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Closer to the total? Long-distance travel of French mobile phone users

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ABSTRACT

Analyzing long-distance travel demand has become increasingly relevant because the share of traffic induced by journeys related to remote activities which are not part of daily life is growing. In today's mobile world, such journeys are responsible for almost 50 percent of all traffic. Traditionally, surveys have been used to gather data needed to analyze travel demand. Due to the high response burden and memory issues, respondents are known to underreport their number of long-distance journeys. The question of the actual number of long-distance journeys therefore remains unanswered without additional data sources. This paper is the first to quantify the underreporting of long-distance tour frequencies in travel diaries. We took a sample of mobile phone billing data covering five months and compared the observed long-distance travel with the results of a national travel survey covering the same period and the same country. The comparison shows that most of the estimates of the number of missing tours by researchers have thus been too low. Our work suggests that the actual number of long-distance journeys is twice as high as that reported in surveys. Two different causes of underreporting were identified. Firstly, soft refusers travelled long distances but reported no long-distance tours. Secondly, respondents underestimated their number of long-distance tours. Consequently, there is a need to use alternative data sources in order to gain better estimates of long-distance travel demand.

1. Introduction

Analyzing long-distance travel behavior has become more important in recent years because the contribution of long-distance journeys to overall traffic is continuously growing. Therefore, the impact on planning urban areas, highways, railroads etc. is becoming greater. Long-distance travel is usually defined as trips which take place outside of a person's environment. However, the definition of a person's environment varies in the literature. It can be defined either spatially, temporally, purpose-based or a combination of these three. This paper utilizes the spatial definition, meaning that all trips within a certain distance of a person's home are considered to be daily life travel. All trips beyond the distance threshold are considered to be a long-distance journeys. Temporal definitions might characterize all overnight stays as long-distance trips. Purpose-based definitions utilize the purpose of a trip to decide whether it is a long-distance journey. In order to develop tools which are able to provide reliable predictions, one needs data sources that describe the current state of long-distance travel demand.

Data collection methods in the field of travel demand research have been investigated in the past (Axhausen et al., 2002; Armoogum and Madre, 2002; Bonnel et al., 2009; Zmud et al., 2013; Richardson et al., 1995; Arentze et al., 2000; Draijer et al., 2000). The most frequently used data sources are surveys. In the case of long-distance travel, the number of available surveys is limited (the main sources are national travel surveys). However, all long-distance travel surveys involve similar problems. Due to the high response burden, surveys tend to have a low number of respondents. Furthermore, it is known that the number of journeys reported in such surveys is too low (Madre et al., 2007; Armoogum and Madre, 2002). Both factors limit the explanatory power of the studies and leave the question of the quality of the results unanswered (Kuhnimhof and Last, 2009).

To overcome these limitations alternative data sources are needed. We propose in this paper to use mobile phone billing data in order to obtain better estimates of long-distance travel demand. The advantage is the large number of people that can be tracked without having being asked to spend a lot of effort on a survey. We analyzed five months of mobile phone billing data covering one third of the total French population. The data was provided by Orange™ France. After reconstructing long-distance journeys from the data, we were able to quantify the error reported by the French National travel survey. The main analysis is split in two parts. Firstly, we quantify the number of persons that do not travel long distances at all. This analysis will show

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that there are more non-travellers among survey respondents than among the Orange customers. Secondly, we quantify the number of long-distance tours that are done by the mobile persons. It will be shown that mobile Orange customers travel significantly more than survey respondents. Both results indicate that the number of tours was heavily underreported in the survey. The aim of this paper to confirm the assumed underestimation of long-distance tours and demonstrate that there is a need of alternative data sources.

This paper is structured as follows: After a literature review we describe in detail the mobile phone data made available for our studies as well as the French national travel survey. In section four, our tour reconstruction methodology is described. Afterwards, we present outcomes and comparisons. We then offer a discussion and a conclusion.

2. Previous work

Data collection has always been an important issue in the field of travel demand research. Different methods of data collection have been investigated in the past (Axhausen et al., 2002; Armoogum and Madre, 2002). The data sources used have mostly been various forms of surveys to suit the diverse requirements of the researchers (Dillman, 2000).

In the case of long-distance travel, the number of recent surveys is limited. For Europe, *Mobidrive* studies are available (Zimmermann et al., 2001; Axhausen et al., 2002; Chalasani and Axhausen, 2004). Each of these studies encompasses a six-week period, which is usually not sufficient for a deep analysis of long-distance travel behavior. Other sources are national travel surveys like the French (Armoogum et al., 2008), British (Department for Transport, 2016) or Austrian (BMVI, 2012) ones. An additional longitudinal perspective is provided by the INVERMO study from Germany(Chlond et al., 2006). Several European studies have been combined for an analysis of long-distance travel demand in Europe (Frick and Grimm, 2014). A similar approach led to a nationwide model for the United States (Outwater et al., 2015a; Outwater et al., 2015b; Bradley et al., 2015).

An overview of available studies of annual long-distance travel rates can be found in Table 1, which reports the study area and year. Variations in the definition of long-distance travel are also reported, which include the distance-threshold used, the destinations included in the analysis and whether single-day tours were excluded from the set of long-distance journeys. Finally, the main indicator, the annual number of long-distance tours, reported in the studies are presented. The values that had to be extrapolated are marked. The studies included are: the California Statewide Household Travel Survey (CSHTS) (Bierce and Kurth, 2014; Cambridge Systematics Inc., 2013), an ifmo study (Frick and Grimm, 2014; Kuhnimhof et al., 2014), the INVERMO project (Zumkeller et al., 2005; Chlond et al., 2006), the Knowledge Base for Intermodal Passenger Travel in Europe (KITE) (Frei et al., 2010), the DATELINE study (Neumann, 2003), the French national travel survey (ENTD) (Armoogum et al., 2008), the Microcensus Switzerland (MCS) (Swiss Federal Statistical Office (BFS), 2010) a Eurostat report (Weckström-Eno, 1999), Methods for European Surveys of Travel Behaviour (MEST) (Axhausen and Youssefzadeh, 1999), and US National Transportation Statistics (US NTS) (Bureau of Transportation Statistics, 2016). All of these studies surveyed 8–12 weeks of long-distance travel and estimated annual tour rates. A correction factor is incorporated in most of the tour rates. The ifmo study reports a higher value than the other studies due to several reasons. Firstly, it is one of the most recent studies and it is known that the amount of long-distance journeys is growing. Secondly, it is combining several studies to get a full picture and, in particular, it estimates 5.0 everydays long-distance tours (e.g. commuting) which is more than in any other study.

Other long-distance travel studies have been performed with a special emphasis on tourism. Guidelines for tourism studies (Harris et al., 1994) and preferred analysis methods (Crouch, 1994) have been presented in the past. Many tourism studies have been performed, including the Travel Market Switzerland study (Bieger and Lässer, 2008) and the Net Traveler Survey (Schonland and Williams, 1996). Almost all of them focus on tourism activities within a single country. A summary of international studies can be found in Lennon, 2003 or the Eurostat database (Eurostat, 2016). However, the results of tourism surveys are limited due to the known issue of unobserved tourism (De Cantis et al., 2015).

