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Variability of daily car usage and the frequency of long-distance driving

Patrick Plötz [a,*], Frances Sprei [b]

[a] Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48, 76139 Karlsruhe, Germany
[b] Chalmers University of Technology, Department of Space, Earth and Environment, Hörsalsvägen 11, 412 96 Göteborg, Sweden

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ABSTRACT

The limited electric range of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) requires an understanding of the variation in day-to-day driving and the frequency of long-distance driving. Existing literature suggests high regularity of human mobility. However, large longitudinal mobility samples for empirical tests are hardly available. Here, we analyze the regularity of daily vehicle kilometers travelled (VKT) of 10,000 vehicles observed between two months and several years and quantify the regularity of daily VKT and the frequency of long-distance driving. Our results indicate limited regularity of daily VKT beyond one day of time lag (mean autocorrelation ≤ 0.11). Long-distance driving with daily km over 100 km (200 km) typically take place on less than 20% (5% for 200 km) of driving days but make up 40% (18%) of annual VKT. Our results have implications for sustainable transport research and the design of travel surveys.

1. Introduction

To achieve stringent climate targets the transportation sector should achieve net-zero emissions by mid-century (IPCC 2018). This is a major challenge especially since the transportation sector is dominated by the combustion of fossil fuels and has showed little evidence of decoupling even in regions with climate targets such as the EU (Creutzig et al. 2015; Davis et al. 2018). For personal mobility the challenge is coupled with the dominance of the privately-owned vehicle, which is also a problem for cities that are struggling with local air pollution and congestion (Kelly & Zhu 2016). Strategies to reduce emissions need to be coupled with measures that ensure maintained accessibility and public acceptance. Partly to address these challenges, but also due to technological development, the transport sector is facing three major trends: electrification, automation and shared mobility (Fulton et al. 2018). These might alleviate the problems but may also exasperate them if not coupled with behavioral changes (Sprei 2017). Pro-active planning and steering will be necessary to ensure that these trends contribute to emission reductions and a sustainable transition.

To achieve behavioral change, we need to better understand the underlying behavior we are trying to change (Creutzig et al. 2018). An over-simplification of this behavior will be counterproductive. The more variable and complex the travel behavior is the more flexible the supply side needs to be (Schlich & Axhausen 2003). This has implications for the design of services such as Mobility-as-a-Service that aim to replace personal car driving, and in the long run, for the planning and routing of autonomous shared vehicles. Driving patterns are also important for dimensioning of batteries for electric vehicles (Plötz et al 2017; Björnsson & Karlsson 2015;

* Corresponding author.
E-mail address: patrick.ploetz@isi.fraunhofer.de (P. Plötz).

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Table 1
Descriptive Statistics.

	Observation days	Driving days	Mean daily km	Share of missing
Filtered sample N = 3,098 (at least 100 observations days and no NA chain longer than 13 days)				
Min	101	15	4.6	0.002
Median	270	235	57	0.044
Mean	344	302	62	0.056
Max	2,218	1,679	266	0.451
Full sample N = 10,004 (at least 60 days of observation)				
Min	61	3	0.2	0.002
Median	372	319	55	0.123
Mean	497	425	60	0.181
Max	2,751	2,500	308	0.922

Mattioli et al., 2019), the need for charging infrastructure (Funke et al. 2019) and the interaction with the grid (Taljegard et al. 2019). Long-distance driving, which will affect the variability, is important for both battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). For BEV it might hinder their utility since all driving may not be easily fulfilled and for PHEVs it largely affects the utility factor (UF), i.e., the share of km driven on electricity (Plötz et al. 2021). Understanding variability is also important in the context of shifting urban policies from transport investments without limitations in demand to more management of travel behavior through, e.g., congestion charging or distance-based taxes (Jones & Clarke 1988).

The perception that mobility and car driving are highly regular stems mainly from two research areas. One area consists of studies based on tracking of mobile phones, which find that human mobility is highly predictable (Gonzalez et al. 2008; Song et al. 2010). The high level of predictability is largely due to one or two common destinations (such as work and home). The second research area deals with the role of habits in mobility (Gärling & Axhausen 2003; Verplanken et al. 1997, Scheiner & Holz-Rau 2013; Müggenburg et al. 2015). These studies focus more on mode choice and psychological reasoning behind behaviors than on driving distances. Studies that analyze longitudinal data on mobility find a substantial intrapersonal variability in daily travel patterns (Pas & Koppelman 1986; Huff & Hanson 1986, Stopher et al. 2007; Heinen & Chatterjee 2015; Mattioli et al. 2020). The few studies that use longer panel data to analyze variability in mode choice find that both spatial aspects such as trip distance and temporal aspects, e.g., repetitions over time, can explain intrapersonal variations (Cherchi & Cirillo 2014; Thomas et al. 2019; Axhausen et al. 2002). Longer observation periods seem to capture more variability, still there is limited information on the effects of long data set in the modelling of travel behavior (Stopher et al. 2008). This is particularly true for studies on car mobility, despite it being the dominant mode of personal transport with the greatest need of a shift both in propulsion technology and mode. Especially the limited electric range of BEV and PHEV has led to considerable interest in the frequency of long-distance travel (e.g., Jakobsson et al. 2017, Raykin et al. 2012, Plötz et al. 2018, He et al. 2019). Yet, to the best of the authors' knowledge, only one study has specifically investigated the regularity of daily driving in a data set with several months of observations period (Plötz et al. 2017). Plötz et al. (2017) tests the assumption of identically and independently distributed (iid) for daily vehicle kilometers travelled (VKT) of four data sets. They find low correlation between daily driving distances of subsequent days. However, the number of observed days was only seven for the majority of the data and longer than a few weeks for about 5% of their sample and the authors analyzed only lag one autocorrelation.

