Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

Effects of Ticket Inspection Levels: a Quasi-Experimental Approach

Stephan Keuchel [a*], Carla Swertz [a]

[a] *Westphalian University of Applied Sciences, August-Schmidt-Ring 10, 45665 Recklinghausen, Germany*

Abstract

When introducing electronic ticketing it can be economically sensitive for bus transport companies also to introduce an honour-based ticketing which makes fare evasion an issue. In a quasi-experimental setting effects of increasing ticket inspection levels, changing the clothing of the inspectors from official to civil clothing, and varying sizes of inspection teams on different reported reasons for passengers without a ticket are analysed by means of Poisson regression. As expected higher ticket inspection levels have a decreasing effect on the share of passengers who are reported to have 'no (validated) / valid ticket' as well as passengers who have their 'ticket forgotten'. A change from official to civilian clothing of the inspectors reveals higher shares of passengers with 'no (validated) / valid ticket' but seems to have a decreasing effect on the share of the group 'ticket forgotten', and the size of the inspection team reveals a small but significant higher shares of both groups. Furthermore, this quasi-experiment shows that when combined the measures mentioned above lead to a substantially lower share of the group 'ticket forgotten' but reveals a higher share of the other group. Knowledge of the differences of the effects on the reported reasons are relevant for revenue effects as well as for comparisons of fare evasion between different public transport systems.

Keywords: public transport;bus transport system; fare evasion; quasi-experiment; poisson regression

1. Introduction

Fare evasion occurs when a passenger has no ticket or a ticket not valid for the intended journey. Therefore, fare evasion causes loss of revenues for the public transport companies and social inequity in terms of forcing paying passengers to cover the financial losses and/or higher subsidies needed to maintain the public transport system.

* Stephan Keuchel. Tel.: +49-2361-915-428; fax: +49-2361-915-756.
E-mail address: stephan.keuchel@w-hs.de

Fare evasion affects different transport systems in different ways. In many subway systems passengers have to proof payment by means of turnstiles, sometimes guarded by authorised staff. Fare evasion in these systems is rather low. For bus transport systems the context can vary substantially. In many cities around the world boarding of busses is limited to the front door. Passengers show their ticket to the driver or buy a ticket from him. In some systems a conductor sells tickets to the passengers. Fare evasion then is of no real concern for the transport company. Though, these strategies lead to increased boarding times or require additional staff. In order to decrease costs many transport companies opened the back doors for boarding and rely on an honour ticketing system which requires passengers to validate their tickets. Bonfanti and Wagenknecht (2010) found an average fare evasion rate of around 4 percent. Fare evasion rates can vary substantially due to several reasons, such as routes, locations, time period, level of enforcement, and door of entry (Lee, 2011). Guardia et. al. (2016) reported a monthly evasion rate on Transantiago busses between 12% and 16% in 2007. After the introduction of a smartcard system with boarding and validating at all doors the rate ranged between 20% and 27% in 2012. They modelled the joint influence of level of income of the area where the bus stops, bus door operation, period of the day, and day of the week.

Other authors point out different groups of fare evaders. From self-reported reasons for fare evasion passengers are clustered mainly into accidental evasion (e.g. ticket machines did not work), calculated evasion (e.g. travelling just a few stops), and unintentional evasion (e.g. ticket forgotten). Incorporating these groups of passengers into approaches to model fare evasion seems to be complex. (Delbosc, A., Currie, G., 2016a; Delbosc, A., Currie, G., 2016b; Currie, G., Delbosc, A., 2017)

Different fare evasion rates can be associated with different economic consequences. A major approach to deal with fare evasion is ticket inspection. Higher inspection rates lead to increasing costs. The question then is, whether a reduction of evasion rates actually leads to an increase in revenues. Reported fare evaders can buy tickets or just not forget to travel without their ticket, but, alternatively, they can better watch out for ticket inspectors or they can change the mode of transport. Models which take these effects into account become quite complex. And quite a few data needed are not available to the bus transport companies. (Barabino, B., Salis, S., Useli, B., 2013; Barabino, B., Salis, S., Useli, B., 2014; Barabino, B., Salis, S., Useli, B., 2015; Bijleveld, C., 2007)

The purpose of the paper presented here is to model the effect of the ticket inspection level in combination with the clothing of inspectors and the size of the team of inspectors on reported reasons for passengers travelling with no ticket in a bus transport system differentiated by groups of passengers in a quasi-experimental approach. In this approach two groups of passengers are distinguished: those who travel with ‘no (validated) / valid ticket’ and those who have their ‘ticket forgotten’.

