van Hasseltweg - la. Mosplein - Van der Pekstraat - Ranonkelkade - Buiksloterweg en keren bij de pont, vice versa.

Lijn 301, 304, 306, 307, 308, 311, 312, 314, 315 en 316;
- Buikslotermeerplein - Waddenweg - ra. Nieuwe Purmerweg - la. toerit richting centrum - Nieuwe Leeuwarderweg - ra. afrit naar Johan van Hasseltweg - ra. Johan van Hasseltweg - la. Mosplein - Van der Pekstraat - Ranonkelkade - Buiksloterweg en keren bij de pont, vice versa.

Voor alle lijnen geldt dat er geen tijd afgewacht kan worden bij de pont, i.v.m. te weinig opstelruimte.

Lijn 110, 118, 124 en 125, rijden niet verder dan het Buikslotermeerplein en keren daar.

De **nachtlijnen 361, 363, N1, N04, N10, N14, N92 en N94**, krijgen voor deze afsluiting de volgende omleiding:

Lijn 361;
- Mr. Visserplein - Valkenburgerstraat - ra. afrit Nieuwe Foeliestraat - ra. Prins Hendrikkade - Kattenburgerstraat - ra. Piet Heinkade - la. Piet Heintunnel - la. Zuiderzeeweg - ra. IJdoornlaan, eigen route tot rotonde Meeuwenlaan - Meeuwenlaan - Waddenweg - ra. Nieuwe Purmerweg - Purmerweg - Volendammerweg - ra. IJdoornlaan - Zuiderzeeweg - ra. Piet Heintunnel - ra. Piet Heinkade - la. Kattenburgerstraat - Prins Hendrikkade, eigen route naar Centraal Station.

Tijdelijke maatregel

Nummer 13036 AH

Datum 21 februari 2013

Lijn 363;
- Mr. Visserplein - Valkenburgerstraat - ra. afrit Nieuwe Foeliestraat - ra. Prins Hendrikkade - Kattenburgerstraat - ra. Piet Heinkade - la. Piet Heintunnel - la. Zuiderzeeweg - ra. IJdoornlaan - la. Buikslotermeerplein - Waddenweg - Meeuwenlaan - Havikslaan, eigen route tot Buikslotermeerplein - IJdoorlaan - Zuiderzeeweg - ra. Piet Heintunnel - ra. Piet Heinkade - la. Kattenburgerstraat - Prins Hendrikkade, eigen route naar Centraal Station.

Lijn N92;
- Prins Hendrikkade - Kattenburgerstraat - ra. Piet Heinkade - la. Piet Heintunnel - la. Zuiderzeeweg - ra. IJdoornlaan, eigen route vice versa.

Lijn N94;
- Prins Hendrikkade - Kattenburgerstraat - ra. Piet Heinkade - la. Piet Heintunnel - la. Zuiderzeeweg - ra. IJdoornlaan - ra. toerit Leeuwarderweg, richting Centrum - Nieuwe Leeuwarderweg - ra. afrit Johan van Hasseltweg - ra. Johan van Hasselweg, eigen route.

Lijn N1, N4, N10 en N14;

Vervallen haltes:

Centraal Station	05003 voor 33
Centraal Station	05005 voor 391 en 394
Centraal Station	05006 voor 35
Centraal Station	05007 voor 32
Centraal Station	05019 voor 34
Centraal Station	05095 voor 308
Centraal Station	05096 voor 304
Centraal Station	05097 voor 306
Centraal Station	05098 voor 301
Centraal Station	05100 voor 110, 118, 124, 125, 307, 311, 312, 314, 315 en 316
Prins Hendrikkade	08029 voor 110, 118, 124, 125, 225, 311, 312, 314, 315, 316 en 317
Prins Hendrikkade	08030 voor 32, 33, 301, 304, 306, 307 en 308
Prins Hendrikkade	08031 voor 34, 35, 48, 391, 392 en 394
IJtunnel	08232 voor 32, 33, 34 en 35

Tijdelijke haltes:

Hagendoornweg	01134 voor 32, 33, 34, 35, 391, 392, en 394
Hagendoornweg	01135 voor 32, 33, 34, 35, 391, 392, en 394
Van der Pekstraat	01136 voor 32, 33, 34, 35, 391, 392, en 394
Van der Pekstraat	01137 voor 32, 33, 34, 35, 391, 392, en 394
Buiksloterweg	09906 voor 32, 33, 34, 35, 391, 392, en 394

Appendix B: GVB service lines included in analysis

Service line number	Modal type	From → to	Remarks
1	Tram	Osdorp De Aker to Amsterdam Central Station	Via Leidseplein
2	Tram	Nieuw Sloten to Amsterdam Central Station	Via Leidseplein
4	Tram	Station RAI to Amsterdam Central Station	Via Station Amsterdam RAI
13	Tram	Geuzenveld to Amsterdam Central Station	
16	Tram	De Boelelaan/VU to Amsterdam Central Station	
17	Tram	Osdorp Dijkgraafplein to Amsterdam Central Station	Via Station Amsterdam Lelylaan
18	Bus	Slotervaart to Amsterdam Central Station	Via Station Amsterdam Lelylaan
21	Bus	Geuzenveld to Amsterdam Central Station	
22	Bus	Indische Buurt to Spaarndammerbuurt	Also stops at Amsterdam Central Station
24	Tram	De Boelelaan/VU to Amsterdam Central Station	
25	Tram	President Kennedylaan to Amsterdam Central Station	
26	Tram	IJburg to Amsterdam Central Station	
32	Bus	Buikslotermeerplein to Amsterdam Central Station	Goes through IJTunnel in regular timetable
33	Bus	Nieuwendam to Amsterdam Central Station	Goes through IJTunnel in regular timetable
34	Bus	Buikslotermeerplein to Amsterdam Central Station	Goes through IJTunnel in regular timetable
35	Bus	Molenwijk to Amsterdam Central Station	Goes through IJTunnel in regular timetable
36	Bus	Station Sloterdijk to Banne Buiksloot	
37	Bus	Molenwijk to Amstelstation	
38	Bus	Molenwijk to Nieuwendam Amerbos	Stops at Buiksloterwegveer (ferry boat)
48	Bus	Station Sloterdijk to Borneo Eiland	Via Station Amsterdam Sloterdijk

Appendix C: List of Temporary traffic arrangements

The table below shows the temporary traffic arrangements included in the panel data analysis. This involves the twenty included service lines in the period February 1st 2012 to July 31st 2013. The IJtunnel closures are shown in italics.