Building on the work of Plötz et al. (2017), the aim of the present study is to use different statistical measures to analyze the regularity of daily driving distances. Our analysis covers the temporal and non-temporal regularity of daily driving distances, within-person variability, weekly patterns, and the frequency of long-distance driving. These measures give a comprehensive view of regularity and allows the analysis of the relation between the measures. Temporal measures allow us to identify repeating patterns between subsequent days or days with a certain interval such as weekly patterns. Non-temporal measures on the other hand help to identify a dominance of repeating daily VKT or highly similar daily VKT as one would expect, e.g., from commuters that drive almost the same distance every workday and some other less regular distances on weekends. The results can be used for various implementations. The frequency of long-distance driving can, e.g., inform the need for range in electric vehicles, and regularity measures and weekly patterns can give an indication of the demand and the design of different mobility services.

Our sample consists of daily VKT of several thousand Chevy Volt, a PHEV, in North America (cf. Table 1). The data is measured by a vehicle on-board diagnostics tool and the sample mainly consists of privately-owned vehicles. Our sample consist of N = 10,004 vehicles with at least 60 days of observation. The average number of observation days is almost one year (344 days mean observation period and 270 days median), clearly going beyond the common 28 day (or shorter) observation period in many transportation studies. As a measure for temporal regularity, we calculate the autocorrelation function at different time lags for each vehicle and study their statistical significance at individual vehicle level. If daily driving was highly regular, this should reveal itself as high inter-vehicle average autocorrelation among subsequent days and as high share of autocorrelations significantly different from zero. Furthermore, we analyze measures of dispersion of the daily VKT that allow us to identify regularity in daily distances travelled irrespective of the temporal order. If daily VKT are highly regular the vehicle-individual daily VKT distribution should be clearly peaked (with one or very few peaks). We then calculate the share of variability that is not explained by external variables such income, age, or occupation; the so called within-person variability. Finally, we study the frequency of long-distance driving, often perceived as rare irregular events that have a large influence on vehicle and mode choice (Sprei & Ginnebaugh, 2018).

Our analysis is based on driving data from PHEV, and we consider this a baseline for general driving data given that there are no actual range limitations for this type of vehicle. Our approach could be interpreted that when applying our results to other vehicle kinds, such as BEV or other mode choices such as MaaS, we presume that the mobility needs will not change and that the new technologies will have to adapt to these mobility patterns. However, our results could also be used to better understand how car driving patterns have to change in order to better adapt to new innovations.

Our study contributes to the literature in several ways. To the authors' best knowledge, it is the first empirical study to analyze longitudinal car driving data with several hundred days of observation for most users. Thus, our data is likely to include rare but important long-distance travel events such as holidays (Mattioli & Adeel 2021) which are particularly important for limited range electric vehicles. Second, driving distances recorded through onboard diagnostics are more reliable than travel diaries and allow us to capture even rare events such as long-distance driving with high accuracy. Third, relying on daily driving distances and long observation periods we develop a methodological approach that combines both temporal and non-temporal methods to measure the regularity of vehicle usage and explain the relation between the two approaches. More specifically, we also calculate individual high order Auto Correlation Functions (ACF) for daily km of vehicles which are new in the literature.

The outline is as follows. Section 2 introduces the data and the methods used to measure regularity of daily km travelled. Section 3 contains the results, followed by a discussion in section 4. We state our conclusion in section 5.

2. Data and methods

2.1. Data

For our analysis, we use publicly available data representing real-world driving behavior from an online source, with driving data on a daily basis: Voltstats.net. Voltstats.net is an online database that collects automatically (from an additional on-board device) real-world fuel consumption performance data of Chevrolet Volt vehicles in the United States and Canada. The site contains data of 11,073 individual user profiles. For our analysis, we use a sub sample with at least 100 observation days and no gap of missing values longer than 13 days with N = 3,098 users and a larger sample with at least 60 days of observation and no restriction on the number of missing values (N = 10,004 users) (Table 1). Please note that missing values are not days with zero km daily VKT as the full data set (before filtering) contains 7.7 million days with 1.8 million missing km data and about 1 million days with zero km daily VKT. The average number of observation days is in the filtered sample is almost one year (344 days mean observation period and 270 days median). Every user profile on the website contains cumulative daily data on the driven kilometers. The data was pre-processed, cleaned and cumulative mileage values where converted to daily driven km. Data cleaning comprised the exclusion of values with daily VKT greater than 1,500 km and with negative VKT. The data set comprises data from registered users with a comprehensive set of user specific performance data from April 2011 to January 2020, with a total of 1.06 million observation days and 0.94 million driving days. Please note that the data covers a span of almost ten years but typically only about one year for a specific vehicle.

The data set is not a random sample of North American vehicles as all vehicles are of the same make and model which is a PHEV. The owners are thus early adopters but PHEVs have no fundamental range limitation affecting the daily VKT. The annual driving distance in our sample is also comparable to the US national average (22,260 km annual driving distance for our sample compared to 21,700 km US average (FHWA 2020)) indicating representativeness in terms of average vehicle usage. Here, we focus on daily VKT which is most likely hardly affected by the specific vehicle technology.\

In the full sample, the median of the longest sequence of missing values in the daily VKT is 29 days (and the mean is 83.8 days), compared to a median of 7 days (and mean of 6.1 days) in the filtered sample. Missing values in daily VKT were imputed with an ARIMA model (Hyndman and Khandakar, 2008) for the ACF computation.

3. Methods

Compared to previous regularity studies our data was collected from the vehicles and thus follows the movements of these rather than individuals. This difference combined with a very long observation period warrants a new methodological approach compared to traditional regularity studies. Our approach gives a statistical description of regularity of car driving which has been lacking in the literature. It takes into consideration the strengths of the data set (large sample and long observation period) allowing us to capture regularity by computing the correlation between subsequent days and to measure the statistical significance of this correlation. Thus, we understand if there is any strong regularity in daily driving distances of a vehicle or not. We complement this analysis with other non-temporal measures of regularity, and with the relation between temporal and non-temporal measures. We combine this regularity analysis with a closer look at the role of long-distance driving. The following paragraphs individually introduce the measures for temporal regularity, non-temporal regularity, long-distance driving and our approach in the combination of these measures. All regularity measures introduced below are first computed on the daily VKT of a fixed vehicle and afterwards the values of the regularity measure among all vehicles are compared.