Due to the high response burden that is usually associated with long-distance surveys (Axhausen et al., 2015; Axhausen and Weis, 2010), it can be expected that the number of long-distance trips is usually underreported. This is due to non-responding frequent travellers as well as travellers claiming not to travel while answering other questions, or so-called soft refusers (Madre et al., 2007). Furthermore, there is a memory effect. Respondents tend to forget tours, which happened some time before the survey (Smith and Wood, 1977; Bradburn et al., 1987; Tourangeau, 1999). Additionally, the vehicle miles travelled are usually heavily underestimated as shown by Wolf et al. (2003). Consequently, there is a need for survey weighting and expanding (Bar-Gera et al., 2009). Assumptions about underreporting long-distance tour rates in surveys led researchers to introduce correction factors in several studies (Cambridge Systematics Inc., 2013; Armoogum et al., 2008). In the case of tourist surveys, a weight correcting for the response bias is essential (Leeworthy et al., 2001). A correction factor is the only method currently available to account for underreporting. Assumptions about the inaccuracy of long-distance travel surveys are supported by evidence that two surveys of the same scope can suggest non-consistent travel behavior (Perdue and Botkin, 1988).

In order to estimate the level of underreporting in surveys, one

Table 1
Annual long-distance tour frequencies: Other studies (* based on own extrapolation).

Study	Year	Area	Destination	Long-dist. definition	Exclude single-day	Annual tours per capita
DATELINE (Neumann, 2003)	2001–02	Europe	international	75 km	No	2.7
DATELINE (Neumann, 2003)	2001–02	France	international	75 km	No	3.8
ENTD (Armoogum et al., 2008)	2007–08	France	France	80 km	No	5.1
MEST (Axhausen and Youssefzadeh, 1999)	1997–98	France	international	100 km	No	*7.4
MCS (Swiss Federal Statistical Office (BFS), 2010)	2010	Switzerland	international	100 km	No	*7.8
MEST (Axhausen and Youssefzadeh, 1999)	1997–98	Europe	domestic	100 km	No	*7.9
KITE (Frei et al., 2010)	2008–09	Switzerland	international	100 km	Yes	8.2
KITE (Frei et al., 2010)	2008–09	Portugal	international	100 km	Yes	8.2
CSHTS (Bierce and Kurth, 2014; Cambridge Systematics Inc., 2013)	2012	California	state-wide	50 miles	No	8.2
Eurostat (Weckström-Eno, 1999)	1999	France	international	100 km	No	8.5
INVERMO (Chlond et al., 2006)	2001–03	Germany	international	100 km	No	8.8
MEST (Axhausen and Youssefzadeh, 1999)	1997–98	Europe	international	100 km	No	*8.9
KITE (Frei et al., 2010)	2008–09	Czech Rep.	international	100 km	Yes	9.0
US NTS (Bureau of Transportation Statistics, 2016)	2001	USA	international	50 miles	No	*9.4
ifmo (Frick and Grimm, 2014; Kuhnimhof et al., 2014)	2011	Germany	international	100 km	No	15.9

needs alternative data sources. Nowadays, two main alternative sources are available for analyzing travel demand. Both use passive data collection. Firstly, GPS data can be used to collect information about travel behavior (Montini et al., 2014). But the collection of GPS data is limited because the cooperation of the respondents is needed, and smartphone GPS collection is battery-consuming, thus discouraging participation. Secondly, mobile phone network operators produce mobile phone billing information that provides an enormous amount of data. This has already been utilized in various fields (Blondel et al., 2015) including transportation. One of the first applications was an analysis of travel demand induced by tourism (Ahas et al., 2008; Ahas et al., 2007). GSM data has also been used to estimate OD-matrices (Friedrich et al., 2010; Pan et al., 2006; Cik et al., 2014). Furthermore, mobile phone data is suitable for pattern analysis due to large sample sizes. Mobility patterns (Calabrese et al., 2013; Gonzalez et al., 2008) were analyzed as well as patterns in urban road usage (Wang et al., 2012). Finally, activity location identification was performed based on mobile phone data (Chen et al., 2014).

Several studies have comparatively investigated data quality. For instance, studies have compared GSM data with GPS trajectories (Iovan et al., 2013; Hoteit et al., 2014; Smoreda et al., 2013). In addition, sociological aspects of mobile phone usage have been investigated, for instance with regard to analysis of places relevant in transport science (Licoppe et al., 2008). Mobile phone billing data was utilized several times to obtain an OD-matrix, which can be done without a lot of effort, because mobile phone billing data consists of space–time points. An early study in England (White and Wells, 2002) showed that the accuracy of billing data is not good enough to compute a reliable OD-matrix. Therefore, other researchers combined this data sources with others to get better results for OD-matrices. Some of these additional sources are signalling data in a Spanish region (Caceres et al., 2007) and the Ile-de-France (Bonnel et al., 2015), smartphone application data in Sweden (Mellegard, 2011), geo-spatial data together with census data in cities in USA, Portugal, Brazil (Toole et al., 2015). Most of the findings suggest that mobile phone billing data can be a good proxy for overall tendencies of human mobility, thanks among other things to the large samples of persons and days involved. Altogether, GSM data is a powerful tool for analyzing human mobility (Song et al., 2010) as it is shown by the increasing interest of researchers. Nevertheless, usually further data sources are needed to get reliable results. We will show in this paper why estimates based on mobile phone billing data are valuable in case of long-distance travel demand.

Mobile phone data and national travel surveys have only been sporadically compared so far. Bekhor et al., 2013 conducted an evaluation in Israel. However, the study sample was comparatively small in terms of person-days, the focus was not on longitudinal travel behavior, and the first data source preceded the second one by 10 years (with a 25% population increase). Similar work has been done in the USA (Huntsinger and Donnelly, 2014), but was also limited to a regional level (North Carolina). Neither of the two studies provides statements about long-distance travel demand, since they focus on other aspects of travel behavior. We will close the gap in this paper.

3. Data sources

3.1. Mobile phone billing data

The study described in this paper is based on an anonymised mobile phone billing data set recorded by Orange™ France. It consists of Call Detail Records (CDRs) covering the mobile phone usage of around 23 million users of the Orange™ network in France during a period of 154 consecutive days (13 May 2007 to 14 October 2007). Given a population estimate of 63.9 million inhabitants in 2007, that is roughly 35.9% of the French population. The population estimate is the average of the monthly estimates for the period between May and October 2007 obtained from the French National Institute of Statistics and Economic Studies website (www.insee.fr) The numbers correspond with estimates made by Orange™ that mobile phone penetration in France in 2007 was 86% (ARE, 2016), and with the estimated market share of Orange™ in that year (43.5%).

Each CDR contains information about an action (outgoing/terminating call or SMS) which took place in the network. The information needed for our purpose is the caller ID, the time and duration of the action, and the Base Transceiver Station (BTS) that was the connection point for the mobile phone at the start of the action. A BTS is responsible for the wireless communication between the network and the mobile device. Several BTS can be located on a single tower serving different directions and/or technologies. The location of every tower is known. Given information on the location and time of each action, individual users can be traced and their movements can be extracted. The accuracy of reconstructed movements depends on the frequency of actions since no information on the phone in idle mode is given in the data.

The CDR data set has several limitations. Firstly, the action frequency is comparably low, because mobile data usage was not as intense in 2007 as it is today. Secondly, the data set does not cover a full year. Thus, any estimates for the missing time periods must be supported with complementary data sets. In addition to temporal inaccuracy due to the low call frequency, there is also spatial inaccuracy. The spatial information gained from CDR data is limited by the positions of the mobile network towers handling the BTS. For less densely populated areas of the country, a BTS can be several kilometers away from the actual position of a mobile phone. Finally, no information about phone calls made abroad is available in this data set. Even though it is known that France has one of the highest ratios of domestic trips to trips abroad within Europe (OECD, 2012; Eurostat, 2016) this circumstance limits the range for which we can make valid estimates. We will account for this limitation with respect to the special situation of a large central European nation in the results section below.

