Identifying different types of observed immobility within longitudinal travel surveys

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Summary
In every travel survey there are respondents who did not report any trips on a given day. It is important to distinguish truly immobile respondents from respondents who simply stated that they were immobile (soft refusers). Three methods are proposed in this paper to identify possible soft refusers and tested on the Netherlands Mobility Panel. Identification is done based on attrition, determinants of out-of-home activity, and questionnaire response behaviour. All three methods identify a group of respondents who are at risk of exhibiting soft refusal. By combining the three methods, approximately 5% to 10% of respondents were found to be at high risk of exhibiting soft refusal, and their data should therefore be treated with extra caution.

Keywords: Netherlands Mobility Panel, immobility, soft refusal, longitudinal travel survey

1. Background

Travel surveys are often conducted to analyse developments in people's travel behaviour. To achieve this, it is crucial that respondents report their travel behaviour accurately. However, every travel survey will encounter respondents who appear to be immobile because they report very few or no trips at all. Immobile respondents are often defined as people who did not report any trips during a certain period - usually one day (Axhausen, 2003). Immobile respondents can be divided into roughly two groups: the first are the respondents who genuinely did not travel on the reporting day, because they were, for instance, house-bound or had no out-of-home activities on that reporting day; the second are those respondents who either forgot the trips they made or who did travel but deliberately reported that they did not travel on the reporting day as a means of reducing their response burden (soft refusal).

Although this is a widely used definition of immobility, it should be noted that it does not necessarily include all immobile people. This definition only identifies immobile people from a pure data point of view; when they did not report any mobility. With this definition only people who are truly house-bound and people who did not have any reason to leave their house will be regarded as immobile. There is, however, also an additional group of people who can be defined as immobile from a transport perspective. People who do travel, but are only able to do so under certain conditions (i.e. only accompanied by someone, only for very short distances, only with certain travel modes), will not be regarded as immobile with this definition, while their limitations suggest otherwise. This last type of immobility is, however, not the focus of this paper. In this paper, people are defined as immobile on a reporting day when they did not report any trips that day.

As a result, soft refusal is defined as not reporting any trips on a reporting day, while the respondent did, in fact, make one or more trips that day. Soft refusal is, however, not limited to not reporting any trips at all. Soft refusal can also be defined as underreporting trips. If a respondent did report some, but not all, of their trips, this is also soft refusal. Since the focus in this paper is on immobility defined as not reporting any trips on a given day, this last form of soft refusal will not be addressed in this paper.

Madre et al. (2007) found a number of factors that influenced genuine immobility. The main determinants of immobility include old age, retirement and disabilities, living in a low density area and working at home, being unemployed or having a non-fixed workplace. Other factors included the absence of a car in the household, low incomes, and weather conditions. Based on a meta-analysis, Madre et al. (2007) estimated that the share of immobile respondents should be in the range of 8% to 12% for a standard one-day, weekday-only travel diary. A lower share of immobility in a travel survey could indicate some form of self-selection of highly mobile persons, while higher shares could indicate that the survey suffers from a high frequency of soft refusal.

Wide ranges of immobility can be found in travel surveys. In the Belgium daily mobility survey (BELDAM), conducted in 2009 among Belgian households, 29% of respondents reported no trips and were therefore immobile (Cornelis et al., 2012). The Danish National Travel Survey (TU) reported an immobility level of 17% from 2006 to 2010 (Armoogum et al., 2014). In the German Mobility Panel (MOP), an annual household survey, a considerably lower share of immobility of approximately 8 to 9% was found for the waves between 2005 and 2015 (Weiß et al., 2015). These wide ranges clearly indicate that certain travel surveys may be more affected by soft refusal than others. Soft refusal negatively affects the data quality, as the data is no longer an accurate representation of the respondents' travel behaviour. It is therefore important to be able to distinguish the different types of immobile respondents. On the one hand, genuinely immobile people are an interesting and important group to study in relation to policy, while on the other hand there are the 'soft refusers' who can negatively impact the data quality, and, consequently, it is important to identify them from a research point of view.

In this paper, different methods to distinguish soft refusers from the truly immobile respondents in longitudinal travel surveys are proposed. Their effectivity is assessed based on an application on data from the Netherlands Mobility Panel (MPN). In the next section of this paper the three different methods are discussed, followed by a description of the data that has been used to test the different methods. Next, the results of the application of the methods on the data are discussed and the different methods are combined to identify soft refusers with more certainty. In the paper's final section, conclusions are drawn about the possibilities to distinguish soft refusers from true immobile respondents in longitudinal travel surveys. Implications for cross-sectional travel surveys are also shorty addressed and directions are suggested for further research.

2. Methods

To identify soft refusers in longitudinal travel surveys, three different methods are proposed and it is assessed whether they can effectively distinguish soft refusers from true immobile respondents. The first method is focused on using multiple years of data to assess whether certain type of respondents are at higher risk of showing soft refusal. For this, information about respondent fatigue and attrition levels are used. It is well known that multi-day and longitudinal travel surveys can suffer from respondent fatigue, which in turn could significantly impact the reported mobility. Golob and Meurs (1986) showed that the share of respondents reporting no trips for an entire day increased over time during a seven-day travel diary. In an analysis of a six-week travel diary survey, however, it was shown that, although there was some variation, no trend was observed for the share of immobile days (Axhausen et al., 2007). If respondent fatigue (in the form of rising immobility rates) is present in the travel survey, this might indicate the presence of soft refusal with respondents who are participating in the panel for a longer period of time.

When respondents drop out of a panel, it is likely that they lost motivation to keep participating. It might therefore also be the case that their dedication to the survey in their final wave is rather low. Information about attrition is used to assess whether respondents who dropped out of the panel show a higher level of immobility and thereby possibly soft refusal.

The second method that is proposed and tested is focused on respondent's questionnaire response behaviour. Travel surveys usually do not only consist of reporting all travel activities for a predefined period of time in a travel diary, but also include one or more questionnaires to gather background information of the respondent. This method is aimed to identify respondents that show poor response behaviour in these questionnaires, which might indicate poor response behaviour in their travel diary. To do so, it is assessed whether respondents showed any straightlining of grid questions. Straightlining is defined as providing the same answer to every item in the grid and is an indicator of measurement error (Struminskaya et al., 2015).