Table 11: List of temporary traffic arrangements included in the dataset

TVM ID	Date/period (mm-dd-yyyy)		Service lines	Remarks
	From	Until		
12003 DH	3-12-2012	5-25-2012	13, 18	
12072 AH	4-21-2013		37	
12075 AH	4-16-2012	4-20-2012	22, 37	
12076 AH	4-23-2012	4-27-2012	22, 37	
	4-30-2012		1, 2, 4, 13, 16, 17, 18, 21, 22, 24, 25, 26, 48	Queensday 2012
12131 AH	5-21-2012	6-1-2012	34, 35	
12149 AH	6-4-2012	6-15-2012	34, 35	
12164 RW	6-17-2012	6-18-2012	16, 24	
12165 AH	6-16-2012	6-17-2012	37	
12171 RW	6-23-2012	6-24-2012	16, 24	
12215 EW	*7-29-2012*		*32, 33, 34, 35*	*IJtunnel closure*
12216 AH	*8-5-2012*		*32, 33, 34, 35*	*IJtunnel closure*
12216 AH	*8-25-2012*	*8-26-2012*	*32, 33, 34, 35*	*IJtunnel closure*
12226 AH	8-20-2012	9-13-2012	32	
12238 AH	*9-1-2012*	*9-2-2012*	*32, 33, 34, 35*	*IJtunnel closure*
12246 AH	9-8-2012	9-9-2012	37	
12257 DH	9-23-2012		4, 16, 22, 24, 25, 26, 32, 33, 34, 35, 36, 38, 48	Dam to Dam run
12287 DH	10-21-2012		2, 4, 16, 22, 24, 25, 37	Amsterdam Marathon
12288 DH	10-22-2012	12-20-2012	1, 2, 13, 17	Only on Mondays, Tuesdays, Wednesdays and Thursdays
12306 AH	11-17-2012	11-18-2012	37	
12308 RW	11-13-2012	11-14-2012	18, 24	
12319 DH	11-18-2012		1, 2, 4, 16, 22, 24, 25, 26, 32, 33, 34, 35, 48	
12340 AH	*11-24-2012*	*11-25-2012*	*32, 33, 34, 35*	*IJtunnel closure*
13010 AH	2-2-2013	2-3-2012	34, 37	
13020 EW	3-4-2012	4-19-2012	18	

13021 EW	3-23-2013	3-24-2013	13	
	4-30-2013		1, 2, 4, 13, 16, 17, 18, 21, 22, 24, 25, 26, 38, 48	Queensday 2013
13036 AH	***3-2-2013***	***3-31-2013***	***32, 33, 34, 35***	***IJtunnel closure: during 5 subsequent weekends***
13084 AH	9-5-2013	5-12-2013	36	
13106 AH	5-13-2013	6-3-2013	34	
13117 AH	5-21-2013	5-24-2013	37	
13120 AH	5-27-2013	6-29-2013	48	
13131 AH	6-3-2013	6-24-2013	37	
13132 AH	6-9-2013		4, 16, 24, 25	
13133 AH	6-9-2013		26	
13153 AH	6-24-2013	6-28-2013	34, 37	

Appendix D: Hausman test

The Hausman test was performed for each model to determine whether fixed effects or random effects estimation was preferred. One example of the output of the test is shown below. As this output is almost similar for each model the output of only one test will be displayed.

```
. * Hausman test: FE or RE?
. hausman fe1A re1A

Note: the rank of the differenced variance matrix (28) does not equal the number of coefficients being tested (29); be sure this is
        what you expect, or there may be problems computing the test.  Examine the output of your estimators for anything unexpected
        and possibly consider scaling your variables so that the coefficients are on a similar scale.

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |      fe1A         re1A        Difference          S.E.
-------------+----------------------------------------------------------------
 lnfrequency |    1.316879     1.326799       -.0099201        .0013772
Dlnroutele~h |    7.309095     7.307436        .0016593               .
 punctuality |    .1429163     .1428307        .0000856               .
Dlnpetrolp~e |    .6854086     .6881032       -.0026946               .
  lnrainfall |    .0077368     .0077072        .0000296               .
  lnsnowfall |    .0046886     .0046859        2.68e-06               .
 temperature |    -.007224    -.0072287        4.65e-06               .
temperature2 |    .0000216     .0000219       -3.01e-07               .
   dijLtunnel |   -.2031694    -.2034872        .0003178               .
    dijLadamN |    .0819934     .0834393       -.0014459               .
    dothertta |   -.0150298    -.0148318        -.000198               .
      dyear12 |   -.0226539    -.0228089         .000155               .
         dfeb |    .0546379     .0547123       -.0000744               .
         dmar |    .0781681      .078228       -.0000599               .
         dapr |    .1095995     .1096879       -.0000884               .
         dmay |    .0757241     .0757935       -.0000694               .
         djun |    .1219509     .1220362       -.0000853               .
         djul |    .1225331     .1236565       -.0011234               .
         daug |    .0741867     .0759308        -.001744               .
         dsep |    .0715965     .0717123       -.0001158               .
         doct |    .1023723     .1024935       -.0001213               .
         dnov |    .1112036     .1112969       -.0000934               .
         ddec |    .0314788     .0315931       -.0001142               .
      dmonday |    .2205523     .2180396        .0025127               .
     dtuesday |    .2974231     .2949186        .0025045               .
   dwednesday |    .3243837     .3218813        .0025024               .
    dthursday |    .3642641      .361734        .0025301               .
      dfriday |    .3525663     .3500675        .0024988               .
    dsaturday |    .2090566     .2079441        .0011124               .
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(28) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       51.72
                Prob>chi2 =      0.0041
                (V_b-V_B is not positive definite)

. * --> Reject H0, use fixed effects.
```

This output shows that the results of fixed and random effects estimation differ so that fixed effects estimation would be preferred. The Hausman test was performed for each model to determine whether fixed effects or random effects estimation was preferred. Table 12 shows the preferred estimation techniques for the models estimated per time period.