To this end the paper is organised as follows. The method is outlined in chapter 2. The design of the quasi-experiment is provided, as well as the differentiation of reported reasons for passengers travelling with no ticket, and a brief outline of the Poisson Regression. In chapter 3 follows a description of the distributions of the reported reasons for passengers travelling with no ticket, differentiated according to passengers with ‘no (validated) / valid ticket’ and ‘ticket forgotten’. In chapter 4, results on rates of the two groups of passengers are provided. Further, for each group of passengers estimated coefficients of a model are provided showing the effects of ticket inspection level in context with other variables. The paper ends with a discussion and conclusion in chapter 5.

2. Method

2.1. Design of the Quasi-Experiment

In the city of Münster (Westphalia, Germany) the public transport company (Stadtwerke Münster GmbH) provides the inner-city bus service for about 300,000 inhabitants. In addition, there are some connections between the seven local train stations. Next to the car the major competitor of the public transport system is the bicycle due to the fully developed cycling infrastructure.

The public transport company offers different season tickets for people who use the bus on a regular basis, as there are: a season ticket, a season 9am ticket which gives access to the bus system after 9am, a job ticket for commuters, a 60plus season ticket for pensioners, and a 60pluspartner season ticket. Further, there are season tickets for pupils, apprentices, and students. As from 2013, these tickets are issued as smartcards based on a check-in system. In addition, the public transport company launched an electronic season ticket which allows for peak load pricing.

The public transport company also offers several tickets for occasional bus users. There are: a single ticket, a day ticket, a 9am day ticket, a weekly ticket and a monthly ticket. In 2013 the public transport company also launched an electronic single ticket issued as smartcard, which allows to travel for 90 minutes regardless of the direction and number of trips.

The number of passengers has increased over the years to around 41.6 m in 2015, 45.1 m in 2016, and 45.4 m in 2017. The share of passengers using annual season tickets slightly decreased from 70.7 % to 69.6 %, and 69.2 %, respectively. Vice versa the share of other tickets increased slightly from 12.7 % to 13.9 %, and 14.5 %, respectively. The remaining 16.5 %, 16.6 %, and 16.4 % of passengers travel on an allowance basis, mainly children. Both new electronic tickets show increasing numbers of passengers. These estimated shares are based on figures on the average usage of season tickets and ticket sales. They also hold for the monthly shares. Only during December, the share of other tickets increases up to almost 20 % in different years due to some specific events attracting many people to the city.

Until the introduction of the electronic tickets ticket inspection was not of much concern since passengers boarded through the front doors of the busses and showed their tickets to the driver or bought the tickets from him. With the introduction of the electronic tickets the boarding process took more time due to the validation process of the tickets. Therefore, as from 2014, all doors of the busses, in most cases three, were opened for boarding and equipped with validators in order to speed up the boarding process, and ticket inspection became a concern of the public transport company.

In June 2015 there was a first reorganisation of ticket inspection. Since then, ticket inspectors board busses according to a schedule. As is shown in figure 1, in 2016, the number of ticket inspectors boarding busses (number of cases) increased significantly but decreased back to the former level in October 2016. As from July 2017 the number of cases increased again. The inspection was outsourced to another company. Further, in December 2016 the ticket inspectors changed clothing from service to civilian. Therefore, the effects of the increases in ticket inspection as well as clothing can be analysed here.