Regularity is often understood as repeating patterns or some temporal order. We use several statistical measures to quantify temporal regularity. The autocorrelation functions (ACF) are defined as $\mathrm{ACF}(l) = \mathrm{Cov}(x_t, x_{t-l})/\mathrm{Var}(x_t)$ of the time series of daily VKT x_t on day t for each vehicle for lag $l = 1, \cdots, 28$. The ACFs are calculated for each vehicle and each lag individually. Thus, we obtain an ACF value for each vehicle and for each time lag. We study the share of vehicles with ACF at given time lag l that is statistically different from zero but also calculate the mean ACF over all vehicles for given time lag. An $\mathrm{ACF}(l)$ for an individual vehicle's times series of length n days is statistically different from zero at 5% (1%) percent level if its absolute values is greater than $1.96/\sqrt{n}$ $(2.58/\sqrt{n})$ (Brockwell & Davis 2016). To analyze the ACFs for one vehicle with all time lags simultaneously, the Ljung-Box test for no

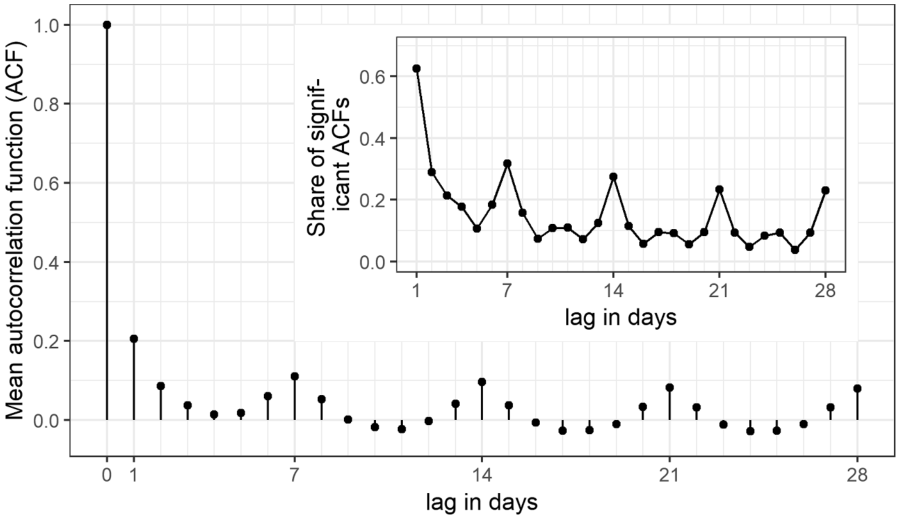

Fig. 1. Mean of the autocorrelation functions for all vehicles versus time lag. The inset shows the share of vehicles with autocorrelation different from zero ($p < 0.01$).

autocorrelation is applied with test statistic $Q = n(n+2)\sum_{l\geq 1}\frac{\mathrm{ACF}(l)^2}{n-l}$, where n is the length of the time series. These measures give a clear statistical indication of the temporal regularity of daily VKT on an individual level but also for the sample average.

The second group of regularity measures ignores the temporal order of the observed daily VKT of a given vehicle. These measures help to identify a dominance of repeating daily VKT or highly similar daily VKT as one would expect, e.g., from commuters that drive almost the same distance every work day and some other less regular distances on weekends. The non-temporal measures of regularity applied are three measures that characterize the individual daily VKT distribution and one that looks at the total and individual daily VKT variances.

In the first group of the distributional measures, the coefficient of variation $\mathrm{CV}(x) = \mathrm{SD}(x)/\mathrm{mean}(x)$ which quantifies the spread in an individual vehicle's daily VKT distribution. Likewise, the coefficient of dispersion $\mathrm{CD}(x) = (Q_3 - Q_1)/(Q_3 + Q_1)$, which uses the first and third quartiles Q_1 and Q_3 and is more robust against outliers in measuring the width of the daily VKT distribution. Lastly, the Gini coefficient of inequality, i.e. the deviation from perfect equality under a Lorenz curve $G = \frac{1}{2\mu}\sum_{i,j=1}^{n} f(x_i)f(x_j)|x_i - x_j|$ for daily driving distances x_i, with the probability density function (PDF) $f(x)$ and $\mu = \sum_i x_i f(x_i)$. The Gini coefficient is often used to quantify inequality in income distributions. Here, we apply it as measure on the skewness or inequality of daily VKT of one vehicle. If a vehicle has exactly the same daily VKT every driving day, than all days are perfectly equal and the Gini is zero. If, on the other hand, there are many low daily VKT days, some high daily VKT days and a few extremely high daily VKT for one vehicles, than the Gini of this vehicle's daily VKT distribution would be greater than zero and closer to one, with perfect inequality for Gini equal to one.

The second type of a non-temporal measure used here, compares the variability within one vehicle's daily VKT to the total variability in all vehicles' daily VKT. Variability in daily mobility can have several sources. Socio-demographic variables and other factors such as income, age, or occupation can explain a share of variability in daily driving. This share of variability in daily mobility is inter-person variability in mobility, the remaining share of variability in mobility is within-person variability and is a different measure of irregularity of day-to-day mobility. Specifically, we study the within-person variability, denoted as $\mathrm{WPSS}/\mathrm{TSS}$, which is defined as the within-person sum of squares, $\mathrm{WPSS} = \sum_i\sum_j (t_{ij} - \bar{t}_i)^2$ divided by the total sum of squares, $\mathrm{TSS} = \sum_i\sum_j (t_{ij} - \bar{t})^2$. In the equations t_{ij} is the driving distance made by vehicle i on day j, $\bar{t}_i$ is average daily driving distance for vehicle i, and $\bar{t}$ is the overall sample average daily driving distance (Pendyala 1999). This measure is similar to the well know R2 in linear regression analysis, i.e., the share of variance in the depended variable explained by the regression model. In our case, the within-person variability WPSS/TSS is the variance in daily VKT that cannot be explained by external variables, such as e.g. socio-demographic. All the external factors explain differences in daily VKT between individuals and the remaining within-person variability is a measure for non-temporal irregularity in daily VKT. Please note that we do not have additional variables characterizing the trip, the vehicle owner or household. However, following the method of comparing the total sum of squares to the sum of person-specific sums of squares, this is not required as all within-person variability cannot stem from differences in external factors since it only refers to the individuals (Pendyala 1999).