Table 12: Preferred estimation technique based on the Hausman test

	Number of passengers	**Number of passengerkilometres**
Analysis per day	FE	RE
Morning Peak	FE	FE
Afternoon Peak	FE	FE
Off-peak	FE	FE

The Hausman test results show that the fixed estimator is preferred for all models except for the analysis per day on the number of passengerkilometres. When random effects estimation is preferred by the Hausman test, this implies that the estimates of random effects and fixed effects are similar and random effects is consistent and more efficient. However, when fixed effects are preferred it is assumed that the unobserved effects are correlated to the explanatory variables so that random effects cannot be used. As the analysis per day on the number of passengerkilometres is the only exception regarding the preferred estimator, this research follows a more conservative approach in which it is assumed that the unobserved effect is correlated with the explanatory variables (ANU, 2009). Therefore fixed effects estimation is used for all models in this research.

Appendix E: Assumptions for fixed effects estimation

A fixed effects estimation is used to estimate the models on the demand for transport. Just as with cross-sectional data, there are multiple assumptions which should be taken into account in order for the fixed effects estimator to be the Best Linear Unbiased Estimator. These are (1) linearity in parameters, (2) random sampling, (3) no perfect collinearity, (4) strict exogeneity (zero conditional mean), (5) homoskedasticity, (6) no serial correlation in the error terms and (7) u_{it} follows normal distribution (Wooldridge, 2002). In this appendix these assumptions will be discussed in more detail.

1. *Linearity in parameters* is assumed so that:

$$y_{it} = \beta_1 x_{it1} + \cdots + \beta_k x_{itk} + a_i + u_{it}, t = 1, \ldots, T,$$

   Where β_j are the parameters to estimate.

2. *Random sampling in the cross-sectional dimension* implies that each individual in the sample as subset of a larger set is chosen randomly; that is each individual has the same probability of chosen.

3. *No perfect collinearity* implies that there are no perfect linear relations between explanatory variables and that each variable changes over time (at least for some *i*). When a model suffers from perfect collinearity, the model cannot be estimated by OLS (Wooldridge, 2002). Before adding the independent variables into a multiple regression, the variables in the dataset are therefore analysed with respect to perfect multicollinearity, which refers to an exact linear relationship between independent variables (Wooldridge, 2002). As a consequence of multicollinearity, standard errors may be large and t-statistics tend to be small, which may lead to wrong inference of results. In addition, multicollinearity may result in incorrect signs or insignificance for theoretically important variables. Even though perfect collinearity causes problems, this assumption does allow for some correlation between the independent variables (Wooldridge, 2002). Appendix F shows the correlation table for the included variables in the dataset, in which the stars indicate a significant correlation between variables at the 5% significance level. The correlation table shows that there is no perfect collinearity (that is; none of the correlation coefficients in the table is equal to 1) between any of the included variables in the dataset. Though, some variables show a relatively high correlation, which implies that the variables share (to some extent) similar information and have the same explanatory power. This forms a risk for multicollinearity problems. The correlation coefficient between the number of boarding passengers and passenger kilometers is equal to 0.9173. This is not surprising, as the number of passenger kilometres is a function of the number of boarding passengers. However, this will not cause any problems as these variables are not included in the same model, after all they are dependent variables which will be used in separate models. Then there is the variable frequency,

which is highly correlated to both the number of boarding passengers (0.8274) and the number of passenger kilometres (0.8625). As frequency is a measure of the supply of transport, this high correlation can be explained by the twoway relationship between the demand for transport and the supply of transport (see Section 3.2.1 under service quality). Even though frequency may cause multicollinearity problems, the variable is included in the models as it is an important determinant for the demand for transport.

4. The *strict exogeneity (or zero conditional mean)* assumption holds that the explanatory variables are uncorrelated to the error term u_{it} across all time periods so that the explanatory variables are said to be exogenous (Wooldridge, 2002).

When these four assumptions hold the estimator is said to be unbiased and consistent.

5. *Homoskedasticity (=no heteroskedasticity)* implies that the variance of the error term is the same regardless of the values of the independent variables, so that:

$$Var(u_{it}|X_i, a_i) = Var(u_{it}) = \sigma_u^2 \; for \; all \; t = 1, .., T.$$

As a consequences of heteroskedasticity the standard errors of the estimated parameters are incorrect, so that t-statistics and confidence intervals are no longer valid. As it appears from the Wald test for groupwise heteroskedasticity in Appendix H, heteroskedasticity is apparent in the estimated models. In order to correct for heteroskedasticity, heteroskedasticity-robust standard errors should be applied which can be used for inference.

6. The sixth assumption is that there is *no serial correlation (autocorrelation) in the error terms* conditional on all explanatory variables and a_i so that:

$$Cov\left(u_{it,}u_{is}\middle|X_i, a_i\right) = 0 \; for \; all \; t \neq s$$

The problem with serial correlation is that it leads to estimated standard errors which are smaller than the true standard errors. This in turn affects the t-statistics and confidence intervals which may lead to wrong inference. In order to check whether serial correlation is an issue, the Wooldridge test for autocorrelation in panel data was performed (see Appendix H). This test shows that there is serial correlation in the error terms. As both heteroskedasticity and serial correlation are apparent, clustered standard errors are used to correct for these problems.

When assumption 1-6 hold, the fixed effects estimator is said to be the Best Linear Unbiased Estimator (BLUE).

7. Finally, the *normality* is assumed which implies that conditional on X_i and a_i, the $u_{it,}$ are independent and identically distributed as Normal(o, σ_u^2), that is: the error terms follow a normal distribution so that the obtained t- and F-statistics have an exact t and F distributions.

Appendix F: Correlation table

Table 13 shows the correlation between the included variables in the model. The table is divided over two pages due to the large size.