The third method is aimed at identifying soft refusers based on several personal- and household characteristics. These characteristics are used to estimate a binary logit model that can predict whether a respondent will report any trips on any given day, much like the method used by Madre et al. (2007). With this model, respondents who reported to be immobile, but, based on their background characteristics, were expected to be mobile can be identified.

To increase the certainty of truly identifying soft refusers, the three different methods are combined. If certain respondents are identified as a possible soft refusers with multiple methods, it is expected that there is a high chance that the respondent truly is a soft refuser.

3. Data

To test the different methods, data from the first four waves of the Netherlands Mobility Panel (MPN) is used. In this section, the structure and composition of the MPN is shortly discussed.

The MPN is a household panel that was set-up to study the short-run and long-run dynamics in the travel behaviour of Dutch individuals and households, and to determine how changes in personal and household characteristics, and in other travel-related factors, correlate with changes in travel behaviour (Hoogendoorn-Lanser et al., 2015). The first wave of data collection started in 2013, with the sample being drawn from an existing access panel. The MPN consists of a screening questionnaire (only the first wave of participation) and a household questionnaire that are filled out by an adult household member (gatekeeper), and an individual questionnaire and a three-day travel diary that are filled out by each household member aged 12 and older. Annually, respondents are asked to fill in these questionnaires and the travel diary.

In the three-day travel diary, respondents are asked to report all trips made during three predefined days. Respondents are equally divided over the days of the week, so that on all days of the week, approximately the same number of respondents are reporting their travel activities. Every year, respondents are assigned the same three days to prevent a bias between waves due to the fact that a respondent is reporting different days of the week and to be able to study changes in travel behaviour over the years. So, if a respondent is assigned Thursday through Saturday in his first wave, he is assigned to these three days in every wave he participates in. In order to account for attrition and to keep a representative sample, additional households were recruited in the second and fourth wave of the MPN. In the second wave, extra focus was on recruiting certain groups (such as young and low educated people) since they were somewhat underrepresented in the first wave and had higher nonresponse levels. In the third wave, no extra households were recruited.

Table 1 shows an overview of the number of complete respondents in the MPN per wave, dependent on their starting wave. Complete respondents are respondents who filled in all questionnaires and completed their three-day travel diary. Completing the travel diary does not necessarily include reporting travel activity. A respondent is also able to report that he did not travel on all three reporting days. Furthermore, there are also respondents who only filled in the questionnaires but failed to complete their travel diary. However, since this paper is focused on immobility, as based on the travel diary, only complete respondents are included. It should also be noted that some respondents did not participate all consecutive waves, but skipped a wave. For instance, from the 1,659 respondents that started in wave 1 and also participated in wave 4, 1,228 participated all four consecutive waves. The remaining 431 respondents did not participate in wave 2 or 3.

Table 1. Number of complete respondents per wave in the MPN

	Number of respondents			
	Wave 1	**Wave 2**	**Wave 3**	**Wave 4**
Start wave				
Wave 1	3,950	2,507	2,083	1,659
Wave 2	-	2,914	1,452	1,121
Wave 3	-	-	367*	177
Wave 4	-	-	-	1,219
Total	3,950	5,421	3,902	4,176

*No new households were recruited in wave 3, the new respondents were part of a household that was already recruited before wave 3

Table 2 shows the sample composition of the complete respondents for the different waves, as well as the composition of the Dutch population as based on the so-called Gold Standard (MOA, 2017). As can be seen there are some slight variations between the waves due to attrition and recruitment of new respondents. Especially in wave 2 is can be seen that the recruitment of new households was focused on certain groups. There is a relatively large increase in young and low educated respondents from the first to the second wave. Furthermore, it can be seen that the sample is fairly representative for the Dutch population. The largest deviation is found on educational level, with an underrepresentation of low educated people and an overrepresentation of high educated people.

Table 2. Sample composition in the different waves

		Gold Standard (2015)	Wave 1	Wave 2	Wave 3	Wave 4
Gender	Male	49,4%	46,5%	46,4%	46,2%	46,1%
	Female	50,6%	53,5%	53,6%	53,8%	53,9%
Age	<24 yo	18,4%	14,2%	23,3%	18,4%	17,9%
	25 - 34 yo	14,0%	16,1%	13,4%	14,5%	18,1%
	35-44 yo	15,5%	18,1%	14,4%	13,5%	15,5%
	45-54 yo	17,6%	17,7%	21,5%	20,6%	19,0%
	55-64 yo	15,2%	17,0%	13,5%	15,5%	14,8%
	>65 yo	19,3%	17,0%	13,8%	17,5%	14,7%
Education level	Low	37,1%	30,5%	34,8%	30,7%	26,4%
	Medium	39,9%	37,7%	36,9%	37,6%	39,2%
	High	22,9%	31,7%	28,2%	31,6%	34,2%
Work situation	Employed	50,3%	56,9%	52,0%	52,9%	57,2%
	Does household/volunteer	7,7%	6,3%	8,6%	8,3%	8,0%
	Student	13,1%	10,9%	18,8%	15,2%	14,1%
	Jobless/disabled	8,4%	7,8%	7,7%	7,3%	7,1%
	Retired	20,6%	18,1%	13,0%	16,3%	13,6%
Household situation	Single household	19,3%	22,6%	16,2%	17,9%	18,3%
	Adult household	44,7%	42,8%	44,4%	46,7%	47,2%
	Youngest child <12 yo	23,6%	19,3%	20,4%	18,3%	19,3%
	Youngest child 12-17 yo	11,4%	14,7%	19,0%	16,9%	15,0%
Household size	1	19,4%	22,6%	16,2%	17,9%	18,2%
	2	34,2%	36,9%	27,2%	30,7%	29,3%
	3	16,3%	13,6%	16,6%	16,0%	15,7%
	4	19,8%	18,7%	24,0%	22,1%	24,5%
	5	7,4%	6,4%	12,2%	9,7%	9,1%
	6 or more	2,9%	1,7%	3,8%	3,5%	3,1%

4. Reported immobility in the MPN

As previously stated, immobility is often defined as not reporting any travel activity during a certain period of time. How this period of time is defined can greatly influence immobility figures. Table 3 reveals the share of respondents in the MPN's first four waves that reported travels during either none, one, two or all three reporting days. It can be seen that if immobility is defined as not reporting any travels for at least one day, more than one-third of all respondents would be defined as immobile. However, if a respondent is only regarded as immobile when not reporting any travels during the entire reporting period, around 4% of respondents would be regarded as immobile. As stated in section 1, in this paper immobility is defined as not reporting any travel activity during a single day.