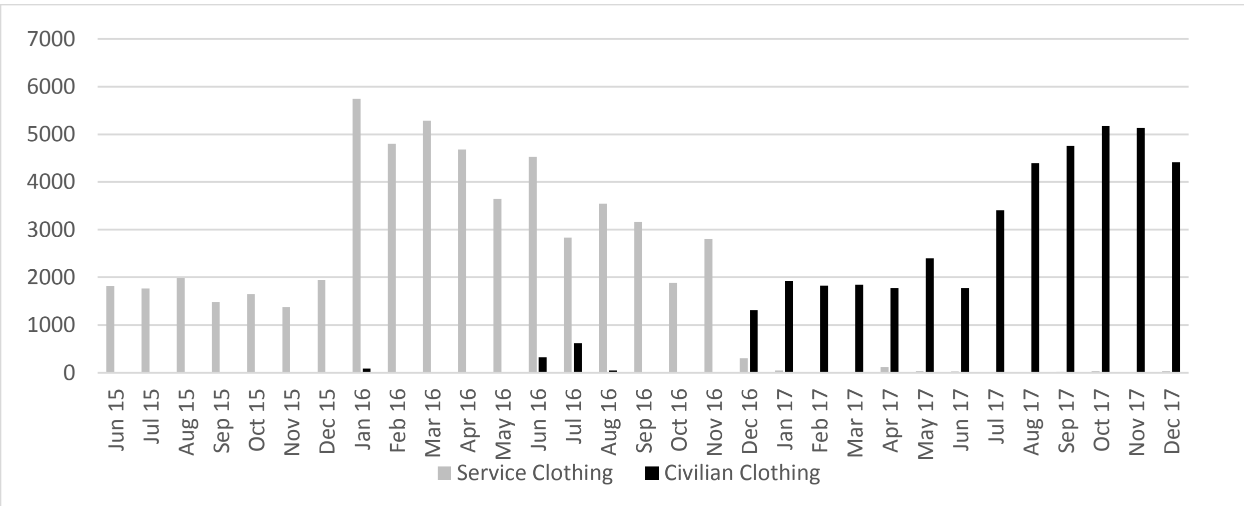

Fig. 1. Number of cases and clothing of ticket inspectors.

As is shown in figure 2, ticket inspection level is substantially lower in the afternoon, especially throughout the years 2015 and 2016. Finally, the size of the inspection teams varied between two and three inspectors which is assumed to be of relevance since almost all of the busses are provided with three doors.

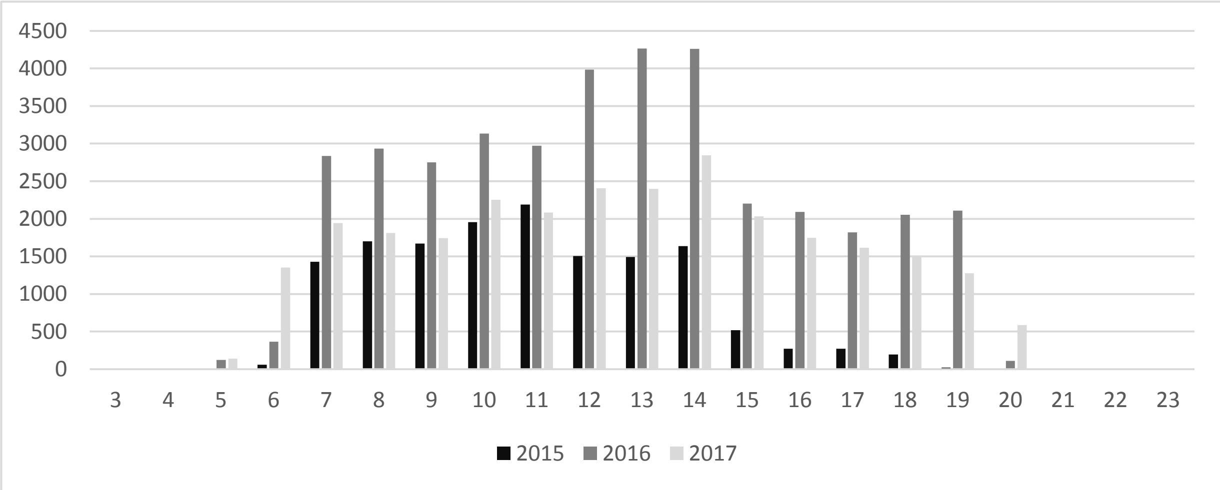

Fig. 2. Number of cases throughout a day.

2.2. Reported reasons for passengers travelling without a ticket

Ticket inspectors enter data into a handheld. These data include date, time and bus station they board and alight a bus, the number of passengers whose tickets they inspected, the number of passengers providing no (valid) ticket, and the reason why a person cannot show a (valid) ticket. The inspectors select the reason they enter for a report from a menu index. For the purpose of this survey these reported reasons are grouped into four different categories.

The first category includes the reasons why a passenger does not show a ticket. This includes ‘the person does not show a ticket at all’, ‘the ticket is validated during the inspection’, ‘the ticket is validated several times’, or ‘the ticket is not validated’. Further, the reasons ‘the ticket is blocked’, ‘the ticket is fraudulent’, and ‘the ticket is not testable (single ticket)’ belong to this category.

The second category includes those passengers who provide a ticket which is not valid. Major subcategories are ‘the passenger holds a ticket with a not valid tariff’ and ‘the ticket is used during a wrong period of time’ Often these passengers make use of a season ticket named Funticket, and use it before 2 pm, a time period the ticket does not cover. This ticket is an additional season ticket to the school season ticket of pupils. Another group of passengers show tickets which are valid for another time period, usually they are expired already. Another notable group of passengers use a not transferable season ticket which is not issued on their name, namely a student season ticket or a goCard, which is issued for apprentices. Holders of the 60+season ticket and the 9am season ticket don’t very often make use of theirs season ticket too early during the day.