It has been shown that mobile phone billing data should be used with caution when analyzing mobility (Ranjan et al., 2012). Nevertheless, most limitations do not have a substantial impact when focusing on long-distance travel demand. The spatial and temporal inaccuracies described above are relatively small since we are working on large spatial and temporal scales. Additional signalling data as it is used in Bonnel et al. (2015) would improve the quality of the results since it offers more frequent data, but is not available in this case. Signalling data is an additional information recorded by the network companies, e.g. when an idle mobile phone leaves specific pre-defined areas. Still, mobile phone billing data can provide a lower bound to the actual value. When comparing CDR data with survey data, we have to account for the missing roaming data and focus on the national travel. A detailed discussion on the limitations of the data and the methodology can be found in Section 7.

3.2. Survey data

The results of the CDR data analysis were compared to a national travel survey. We used the *Enquête Nationale Transports et Déplacements (ENTD)*, the French national travel survey. The ENTD is conducted every 10–15 years (1967, 1974, 1982, 1994, 2007–08). Various actors are involved in the ENTD, including the French Ministry of Transport, INSEE (the French National Institute of Statistics and Economic Studies) and IFSTTAR (French Institute of Science and Technology for Transport, Development and Networks). The latest ENTD was performed from April 2007 to April 2008, and most parts are publicly available (IFSTTAR, 2016). We used the ENTD 2008 because it includes the time period covered by the CDR data described above. Moreover, one of its goals was to analyze long-distance mobility, which is advantageous because it enabled us to compare the two data sources in terms of long-distance travel behavior.

However, the sample size of the ENTD 2008 is much smaller than

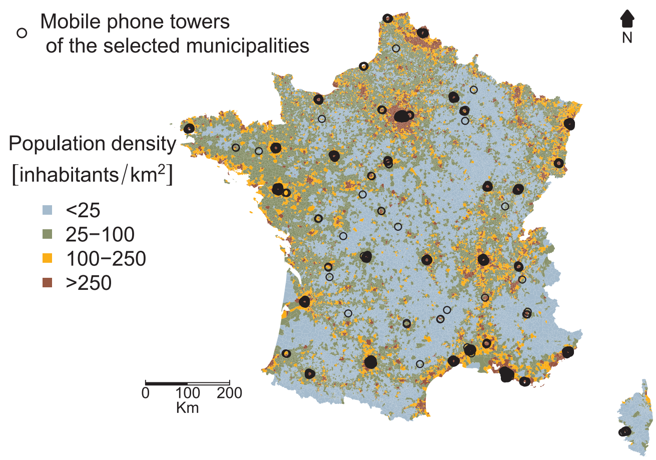

Fig. 1. Mobile phone tower locations of the selected municipalities.

the available CDR data. In total, 20,178 households and 44,958 individuals were surveyed. Just 18,632 (representative) persons were chosen for the long-distance travel module of the survey (Armoogum et al., 2008). The latter were asked to report their long-distance travel practices within the preceding four weeks as well as the preceding 13 weeks. Detailed information on tours taken during the four-week period is publicly available, while just the absolute number of tours is available for the 13-week period. Consequently, the results of the 13-week questionnaire are only used for a comparison of the total number of trips, while the four-week data was used for further analysis like distance distribution. In the ENTD 2008 a long-distance journey is defined as either a journey with the furthest destination more than 80 km from home as the crow flies or 100 km actual travel distance. Journeys, which include at least one overnight stay, were added in the survey, but were removed from the data set for this work in order to compare the actual long-distance travel behavior. We will account for the differences between the data sources in the comparisons (Section 6). Unless otherwise stated, we compared the four-week ENTD records to the CDR data due to the lack of detailed 13-week records.

4. Methodology

The mobile phone billing data set described above was far too big to be analyzed completely within the framework of this study. The reason is the limited server access time that was granted to the authors for this work in combination to the computational heavy tour extraction algorithm that is described in detail in subSection 4.3. Therefore, we had to limit the number of mobile phone users and their CDRs to study. We performed two selection steps. Firstly, a set of municipalities was chosen. Secondly, from each municipality a subset of customers was selected in order to investigate their travel behavior. Even though the analyzed data set is just a sample of the whole data set, the sample size analyzed here exceeds by far the size of any data set collected with a traditional survey.

We want to see how much of an impact population size had on the long-distance travel of the cities' residents, as the German literature suggests that inhabitants trade off daily travel against more long-distance travel (Holz-Rau et al., 2014; Schlich, 2001). In the following sections, both selection processes are described in detail, and the algorithm used to extract the long-distance tours from the mobile phone data is presented.

The following definitions will be used henceforth in this paper:

- Home environment: The area within a radius of 80 km from the home location.
- (Home-based) tour: A chain of activities and trips starting and ending at the home location (sometimes referred to as a 'journey').
- LD tour: A tour which leaves the home environment and therefore is a long-distance tour, because the destination is at least 80 km away.
- LDF tour: A domestic LD tour. Thus an LD tour with a destination within France.

We will focus on analyzing LDF tours in this paper due to the limitation of the CDR data of missing roaming information.

4.1. Municipality selection

As described above, we wanted to limit the number of tracked persons in the CDR data. As a first step, we chose a set of municipalities and focused our analysis on the inhabitants of those municipalities. The municipalities were selected such that they are well distributed spatially as well as in terms of size of population. In the end, every major city was selected and a random sample of smaller communities was added to the selection.

We identified all mobile phone towers and their Base Transceiver Stations within the chosen municipalities. Each mobile phone tower can hold several BTS (serving different directions and/or technologies). Furthermore, several towers can be at the same location, e.g. on top of the same building. Our final selection of mobile phone towers is shown in Fig. 1. In total, 23,438 Base Transceiver Stations in 3631 distinct locations served the chosen municipalities. There can be several BTS at the same location for two different reasons. Either there is one tower operating several BTS, or there are several towers at the same location (e.g. one for each technology). These BTS cover the 58 municipalities chosen for analysis. They were used to identify the inhabitants of the municipalities. Bold circles indicate where there were many towers in close proximity. This was the case in dense cities. The cities located closest to a border are Calais (on the coast), Lille, Strasbourg and Mulhouse. It was expected that the limitation to domestic travel will reduce the number of observed long-distance tours substantially in these cities. Furthermore, all regional centers (identified by high population densities) were included in our selection.

4.2. Identification of residents of the selected municipalities

In order to decide whether a customer was an inhabitant of one of the municipalities considered one needed to infer the customer's place of residence. An analysis of home anchors (Ahas et al., 2008; Ahas et al., 2010) was undertaken for this purpose. Anchors are the mobile network towers which were most frequently used by a customer during a specific time of day. To compute home anchors we focused on nighttime hours (9 p.m.–6 a.m.), because most people are expected to be home for the majority of nights. An additional requirement was needed to avoid wrongly setting a home anchor by the call actions of a single night. Thus, we determined that a tower was a home anchor candidate only if the phone was in use at that location for at least seven distinct days in a month. Following these rules, home anchors were computed for each customer and for each of month. Thus, each customer had up to six home anchors. Many persons did not have an anchor for May and October since these months were just partly covered by the CDR data. A monthly analysis was performed in order to identify persons that relocated their home (e.g. to a summer house).

For around 18 million users there was at least one month when it was possible to identify a home anchor. A customer was considered to be a resident of a municipality if he or she had at least three home anchors within the given municipality. This threshold was chosen because there were just half a month of observations during two of the six monitored months. Thus, there was a substantial share of customers who did not have home anchors in those months. Therefore, most of the persons had just four home anchors. Hence, we assumed that people lived at a place if they had three quarters of their potential home anchors at the same place. We chose all customers who were inhabitants of any of the selected municipalities. This subset contains more than 1.4

million customers and therefore captures over 17% of the population of the selected municipalities.