Table 3. Number of days with travel activity per respondent in the MPN

	Wave 1	Wave 2	Wave 3	Wave 4
Number of respondents	3,950	5,421	3,902	4,176
Respondents that reported travel activity on 3 days	66.7 %	65.4 %	64.6 %	64.1 %
Respondents that reported travel activity on 2 days	22.9 %	23.2 %	24.0 %	23.8 %
Respondents that reported travel activity on 1 day	6.1 %	7.3 %	6.8 %	8.2 %
Respondents that reported no travel activity at all	4.3 %	4.2 %	4.6%	3.9 %

The type of reporting day is a factor that substantially impacts the derived immobility figures. Madre et al. (2007) estimated that the share of immobile respondents should be in the range of 8% to 12% for a standard one-day, weekday-only travel diary. From Table 4 it becomes clear that this estimation cannot be used for a travel study's weekend days. The table shows the share of reporting days with no reported travels per day of the week for the first four waves of the MPN. On 12 to 14.5% of weekdays, no travels are reported, accounting for an average of 13.1% across all waves. As this figure is slightly above the 12% maximum share of immobility that Madre et al. (2007) suggest, the MPN could suffer from some type of soft refusal. However, when examining weekend days, the share of immobile days increases. For Saturdays, an average of 19.4% of respondents reported no travels. For Sundays this further increases to an average of 32.7%; however, it is difficult to draw any conclusions about the presence of soft refusal within the MPN for weekend days, as it can be expected that the share of weekend days with no reported travels would be higher than weekdays. This is also reflected in the Dutch National Travel survey in 2015 where the reported immobility rises from 16.7% on weekdays, to 20.6% on Saturdays and 30.5% on Sundays (CBS, 2016).

Table 4. Average reported immobility per day of the week in the MPN

	Wave 1	Wave 2	Wave 3	Wave 4
Monday	12.8 %	13.9 %	12.6 %	14.2 %
Tuesday	12.9 %	13.1 %	13.6 %	12.5 %
Wednesday	12.2 %	12.4 %	12.7 %	13.5 %
Thursday	12.3 %	12.0 %	14.5 %	14.5 %
Friday	12.6 %	13.4 %	13.2 %	12.9 %
Saturday	16.5 %	20.1 %	20.1 %	20.9 %
Sunday	32.1 %	32.2 %	33.8 %	32.8 %

5. Identifying soft refusers based on respondent fatigue and attrition

This section assesses the impact that respondent fatigue and attrition had on immobility, as reported in the MPN. Previous studies have shown that multiple-day travel surveys could suffer from respondent fatigue (Golob & Meurs, 1986; Kitamura & Bovy, 1987). The number of trips that respondents report could therefore decline on subsequent reporting days, owing to an increase in soft refusal, which in turn could lead to an increasing number of days for which no trips were reported. Table 5 shows the day-to-day variations in immobility per wave: it shows that for 2013 the share of reporting days with no trips decreased as the reporting days progressed. For the other waves, slight variations can be observed. For all waves, the within-wave differences between reporting days are insignificant at a 95% level. It can therefore be assumed that, in terms of immobile days, panel fatigue is not present during waves.

Table 5. Within- and between-wave variations of reported immobility per reporting day in the MPN (all respondents)

	Wave 1	Wave 2	Wave 3	Wave 4
Diary day 1	16.7 %	17.3 %	17.0 %	17.7 %
Diary day 2	15.8 %	16.4 %	17.0 %	16.2 %
Diary day 3	15.5 %	16.5 %	17.5 %	18.0 %
Pearson Chi-Square p-value	0.338	0.338	0.839	0.075
Number of respondents	3,950	5,421	3,902	4,176
Average immobility	16.0 %	16.7 %	17.2 %	17.3 %

**To calculate the average reported immobility, both weekdays and weekend days are included*

When examining the group of respondents that participated in all four waves, some increase in immobility over the waves can be observed (Table 6). Again, within-wave differences are insignificant, but the average level of immobility increased from 12.0% in wave 1 to 14.2% in wave 2: this difference is significant at a 95% confidence level. In waves 3 and 4, the level of immobility for this group increased slightly to 14.8% and 16.1%, but these differences are not significantly higher compared to the immobility in wave 2. For all waves, the level of immobility for the group that participated in all waves was significantly lower compared to the other respondents. The largest difference was found between respondents who only participated in a single wave and respondents who participated in all four waves; for instance, the level of immobility in the first wave for the first group was 21.0%, compared to 12.0% for the group that completed all four waves. This could indicate that soft refusal is less of a problem for the group of respondents that participated in the panel for a longer period of time. However, it should be noted that the level of immobility for respondents who participated in all four waves increased in every wave. Respondent fatigue could therefore be an issue for respondents who participate in multiple waves.

Table 6. Within- and between-wave variations of reported immobility per reporting day in the MPN (respondents who participated all four waves)

	Wave 1	Wave 2	Wave 3	Wave 4
Diary day 1	11.6 %	14.3 %	13.1 %	16.3 %
Diary day 2	12.5 %	14.5 %	15.3 %	15.1 %
Diary day 3	11.8 %	13.8 %	16.0 %	16.9 %
Pearson Chi-Square p-value	0.805	0.891	0.104	0.466
Number of respondents	1,228	1,228	1,228	1,228
Average reported immobility	12.0 %	14.2 %	14.8 %	16.1 %

**To calculate the average reported immobility, both weekdays and weekend days are included*

Table 7 compares the average level of immobility per wave between respondents who dropped out of the panel after a specific wave and respondents who did not. Considering all reporting days, the level of immobility of respondents who dropped out of the panel is between 41% and 48% higher than for respondents who did not drop out. For weekdays only, respondents who dropped out of the panel showed a 47% to 60% higher immobility rate in their final wave compared to respondents who remained MPN participants. These statistics clearly indicate that extra attention should be given to the data from the last wave that respondents participated in before dropping out of the panel, as soft refusal might be an issue for these respondents. The weekday immobility rate for respondents who remained in the panel is well within the 8 to 12% range, which Madre et al. (2007) indicated as an acceptable level of immobility. However, note that this table only includes statistics from the first three waves, as it is currently unknown which respondents dropped out of the panel after wave 4.