The third category comprises those passengers who have their ticket forgotten. Especially for some season tickets a monthly sticker is needed and some passengers forget to update the sticker. Another reason is that passengers forget their customer ID. In these cases, passengers can provide the season ticket and customer ID later on and are charged an administration fee only. Another reported reason is that the season ticket is not testable. The passengers of this group form the fourth category.

2.3. Poisson Regression

The cases to be analysed are defined by the time and station a ticket inspector boards a bus until the time and station he alights the bus. For every case there is a report of the number of controlled passengers and of the missing tickets. In most cases there are no missing tickets, in some cases one missing ticket, and in rare cases several missing tickets among the controlled passengers (see table 2). Since there is a large number of passengers controlled n and a small share of passengers without a ticket θ the basic method to model these count data is Poisson regression, based on Poisson PDF (Hilbe, 2014).

The probability of a specific number of missing tickets y in a case is defined as:

$$P(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!} \qquad \text{with } \lambda = \mathrm{n} * \theta = \mathrm{E}(Y). \tag{1}$$

Since we have many cases i it is possible to model λ depending on K structural variables x_k:

$$P(Y_i = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \tag{2}$$

$$with\ \ln(\lambda_i) = \sum_{k=0}^{K} \beta_k x_{i,k} \qquad \text{as link function.} \tag{3}$$

The log-values of the K parameters β_k can be estimated by means of Maximum Likelihood procedure. Further, their statistical significance can be tested.

According to (3) λ_i can be calculated as:

$$\lambda_i = e^{\beta_0 + \beta_1 * x_{i1} + \dots + \beta_K * x_{iK}}. \tag{4}$$

The cases represent different sizes n_i which can affect the probabilities of missing tickets. The different sizes n_i can be taken account of by an offset:

$$\ln\left(\frac{\lambda_i}{n_i}\right) = \sum_{k=0}^{K} \beta_k x_{i,k} \Leftrightarrow \ln(\lambda_i) = \ln(n_i) + \sum_{k=0}^{K} \beta_k x_{i,k}. \tag{5}$$

With $\ln(n_i) = 1$ λ_i is:

$$\frac{\lambda_i}{n_i} = e^{\beta_0 + \beta_1 * x_{i1} + \dots + \beta_K * x_{iK}} \Leftrightarrow \lambda_i = e^{1 + \beta_0 + \beta_1 * x_{i1} + \dots + \beta_K * x_{iK}} \tag{6}$$

Applying this the probability of missing tickets per passenger can be described as:

$$\lambda_0 = e^{\beta_0} \tag{7}$$

This probability can be differentiated according to the estimated parameters β. If, for example, the data of different months, here June 2015 and July 2015, are taken account of by a structural variable $x_{July2015}$, which equals zero for cases of June 2015 and one for cases of July 2016, the probabilities of missing tickets per passenger in June 2015 and July 2015 can be described as:

$$\lambda_{June\ 2015} = e^{\beta_{June\ 2015}} \tag{8a}$$

$$\lambda_{July\ 2015} = e^{\beta_{June\ 2015}} * e^{\beta_{July2015}} \tag{8b}$$

This is used to describe the monthly rates of ‘no (validated) / valid ticket’ and ‘ticket forgotten’ throughout the experimental period. Similarly, the determinants of fare evasion can be incorporated into a model, i.e. periods of higher ticket inspection levels, size of inspection team, and clothing of inspection team.

3. Data

3.1. Sample

Ticket inspectors enter the busses in groups of two or three. Since June 2015 they are scheduled according to a central plan. The ticket inspectors are assigned to different regions and lines of the bus network as well as to two working shifts.

The data ticket inspectors report in a handheld are related to the date, time, and bus stations they board and alight a bus, the number of passengers whose tickets they inspected, the number of passengers providing no (valid) tickets, the reason for fare evasion, as well as the data on the ID of passengers travelling with no ticket. The latter were not available for this study due to reasons of data protection. Table 1 gives an overview on the average number of tickets controlled in a case, varying between 8.5 and 10.2. The number of tickets controlled in a case varies between 1 and 192 at the most. The number of cases is low in 2015 since the survey period starts in the middle of the year of 2015 due to the reorganisation of the scheduling of the ticket inspectors.

Table 1. Tickets controlled in a case

Year	Mean	Std. Dev.	Min	Max	NoC
2015	8.5327	5.2764	1	65	10684
2016	10.2359	6.8827	1	148	38007
2017	10.1414	7.3376	1	192	27725

Source: own survey.