Our methodological approach combines the above mentioned quantitative measures of both temporal and non-temporal regularity. This yields a comprehensive picture of different aspects of regularity in daily car driving distances. Furthermore, we analyze the correlation between these measures in Section 3 below to analyses their relationship.

Finally, long-distance driving events are particularly important for the limited electric range of BEV and PHEV. These are often perceived as rare events that fall outside regular daily travel patterns such as commuting. Accordingly, a relation between regularity and the frequency of long-distance daily driving can be hypothesized. Here, we use 50 km, 100 km, and 200 km of daily VKT as thresholds for long-distance driving as is common in many studies of long-distance driving (cf. Mattioli & Adeel 2021). We extract the days with more than 50, 100, or 200 km of daily VKT from the daily VKT data on a vehicle specific level and calculate the share of long-distance days and the share of long-distance km in annual VKT for each individual vehicle.

4. Results

4.1. Empirical assessment of regularity

4.1.1. Temporal irregularity

High regularity in day-to-day car movements of individual vehicles implies high autocorrelation between the daily VKT of subsequent days. We calculate the autocorrelation function ($\mathrm{ACF}(l) = \mathrm{Cov}(x_t, x_{t-l})/\mathrm{Var}(x_t)$ with the daily VKT x_t on day t – see methods for details) for all vehicles with at least one hundred days of observation period (cf. Fig. 1). We find a low average correlation between subsequent daily driving distances ($\overline{\rho}_{l=1} = 0.20$ – compare Fig. 1 and the appendix for results on the full sample). The correlation is even lower for the following days. We do see a weekly pattern with higher $\overline{\rho}$ (i.e., mean ρ) for lags with a multiple of 7, however the average correlation is weak ($\overline{\rho} \approx 0.1$ for $l = 7, 14, 21, 28$). A majority of vehicles show day-to-day correlation (at lag $l = 1$) significantly different from zero (62 % of the vehicles at 1 % sign. threshold and 72 % at 5 % threshold if only vehicles with at least one hundred observations days and less than two weeks of subsequent missing values). For these vehicles the average coefficient of correlation at lag $l = 1$ is $\overline{\rho}_{l=1} = 0.28$ (if 1 % level of significance is required and $\overline{\rho}_{l=1} = 0.27$ if 5 % level is required). The share of vehicles with significant correlation declines with increasing time lag between days (compare inset in Fig. 1). Even here weekly patterns are detectable: every third or fourth vehicle (depending on the level of significance and the time lag) shows a significant weekly correlation in daily km travelled. Yet, the average correlation is weak ($\overline{\rho}_{l=7} = 0.11$ for all vehicles and $\overline{\rho}_{l=7} = 0.26$ (0.23) for vehicles with 1% (5%) significant correlation at time lag $l = 7$). Thus, only a minority of the vehicles shows significant regularity for more than one day of time lag and generally the autocorrelation is weak.

We also tested for any serial correlation in the daily driving distances of individual vehicles (Ljung-box test for the null hypothesis of no autocorrelation in the daily distances travelled – see methods for details) and find that most vehicles exhibits at least some kind of autocorrelation ($p < 0.001$ for 63 % of the vehicles, $p < 0.01$ for 72 % and $p < 0.05$ for 79 %). However, as most ACF are small, the total serial correlation cannot be large and statistical significance is also strongly influenced by the length of the time series which is quite high for our sample. In summary, the temporal distribution of daily driving distances is usually not completely random, but autocorrelation for specific time lags is usually small and only a minority of vehicles has autocorrelation significantly different from zero for more than one day of time lag. Even for lag one, the share is only about 60 % and the average autocorrelation is weak with a value of 0.2.

4.2. The relation between the regularity measures

Similar patterns of variability are present in other dimensionless measures of daily distance variability. The average coefficient of variation (CV) (i.e., the ratio between mean and standard deviation of daily VKT – see methods for the definition of this and the following measures) is 1.06 with 90 % of coefficients of variation larger than 0.61, indicating that the distribution of daily VKT per user is as broad as the average daily distance travelled. It is not a simple narrow bell-shaped distribution of daily km. Similarly, the coefficient of dispersion (CD) (i.e., the ratio between the inter quartile range and the sum of first and third quartile) is a measure of the broadness of a distribution and is robust against a few extremely long daily distances travelled. The average coefficient of dispersion is 1.12 with 90 % of the coefficients of dispersion larger than 0.67. Again, this indicates that the width of the distribution has the same order of magnitude as the median demonstrating that daily travelled distances are not dominated by a single distance such as the daily commute with slight variations around it, but instead many daily distances appear with noteworthy frequency. Likewise, the Gini coefficient which measures the skewness of the individual daily driving distance distributions is larger than 0.33 for 90 % of the vehicles with an average of 0.46. The Gini coefficient is equal to zero for a perfectly equal uniform distribution, i.e., when all distances appear with the same frequency, and equal to unity for a perfectly unequal distribution, i.e., there is only one daily distance travelled. For example, income distribution in Western countries have a Gini of around 0.3, significantly smaller than the average Gini of 0.46 in the daily driving distance observed in our sample.

We now study the relation between different regularity measures which has not previously been done in the literature. This can give a better understanding of the how well each measure captures the regularity of daily driving and if there are any aspects that might be missing if only one measure is used. Our analysis also gives us a better understanding in which way the driving is irregular or regular, e.g., how the weekly pattern might affect even non-temporal measures. We find that the temporal measures of variability in daily driving distances are correlated with the non-temporal variability measures. Fig. 3 and Table A1 (see appendix) show the correlation matrix of the different dimensionless variability measures. For the temporal measures we use ACF1, 2, 3, 7, 14, 21, 28. The three first (ACF1, 2, 3) capture the short-term correlation with the adjacent days, while ACF7, 14, 21, and 28 depict a weekly variability, e.g., it there is correlation between subsequent Mondays or other days of the week.