Table 13: Correlation table

	lnpassengers	lnpassengerkms	lnfrequency	lnroutelength	Dlnroutelength	punctuality	lnpetrolprice	Dlnpetrolprice	lnrainfall
lnpassengers	1								
lnpassengerkms	0.9173	1							
lnfrequency	0.8274	0.8625	1						
lnroutelength	-0.2853	-0.0888	-0.3183	1					
Dlnroutelength					1				
punctuality	0.0979	0.0617	0.0924	-0.0894		1			
lnpetrolprice							1		
Dlnpetrolprice					-0.0519			1	
lnrainfall							-0.0411	-0.0614	1
lnsnowfall	0.019							-0.0252	0.0557
temperature	-0.0795	-0.0822	-0.0863			-0.0361		0.0383	0.0274
dijLtunnel	-0.1002	-0.1008	-0.0468			-0.0308	0.0384	-0.0314	0.0247
dijLadamN	-0.1311	-0.1161	-0.1763	0.1106		-0.0348	0.0348	-0.0278	
dijLtunnelm13	-0.0717	-0.0779	-0.0318				0.0191	-0.0399	
dijLtunnelother	-0.0699	-0.0637	-0.0346			-0.0341	0.0362		0.0512
dijLadamNm13	-0.0983	-0.0851	-0.1419	0.085				-0.0345	
dijLadamNother	-0.0866	-0.0791	-0.1048	0.0706		-0.0369	0.0344		0.0356
dothertta	0.0519	0.0536	0.0401	0.0283			0.0313	-0.0617	

Table 13 (continued): Correlation table

	lnsnowfall	temperature	dijLtunnel	dijLadamN	dijLtunnelm13	dijLtunnelother	dijLadamNm13	dijLadamNother	dothertta
lnpassengers									
lnpassengerkms									
lnfrequency									
lnroutelength									
Dlnroutelength									
punctuality									
lnpetrolprice									
Dlnpetrolprice									
lnrainfall									
lnsnowfall	1								
temperature	-0.4272	1							
dijLtunnel	0.0432	-0.0295	1						
dijLadamN	0.0396	-0.0306		1					
dijLtunnelm13	0.0714	-0.069	0.7443		1				
dijLtunnelother		0.0329	0.6654			1			
dijLadamNm13	0.0618	-0.0601		0.7662			1		
dijLadamNother		0.0241		0.6408				1	
dothertta	-0.0216								1

Appendix G: Stationarity of the data

In addition to the discussed assumptions, it is necessary to know whether variables are stationary or non-stationary over time in order to avoid problems of spurious regression (Humboldt University Berlin, no date). A stationary time series is one whose statistical properties such as mean, variance and autocorrelation are constant over time (Duke University, 2005). However economic time series often contain a time trend so that its statistical properties are not constant over time, that is: the time series is non-stationary. Consider the following equation:

$$Y_t = \rho Y_{t-1} + \varepsilon_t$$

where Y_t is the variable being tested, ε_t is the error term and t indicates the time dimension. When $|\rho|<1$ the variable is stationary, so that the shocks die out according to the value of ρ (New York University, no date). On the other hand, when $|\rho|>1$ the variable is non-stationary and explosive, so that past shocks have a larger impact than current shocks. When $|\rho|=1$ the variable is non-stationary and is said to have a unit root. This is a so called random walk model, in which the value at time t will be equal to last period's value plus a stochastic component ε_t which is independent and identically distributed with a zero mean and variance. The variance of a random walk goes to infinity over time, so that a random walk cannot be predicted (Iordanova, 2009).

Using non-stationary time series in a regression model leads to the problem of spurious results; a significant relationship may be obtained between variables which actually are unrelated (Humboldt University Berlin, no date). Spurious regression is therefore defined as "*a problem that arises when regression analysis indicates a relationship between two or more unrelated time series processes simply because each has a trend, is an integrated time series, or both*" (Wooldridge, 2002). As non-stationary data cannot be used for modelling or forecasting purposes, this data are transformed into stationary data by first-differencing (Duke University, no date). The first-difference of the process is often stationary (Wooldridge, 2002, p.363).

The panel data were tested for stationarity by a Fisher-type panel unit-root test for panel data as proposed by Maddala and Wu (1999). This test has two advantages; first the test can be performed with any unit root test on a single time-series and does not require the same unit-root in each cross-section. Second, contrary to other unit root tests, this test does not require a balanced panel dataset (Hoang and McNown, 2006). As the dataset in this research is unbalanced, this test is especially applicable.

The specified test performed an Augmented Dickey-Fuller unit-root test on each panel within the dataset. Here the tested null hypothesis is that all panels contain a unit root, the alternative hypothesis is that at least one panel is stationary. This test includes a number of lags and whether there is a time trend. As no lag length selection criteria for daily data was available in the literature, the test was performed for both one and two lags. In addition, the test can include a linear time trend in the model which describes the process by which the time series. Therefore, all variables have been tested both with and without a time trend. The results from these test specifications are similar and are shown below. The variables *petrol price* and *route length* have non-stationary properties (contained a unit root) in all tests. In order to eliminate potential spurious regression problems, the data on these variables were transformed into stationary data by taking first differences.