Table 7. Average level of immobility of respondents who dropped out of the panel and respondents who did not

		Wave 1	Wave 2	Wave 3
Average immobility	Respondents who dropped out	21.0 %	20.8 %	21.1 %
	Respondents who did **not** drop out	14.2 %	14.8 %	14.8 %
Immobility on weekdays	Respondents who dropped out	17.3 %	16.6 %	16.8 %
	Respondents who did **not** drop out	10.8 %	11.3 %	11.3 %
Attrition rate		27.0 %	32.1 %	37.6 %

Table 8 shows the average reported immobility of respondents, depending on the number of waves they participated in. From this table it becomes clear that both respondent fatigue and attrition impacted the reported immobility. For respondents who participated in multiple MPN waves, the reported immobility level increased in every wave. The reported immobility was always highest in the last wave that a respondent participated in before dropping out. From the analyses on respondent fatigue and attrition it can be concluded that, although respondent fatigue seems to be present in the MPN, attrition is a stronger indicator of possible soft refusal. Besides, attrition is easier to identify and it is therefore recommended to use information about attrition over information about respondent fatigue to identify soft refusal.

Table 8. Average immobility per wave depending on number of waves respondents participated in

	Reported immobility		
Number of waves participated	**Wave 1**	**Wave 2**	**Wave 3**
One	21.0 %	20.6 %	21.2 %
Two (started wave 1)	16.7 %	21.4 %	-
Two (started wave 2)	-	15.8 %	19.6 %
Three	15.3 %	17.0 %	20.9 %
Four	12.0 %	14.2 %	14.8 %

**To calculate the average reported immobility, both weekdays and weekend days are included*

In terms of number of trips and average travelled distance per day, differences can also be observed between waves and the sample average, and between respondents who participated all four waves and respondents who dropped out, as shown in Table 9. When examining the entire sample, a significant decrease in number of trips per day from the first to the second wave is observed. The average number of reported trips was largely constant in the subsequent waves. However, the average distance per trip increased in every wave. The average distance per trip in waves 1 and 2 was significantly lower than in wave 4, which could indicate that short trips were underreported in later waves. The same holds for the group of respondents that dropped out of the panel after a specific wave; it is clear that this group reports significantly fewer trips and has a higher average distance per trip, which is in line with the findings of Kitamura and Bovy (1987), who stated that the respondents who underreport their trips and respondents who are less mobile have a higher propensity to drop out of a panel. It should, however, be noted that these statistics are not corrected for changes in sample composition. Attrition and recruitment of new households lead to changes in sample composition, as shown in Table 2. This could have an influence on the total reported mobility of the sample. To draw conclusions about differences between waves in terms of average reported number of trips and distances, the statistics should be corrected for changes in sample composition in terms of, for instance, gender, age and education level.

Compared to the entire sample, the respondents who participated all four waves reported significantly more trips; however, their average number of trips significantly decreased over the various waves, except for between waves 2 and 3, while their average distance per trip fluctuated over the various waves. In terms of days without any reported trips, the group of respondents that participated in all waves had significantly lower immobility levels than the entire sample, although it was observed that the level of immobility increased across each wave. If the average number of trips made by respondents who participated in all waves is corrected for the increase in immobility, the differences between waves becomes smaller, yet they are still significant. Consequently, in terms of reported trips, this group might also suffer from some type of soft refusal due to respondent fatigue. In this paper, however, the focus is on soft refusal in the form of not reporting any trips on a certain day, as stated in section 1.

Table 9. Average number of reported trips per day and distance per trip in the MPN

		Wave 1	Wave 2	Wave 3	Wave 4
Average trips per day	All respondents	3.10	2.92	2.89	2.88
	Respondents who participated all four waves	3.40	3.21	3.18	3.01
	Respondents who dropped out	2.80	2.63	2.62	NA
Average distance per trip (km)	All respondents	11.87	11.74	12.26	12.73
	Respondents who participated all four waves	11.71	10.81	11.23	11.74
	Respondents who dropped out	12.39	12.88	13.09	NA

6. Identifying soft refusers based on questionnaire response behaviour

Another option for identifying possible soft refusal in the travel diaries is to use the respondents' questionnaire response behaviour. Each year MPN respondents fill out several questionnaires. In waves 2 and 4, the questionnaires contain a relatively large number of grid questions. Respondents filled out 4 to 10 grid questions, depending on age and modality use (80% of the respondents filled out at least eight grid questions). In questionnaires, an indicator of measurement error is the amount of straightlined grid questions (Struminskaya et al., 2015). A respondent is deemed to be straightlining when he provides the same answer to every item in the grid. If a respondent straightlines one or more grid questions, this could indicate laziness or low commitment to the study. By straightlining grid questions, respondents lower their response burden. Soft refusal is also a way to lower the response burden. Straightlining in questionnaires could therefore be related to soft refusal in the travel diary.

To assess whether straightlining is an indicator of soft refusal in the travel diary, respondents were divided into four groups: a group that never straightlines, a group that straightlines up to 25% of their grid questions, a group that straightlines between 25 and 60%, and a group that straightlines more than 60% of their grid questions. The relationship between immobility and straightlining is shown in Table 10. It is clear that there is a relationship between straightlining in questionnaires and reporting to be immobile in the travel diaries. Approximately 90% of the respondents did not straightline any of their grid questions or only a small percentage. Part of the grid questions in the MPN are focused on attitudes towards different transport modes. If a respondent has, for instance, an extremely positive attitude towards the car, it can be imagined that he indicates to strongly agree with all items in the grid question about car (the grids contain items like travelling by car is comfortable, safe and flexible). This is identified as straightlining, but in fact the respondent answered the questions truthfully. It is therefore assumed that when a respondent only straightlines a small part of the grid questions (up to 25%), this does not per se indicate poor response behaviour.