We observe a close connection between the non-temporal measures of regularity coefficient of variation, coefficient of dispersion and Gini coefficient. The correlation between these measures and the autocorrelation function is low for ACF at lag $l = 1, 2, 3$ and negatively correlated with the weekly ACFs (ACF lag $l = 7, 14, 21, 28$, abbreviated as ACF l) which is expected since a higher ACF implies more regularity as does lower non-temporal variability measures. More surprising is the negative correlation between ACF ($l = 3$) and the weekly ACFs. However, this can be explained by the weekly pattern. Studying ACFs more closely related to the day of the

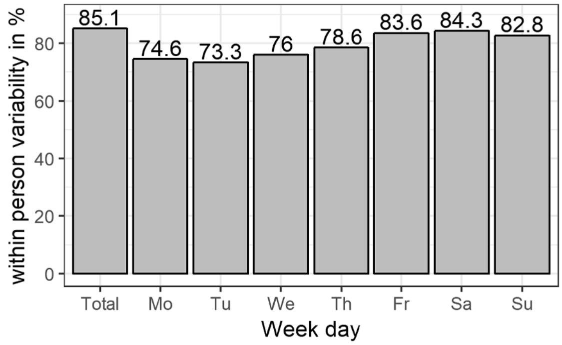

Fig. 2. Within-person variability of daily travelled distances. The figure shows the within-person variability for all daily VKT and for the daily VKT of individual weekdays only.

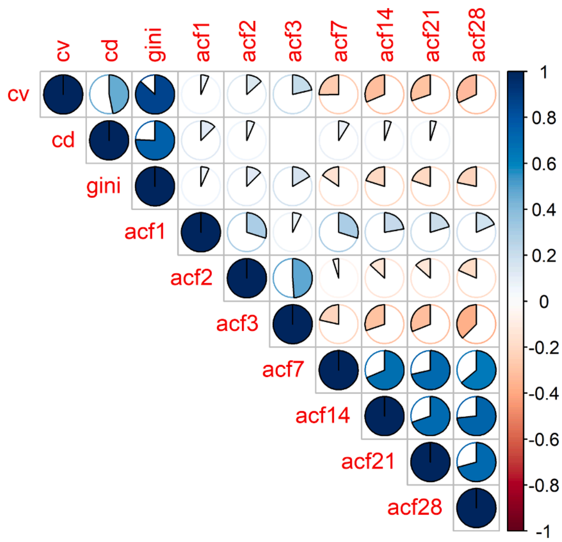

Fig. 3. Correlation matrix for measures of regularity. Positive correlation in blue and negative correlation in red. Strength indicated by angle. Insignificant (p greater than 0.01) correlations omitted. Abbreviations: CV = coefficient of variation, CD = Coefficient of D, Gini = Gini-index, acf1 = ACF($l = 1$) , acf2 = ACF($l = 2$) , acf3 = ACF($l = 3$) , acf7 = ACF($l = 7$) , acf14 = ACF($l = 14$) , acf21 = ACF($l = 21$) , acf28 = ACF($l = 28$) .

week (see section 3.3.2) we find that Monday to Thursday have higher autocorrelation among each other and thus a more regular patterns, while Friday to Sunday are more irregular. ACF3 is the coefficient that most often will be measuring the correlation between a workday (Monday to Thursday) and weekend day (Friday to Sunday) and thus has the lowest correlation and largest discrepancy with the more regular ACFs. We do find a stronger correlation between ACF7, 14, 21, and 28 which is not surprising and rather indicates that the weekly correlation holds even for subsequent weeks.

4.3. Within-person and between-person variability of daily km

Variability in daily mobility can have several sources and can be divided into within-person and between-person variability. The between-person (or inter-personal) "variability refers to the differences in the behavior among different individuals on the same or different days" (Pendyala 1999) and can partly be explained by differences among the individuals travelling (see methods for the definition of variability types based on sums of squared mobility variables). On the other hand, the share of variability within one person's daily VKT is called within-person (or intra-personal) variability. By comparing the within-person variability to the total variability in the daily VKT sample, we obtain another measure of irregularity of day-to-day mobility. A small share of within-person variability indicates little day-to-day variation for each individual and that variability in the total sample mainly originates in variability in the individuals' characteristics.

We calculate within-person variability of daily VKT for all vehicles in the sample. We find that 85 % of the total variability in the daily km is within-person variability and cannot be explained by external variables (Fig. 2). If the analysis is limited to specific days of the week, the variability is reduced to 73 – 84 % depending on the weekday (see Fig. 2 for the total within-person variability and for the results for specific weekdays). This indicates that a slight share in variability of individual daily VKT is due to different travel behavior