Appendix G (continued): Test results of Augmented Dickey-Fuller unit-root test

One lag, without time trend

```
. * Test for unit root (non-stationarity)
. * --> one lag, without time trend
. xtunitroot fisher lnpassengers, dfuller lag(1)

Fisher-type unit-root test for lnpassengers
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots          Number of panels       =     20
Ha: At least one panel is stationary       Avg. number of periods = 544.35

AR parameter: Panel-specific               Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                 ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1441.7461       0.0000
 Inverse normal            Z       -36.3401       0.0000
 Inverse logit t(104)      L*      -89.3044       0.0000
 Modified inv. chi-squared Pm      156.7200       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnpassengerkms, dfuller lag(1)
(2 missing values generated)

Fisher-type unit-root test for lnpassengerkms
Based on augmented Dickey-Fuller tests
---------------------------------------------
Ho: All panels contain unit roots          Number of panels       =     20
Ha: At least one panel is stationary       Avg. number of periods = 544.25

AR parameter: Panel-specific               Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                 ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1441.7461       0.0000
 Inverse normal            Z       -36.3401       0.0000
 Inverse logit t(104)      L*      -89.3044       0.0000
 Modified inv. chi-squared Pm      156.7200       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnfrequency, dfuller lag(1)

Fisher-type unit-root test for lnfrequency
Based on augmented Dickey-Fuller tests
-----------------------------------------
Ho: All panels contain unit roots          Number of panels       =     20
Ha: At least one panel is stationary       Avg. number of periods = 544.35

AR parameter: Panel-specific               Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                 ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1323.3605       0.0000
 Inverse normal            Z       -33.8615       0.0000
 Inverse logit t(104)      L*      -81.9136       0.0000
 Modified inv. chi-squared Pm      143.4841       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnroutelength, dfuller lag(1)

Fisher-type unit-root test for lnroutelength
Based on augmented Dickey-Fuller tests
--------------------------------------------
Ho: All panels contain unit roots          Number of panels       =     20
Ha: At least one panel is stationary       Avg. number of periods = 544.35

AR parameter: Panel-specific               Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                 ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P         2.3871       1.0000
 Inverse normal            Z         2.2386       0.9874
 Inverse logit t(34)       L*        2.0759       0.9772
 Modified inv. chi-squared Pm       -4.2052       1.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

```
. xtunitroot fisher punctuality, dfuller lag(1)
(13 missing values generated)

Fisher-type unit-root test for punctuality
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 543.70

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1066.3289       0.0000
 Inverse normal            Z       -31.2226       0.0000
 Inverse logit t(79)       L*      -76.3885       0.0000
 Modified inv. chi-squared Pm      114.7471       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnpetrolprice, dfuller lag(1)

Fisher-type unit-root test for lnpetrolprice
Based on augmented Dickey-Fuller tests
--------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P        44.0730       0.3033
 Inverse normal            Z        -1.9367       0.0264
 Inverse logit t(104)      L*       -1.7273       0.0435
 Modified inv. chi-squared Pm        0.4554       0.3244
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnrainfall, dfuller lag(1)
(5838 missing values generated)

Fisher-type unit-root test for lnrainfall
Based on augmented Dickey-Fuller tests
-----------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 252.45

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P       816.9567       0.0000
 Inverse normal            Z       -26.5959       0.0000
 Inverse logit t(104)      L*      -50.6038       0.0000
 Modified inv. chi-squared Pm       86.8664       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher temperature, dfuller lag(1)

Fisher-type unit-root test for temperature
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P       247.9275       0.0000
 Inverse normal            Z       -12.8470       0.0000
 Inverse logit t(104)      L*      -15.3520       0.0000
 Modified inv. chi-squared Pm       23.2470       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

The null-hypothesis in these test is that all panels contain a unit root. From the p-values in the tests above, it can be concluded that the null-hypothesis cannot be rejected for the variables *lnpetrolprice* and *lntourelength.* That is, these variables show non-stationary properties.

One lag, with time trend

```
. * --> one lag, with time trend (trend includes a linear time trend in the model that describes the process by which the series is
> generated)
. xtunitroot fisher lnpassengers, dfuller trend lag(1)

Fisher-type unit-root test for lnpassengers
Based on augmented Dickey-Fuller tests
---------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1441.7461       0.0000
 Inverse normal            Z       -36.3401       0.0000
 Inverse logit t(104)      L*      -89.3044       0.0000
 Modified inv. chi-squared Pm      156.7200       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnpassengerkms, dfuller trend lag(1)
(2 missing values generated)

Fisher-type unit-root test for lnpassengerkms
Based on augmented Dickey-Fuller tests
---------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.25

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1441.7461       0.0000
 Inverse normal            Z       -36.3401       0.0000
 Inverse logit t(104)      L*      -89.3044       0.0000
 Modified inv. chi-squared Pm      156.7200       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnfrequency, dfuller trend lag(1)

Fisher-type unit-root test for lnfrequency
Based on augmented Dickey-Fuller tests
---------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1305.8447       0.0000
 Inverse normal            Z       -33.8858       0.0000
 Inverse logit t(104)      L*      -80.8843       0.0000
 Modified inv. chi-squared Pm      141.5257       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnroutelength, dfuller trend lag(1)

Fisher-type unit-root test for lnroutelength
Based on augmented Dickey-Fuller tests
---------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P         7.0859       1.0000
 Inverse normal            Z         0.3329       0.6304
 Inverse logit t(34)       L*        0.2977       0.6161
 Modified inv. chi-squared Pm       -3.6799       0.9999
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

```
. xtunitroot fisher punctuality, dfuller trend lag(1)
(13 missing values generated)

Fisher-type unit-root test for punctuality
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 543.70

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1081.3096       0.0000
 Inverse normal            Z       -31.4714       0.0000
 Inverse logit t(79)       L*      -77.4617       0.0000
 Modified inv. chi-squared Pm      116.4220       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnpetrolprice, dfuller trend lag(1)

Fisher-type unit-root test for lnpetrolprice
Based on augmented Dickey-Fuller tests
--------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P        23.4216       0.9830
 Inverse normal            Z         0.6431       0.7399
 Inverse logit t(104)      L*        0.5692       0.7148
 Modified inv. chi-squared Pm       -1.8535       0.9681
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnrainfall, dfuller trend lag(1)
(5838 missing values generated)

Fisher-type unit-root test for lnrainfall
Based on augmented Dickey-Fuller tests
-----------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 252.45

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P       727.0956       0.0000
 Inverse normal            Z       -24.9015       0.0000
 Inverse logit t(104)      L*      -45.0377       0.0000
 Modified inv. chi-squared Pm       76.8196       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher temperature, dfuller trend lag(1)

Fisher-type unit-root test for temperature
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P       175.5766       0.0000
 Inverse normal            Z       -10.0348       0.0000
 Inverse logit t(104)      L*      -10.8444       0.0000
 Modified inv. chi-squared Pm       15.1579       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

The tests shown above include a time trend. From the p-values in these tests, it can be concluded that the null-hypothesis cannot be rejected for the variables *petrol price* and *route length*. Also under this test specification these variables thus show non-stationary properties.