The following table 2 displays the frequencies of numbers of reported tickets per case in total as well as differentiated according to three categories of reasons: no (validated) or no valid ticket, ticket forgotten, and ticket not testable. For all three years as well as for all three categories of reasons a right-skewed distribution of the number of reported tickets is found.

Table 2. Reported tickets in a case.

Report	Total	No (validated) / valid ticket	Ticket forgotten	Ticket not testable
		2015 (June – Dec.)		
0	8861	9509	10288	10498
1	1695	1116	385	183
2	115	54	9	3
>=3	13	5	2	0
		2016		
0	30620	32711	37252	37000
1	6917	5063	746	980
2	432	215	8	26
>=3	38	18	1	1
		2017		
0	19768	21096	27390	27023
1	7158	6083	328	689
2	715	505	7	13
>=3	84	41	0	0

Source: own survey.

4. Results

4.1. Evasion rates differentiated by groups of passengers travelling with no ticket

In a first purely descriptive model the log-rates of the different years were calculated with 2015 as a reference. Structural dummy variables were introduced for the years 2016 and 2017. The overall rate of passengers travelling with no ticket increased from 1.74 (2015) to 2.03 (2016) and 3.15 (2017).

In a second model the log-rates of the different months were calculated with June 2015 as a reference. Structural dummy variables were introduced for every month until December 2017. Further, data were differentiated by the categories ‘no (validated) / valid ticket’ and ‘ticket forgotten’. Figure 3 describes the monthly rates of these two groups of passengers. It can be clearly seen that the rates ‘no (validated) / valid ticket’ vary while showing an increasing tendency whereas the rates ‘ticket forgotten’ show a clear lasting decrease in January 2016 after the first increase of the ticket inspection level. Interpreting these rates needs to take into account that the categories ‘no (validated) / valid ticket’ and ‘ticket forgotten’ relate to different shares of passengers. The category ‘ticket forgotten’ relates to holders of annual season tickets. Holders of these tickets account for around 70% of the passengers. This means that the rates can be assumed to be slightly higher. Since the share of the passenger with other tickets is less than 20 %, rates of the category ‘no (validated) / valid ticket’ can be assumed to be much higher.

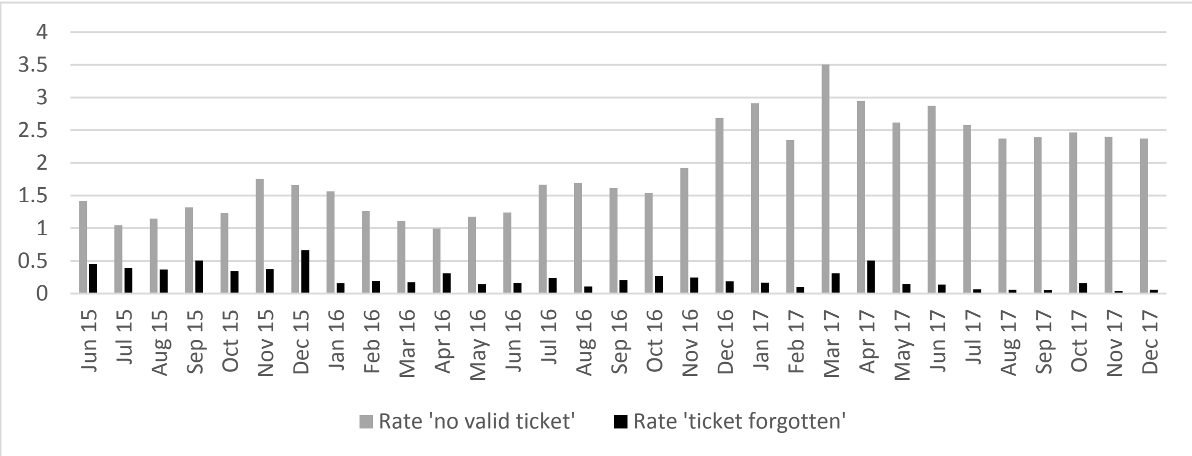

Fig. 3. Rates of different reported reasons of passengers without a ticket.

4.2. Factors determining evasion differentiated by groups of passengers travelling without a ticket

In order to determine the factors affecting the rates and to account for the different categories of the reported reasons ‘no (validated) / valid ticket’ and ‘ticket forgotten’ two separate models were estimated.