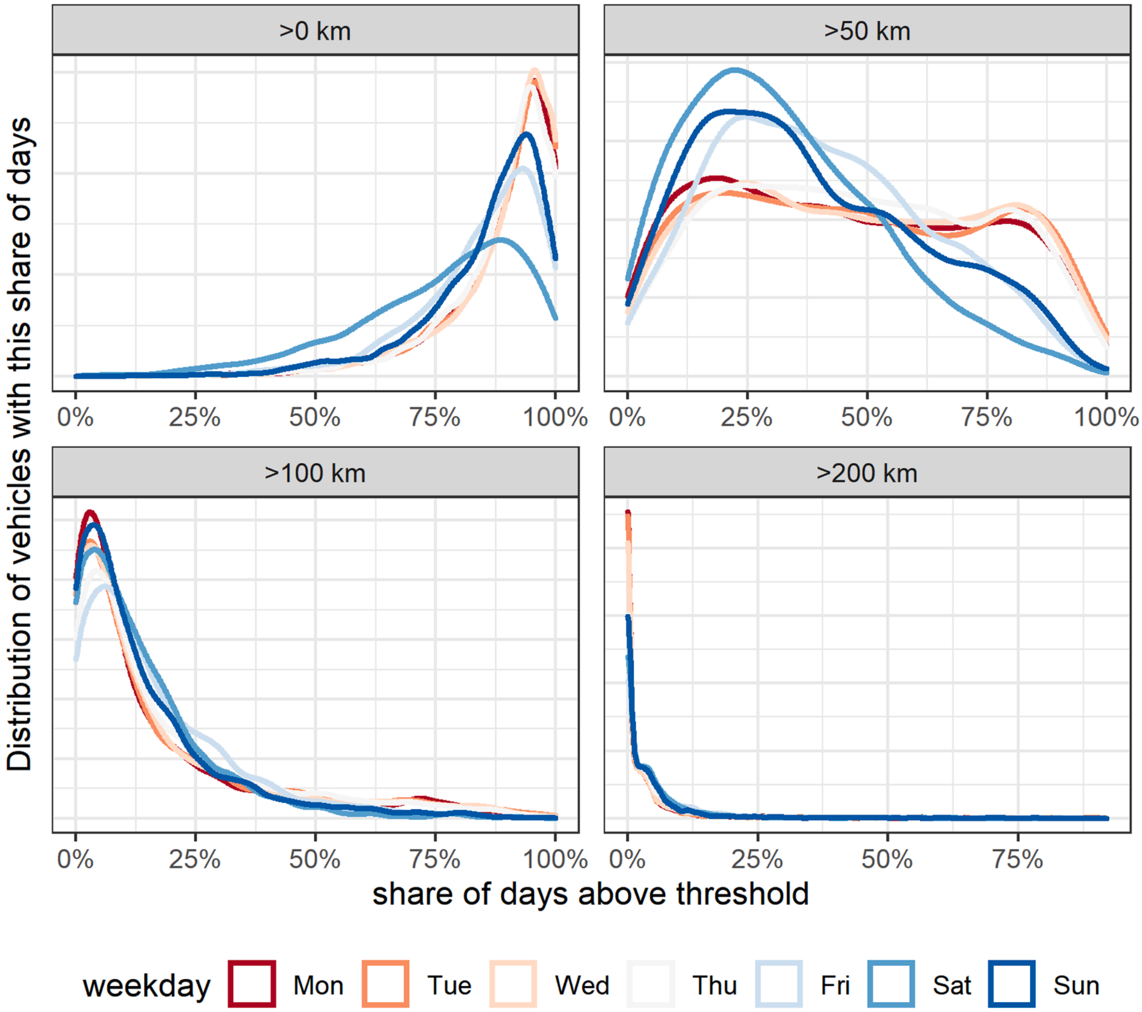

Fig. 4. Density distribution of the share of long-distance days among all observation days by threshold (top left: 0 km; top right: 50 km, bottom left: 100 km, bottom right: 200 km) and week day (different colors).

on different week-days but only a limited share. In summary, the high share of within-person variability provides further evidence that daily car mobility as measured by vehicle kilometers is mostly irregular.

Our results show a much higher variability compared to previous studies that report a variability between 50 and 70% (Pendyala 1999, Pas & Koppelman 1987). The discrepancy can be explained through the fact that our data is based on vehicles instead of individuals and the longer observation time of our data with an average of 344 days (in the filtered sample and 497 in the full sample – see section on Robustness checks and appendix) compared to 3–5 days in earlier studies (Pendyala 1999, Pas & Koppelman 1987). Within-person variability increases with observation time partly due to a higher probability to capture travels to new destinations and long-distance travel (Creutzig et al. 2015; Liao et al. 2019). This implies that surveys and GPS measurements with shorter observation times underestimate the variability in daily driving and most probably daily mobility as well.

4.4. *Frequency of long-distance driving*

We examine the frequency of long-distance driving, i.e., daily driving distance above 50 km, 100 km and 200 km, as long-distance driving is particularly important for the limited electric driving range of BEV and PHEV and at the same time often perceived as rare irregular events.

We compute the share of days with more than 50, 100, or 200 km per vehicles by weekday. The resulting density distributions are shown by threshold and week day in Fig. 4. The mean and median shares of long-distance driving are shown by weekday in Fig. 5. From both Figs. 4 and 5 we see that daily driving distances above 50 km dominate during weekdays. In Fig. 4, depicting the density distribution, we observe a flat distribution for the share of driving days above 50 km on Monday to Thursday, while weekends have a peak at much lower values. This indicates that the typical share of driving days above 50 km daily VKT is lower on weekends that working days. This is also reflected in Fig. 5 where we find that Monday through Thursday has 50% of mean and median share of driving days