Then, an algorithm was applied to identify machine-to-machine devices. Such machines are SIM-card devices that are not used by humans but are automated. One can detect these machines by looking for specific periodic behavior. This behavior is relatively easy to identify since the machine communication follow pre-defined rules. For example, a device communicating with a specific other device over a series of days at the same time of day is likely to be a machine-to-machine device. All of the identified machines were removed from the subset. As a consequence, the size of the subset of customers was reduced to 1.39 million.

In order to identify the persons who actually made at least one LDF tour, an additional filter had to be implemented. We chose a single month (June 2007) and investigated whether the persons left their home environment during that month. More than 814,000 of the identified residents did so. Of those, we randomly selected a subset of persons for a detailed analysis of their long-distance travel behavior. In total, 5,000 residents of Paris, 2000 persons from the other major cities and all identified persons from the smaller municipalities were chosen. After additional data cleaning 79,874 persons were left, and their long-distance travel behavior was studied. Table 2 shows the number of persons and municipalities by population size.

Table 2
Number of tracked persons by size of municipality.

Population [in 1000s]	Tracked persons	Number of municipalities
Paris	4,953	1
200–900	19,394	10
100–200	25,294	13
50–100	9,580	5
20–50	7,461	4
10–20	7,730	5
5–10	3,190	5
1–5	1,376	7
Rural (< 1)	896	8
Total	79,874	58

4.3. Reconstruction of long-distance tours from CDR data

Unlike surveys, mobile phone data does not directly provide information about tours undertaken. The available information is a series of time–space points. We have shown how the series can be used to infer the home locations of mobile phone users. In the following, the extraction of long-distance tours is described in detail.

When scanning the users' CDRs we supposed that an LDF tour started every time a CDR with a location outside the home environment occurred following a CDR located within the home environment. The tour was assumed to end with the first CDR back in the home environment. A sketch of a single construction process can be found in Fig. 2a). The initial situation consists of the home anchor (H) and the home environment (green circle). The locations of the CDRs are then identified as C1, C2, … C6, whereby their sequence is given by their numbers. The black dashed arrows show a possible path of the user, while the red solid arrows form the reconstructed tour. In the sketch in Fig. 2a) the reconstructed tour fits the initial real-world tour quite well. This was not always the case. A problem is the boundary of the traced time period. Tours that had not finished before the end of the observed time period had to be truncated without any information on their further duration (Fig. 2b)). Likewise, tours that started before the recorded time had to be truncated (Fig. 2c)).

Moreover, the character of the CDR data caused further limitations. Firstly, there is no information about mobile phone usage outside of France. This lack of information led to wrongly inferred final destinations during tour reconstruction (Fig. 3a)). Without any mobile phone activity between the home environment and the border, even an around-the-world tour would be missed. This was likely the case for most of the international tours. Secondly, low-frequency mobile phone users could go on two distinct tours without any mobile phone activity within the home environment between them. In such cases, the tour reconstruction algorithm merged the two tours due to the lack of a separating CDR (Fig. 3b)). Thirdly, the worst case was a user without any CDRs that related to his or her long-distance travel. Without CDRs indicating an exit of the home environment, no tour could be reconstructed (Fig. 3c)). This was the most critical and probably the most frequent reason for a failed tour reconstruction. In addition, it was also possible to miss certain parts of a tour or its final destination. Note that all limitations led to a lower number of tours in comparison to the real world. Therefore, we can assume that the number of LDF tours identified by the algorithm is a lower bound of the total.

It is possible that one person had two devices, e.g. a business phone and a private phone. Therefore, a duplicate check was performed. It was checked whether there were two customers with home locations close to each other (less than 500 m) and had similar travel behavior. Similar travel behavior occurs, if more than 75% of the LDF tours overlap in time and had a close destination (at most 5 km deviation). Just 34 duplicates were found. One of the duplicates was removed from each pair of look-alikes.

4.4. Accuracy of the estimate of the number of domestic tours

The number of tours (per capita) is the main indicator that is analyzed in this work. Therefore, the accuracy of this measure is discussed here. There are several reasons to assume that the number of long-distance tours reconstructed from the CDR data is still lower than the actual number of tours. Firstly, it is very likely that many tours were merged (see Fig. 2b)) or just not recognized (see Fig. 2c)). Especially the latter is assumed to lower the actual number of tours substantially since persons do not always place a call, when they leave the home environment. Secondly, it is assumed in the remainder of the paper that persons, which did not do a long-distance tour in the reference period (June 2007), did not perform any long-distance tour. This is due to the way the customer selection is performed. Again, this is assumed to lead to a substantial underreporting on the number of long-distance tours. In contrast, the focus on domestic tours might lead to a slight overestimation of domestic long-distance tours, because an international tour might be recorded in the CDR data and therefore counted as domestic tour. However, this is not assumed to happen very often. In addition, the effect of the underreporting is likely to be much higher than the latter opposing effect.

4.5. Seasonal tour frequencies in survey data

Our CDR data analysis was performed in comparison with the French national travel survey. Therefore, the survey data had to be adjusted in order to make the two data sets comparable (e.g., international journeys had to be excluded). A major difference between the available CDR data and the survey data is the time periods covered. While the French national survey covers a whole year, the CDR data is limited to five months (mid-May to mid-October). Consequently, the share of tours within these five months had to be computed for the survey.

We performed a detailed analysis of the tour frequency distribution in the ENTD. For each day of the year, the number of tours and the number of persons reporting for the given day were computed. Subsequently, the number of tours was summed up and scaled by the number of respondents. Our computation shows that around 46.2% of all LDF tours took place within the five summer months. The share is higher than 5/12, thus confirming our assumption that people tend to travel more during the summer. We will account for the higher share of journeys in the summer in the next section.

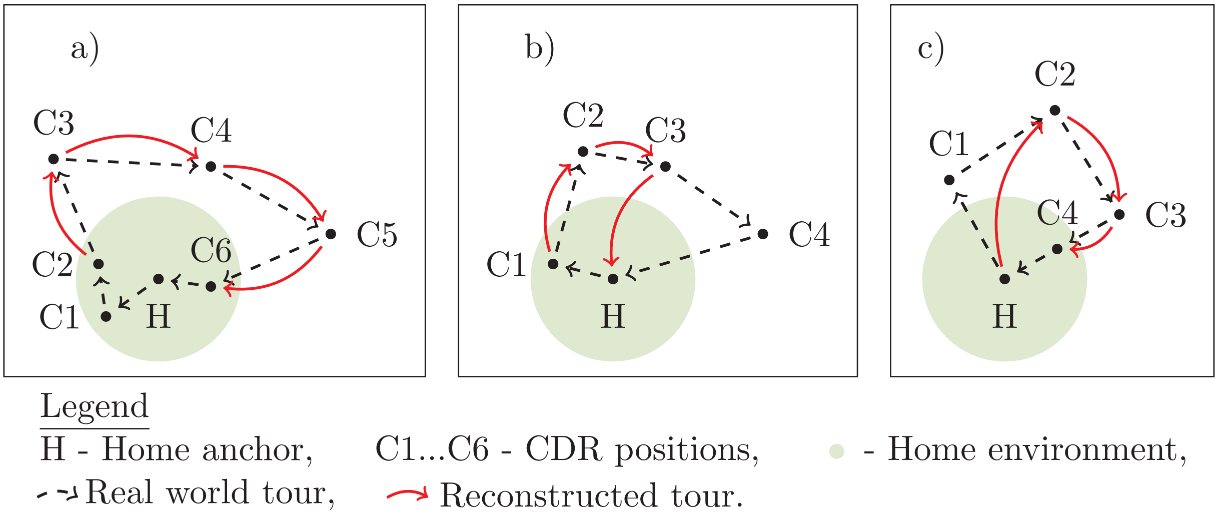

Fig. 2. Visualization of the tour reconstruction algorithm a) Perfect tour reconstruction, b) Tour with unobserved end: C4 is after 14 Oct, c) Tour with unobserved start: C1 is before 13 May.