Two lags, without time trend

```
.
. * --> two lags, without time trend
. xtunitroot fisher lnpassengers, dfuller lag(2)

Fisher-type unit-root test for lnpassengers
Based on augmented Dickey-Fuller tests
--------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1441.7461       0.0000
 Inverse normal            Z       -36.3401       0.0000
 Inverse logit t(104)      L*      -89.3044       0.0000
 Modified inv. chi-squared Pm      156.7200       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnpassengerkms, dfuller lag(2)
(2 missing values generated)

Fisher-type unit-root test for lnpassengerkms
Based on augmented Dickey-Fuller tests
----------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.25

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1441.7461       0.0000
 Inverse normal            Z       -36.3401       0.0000
 Inverse logit t(104)      L*      -89.3044       0.0000
 Modified inv. chi-squared Pm      156.7200       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnfrequency, dfuller lag(2)

Fisher-type unit-root test for lnfrequency
Based on augmented Dickey-Fuller tests
-------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1199.5299       0.0000
 Inverse normal            Z       -31.6560       0.0000
 Inverse logit t(104)      L*      -74.1793       0.0000
 Modified inv. chi-squared Pm      129.6394       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnroutelength, dfuller lag(2)

Fisher-type unit-root test for lnroutelength
Based on augmented Dickey-Fuller tests
---------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P         2.3907       1.0000
 Inverse normal            Z         2.2363       0.9873
 Inverse logit t(34)       L*        2.0737       0.9771
 Modified inv. chi-squared Pm       -4.2048       1.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

```
. xtunitroot fisher punctuality, dfuller lag(2)
(13 missing values generated)

Fisher-type unit-root test for punctuality
Based on augmented Dickey-Fuller tests
-------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 543.70

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1033.2470       0.0000
 Inverse normal            Z       -30.6054       0.0000
 Inverse logit t(79)       L*      -74.0187       0.0000
 Modified inv. chi-squared Pm      111.0484       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnpetrolprice, dfuller lag(2)

Fisher-type unit-root test for lnpetrolprice
Based on augmented Dickey-Fuller tests
---------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P        52.3787       0.0909
 Inverse normal            Z        -2.7375       0.0031
 Inverse logit t(104)      L*       -2.4624       0.0077
 Modified inv. chi-squared Pm        1.3840       0.0832
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnrainfall, dfuller lag(2)
(5838 missing values generated)

Fisher-type unit-root test for lnrainfall
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 252.45

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P       329.3465       0.0000
 Inverse normal            Z       -15.4826       0.0000
 Inverse logit t(104)      L*      -20.3996       0.0000
 Modified inv. chi-squared Pm       32.3499       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher temperature, dfuller lag(2)

Fisher-type unit-root test for temperature
Based on augmented Dickey-Fuller tests
-------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P       205.3573       0.0000
 Inverse normal            Z       -11.2625       0.0000
 Inverse logit t(104)      L*      -12.7055       0.0000
 Modified inv. chi-squared Pm       18.4875       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

The tests shown above includes two lags but no time trend. From the p-values in these tests, it can be concluded that the null-hypothesis cannot be rejected for the variables *petrol price* and *route length*. Also under this test specification these variables thus show non-stationary properties.

Two lags, with time trend

```
. * --> two lags, with time trend (trend includes a linear time trend in the model that describes the process by which the series is
>  generated)
. xtunitroot fisher lnpassengers, dfuller trend lag(2)

Fisher-type unit-root test for lnpassengers
Based on augmented Dickey-Fuller tests
-------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1441.7461       0.0000
 Inverse normal            Z       -36.3401       0.0000
 Inverse logit t(104)      L*      -89.3044       0.0000
 Modified inv. chi-squared Pm      156.7200       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnpassengerkms, dfuller trend lag(2)
(2 missing values generated)

Fisher-type unit-root test for lnpassengerkms
Based on augmented Dickey-Fuller tests
---------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.25

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1437.1853       0.0000
 Inverse normal            Z       -36.2772       0.0000
 Inverse logit t(104)      L*      -89.0219       0.0000
 Modified inv. chi-squared Pm      156.2101       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnfrequency, dfuller trend lag(2)

Fisher-type unit-root test for lnfrequency
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1154.3770       0.0000
 Inverse normal            Z       -31.1047       0.0000
 Inverse logit t(104)      L*      -71.4826       0.0000
 Modified inv. chi-squared Pm      124.5911       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnroutelength, dfuller trend lag(2)

Fisher-type unit-root test for lnroutelength
Based on augmented Dickey-Fuller tests
--------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P         7.0620       1.0000
 Inverse normal            Z         0.3398       0.6330
 Inverse logit t(34)       L*        0.3039       0.6185
 Modified inv. chi-squared Pm       -3.6826       0.9999
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

```
. xtunitroot fisher punctuality, dfuller trend lag(2)
(13 missing values generated)

Fisher-type unit-root test for punctuality
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 543.70

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P      1061.8632       0.0000
 Inverse normal            Z       -31.1499       0.0000
 Inverse logit t(79)       L*      -76.0686       0.0000
 Modified inv. chi-squared Pm      114.2478       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnpetrolprice, dfuller trend lag(2)

Fisher-type unit-root test for lnpetrolprice
Based on augmented Dickey-Fuller tests
--------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P        29.1500       0.8976
 Inverse normal            Z        -0.1914       0.4241
 Inverse logit t(104)      L*       -0.1694       0.4329
 Modified inv. chi-squared Pm       -1.2131       0.8874
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher lnrainfall, dfuller trend lag(2)
(5838 missing values generated)

Fisher-type unit-root test for lnrainfall
Based on augmented Dickey-Fuller tests
-----------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 252.45

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P       300.0631       0.0000
 Inverse normal            Z       -14.5775       0.0000
 Inverse logit t(104)      L*      -18.5849       0.0000
 Modified inv. chi-squared Pm       29.0759       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------

. xtunitroot fisher temperature, dfuller trend lag(2)

Fisher-type unit-root test for temperature
Based on augmented Dickey-Fuller tests
------------------------------------------
Ho: All panels contain unit roots           Number of panels       =     20
Ha: At least one panel is stationary        Avg. number of periods = 544.35

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 2 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(40)   P       138.7732       0.0000
 Inverse normal            Z        -8.3368       0.0000
 Inverse logit t(104)      L*       -8.5173       0.0000
 Modified inv. chi-squared Pm       11.0432       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

The tests shown above includes two lags and a time trend. From the p-values in these tests, it can be concluded that the null-hypothesis cannot be rejected for the variables *petrol price* and *route length*. Therefore, all four test specifications (one/two lags, with/without time trend) result in the same conclusion. That is, petrol price and route length show non-stationary properties which may cause spurious regression. These variables are therefore transformed into first-differences.