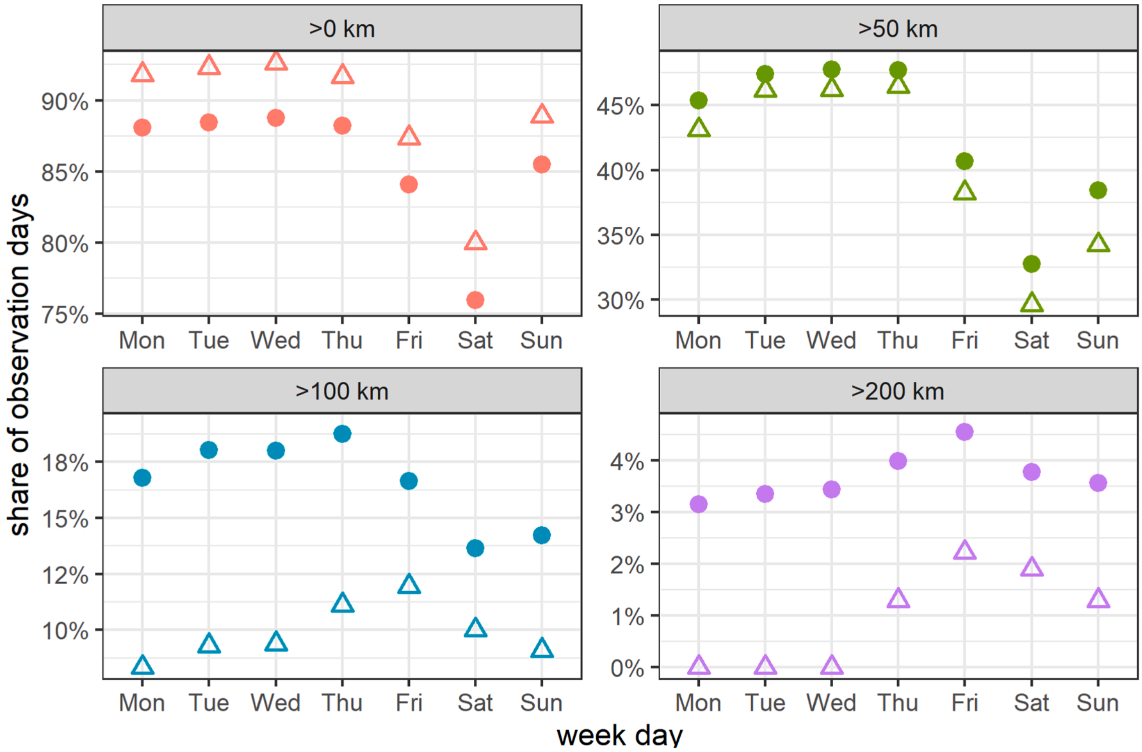

Fig. 5. Mean (dots) and median (triangles) share of observation days among all vehicles with daily VKT above 0 km (top left), 50 km (top right), 100 km (bottom left), and 200 km (bottom left) by week day.

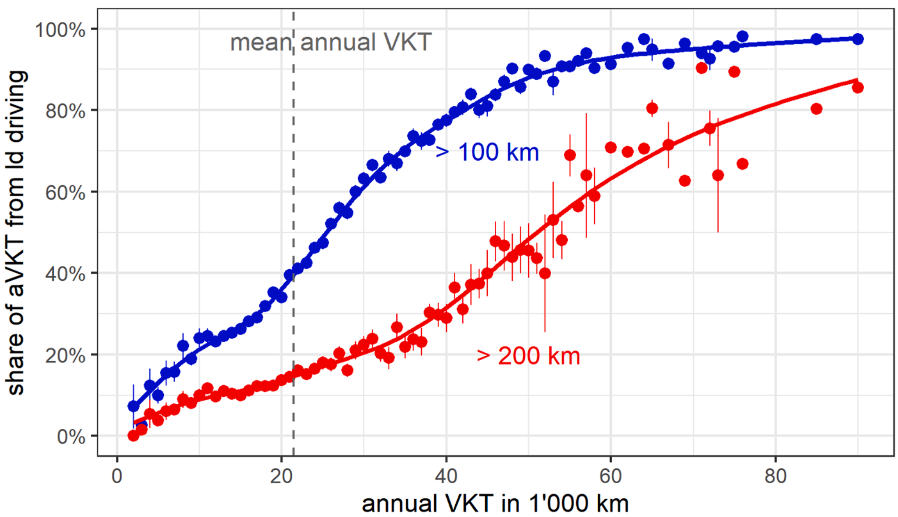

Fig. 6. Share of annual VKT (aVKT) from long-distance driving days over 100 km daily VKT (blue) and over 200 km (red) as a function of annual VKT. Show are mean shares of annual VKT from long-distance driving days for users with similar annual VKT (rounded to 1,000s of km) including one standard error (small points with error bars) along with a local scatter plot smoother (solid lines). Mean annual VKT in the sample is around 22,000 km (highlighted as dashed vertical bar) and close to the US national average. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

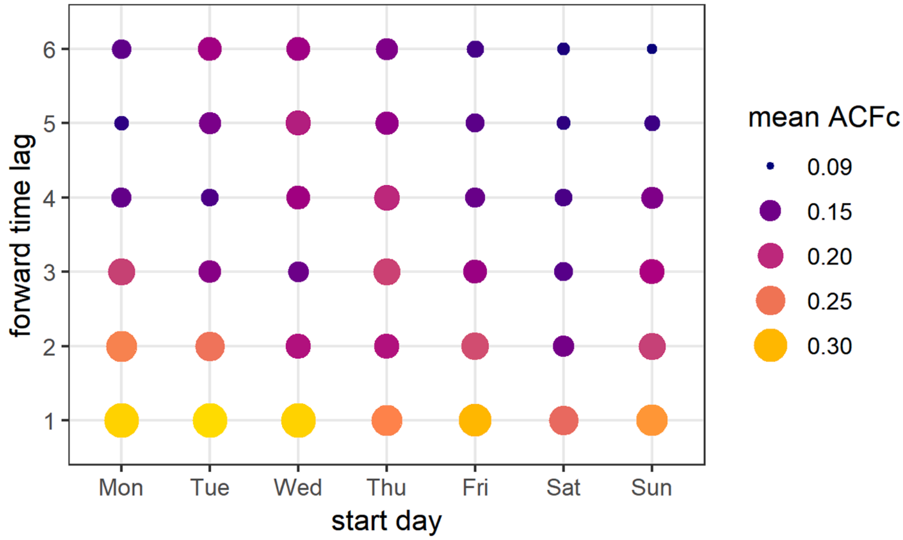

Fig. 7. Mean conditional ACF for different start days and time-lags.

with at least 50 km driving. The mean and median shares are lower on weekends, with the lowest on Saturday with roughly 40% of driving days. Our sample thus seems to have a noteworthy share of vehicles with a slightly longer daily driving distance, possibly related to commuting (at least 25 km one way) which could partly be an effect of being PHEVs with low operating costs.

Daily driving distances above 100 km are less common and occur around typically on 10 – 20% of the days. This distribution is more skewed as can be seen in Fig. 5 and thus while the mean share of days decreases during the weekends, the median increases especially on Fridays and Saturdays. A slight increase in density can also be observed in Fig. 4 for Saturday and Sundays. For the daily driving distances above 200 km Fridays and Saturdays have a higher share of days both regarding mean and median – even if these shares are only between 2 and 5%. The distributions in Fig. 4 show that long-distance driving with more than 200 km per day is quite exceptional and is a rare event (only a few percent of driving days) for most users.