4.6. Indicators for analysis of long-distance travel

Several indicators of long-distance travel demand will be analyzed in the following section. While these indicators usually are reported directly in a survey, they have to be calculated in a CDR-based data set. We will show in the following which indicators were chosen and how they were extracted from the data:

- Tour distance: The distance of a tour is defined as the crow-fly distance between the home location and furthest point visited on the respective tour. We are particularly interested in the distribution of the tour distances.
- Destination: Again, the furthest point is defined as the destination of a tour. Since this definition is not accurate, the analysis of destinations is limited to the regional level.
- Share of long-distance travellers: A sample of 30 days and 1.4 million persons was selected to analyze how many persons are long-distance mobile. In other words, the share of persons that did at least one long-distance tour in the sampled period was calculated.
- Tour rates of mobile persons: For those, who did long-distance travel, the number of tours per person was calculated.
- Long-distance travel demand: The share of mobile persons is combined with the number of tours of mobile persons to get an estimate of total number of long-distance tours per capita.

5. Comparability of the data sets

Before the two data sets can be compared, it is necessary to discuss whether the data sets cover the same scope, and therefore, whether they should be compared.

The respondents of the ENTD 2008 survey cover a variety of socio-demographics. The survey analysts claim to have a representative sample of the French population after weighting. Nevertheless, the results of long-distance travel demand are based on the responds of 5,000 persons, namely those that actually claim to do long-distance tours. In contrast, the CDR data does not report socio-demographics. We draw a random sample of 80,000 customers from a pool that covers 36% of the actual population. We account here for spatial distribution and population size. Due to privacy regulations, it is not possible to get socio-demographics of Orange customers individually or for the whole sample. However, there is no reason to assume that mobile phone users (86% of the whole populations) or Orange customers (43% of mobile phone users) differ substantially from the whole population. In addition, it is known that respondents of long-distance travel surveys underreport their travel behavior. Thus, it is not clear that 5000 persons with representative socio-demographics give results, which are more

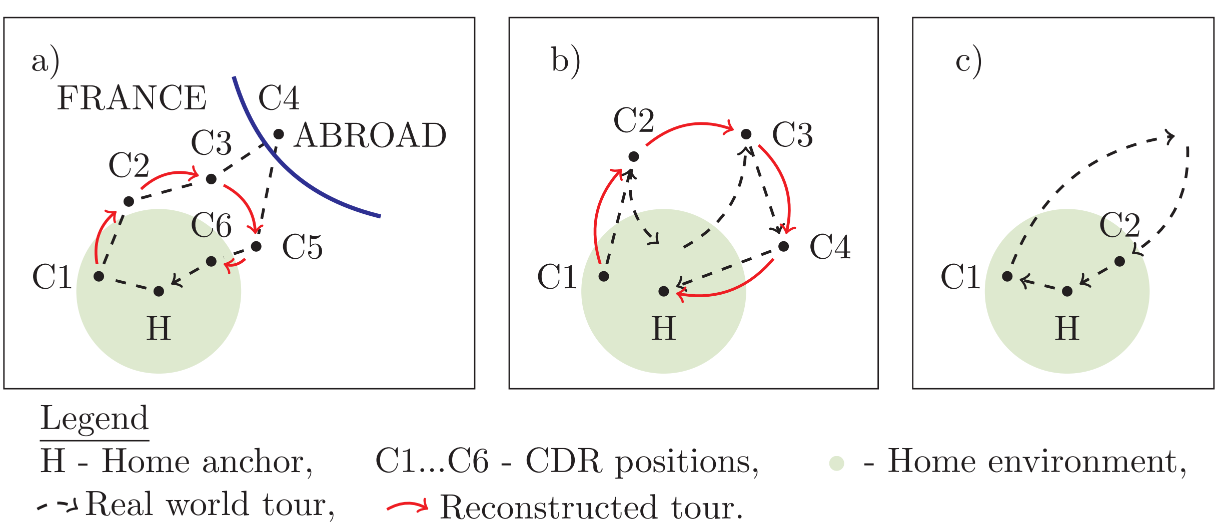

Fig. 3. Failed tour reconstructions: a) Missed tour abroad, b) Two tours merged c) Tour completely missed.

accurate, than 80,000 randomly drawn persons.

Therefore, a comparison is reasonable and valuable. Differences in the two data sets should not be treated as a fact. Likely, neither of the two data sets tell the ground truth. The following section with results will rather indicate problems with survey-based long-distance travel demand data, show that results should be treated with caution and illustrate that there is a need for alternative data sources.

6. Results

We obtained information regarding long-distance travel behavior (e.g., tour distances, tour frequency) from mobile phone data and compared it with the ENTD 2008. The main differences between the two data sets will be pointed out in the following section. The most important result is that the long-distance travel demand for a whole year would be heavily underestimated if one relied solely on the numbers given in the ENTD 2008. All of the results presented in this section are limited to journeys within France with a destination of more than 80 km away from the home location.

6.1. Tour distance distribution

We investigated the distribution of LDF tour distances. For the CDR data, the distance of a tour is defined as the distance as the crow flies between the home anchor and the furthest known point (mobile phone tower) away from home during this tour. In case of the ENTD, the respondents were asked to report the crow-fly distance to the main destination.

We focus in this subsection on the inhabitants of a single municipality since the LDF tour distance is dependent on the location of the home (e.g. based on distance to the border, distance to the next big city, surrounding sea/mountains, etc.). Paris was chosen for this analysis, because it is a city that is well represented in both data sets.

The results are shown in Fig. 4. We compared the cumulative frequency of tour distances for both data sources. One can see that the CDR data almost perfectly reflects the survey data for residents of Paris. In the range of 450–650 km, the ENTD reports a slightly higher share of LDF tours than the CDR data. This may be explained by the respondents' underestimation of travelled kilometers for very long tours, i.e. tours of around 1000 km (see Wolf et al., 2003). Using the Kolmogorov–Smirnov test to compare the two distributions shows that the distributions are significantly different (p-value $<10^{-15}$). This is not surprising since this kind of tests is very sensitive for variations around the mean, which is the case here. In addition to the Kolmogorov–Smirnov test, we sub-divided the scope in 25 km-bins and performed the Chi-Square test. The Chi-Square test shows that the hypothesis that the two discretized distributions are drawn from the same main distribution can not be rejected (p-value = 0.29). This result indicates that the two data sets cover the same travel patterns.

6.2. Trip distribution

Trip distribution is an important part of travel demand models. Therefore, we compare the trip distributions in the two data sets. We assume that the furthest point on a tour in the CDR-based data was the main destination of a trip starting at the home location. The survey reports the main destination of the home-based tour. The difference of the two definitions is not expected to have large influence on a big scale. This analysis was limited to the residents of the Ile-de-France region, which covers the metropolitan area of Paris. This limitation was necessary since this is the only region, which is well represented in both data sets. Additionally, the survey was limited to the months May to October in order to avoid seasonal effects in the analysis.