The first model accounted for the reported reasons ‘no (validated) / valid ticket’. It was hypothesised that with increasing levels of ticket inspection the evasion rates would decrease. Two dummy variables were included into the model. Their values were coded one for the two periods of increased ticket inspection levels, that is from January to September 2016 and from July to December 2017, respectively. The two variables account for the differences in the increase of the ticket inspection levels and for the fact that the second increase coincides with the start of the outsourcing of the ticket inspection. Another three dummy variables were coded one for the afternoon periods of 2015, 2016, and 2017, starting with 4 pm. Three variables were chosen to account for the fact that the ticket inspection level decreased in the afternoon especially in 2015 and 2016, but to a much lesser extend in 2017.

Another dummy variable was introduced to take into account that the clothing of the ticket inspectors changed in December 2016 from official to civil clothing. It was hypothesised that evasion rates of teams in civil clothing would reveal higher evasion rates compared with teams wearing official clothing. Further, a dummy variable covered the size of the team. Since most of the buses had 3 doors it was hypothesised that teams of three inspectors would reveal higher evasion rates compared with teams of two inspectors. Further, an interaction term between clothing and team size was introduced. It was hypothesised that the size of the team only matters when inspectors wear official clothing. Finally, a dummy variable ‘week 1’ was introduced to cover the effect that passengers with monthly tickets sometimes forget to get a new ticket in time.

The estimation of the model was based on 76,416 cases and Maximum Likelihood procedure was applied. Compared with a constant only model the likelihood ratio test statistic equals 1591.01 a value well beyond the critical chi squared value (α=0.01) of 21.6660 with 9 degrees of freedom.

The overdispersion test (Cameron, Trivedi 1990) results in $g = \mu_i^2 = 4.121$. This value can be assumed to follow the chi square distribution with one degree of freedom. The value is below $\chi^2 = 6.635$, the critical value at 0.01 level of significance. Therefore, the null hypothesis of equidispersion is not rejected.

Table 3 displays the estimated coefficients of the model. The reference category is based on a team of two inspectors, during the period before 4 pm, low level of ticket inspection, week 2-4, and official clothing. The coefficient logcase fixed to one indicates the offset for different sample sizes explained above in equation (5). The two coefficients for the increased ticket inspection level TIL16 and TIL17 both show the expected negative sign and are estimated statistically significant. Vice versa the three coefficients TIL15afternoon, TIL16afternoon, and TIL17afternoon for the lower ticket inspection level during the afternoon show the expected positive sign. All three coefficients are estimated statistically significant. As expected, the increase in fare evasion is highest in 2015, when the inspection decreased to a comparatively low level in the afternoon, and lowest in 2017, when there was only a moderate decrease.

Table 3. Coefficients estimated for the model ‘No (validated) / valid ticket’.

No (validated) / valid ticket	Coefficient		Std. Error	z	Prob. z>|Z*|
Constant	-4.30849	***	0.02649	-162.55	0.0000
Logcase	1.0		(fixed parameter)		
TIL16	-0.16376	***	0.02593	-6.32	0.0000
TIL17	-0.12707	***	0.02298	-5.53	0.0000
TIL15afternoon	0.33986	***	0.08874	3.83	0.0001
TIL16afternoon	0.21441	***	0.03067	6.99	0.0000
TIL17afternoon	0.13232	***	0.02692	4.92	0.0000
Week1	0.10679	***	0.01984	5.38	0.0000
CLOTH	0.64528	***	0.03104	20.79	0.0000
T3 | CLOTH	0.06770	*	0.03503	1.93	0.0532
TEAM3	0.03344		0.02409	1.39	0.1650

*, **, ***: Significance at 10%, 5%., 1% level.

Source: Own calculation.

As expected, the change of clothing from official to civilian shows a positive sign and is estimated statistically significant. Further, the team size only matters, as hypothesised, if the ticket inspectors wear official clothing. The coefficient for the team size variable TEAM3, though positive, is not estimated statistically significant, whereas the interaction term T3|CLOTH is statistically significant positive.

Finally, the coefficient WEEK1 shows the expected positive sign and is estimated statistically significant.

The second model accounted for the reported reasons ‘ticket forgotten’. It included the same variables as the first model, though with different hypotheses. Since holders of annual season tickets are frequent travellers, they are more affected by an increase of the ticket inspection level. Therefore, it was expected, that with increasing levels of ticket inspection the fare evasion rates would decrease in general, but that they would not increase much with decreasing inspection levels in the afternoon period.