Appendix H: Test for heteroskedasticity and autocorrelation

The estimated models were tested for heteroskedasticity and autocorrelation. Heteroskedasticity implies that the variance of the error term is the not the same regardless of the values of the independent variables. A modified Wald test for panel data was performed for all estimated models. The output below shows the significant results for one of the heteroskedasticity test of the general model on the number of passengers.

```
. * test for heteroskedasticity
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (20)  =     458.66
Prob>chi2 =      0.0000


. * --> reject H0 of homoskedasticity (constant variance), there is heteroskedasticity so that robust standard errors should be used
>  (robust).
.
```

This test shows that there is heteroskedasticity, so that robust standard errors should be used in order to be able to derive correct inferences. As the results are significant for all sixteen tests, the output is shown only once.

Autocorrelation occurs in time-series when the error terms are correlated to the error terms of the previous period. The Wooldridge test for autocorrelation in panel data was performed for all estimated models. The output is shown below.

```
. * test for serial correlation in error term
. xtserial lnpassengers lnfrequency Dlnroutelength punctuality Dlnpetrolprice lnrainfall lnsnowfall temperature temperature2

Wooldridge test for autocorrelation in panel data
H0: no first order autocorrelation
    F(  1,      19) =     85.614
           Prob > F =      0.0000

. * --> reject H0 of no serial correlation, so there is serial correlation. Use serial correlation-robust standard errors (cluster:
> corrects for both heteroskedasticity and serial correlation)
```

This test shows that autocorrelation is present, which was the case for all other models. As both heteroskedasticity and autocorrelation were present serial correlation-robust standard errors were applied in order to derive correct inferences.

Appendix I: Descriptive statistics for specific line groups

Table 14 shows the descriptive statistics for the IJtunnel service lines in particular, whereas Table 15 shows these statistics for the service lines in Amsterdam North.

Table 14: Descriptive statistics for the IJtunnel service lines (lines 32, 33, 34 and 35)

Variable		Mean	Std. Dev.	Min	Max	Observations	
Passengers	overall	5715.188	2252.175	230	12399	N =	2180
	between		1716.505	4081.528	8055.923	n =	4
	within		1691.592	-1763.74	10058.26	T =	545
Passengerkilometres	overall	26617.88	9569.226	0	54519	N =	2180
	between		6289.261	22227.2	35821.37	n =	4
	within		7867.044	-9202.018	45318.51	T =	545
Frequency	overall	5.535421	1.095783	4	8.275862	N =	2180
	between		0.903444	4.970566	6.885065	n =	4
	within		0.767008	3.439829	6.926218	T =	545
Route length	overall	18.68675	2.420689	16.141	21.425	N =	2180
	between		2.79453	16.141	21.425	n =	4
	within		0	18.68675	18.68675	T =	545
Punctuality	overall	0.807268	0.097512	0.1429	1	N =	2176
	between		0.030986	0.76357	0.834935	n =	4
	within		0.093745	0.115233	1.043697	T =	544
Petrol price	overall	1.758396	0.034905	1.695	1.83	N =	2180
	between		0	1.758396	1.758396	n =	4
	within		0.034905	1.695	1.83	T =	545
Rainfall	overall	3.296239	6.801784	0	54.4	N =	2180
	between		0.047369	3.231193	3.344771	n =	4
	within		6.801661	-0.04853	54.46505	T =	545
Snowfall	overall	0.515596	2.202305	0	19	N =	2180
	between		0	0.515596	0.515596	n =	4
	within		2.202305	0	19	T =	545
Temperature	overall	10.60278	6.858379	-10.1421	27	N =	2180
	between		0.021283	10.58181	10.63142	n =	4
	within		6.858354	-10.1211	26.97136	T =	545

Table 15: Descriptive statistics for the service lines in Amsterdam North (lines 36, 37 and 38)

Variable		Mean	Std. Dev.	Min	Max	Observations
Passengers	overall	4405.358	4034.345	53	14877	N = 1633
	between		4360.379	1495.55	9416.002	n = 3
	within		1893.482	-4957.64	9866.356	T-bar = 544.333
Passengerkilometres	overall	18589.76	17227.43	299	61202	N = 1633
	between		18846.48	6173.746	40263.93	n = 3
	within		7726.772	-21375.2	39527.82	T-bar = 544.333
Frequency	overall	3.687433	0.861842	1.878788	5.0625	N = 1633
	between		0.606117	3.142362	4.339997	n = 3
	within		0.705402	1.987481	5.011919	T-bar = 544.333
Route length	overall	29.39565	7.278145	21.982	39.289	N = 1633
	between		8.908542	21.98278	39.27495	n = 3
	within		0.058926	29.31459	29.52259	T-bar = 544.333
Punctuality	overall	0.819196	0.145178	0	1	N = 1630
	between		0.047672	0.789886	0.874218	n = 3
	within		0.139862	0.02931	1.02931	T-bar = 543.333
Petrol price	overall	1.758382	0.034926	1.695	1.83	N = 1633
	between		1.23E-05	1.758375	1.758396	n = 3
	within		0.034926	1.694986	1.830007	T-bar = 544.333
Rainfall	overall	3.351684	6.927929	0	54.4	N = 1633
	between		0.109555	3.266544	3.475229	n = 3
	within		6.927351	-0.12355	54.48514	T-bar = 544.333
Snowfall	overall	0.516228	2.203748	0	19	N = 1633
	between		0.000547	0.515596	0.516544	n = 3
	within		2.203748	-0.00032	19.00063	T-bar = 544.333
Temperature	overall	10.56221	6.843208	-10.1421	27	N = 1633
	between		0.048811	10.509	10.60488	n = 3
	within		6.843092	-10.1527	26.95733	T-bar = 544.333