The weekday immobility level of respondents who do not straightline is well within the 8 to 12% range estimated by Madre et al. (2007). For respondents who do straightline, but not more than 25% of their grid questions, the immobility level is around the MPN average of 13.1%. Combining the two best performing groups in terms of straightlining results in an average weekday immobility of 11.8%. For the two worst performing groups, it is clear that soft refusal is likely an issue. It can therefore be concluded that the 10% of respondents who straightline a significant part of their grid questions are at risk of exhibiting soft refusal in their travel diaries; consequently, extra attention should be given to assessing the quality of their data. Identifying possible soft refusers based on straightlining is however only possible if the questionnaires contain a considerable number of grid questions. This method therefore cannot be used for waves 1 and 3 of the MPN.

Although this method cannot be applied to waves 1 and 3 of the MPN, the fact that the MPN is a longitudinal panel survey provides some possibilities for these waves. If certain respondents are identified as a risk group based on their questionnaire response behaviour in wave 2 and/or 4, it might be the case that they are also a risk group in wave 1 and/or 3. To confirm this, future research should assess whether poor response behaviour in a certain wave is a predictor of poor response behaviour in another wave.

Table 10. Relationship between straightlining of grid questions and reported immobility in waves 2 and 4

		Reported immobility		
	Share	**Weekdays**	**Saturday**	**Sunday**
0% straightlining	57.8 %	10.7 %	17.2 %	29.7 %
1% - 25% straightlining	32.0 %	13.7 %	21.9 %	33.5 %
26% - 60% straightlining	7.6 %	21.8 %	31.8 %	47.4 %
>60% straightlining	2.7 %	34.4 %	35.7 %	43.3 %

7. Identifying soft refusers based on personal and household characteristics

To gain insight into factors that influence immobility, a binary logit model was estimated. Because, as section 4 illustrated, the level of immobility is significantly different on weekdays compared to Saturdays or Sundays, three different models were estimated: one for weekdays (number of days = 35,939), one for Saturdays (number of days = 7,212), and one for Sundays (number of days = 7,204). These models allow one to calculate the probability that respondents leave their homes on a certain day. The models are however limited in the sense that all of the respondent's reporting days are treated as independent observations. The number of observations per unique respondent depends on the number of waves the respondent participated in and is always a multiplication of three, as only the respondents who completed the three-day travel diary are included. In other words, there are three to twelve observations in the models for every respondent. Table 11 shows the parameter estimates of the three binary logit models. All included variables have one or more significant parameter, with the exception of level of urbanization.

For weekdays, the youngest age group of 12-17 year olds had the highest probability of leaving the home, which is an expected result, as these respondents must attend school each weekday. One interesting result is the fact that the older age groups - up to age 74 - have a significantly higher probability of leaving the home during weekdays, compared to the reference category of 35 to 44 year olds. Moreover, the 65 to 74 years old age group also has a significantly higher probability of leaving their homes on Saturdays and Sundays.

As expected, highly educated people have a lower probability of being immobile. Previous studies have shown that higher educated people tend to commute over longer distances (Schwanen et al., 2002) and are more likely to use active transport, as compared to lower educated people (Scheepers et al., 2013). Higher educated people also have a higher probability of leaving the home on weekend days, compared to lower educated people.

People who have either a part-time or full-time job have a higher probability of leaving the home during weekdays and weekend days, as compared to unemployed people. While it is expected that people with jobs would have a higher propensity to leave their homes during weekdays, it is interesting that the same holds for weekend days. Income was not included in this model, because income levels are unknown for more than 10% of the sample. It could be the case however that the effect of income is partly reflected in the work situation: people with jobs not only have higher incomes than jobless people, but also have more disposable income for undertaking out-of-home activities during weekends.

People who do not work because of a disability have a significantly higher probability of being immobile during weekdays; however, it should be noted that being disabled in this context does not necessarily refer to a physical disability, but rather can also include other non-physical disabilities that make work impossible.

By far the strongest indicator of not reporting any trips is sickness. Respondents are asked in the MPN whether they were sick on their reporting days. It should be noted that it is unknown whether the respondents were dealing with short-term or long-term sickness. Further, it is unknown whether the respondents were genuinely sick or simply reported being sick in order to justify the fact that they did not report any trips. According to Statistics Netherlands (CBS, 2017), the Netherlands had an absenteeism rate of 3.9 to 4.1% between 2013 and 2016. The MPN respondents with jobs reported being sick on 4.1% of their reporting days, while the jobless respondents reported being sick on 5.7% of their reporting days, which is slightly higher than respondents with jobs. It should be noted that this jobless group also includes disabled people, which (partially) explains the higher sickness rate, as, on average, 13.6% of the disabled respondents reported being sick on any given day. It is therefore assumed that respondents do not wrongfully report that they were sick on a reporting day. Starting from wave 5 in 2017, the MPN questionnaires will include a number of questions pertaining to the respondent's health and difficulties travelling, which will provide more options for considering the respondents' health when identifying the various types of immobile respondents.

The respondent's county of origin is also a significant indicator of immobility. On both weekdays and weekend days, immigrants have a significantly lower probability of reporting trips on any given day. Immigrants are defined as respondents who are born outside of the Netherlands. This is an interesting finding, as it could indicate some type of soft refusal among immigrants within the MPN. When the immigrants' work situations were compared to those of the native Dutch respondents, no significant differences were found. Given that the immigrants' work situations do not differ from the native Dutch, it can be assumed that the two groups' level of immobility should be comparable. Since the level of immobility is significantly higher for foreigners, foreigners could perhaps exhibit soft refusal.

Bicycle and car ownership are both significant indicators of out-of-home activity. Bicycle ownership shows stronger parameters than car ownership, but it should be noted that car ownership is included as number of cars in the household, while bicycle ownership is included as personal ownership. It could therefore be the case that one or more cars are present in the household, yet not available to the respondent. In all three models, bicycle ownership is a significant indicator of being mobile, which was expected, as the bicycle is an important modality in the Netherlands, with 27% of all trips being taken by bicycle, accounting for 9% of all travelled kilometres (Kennisinstituut voor Mobiliteitsbeleid, 2016).