If holders of season tickets forget their ticket they get the opportunity to show their ticket during the following days paying only a moderate administration fee. Since there is no penalty, it was hypothesised that the rate would not change with a change of clothing of the inspectors. For the same reason it was hypothesised that the size of the team would not affect the rate in a significant way. During week 1, however, it was hypothesised, that passengers more often forget their season tickets compared with the following weeks of a month.

The model was based on 76,416 cases and estimated by means of Maximum Likelihood procedure. Compared with a constant only model the likelihood ratio test statistic equals 412.70 a value well beyond the critical chi squared value (α=0.01) of 21.6660 with 9 degrees of freedom.

The overdispersion test (Cameron, Trivedi 1990) results in $g = \mu_i^2 = 1.714$. This value can be assumed to follow the chi square distribution with one degree of freedom. The value is below $\chi^2 = 6.635$, the critical value at 0.01 level of significance. Therefore, the null hypothesis of equidispersion is not rejected.

Table 4. Coefficients estimated for the model ‘Ticket forgotten’.

No (validated) / valid ticket	Coefficient		Std. Error	z	Prob. z>|Z*|
Constant	-5.75801	***	0.05913	-97.37	0.0000
Logcase	1.0		(fixed parameter)		
TIL16	-0.65350	***	0.06063	-10.78	0.0000
TIL17	-0.99017	***	0.11306	-8.76	0.0000
TIL15afternoon	0.10958		0.20139	0.54	0.5864
TIL16afternoon	0.01198		0.08242	0.14	0.8853
TIL17afternoon	0.00160		0.12321	-0.01	0.9896
Week1	0.48458	***	0.05531	8.76	0.0000
CLOTH	-0.68669	***	0.09296	-7.39	0.0000
T3 | CLOTH	0.13797		0.12194	-1.13	0.2579
TEAM3	0.17758	*	0.10617	1.67	0.0944

*, **, ***: Significance at 10%, 5%., 1% level.

Source: Own calculation.

Table 4 displays the estimated coefficients of the model. The reference category is based on a team of two inspectors, during the period before 4 pm, low level of ticket inspection, week 2-4, and official clothing. The coefficient logcase fixed to one indicates the offset for different sample sizes explained above in equation (5). The two coefficients for the increased ticket inspection level TIL16 and TIL17 both show the expected negative sign and are estimated statistically significant. But, as expected, the three coefficients TIL15afternoon, TIL16afternoon, and TIL17afternoon are well away from being statistically significant.

Unexpectedly, the coefficient for the size of the inspection team is estimated statistically significant positive, though just at the 10%-level. There is no significant interaction between the clothing of the inspectors and the team size. But unexpectedly, the coefficient for the clothing of the inspectors is estimated statistically significant negative.

Finally, the coefficient WEEK1 shows the expected positive sign and is estimated statistically significant.

5. Discussion and Conclusion

Results indicate that increasing ticket inspection levels have a decreasing effect on the share of passengers reported to have ‘no (validated) / valid ticket’ as well as to have their ‘ticket forgotten’. A major difference is that the share of passengers reported to have ‘no (validated) / valid ticket’ is much larger and at the same time the reduction due to the increase of ticket inspection level is lower compared with the share of passengers reported to have their ‘ticket forgotten’. This is surprising in so far that the first group of passengers has to pay a fine of 60 Euros whereas the second group only has to show their ticket within the next days and pay an administrational fee of only 7 Euros. A possible explanation of this different size of effects is that those passengers who are reported to have their ticket forgotten are holders of season tickets. These frequent travellers are more likely to be affected by an increase of the ticket inspection level. And, therefore, they are more likely to communicate changes of the inspection levels to each other.

Results further show a substantial difference of coefficients for the variable clothing of ticket inspectors. The positive coefficient in the model for the share of passengers reported to have ‘no (validated) / valid ticket’ does not indicate an effect of the clothing of ticket inspectors but rather just reveals a higher rate of fare evasion. As a plausible reason can be assumed that the rather infrequent travellers do not recognise the ticket inspectors when wearing civilian clothing. On the other hand, we find a negative coefficient in the model for the share of passengers reported to have their ‘ticket forgotten’. This in turn can be interpreted as an effect of the clothing of ticket inspectors. The effect is surprising since this group of passengers has only to show their ticket within the next days and pay the comparatively low administration fee. But since they are frequent travellers they are more affected by a ticket inspection and can be expected to communicate a change in the clothing of the inspectors to each other. Changes in the inspection regime can be viewed as reminders to them not to forget their tickets.