Appendix J: Test equality of effects

A test was performed in order to investigate whether the effects IJtunnel closures in March 2013 are significantly different from other IJtunnel closures. The output below shows that the effect on the number of passengers on the IJtunnel service lines does not significantly differ between March 2013 and other closures, whereas the effect does differ for the other lines in Amsterdam North. With respect to the number of passengerkilometres, the effect of the IJtunnel closures in March 2013 is significantly different from the effect of other closures, for both the IJtunnel service lines and the other service lines in Amsterdam North.

Test for number of passengers

```
. * test whether effect of IJtunnel closures in March 2013 on the number of passengers is significantly different from other IJtunne
> lclosures.H0:coefficients are equal.
.
. test dijLtunnelm13=dijLtunnelother

 ( 1)  dijLtunnelm13 - dijLtunnelother = 0

       F(  1,    19) =    4.11
            Prob > F =    0.0569

. *--> do not reject H0, the coefficients are similar so the effects are not significantly different.
. test dijLadamNm13=dijLadamNother

 ( 1)  dijLadamNm13 - dijLadamNother = 0

       F(  1,    19) =    5.01
            Prob > F =    0.0373

. *--> reject H0, the coefficients are not similar so the effects are significantly different.
.
```

Test for number of passengerkilometres

```
. * test whether IJtunnel closures in March 2013 on the number of passengerkilometres is significantly different from other IJtunnel
> closures. H0:coefficients are equal.
. test dijLtunnelm13=dijLtunnelother

 ( 1)  dijLtunnelm13 - dijLtunnelother = 0

       F(  1,    19) =    4.69
            Prob > F =    0.0433

. *--> reject H0, the coefficients are not similar so the effects are significantly different.
. test dijLadamNm13=dijLadamNother

 ( 1)  dijLadamNm13 - dijLadamNother = 0

       F(  1,    19) =   11.75
            Prob > F =    0.0028

. *--> reject H0, the coefficients are not similar so the effects are significantly different.
.
```

Appendix K: Calculation of revenue- and subsidy loss due to closures of the IJtunnel

Note: as the calculation of the revenue- and subsidy losses include confidential information specific to GVB, the actual numbers used in the calculations and the outcomes are not allowed to be published in this thesis. Therefore, this appendix outlines the calculation made but does not provide the actual amounts involved.

Due to the IJtunnel closures GVB experiences a loss of passengers and thus passenger revenues. Moreover the diversion implemented shortens the route for the IJtunnel service lines. GVB receives a subsidy per kilometre from the Stadsregio Amsterdam, which implies that the actual subsidy received is reduced due to the IJtunnel closures. Since the IJtunnel closures were all planned during weekends, the calculations in this appendix were based on average quantities per weekend day.

Table 16 shows the calculation of the revenue- and subsidy loss due to the closure of the IJtunnel per average weekend day. The second column shows the change of the average number of passengers per weekend day due to the IJtunnel closures, this was calculated by means of the average number of passengers per weekend day and the percentage changes estimated by this research[24]. These numbers were multiplied by an average revenue of € x per trip[25], which results in the associated revenue loss in the third column. In the fourth column the change of the average number of kilometres driven per weekend day are shown for each service line. Multiplying these numbers by a subsidy of € x per kilometre for busses, the actual subsidy loss is obtained in the fifth column. The final column shows the total loss of both revenues and subsidy.

[24] The used percentage change for the IJtunnel service lines was -18.37%, for the other service lines in Amsterdam North this was +8.55% (see Table 8 on page 44).

[25] The monetary costs for a trip using the chipcard are based on a standard boarding fare and a basic fare per travelled kilometre (OV-chipkaart, 2013). Though, as multiple ticket types and products are available these fares differ per passengers. For example, children and seniors travel against a reduced tariff, whereas passengers with annual- or season tickets pay a fixed price and can travel unlimitedly. Using the boarding fare and fare per kilometre for this calculation would be less accurate as it would lead to a substantial overestimation of revenue loss. Therefore, the revenue loss was calculated by means of an average revenue per trip in which the use and fares of different ticket types are weighted. Note that this may also result in an overestimation as the number of passengers (check-ins) is larger than the actual number of trips (passengers may check in multiple times during one trip as a consequence of interchanges between modes). Though this overestimation is perceived as less severe than the overestimation of the chipcard tariffs.

Table 16: Calculation of revenue- and subsidy loss per average weekend day due to IJtunnel closures

Service lines	Δ # passengers	Δ € passenger revenue	Δ # kilometres	Δ € subsidy	Δ € revenue loss and subsidy loss
IJtunnel lines					
32	X	X	X	X	X
33	X	X	X	X	X
34	X	X	X	X	X
35	X	X	X	X	X
Net loss	**X**	**X**	**X**	**X**	**X**
Lines in Amsterdam North					
36	X	X	X	X	X
37	X	X	X	X	X
38	X	X	X	X	X
Net gain	**X**	**X**	**X**	**X**	**X**
NET LOSS PER DAY	**X**	**X**	**X**	**X**	**X**

As the effects of the IJtunnel closure appeared to be stronger for the multiple subsequent closures in March 2013 compared to other closures, the total revenue- and subsidy loss for the specific closures in March 2013 were calculated. This calculation was constructed in a similar way as Table 16, but the percentage differences used in the third column differ[26]. Note that the subsidy loss in these calculations are equal as the average reduction of kilometres per day is similar per day.

[26] The used percentage change for the IJtunnel service lines during the specific closures in March 2013 was -21.10%, for the other service lines in Amsterdam North this was +12.98% (see Table 8 on page 44).