Fig. 5 shows the distribution of the destinations in the two data sets. The analysis was performed on the department level. The destination distribution is similar in the two data sets. Areas that are frequently visited are the close Atlantic coast, the Cote d'Azur, Lyon and the area to the south of Paris. Less frequently visited are the Bretagne, the southern Atlantic coast and the surroundings of Paris. The rest of France does not play a big role as a destination of domestic tours for residents of Ile-de-France. However, also small differences between the two data sets can be observed. Frequently visited departments seem to have even a higher share in the CDR data than in the ENTD. This variation might appear due to much larger sample size of the CDR data. Nevertheless, the trip distributions are comparable, which is also confirmed by a statistical analysis of the destination patterns. The shares of visited destinations were transformed into a vector, where the i-th entry of the vector equals the share of visitors in department i. The cosine-similarity of the two vectors for the two data sets has a value of 0.94 confirming that the destination patterns of the two data sets are very similar.

6.3. Share of long-distance travellers

The number of long-distance travellers is a major question in transport demand modelling and thus also in tourism demand analysis. Survey respondents are known to underreport their long-distance tours due to the high response burden of the corresponding items. Therefore, the CDR data was investigated with respect to the share of long-distance traveller. Because of the enormous amount of data, we restricted this analysis to a single month (June 2007). The result and the corresponding values in the ENTD 2008 are shown in Table 3.

Table 3 shows that the share of long-distance travellers within one month of CDR data (58.6%) is more than twice the share of travellers reported in four weeks of the ENTD 2008 (25.7%). While the 13-week reports of the travel survey show a higher share of travellers (46.9%), the value is still lower than 59%, as given in the CDR data, and lower than 61%, as estimated by Weckström-Eno, 1999. The results support the assumption that a substantial number of survey respondents did not report their long-distance journeys. Consequently, long-distance survey

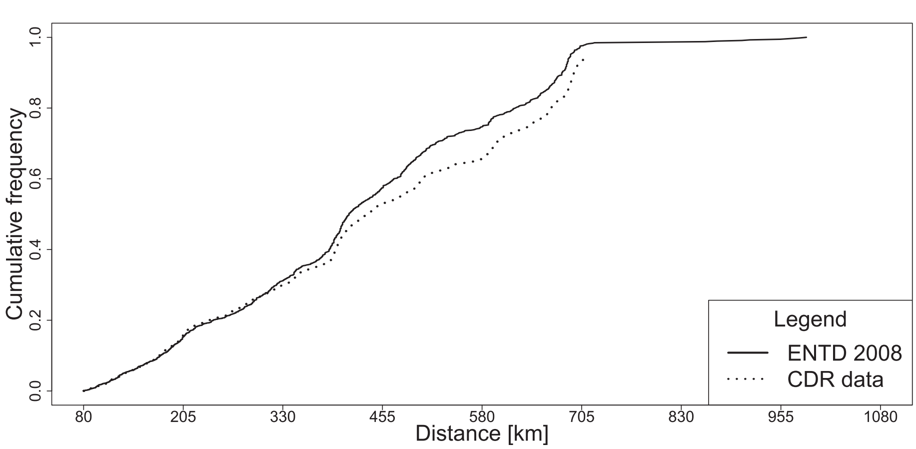

Fig. 4. Cumulative frequency of the LDF tour distances for Paris residents.

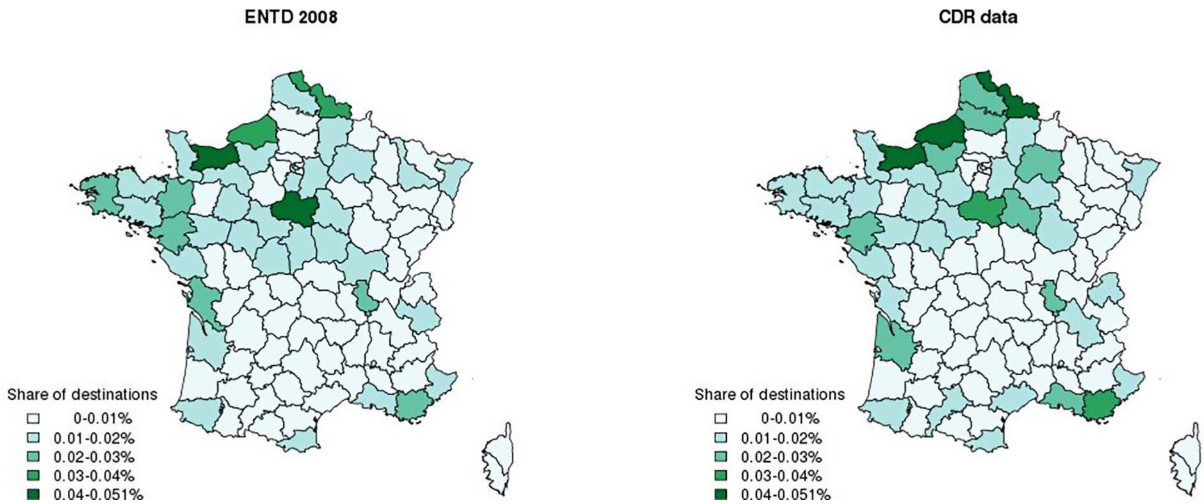

Fig. 5. Destinations of the residents of Ile-de-France (on department level).

Table 3
Number of persons performing LDF tours.

	CDR Data		ENTD 2008		ENTD 2008	
Reporting/Tracked Interval	30 days (June)		28 days		91 days	
Surveyed persons	1,388,941		18,632		18,632	
LDF mobile persons	814,381	(58.6%)	4796	(25.7%)	8743	(46.9%)
Selected for further analysis	79,874		4796		8743	

practice should not only pay attention to response rates, but should also find a way to convince respondents to report their journeys.

6.4. Tour rates for mobile persons

We have shown that the number of persons reporting LDF tours was much lower in the ENTD survey. The next question is whether the tour rates for those who reported tours also differ between the two data sets. We compared the number of tours that took place within three months (in the case of the ENTD, the reported interval is 13 weeks). Fig. 6 shows histograms for the two data sources. One can see that most of the ENTD respondents made just one tour in this period, and just a very small share of persons travelled more than three times. The CDR histogram suggests that many people made two, three or four LDF tours, and a substantial number of tracked persons travelled more than five times within three months. The Kolmogorov–Smirnov test as well as the Chi-Square test were performed in order to test the similarity of the two distributions in Fig. 6. Both tests suggest that the distributions of the number of tours differ significantly when comparing the two data sets (both p-values $<10^{-12}$).

We also compared the tour rates month by month in order to identify seasonal effects that might have had an influence. The monthly LDF tour rates for mobile persons are shown in Fig. 7. The tour rates are substantially higher in the CDR data. This confirms our assumption of underreported tour frequencies in surveys. Two aspects must be mentioned: firstly, the reference intervals differed slightly. While the CDR data was cut into monthly chunks, the ENTD survey responses referred to a four-week period. Secondly, May and October were not fully

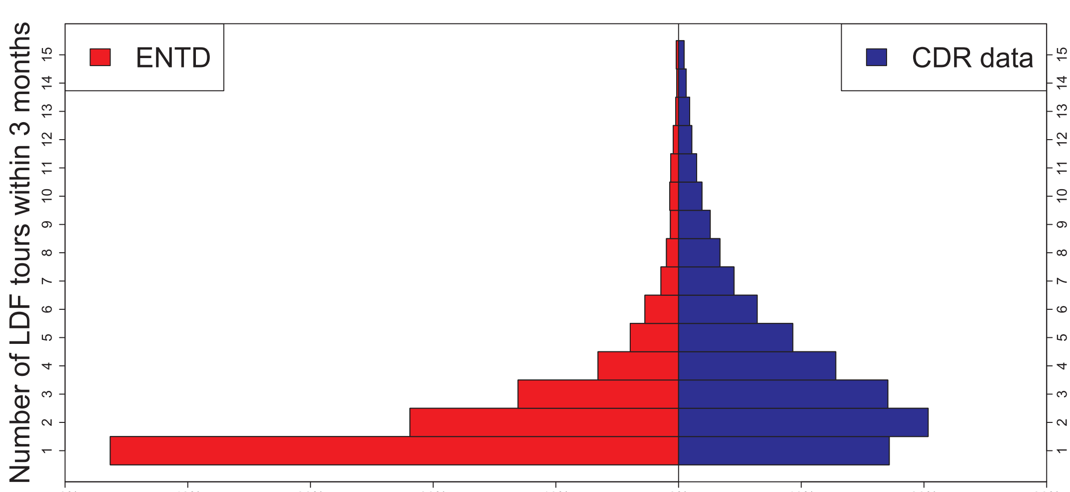

Fig. 6. Histogram of the number of LDF tours for mobile persons.