In addition to the observed mobility in the travel diaries, MPN respondents are asked in one of the questionnaires about how often they usually travel via the various transport modes, such as by car, bicycle and on foot. These stated frequencies also yield a number of significant parameters, all of which are as expected. The lower the stated usage of a certain mode, the lower the probability that a respondent will leave the house. Since the questionnaires are filled out at a different time than the travel diaries, these stated travel frequencies can be very useful for identifying soft refusers. When a respondent stated that he travels more than four times per week with different modes of transport, it is unlikely that he did not travel on his reporting days. It should be noted that these variables are not available for all respondents in wave 1. If possible, the missing values were imputed from wave 2, although this was not possible for the respondents who dropped out of the MPN after wave 1: in order to identify possible soft refusers among this group a separate logit model is estimated that did not include the stated mode use. The parameter estimates for the remaining variables are comparable to the parameter estimates as shown in Table 11.

The degree of urbanisation of the respondent's residential area is included in three levels. No significant parameters were found. In other studies, the level of urbanisation was found to have a significant impact on a person's mobility (Beige & Axhausen, 2008; Dargay & Hanly, 2007; Scheiner & Holz-Rau, 2013), but apparently it has little to no impact on immobility. It could also be the case that these effects are country-specific. The Netherlands is a relatively small and densely populated country. Although there are rural areas, an highly urbanised area is never far away.

Household composition has multiple significant parameters. For the number of adults and young adults (12 years and older) in the household, all but one parameter is significant. The more adults present in the household, the less likely a respondent will leave home, which could be explained by the fact that when multiple adults are present within a household, tasks such as grocery shopping can be divided among them. Only two significant parameters were found for the number of children (under age 12) in the household, and both parameters are positive, as expected. It can be assumed that children younger than 12 years old cannot travel independently and hence their parents must accompany them, which increases the parents' probability of leaving the home.

Table 11. Parameter estimates of the binary logit models predicting whether travel activity will be reported

		Weekday		Saturday		Sunday	
		B	Exp(B)	B	Exp(B)	B	Exp(B)
Intercept		**2.06**	**7.87**	**1.82**	**6.17**	**0.68**	**1.98**
Gender	Male	Reference		Reference		Reference	
	Female	**0.08**	**1.09**	0.06	1.07	0.02	1.02
Age group	12-17 y/o	**1.19**	**3.30**	-0.04	0.96	-0.12	0.89
	18-24 y/o	**0.27**	**1.32**	0.24	1.28	**0.45**	**1.57**
	25-34 y/o	-0.10	0.91	-0.13	0.88	0.11	1.12
	35-44 y/o	Reference		Reference		Reference	
	45-54 y/o	**0.20**	**1.23**	0.18	1.20	0.13	1.13
	55-64 y/o	**0.24**	**1.27**	0.20	1.22	**0.23**	**1.26**
	65-74 y/o	**0.21**	**1.23**	**0.53**	**1.69**	**0.37**	**1.44**
	75+ years old	-0.01	0.99	0.29	1.34	0.16	1.17
Education level	Low	Reference		Reference		Reference	
	Middle	0.07	1.07	0.06	1.07	0.05	1.05
	High	**0.31**	**1.36**	**0.30**	**1.35**	**0.24**	**1.27**
Work situation	No job (0 hours/week)	Reference		Reference		Reference	
	Part-time job (-35 hours/week)	**0.54**	**1.71**	**0.48**	**1.62**	**0.26**	**1.30**
	Full-time job (35+ hours/week)	**0.70**	**2.02**	**0.42**	**1.52**	**0.38**	**1.47**
	Disabled	**-0.22**	**0.80**	0.07	1.07	-0.03	0.97
Origin	Native	Reference		Reference		Reference	
	Immigrant	**-0.32**	**0.73**	**-0.25**	**0.78**	**-0.28**	**0.76**
Sickness on reporting day	Not sick	Reference		Reference		Reference	
	Sick	**-3.22**	**0.04**	**-2.90**	**0.06**	**-2.60**	**0.07**
Bike ownership	No	Reference		Reference		Reference	
	Yes	**0.28**	**1.33**	**0.18**	**1.20**	**0.23**	**1.26**
Number of cars in household	No cars	Reference		Reference		Reference	
	1 or more cars	**0.14**	**1.15**	-0.06	0.94	0.10	1.10
Stated frequency of car use	More than 4 times per week	Reference		Reference		Reference	
	1 - 3 times per week	**-0.33**	**0.72**	**-0.38**	**0.68**	0.01	1.01
	Less than once a week	**-0.40**	**0.67**	**-0.54**	**0.58**	-0.13	0.88
Stated frequency of bicycle use	More than 4 times per week	Reference		Reference		Reference	
	1 - 3 times per week	**-0.50**	**0.61**	**-0.35**	**0.70**	**-0.26**	**0.77**
	Less than once a week	**-0.69**	**0.50**	**-0.65**	**0.52**	**-0.56**	**0.57**
Stated frequency of walking	More than 4 times per week	Reference		Reference		Reference	
	1 - 3 times per week	**-0.09**	**0.92**	-0.05	0.95	**-0.20**	**0.82**
	Less than once a week	**-0.14**	**0.87**	-0.15	0.86	**-0.30**	**0.74**
Level of urbanization	Urban (1500+ inhabitants/km²)	Reference		Reference		Reference	
	Suburban (1000-1500 inhabitants/km²)	0.08	1.08	-0.01	0.99	-0.07	0.93
	Rural (less than 1000 inhabitants/km²)	-0.05	0.96	-0.01	0.99	-0.02	0.98
Number of (young) adults (aged 12+) in the household	1	Reference		Reference		Reference	
	2	**-0.28**	**0.76**	**-0.31**	**0.74**	-0.07	0.93
	3 or more	**-0.47**	**0.63**	**-0.45**	**0.64**	**-0.37**	**0.69**
Number of children (aged 12-) in the household	none	Reference		Reference		Reference	
	1	0.09	1.09	**0.36**	**1.43**	-0.04	0.97
	2 or more	**0.30**	**1.35**	-0.02	0.98	-0.07	0.94