The descriptive models show a substantial increase in the rate of passengers reported to travel with ‘no (validated) / valid ticket’ during the study period and a decrease of the share of passengers reported to have their ‘ticket forgotten’. This can be interpreted as combined effects of ticket inspection levels and clothing of the ticket inspectors. The first increase in the ticket inspection started in January 2016 but decreased until autumn 2016 back to the former level. Accordingly, the rate ‘no (validated) / valid ticket’ decreased during the first half of 2016 but increased in the second half of the year. As from December 2016 until end of 2017 the clothing of the ticket inspectors changed and revealed a substantially higher rate of passengers traveling with ‘no (validated) / valid ticket’ throughout the year 2017, though, somewhat reduced due to the increase in the ticket inspection level as from July 2017.

The rate of passengers reported to have their ‘ticket forgotten’ decreased due to the increase of the ticket inspection level in 2016. It further decreased with the change of the clothing of the ticket inspectors to civilian clothing. And it even further decreased when the ticket inspection level increased in 2017 again. Though, the last effect cannot be distinguished from a possible effect of the outsourcing of the ticket inspection to an external company.

In total we can observe a change in the structure of passengers reported to travel without a ticket. The share of passengers reported to travel with ‘no (validated) / valid ticket’ is increasing due to the substantial decrease of passengers reported to have their ‘ticket forgotten’. This is certainly important for the analysis of revenues since the latter group is not relevant here.

Since the share of frequent travellers holding a season ticket accounts for around 70 percent of the travellers the rate of passengers reported to travel with ‘no (validated) / valid ticket’ related to the other group has to be assumed to be much higher. This issue seems to be important when comparing the rates of passengers travelling without a ticket between different bus transport companies.

Finally it should be noted that the group of passengers reported to travel with ‘no valid ticket’ contain quite a few passengers reported to use their ticket in an inappropriate way. Quite often the reported reason is linked to the inappropriate use of season tickets of pupils, students, and apprentices. In other cases passengers hold season tickets with restrictions of use, e.g. during the time of the day. This raises the question that travellers choose their tickets and, therefore, have some control on the frequency and kind of situations in which incentives to travel without a valid ticket occur. A more differentiated analysis of reported reasons of passengers travelling without a valid ticket in combination with the kind of ticket they actually use is, therefore, needed.

Acknowledgements

We thankfully acknowledge the public transport company Stadtwerke Münster GmbH who provided the data for this research work.

References

Barabino, B., Salis, S., Useli, B., 2013. A modified model to curb fare evasion and enforce compliance: Empirical evidence and implications. Transportation Research Part A 58, 29-39.

Barabino, B., Salis, S., Useli, B., 2014. Fare evasion in proof-of-payment transit systems: Deriving the optimum inspection level. Transportation Research Part B 70, 1-17.

Barabino, B., Salis, S., Useli, B., 2015. What are the determinants in making people free riders in proof-of-payment transit systems? Evidence from Italy. Transportation Research Part A 80, 184-196.

Bijleveld, C., 2007. Fare dodging and the strong arm of law. Journal of experimental criminology 3, 183-199.

Bonfanti, G., Wagenknecht, C., 2010. Human factors reduce aggression and fare evasion. Public Transport International 59, 28-32.

Cameron, A.C., Trivedi, P.K., 1990. Regression-based tests for overdispersion in the Poisson model. Journal of Econometrics 46, 347-364.

Currie, G., Delbosc, A., 2017. An empirical model for the psychology of deliberate and unintentional fare evasion. Transport Policy 54, 21-29.

Delbosc, A., Currie, G., 2016a. Four types of fare evasion: A qualitative study from Melbourne, Australia. Transportation Research Part F 43, 254-264.

Delbosc, A., Currie, G., 2016b. Cluster analysis of fare evasion behaviours in Melbourne, Australia. Transport Policy 50, 29-36.

Guarda, P., Galilea, P., Handy, S., Muñoz, J. C., de Dios Ortúzar, J., 2016. Decreasing fare evasion without fines? A microeconomic analysis. Research in Transportation Economics 59, 151-158.

Guarda, P., Galilea, P., Paget-Seekins, L., de Dios Ortuzar, J., 2016. What is behind fare evasion in urban bus systems? An econometric approach. Transportation Research Part A 84, 55-71.

Hilbe, J. M., 2014. Modeling count data. Cambridge University Press. New York.

Lee, J., 2011. Uncovering San Francisco Muni's Proof-of-Payment Patterns to Help Reduce Fare Evasion. Transportation Research Board 2011 Annual Meeting, Washington, D.C.

Troncoso, R., de Grange, L., 2017. Fare evasion in public transport: A time series approach. Transportation Research part A 100, 311-318.