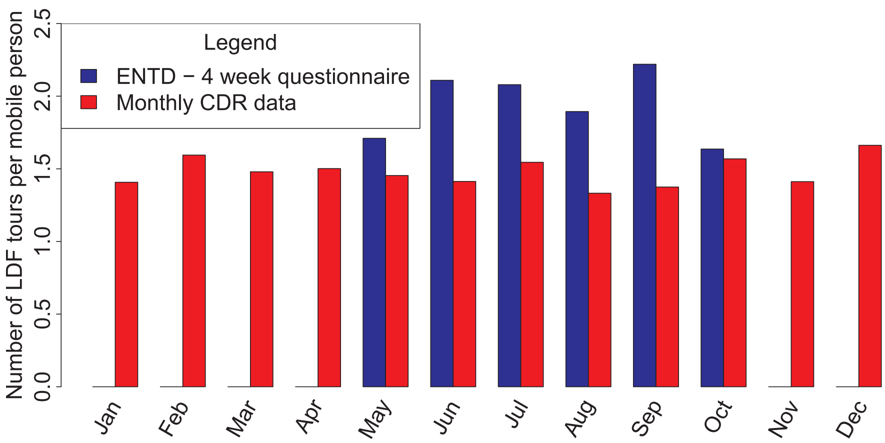

Fig. 7. Average LDF tour rates per mobile person per month.

Table 4
Average number of LDF tours per capita from 13 May to 14 October 2007.

Reference interval	CDR data 5 months	ENTD 4 weeks	ENTD 13 weeks	ENTD weighted 1 year
Total	4.27	2.25	1.96	2.36
Compared to CDR data	100.0%	52.7%	45.9%	55.3%

covered in the CDR data set. Thus, the shown tour rates are likely lower than the actual ones.

6.5. Long-distance travel demand

Lastly, the total long-distance travel demand was analyzed. The number of LDF tours per capita was calculated based on the CDR data as well as on the ENTD data, as shown in Table 4. The reported frequencies refer to tour rates in the period from 13 May to 14 October 2007, henceforth called the *summer period*. Three different data sources from the ENTD were used: firstly, the number of reported tours within four weeks; secondly, the number of reported tours within 13 weeks; and thirdly, the number of projected yearly tours. For the latter we used a weight provided in the ENTD to estimate the yearly travel demand and the information that 46.2% of the yearly LDF tours were undertaken during the summer period.

One can see that the frequencies suggested by the ENTD are approximately half as high as those observed in the CDR data. Furthermore, adding the weighting factor proposed by the ENTD analysts does not change the main finding here. The factor of underestimation is much higher than is usually assumed (e.g. up to 1.3 in Cambridge Systematics Inc., 2013). The seasonal effect has been taken into account, and there was also a spatial effect. Therefore, we analyzed the LDF tour rates according to the size of the home city in order to capture this effect (Fig. 8). Additionally, the 95% confidence intervals are presented in Fig. 9. Due to the smaller sample size, the confidence intervals of the ENTD survey results are wider than the intervals based on the CDR analysis. Once again, one can see that the CDR data suggests a long-distance rate that is twice as high as the ENTD survey outcome.

The differences described in this section have an enormous impact. This can be seen in the resulting absolute numbers. Our analysis of the ENTD 2008 led to the assumption that the French population undertook 325 million long-distance tours per year. Limiting these to national tours and the summer period led to an estimate of 130 million tours. In contrast, the CDR data suggests that there were almost 240 million tours for the same population and time frame. It can be assumed that extending to the whole population, the full year and including international tours would not change the survey's underreporting rate. Consequently, the ENTD 2008 underestimates the annual long-distance travel demand by more than 260 million tours, with all of the attendant economic and environmental impacts. This number is based on simple scaling, assuming that the share of tours in the summer period and the share of national tours reported by the ENTD 2008 apply. Nevertheless, it gives an idea of the magnitude of the error. We must also stress that the tour frequency suggested by the CDR data is just a lower bound to the true value, which might even be much higher.

7. Limitations

The methods we used and the results we obtained are discussed in this section focusing on limitations and their implications. Three different types of limitations can be identified. Firstly, the selection process of municipalities and persons can lead to a biased sample.

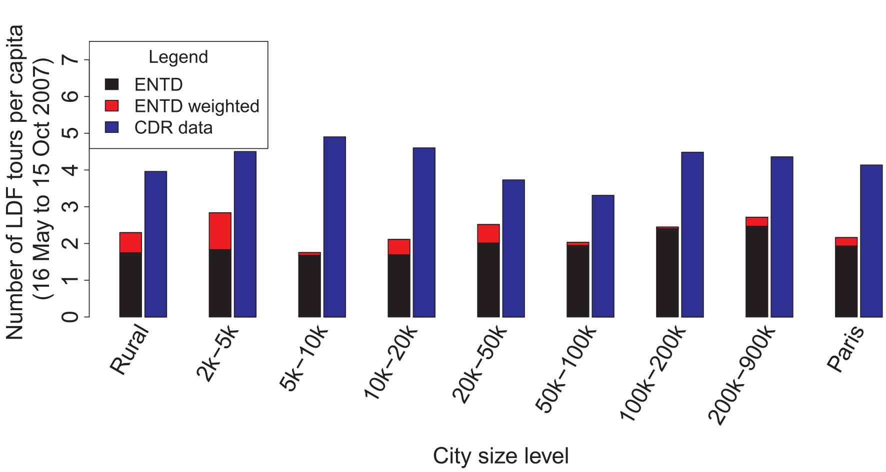

Fig. 8. Average LDF tour rates per capita by municipality size for the summer period.

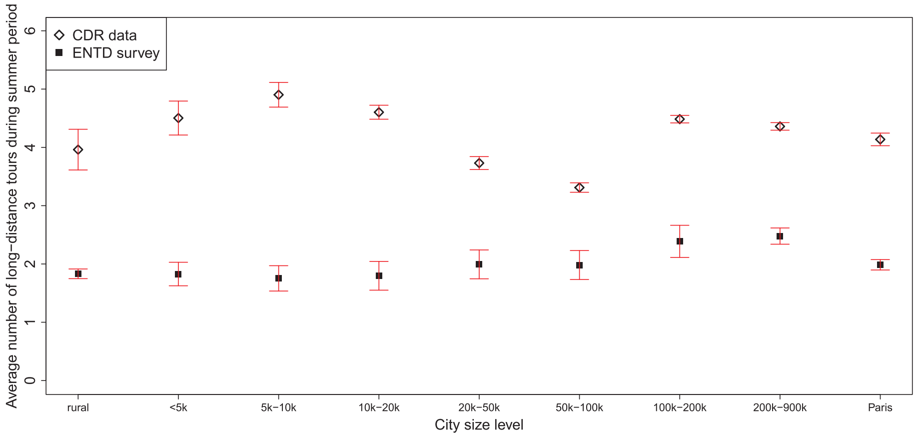

Fig. 9. Confidence Intervals of the per capita LDF tours per capita.