Parameters in bold are significant with p<0.05

The model can predict whether people will leave their homes on any given day or not. Table 12 shows how these predictions performed in the sample. Overall, the model seems to have performed relatively well. For weekdays, the model correctly predicted whether 89.1% of the reported days would be mobile or immobile. For Saturdays and Sundays, this percentage decreases to 82.9% and 70.1%, respectively. There is, however, a large difference in performance if a distinction is made between predicting staying at home and leaving the home. All three models correctly predict that over 97% of the mobile days are indeed mobile, but only 26.2% of the immobile days are identified as immobile on weekdays. For Saturdays, the model can correctly identify just 16.4% of the immobile days, and 13.3% for Sundays. There is apparently a large degree of randomness in whether a respondent is immobile, especially during weekends. For the group of respondents predicted to be mobile, but that did not report any trips, soft refusal could be an issue. Consequently, for weekdays, this could indicate that 73.8% of the reported immobile days are in fact some type of soft refusal. Assuming that the level of immobility should be between 8% and 12% (Madre et al., 2007), it can be calculated that of the respondents that the binary logit model identified as mobile, but reported to be immobile, 10 to 50% are soft refusers. For all reported weekdays, this figure is 1 to 5%.

These 1 to 5% weekdays when soft refusal could be an issue do not necessarily represent 1 to 5% of the respondents. As previously stated, between three and twelve observations per respondent are included in the binary logit models. It was found that per wave approximately 16% of all respondents were identified as possible soft refusers at least once. If it is assumed that between 10 to 50% of these respondents show soft refusal, this implies that every wave between 1.6 to 8% of the respondents is a soft refuser.

Future research could assess how data from multiple waves can be used to further identify the 1.6 to 8% of respondents from the 16% respondents that were identified as possible soft refusers. For instance, if respondents have a fixed day that they work from home, this could explain the reported immobility. In the MPN, there is information about whether respondents sometimes work from home, but it is unknown which day the respondent works from home. If a respondent reports to be immobile on the same day every wave, this could indicate that the respondent works from home that day. Or, if a respondents reported travel activity in one wave, but reported to be immobile in the next wave, but did not report that anything changed or was special about the reporting days, this might indicate that the respondent truly shows soft refusal.

Table 12. Performance of the binary logit model

	Predicted					
	Weekdays		**Saturday**		**Sunday**	
Observed	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Immobile	26.2%	73.8%	16.4%	83.6%	13.3%	86.7%
Mobile	98.5%	1.5%	98.9%	1.1%	97.5%	2.5%
Overall	89.1%	10.9%	82.9%	17.1%	70.1%	29.9%

8. Combining methods to identify soft refusal

In the previous sections, three different methods were proposed to identify possible soft refusal in travel surveys. All three methods indicate that soft refusal could be present within the MPN, and identified a risk group of respondents that could exhibit soft refusal. However, with all three methods, uncertainty remains as to whether the identified respondents are actually soft refusers. The aim of identifying soft refusers is to improve the data quality. However, if respondents are wrongfully identified as soft refusers and removed, this would not improve the data quality. Consequently, in this section, the methods are combined to identify soft refusers. This section focuses on weekdays only; however, the same analogy holds for weekend days, although the binary logit performs considerably worse for weekend days. Extra caution must therefore be taken when identifying soft refusal on weekend days.

It is assumed that if multiple methods identify a respondent as a possible soft refuser, there is a higher probability that the respondent is genuinely a soft refuser. Table 13 shows the share of respondents identified as possible soft refusers, with the various methods combined per wave. It should be noted that not all methods can be applied to all waves. A combination of the three methods is only possible for the second wave, as information about attrition is only available for the first three waves, while information about straightlining is only available for the second and fourth waves. In wave 2, using all three methods, 1.3% of respondents were identified as possible soft refusers. Table 14 shows that this group of respondents has an average immobility level of 68.3% on weekdays. Removing these respondents for weekdays in the MPN's second wave lowers the level of immobility from 12.9% to 12.2%.

Table 13. Combination of methods for identifying soft refusers in the MPN

Possible soft refuser based on binary logit model	**Possible soft refuser based on attrition**	**Possible soft refuser based on straightlining**	**Percentage of respondents in wave 1 ***	**Percentage of respondents in wave 2 ***	**Percentage of respondents in wave 3**	**Percentage of respondents in wave 4 ***
No	No	No	62.7 %	53.7 %	53.8 %	75.2 %
		Yes	-	4.4 %	-	8.0 %
	Yes	No	21.7 %	23.2 %	30.1 %	-
		Yes	-	**3.0 %**	-	-
Yes	No	No	10.4 %	8.7 %	8.6 %	13.8 %
		Yes	-	**1.1 %**	-	**3.0 %**
	Yes	No	**5.3 %**	**4.7 %**	**7.5 %**	-
		Yes	**-**	**1.3 %**	-	-

The bold values indicate respondents who were identified as possible soft refusers by at least two methods.
**For wave 1 and 3 no information about straightlining is available. For wave 4 no information about attrition is available*

Table 14 clearly reveals that the respondents identified as possible soft refusers by two or three methods have a higher level of immobility compared to respondents who were not identified as possible soft refusers or only by a single method. It should be noted that the minimum level of immobility for respondents identified by the binary logit model as possible soft refusers amounts to 33%, because, for the binary logit model to identify them as such, they had to report being immobile on at least one of their reporting days. The bold values in Table 14 indicate the average reported immobility on weekdays for respondents that at least two methods identified as possible soft refusers. This group, which is at high risk of exhibiting soft refusal, amounts to 5.3 to 10.1% of respondents for waves 1 to 3. For wave 4, only 3% of respondents are identified as the high risk group, as it is not yet known which respondents will drop out of the panel. When data from wave 5 becomes available, it is expected that the group of high risk respondents in wave 4 will also be in the range of 5 to 10%.