Secondly, the reconstruction algorithm might be inaccurate, e.g. regarding the home location. Lastly, the data type itself, CDRs, has limitations, e.g. spatial inaccuracy. All types are discussed in the following.

A bias is probable to occur during the person selection. Frequent callers are more likely to be selected, because the home anchor algorithm needs frequent calls to identify a home location. Frequent callers more likely have more long-distance trips due to higher education, higher income, etc. Nevertheless, we draw our sample from a pool of customers that captures more than 17% of the actual population. Considering the market share of 43% and the random selection, the sample set is assumed to have just a small bias, if any.

Furthermore, it is not clear whether the home location computation is precise. The computed home location can have a small spatial error (e.g. the neighboring tower of the actual home was chosen). This error can be neglected since the effect on the computation of (the number of) long-distance tours is rather small. The computed home location might also be far away, e.g. a shift worker is assumed to have his home at his actual work place. In this case it is likely that the number of reconstructed long-distance tours is lower than the actual number, because all of his non-work activities are clustered to a single tour.

Moreover, the question arises whether the municipality selection is representative. The set of municipalities captures all regions of France. In addition, different levels of population size are covered. All major cities are part of the sample. Thus, the concerns are limited to the smaller municipalities. These were chosen randomly and are spread over the whole country. The influence of the distance to the closest border was investigated. It could not be shown that it has a significant impact on the number of domestic tours. There is probably an impact on the number of international tours, but this could not be checked here.

The cleaning of the data does not induce a bias by removing a large subset of usable data. The total share of removed customers is less than 1%. This includes the identification and removal of machine-operated devices, duplicated devices (one person with a private and business device) and network towers with corrupted location information.

CDR data has a limitation, which usually makes it difficult to use for travel behavior analysis, namely the spatial inaccuracy. In rural areas, Base Transceiver Stations cover big areas plus mobile devices are not always connecting to the closest tower. These facts lead to a potential error of several kilometers in the estimated distance of a long-distance tour. In case of long-distance travel behavior analysis, an error of a few kilometers is minor and can be neglected. Another issue related to the spatial inaccuracy has to be considered as well. Tours with a distance slightly above 80 km might not be found, because the location of the tower is closer to home than 80 km. On the other hand, the opposite effect occurs with similar probability. Tours slightly shorter than 80 km are not a long-distance tour by definition, but might be identified as such. It is probable that these opposing effects cancel out.

One obvious limitation of the analyzed CDR-based long-distance travel behavior is the lack of international tours. In case of Lille or Strasbourg, it is likely that a substantial number of long-distance tours are missing. The reference data, the ENTD, reports that 11.5% of all long-distance tours from the department Bas-Shin (the department containing Strasbourg) were international tours. However, international tours were excluded in this paper. We also accounted for the fact that the CDR data was limited to 5 months covering the summer. A monthly analysis of the data has been performed in order to identify potential seasonal effects.

The second major limitation of CDR data is the low frequency of CDRs. Consequently, there are long-distance tours, which can not be identified in the data. Short tours (in terms of duration) are especially affected since the probability to produce at least one CDR outside of the home environment is low for short tours. However, this issue does not lead to overestimation. Rather, the resulting number of long-distance tours is in fact a lower bound to the actual number, which is expected to be substantially higher.

Finally, we assumed in our analysis that LDF tours were only undertaken by those persons, who made at least one LDF tour in June 2007. This assumption lowers the number of LDF tours per capita as presented in Table 4. Adding tours of other mobile persons will lead to an even higher total number of long-distance tours per capita, which is again an indication that the actual number of long-distance tours is substantially higher than the tour rates presented in this work.

8. Discussion

The previous section has shown various limitations of the data analysis as described in this work. It is important to discuss these limitations and their impact on the results in order to value the key finding. We discuss in the following the impact on the analysis of the number of long-distance tours per capita since this is the most important result indicating that the survey is heavily underreporting this rate.

Firstly, there are limitations that were taken into account during the analysis. We focused on domestic tours in both data sets, because no international tours can be identified in the CDR data due to missing roaming information. It was assumed that there are no international tours in the CDR-based data. The error resulting from this assumption is likely to be very small. This is supported by the fact that just 10% of all tours in the ENTD 2008 were international tours. Hence, the main result, namely the under-reporting of long-distance travel, does not change, even in the case of falsely counted international tours.

The potential seasonal effect was eliminated when comparing the travel rates. In addition, mobile devices with similar travel patterns were identified and removed in order to avoid customers with two mobile phones in the data set. Therefore, these constraints can be neglected.

Secondly, there is a concern whether the analyzed sample is representative. Both, municipality selection and customer selection can not be proven to be representative. In case of the customer selection, the high market share of Orange, the large sample size and the random draw ensures that the sampling error can be assumed to be rather small. In case of municipality selection, the selection is representative in terms of spatial distribution and size. Furthermore, the large sample size limits the bias related to other attributes, if there is any.

In addition, there are further limitations either with small impact, e.g. the home location algorithm, or with opposing effects that cancel each other out, e.g. the spatial inaccuracy of CDR data.

Summing up the discussion above, most of the limitations were either taken into account or are assumed to have small impact. This does not hold for the two issues discussed in the following. The assumption that persons do not travel at all if they did not travel in June 2007 has been made for the CDR data. Moreover, the frequency of CDRs is low leading to just few observations per day per person. This two facts are very likely to be responsible for a substantial underestimation of the LDF tour rate. It is also very likely that the impact of these two facts dominates all other effects presented so far. Therefore, it is a valid assumption that the underreporting factor estimated in this paper is just a lower bound and is actually even higher. This finding is relevant for transportation research since it is a justification for further development of alternative data collection methods for the analysis of long-distance travel demand.

The number of annual long-distance tours per capita for the Orange customers has to be compared with the values measured in previous literature (Table 1). Scaling up the value calculated in Table 4 leads to an estimate of more than 9.0 annual tours per capita. Most of the literature reported in Table 1 has a lower number of tours, even though international tours were included in most of the studies. It is very difficult to compare the concrete numbers, because the studies cover different years and study areas. However, the relatively high number of long-distance tours reported in this paper supports the request for investment in alternative data collection methods as mentioned above.

9. Conclusion

We have analyzed the long-distance travel behavior of the French population in the summer period of 2007. The data source used was CDR data covering five months of mobile phone usage within the French Orange™network. We found that the number of long-distance tours reported by the national travel survey for the same period was underestimated. The actual long-distance tour frequency was almost twice as high. Considering that the CDR data just gives a lower bound and that short tours (e.g. single-day commutes) were probably substantially underreported, the long-distance tour frequency is likely even higher than shown in Section 6. We identified two reasons for the underestimated tour frequencies. Firstly, the average tour rates of mobile persons differed significantly between the ENTD survey and the CDR data. Hence, survey respondents underestimated their number of long-distance tours. Secondly, the number of persons reporting any long-distance tour was much higher than suggested by the ENTD data. Therefore, soft refusals were substantially responsible for the underestimated long-distance tour numbers. Consequently, alternative data sources are indispensable for a reliable estimate of long-distance tour frequency. Possible sources are either mobile phone data as presented in this paper or extended GPS studies. Either way, inclusion of the device carried by most of us almost all the time -the mobile phone- is deemed necessary for a better understanding of long-distance travel behavior. Finally, the underestimation of long-distance travel has consequences for transport policy (e.g., wrong estimates of CO_2 emissions) and especially for the tourism sector (e.g., some markets are greater than assumed thus far).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttp://dx.doi.org/10.1016/j.tbs.2017.12.001.

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