Table 14. Average reported immobility on weekdays per wave, respondents grouped based on different methods of identifying soft refusal

Possible soft refuser based on binary logit model	**Possible soft refuser based on attrition**	**Possible soft refuser based on straightlining**	**Average immobility on weekdays in wave 1 ***	**Average immobility on weekdays in wave 2 ***	**Average immobility on weekdays in wave 3**	**Average immobility on weekdays in wave 4 ***
No	No	No	2.2 %	2.9 %	3.5 %	3.1 %
		Yes	-	8.0 %	-	9.2 %
	Yes	No	4.8 %	5.1 %	5.3 %	-
		Yes	-	**13.1 %**	-	-
Yes	No	No	56.0 %	52.3 %	53.8 %	54.5 %
		Yes	-	**63.0 %**	-	**62.5 %**
	Yes	No	**63.2 %**	**55.7 %**	**56.9 %**	-
		Yes	**-**	**68.3 %**	-	-

The bold values indicate respondents who have been identified as a possible soft refuser with at least two methods.
**For wave 1 and 3 no information about straightlining is available. For wave 4 no information about attrition is available*

By removing this high risk group, the average level of reported weekday immobility decreases to approximately 9% in the first three waves, as shown in Table 15, which is well within the 8 to 12% range estimated by Madre et al. (2007). It is however not recommended to disregard the high risk group without first conducting further analysis, as it is not expected that all respondents from the high risk group are genuine soft refusers.

Table 15. Average reported immobility of respondents who have a high risk to exhibit soft refusal compared to the other respondents per wave

	Average immobility on weekdays in wave 1	Average immobility on weekdays in wave 2	Average immobility on weekdays in wave 3	Average immobility on weekdays in wave 4
High risk respondents	63.2 %	46.2 %	56.9 %	62.5 %
Other respondents	9.4 %	9.0 %	9.4 %	11.7 %

9. Conclusions and recommendations

In this paper, three different methods for identifying possible soft refusal in longitudinal travel surveys were proposed and applied to the Netherlands Mobility Panel (MPN). All three methods were used to identify the respondents who had a higher risk of showing soft refusal in the MPN's three-day travel diary.

It was shown that respondent fatigue, in terms of reported immobility, is present in the MPN. A high immobility rate was especially reported in the last wave that respondents participated in. Moreover, it was found that there is a relationship between attrition and reported immobility, and therefore with possible soft refusal. This implies that between 27% and 38% of respondents could exhibit some type of soft refusal in the MPN's first three waves. For wave 4, no information about attrition will be available until data from the wave 5 becomes available. Furthermore, attrition seems to be a stronger indicator of possible soft refusal than respondent fatigue.

Questionnaire response behaviour was used as a second method for identifying soft refusal. It was found that there is a clear relationship between the amount of straightlined grid questions in the MPN questionnaires and the reported immobility in the three-day travel diary. Information about straightlining is, unfortunately, only available for MPN waves 2 and 4. It was found that approximately 10% of respondents could exhibit soft refusal in the travel diary, as based on their questionnaire response behaviour.

Three different binary logit models provided insights into factors that determine out-of-home activity. Due to the major differences in immobility, different models were used to estimate for weekdays, Saturdays and Sundays. The models were used to identify respondents who reported to be immobile, but, based on varying personal and household characteristics, were expected to be mobile. Based on the models, it was estimated that between 1 to 5% of respondents is deemed to be at high risk of exhibiting soft refusal.

The three methods were combined to increase the reliability of identifying genuine soft refusers. Combining all three methods was only possible for the second wave, but all three methods revealed that 1.3% of respondents were identified as possible soft refusers. Respondents identified by at least two methods report a considerably higher immobility rate compared to respondents who were not identified as soft refusers or only by a single method. It is therefore concluded that respondents identified as possible soft refusers by at least two methods are at high risk of exhibiting soft refusal: this high risk group amounts to roughly 5 to 10% of respondents for the first three waves. As no information is available about attrition for wave 4, only 3% of wave 4's respondents are identified as the high risk group. However, it is not expected that all these 'high risk' respondents are genuinely soft refusers, hence they should not be disregarded without further analysis. The reported weekday immobility for respondents not in the high risk group is around 9% for the MPN's first three waves. For wave 4, they show an average immobility of just under 12%, but it is expected that this will also decrease to 9% when information about attrition becomes available for this wave.

This paper showed the applicability of these three methods on data from a longitudinal panel study in the Netherlands. Since it was shown that there is a clear connection between reported immobility and other factors that are not specific to the MPN (such as attrition and respondents' personal- and household characteristics), it is expected that these methods can also be applied to other longitudinal travel surveys. To further develop these methods it is recommended to make more use of the opportunities panel data provide. As already mentioned in section 6, it has not yet been assessed if poor questionnaire response behaviour in a certain waves indicates poor response behaviour in other waves. The same goes for the results of the binary logit models. Doing so could help in improving the reliability of these methods in identifying true soft refusers and thereby improving data quality.

The results have shown that roughly 5 to 10% of respondents is at high risk of showing soft refusal. It can be expected that cross-sectional surveys also suffer from soft refusal. For cross-sectional surveys, however, there are fewer methods to identify these respondents. From the three proposed methods, using information about attrition is not possible with cross-sectional studies and therefore, fewer soft refusers can be identified. Furthermore, also improving the reliability of the other two methods by looking at their results in multiple waves is not possible. It is therefore expected that, compared to longitudinal studies, cross-sectional studies might overestimate immobility, even after applying the proposed methods.

It was shown that soft refusal likely does not only occur in the form of reported immobility, but also in the reporting of fewer trips or underreporting of short trips. Analysis of this type of soft refusal is therefore scheduled for future research, which can be used to further distinguish genuine soft refusers from other respondents in the high risk group. Furthermore, identifying this type of soft refusal is needed before doing research into true immobile respondents. As already stated in section 1, people who are only able to travel under certain conditions (for instance only accompanied by someone, only for very short distances or not using active modes), are not defined as immobile by this definition but, in fact, are immobile. To identify these respondents it is important to assess soft refusal in terms of underreporting trips first.

Future research should also focus on soft refusal on weekends; as expected, it was found that the reported immobility on weekends was significantly higher than weekdays. However, it is considerably more difficult to identify soft refusers on weekends, as there are fewer indicators that can be used for deciding whether a respondent is expected to leave their home during weekends, which was also reflected in the fact that the binary logit models for weekend days performed considerably worse than the models for weekdays. Future research could therefore focus on defining a framework for identifying soft refusers on weekend days.

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