While driving distance above 100 km or 200 km constitute a minority of the driving days, they play an important part in the annual driving distance. In Fig. 6 we show the share of km from long-distance driving days in all annual VKT per vehicle as a function of annual VKT. The figure shows local mean values with annual VKT rounded to 1000 s of km. We show the mean share of annual VKT from long-distance driving for users with similar annual VKT including one standard error (small points with error bars) along with a local scatter plot smoother (solid lines). The mean share of driving days above 100 km is only 19% (median 13%), but the share of annual VKT from these long-distance driving days is 40% (median 38%). For long-distance driving over 200 km per day, the situation is even more extreme: the 4% of driving days (on average with 2% median) make up 16% of annual mileage (on average with 11% median).

More generally, we observe from Fig. 6 that for annual driving distances of 25 ,000 km (slightly above the US average) 50% of the annual driving distance is from days with 100 km and days above 200 km constitute about 20% of the annual driving. For annual VKT of 50 ,000 km driving days above 200 km make up 50% of the share of annual VKT. Thus, while not that frequent these days play an important role of the overall driving and need to be taken into consideration when electrifying driving or when providing an alternative mode.

In summary, while long-distance driving might be a rare event for most vehicles, long-distance driving days are responsible for a noteworthy share in total annual driving. Furthermore, our analysis shows that a small share of vehicles drive longer distances over 50 km or 100 km on many days of the week.

4.5. Robustness checks

Our results come with some uncertainty. The present section contains several robustness checks with respect to the main results.

4.5.1. Full sample

The previous section used a filtered sample with an upper threshold on the number of missing days in the vehicle-individual data. Here, we summaries the main results for the full sample with at least 60 days of observation.

Similar to the filtered sample presented in the main results, we find a low average correlation between subsequent daily driving distances, $\overline{\rho}_{l=1} = 0.20$. The correlation is even lower for the following days. We do see a weekly pattern with higher $\overline{\rho}$ for lags with a multiple of 7, however the average correlation is weak ($\overline{\rho} \approx 0.1$ for $l = 7, 14, 21, 28$). A majority of vehicles show day-to-day correlation (at lag $l = 1$) significantly different from zero (64 % of the vehicles at 1 % sign. threshold and 72 % at 5 % threshold in the full sample). For these vehicles the average coefficient of correlation at lag $l = 1$ is $\overline{\rho}_{l=1} = 0.27$ (if 1 % level of significance is required and $\overline{\rho}_{l=1} = 0.26$ if 5 % level is required). Figure A-1 shows the average ACF with respect to lag and the share of ACFs significantly different from zero. The main plot shows the average ACF according to lag and the inset shows the share of significant ACF (significant at 1% level). Both the values for the mean autocorrelation and the share of significant ACFs is similar to the results in the sub sample with fewer missing values and longer observations periods. Accordingly, the results in the main text are robust with respect to filtering the sample. The share of vehicles with significant correlation declines with increasing time lag between days (compare inset in Fig. A1). Depending on the level of significance and the time lag, 28 – 47 % of the vehicles show a significant weekly correlation in daily km travelled. Yet, the average correlation is weak ($\overline{\rho}_{l=7} = 0.12$ for all vehicles and $\overline{\rho}_{l=7} = 0.24$ (0.22) for vehicles with 1% (5%) significant correlation at time lag $l = 7$). Thus, the result from the main text for the filtered sample is confirmed: only a minority of the vehicles shows significant regularity for more than one day of time lag and generally the autocorrelation is weak. We also tested for any serial correlation in the daily driving distances of individual vehicles (Ljung-box test for the null hypothesis of no autocorrelation in the daily distances travelled – see methods for details) and find that most vehicles exhibits at least some kind of autocorrelation ($p < 0.001$ for 77 % of the vehicles, $p < 0.01$ for 82 % and $p < 0.05$ for 86 %). However, as most ACF are small, the total serial correlation cannot be large and statistical significance is also strongly influenced by the length of the time series which is quite high for our sample. Additionally, one has to keep in mind that the full sample has a higher number of vehicles with longer observations period with more missing values that were imputed to compute the ACFs. Accordingly, we believe the findings from the filtered sample with less missing values to be more accurate.

In summary, the temporal distribution of daily driving distances is usually not completely random, but autocorrelation for specific time lags is usually small and only a minority of the vehicles shows significant regularity for more than one day of time lag.

The results on the inter-personal variability for the full sample without filtering are shown in Fig. A2. Again, the results are highly similar to the findings for the filtered sample. The shares of within-person variability differ maximally by three percentage points.

The pairwise correlations are highly similar for the full and the filtered sample. Fig. A3 shows the correlation plot for the full sample. Table A2 show the pairwise correlations for the filtered sample and the full sample, respectively. The pairwise correlations are highly similar and differ only for some pairs by a few percentage points. Likewise, almost all the pairs are significantly different from zero.

In conclusion, the results for the for full sample and for the filtered sample with less missing values, as presented in the main text, coincide in all aspects and underline the robustness of our findings: daily car mobility on an individual level is mostly irregular.

4.5.2. *Correlation among ACFs*

Interestingly, in Fig. 3, we observe that ACF2 and ACF3 are negatively correlated with ACF7, ACF14, ACF21, and ACF28. We performed additional analysis for the weekdays and time lags to better understand this behavior. We calculate a conditional ACF with the time variable limited to specific days such as $\mathrm{ACF}_c(l) = \mathrm{Cov}(x_t, x_{t+l}|\mathrm{weekday}(t) = \text{"Monday"})/\mathrm{Var}(x_t|\mathrm{weekday}(t) = \text{"Monday"})$ and likewise for other weekdays (the index c indicates conditionality to a specific weekday). That is, we calculate the ACF for a subset of days only. Fig. 7 shows the mean conditional ACFs for all weekdays and different forward time lags. It indicates two regimes of the week: Monday to Thursday and Friday to Sunday.

For interpretation, we have to keep in mind that daily VKT is different on weekends compared to work days. We thus have two regimes of daily VKT and their regularity. One can now count the share of weekdays that are impacted by these two parts of the week for different lags because the ACF (l) crosses the boundary between the two regimes. For example, ACF1 includes data from different regimes for Thursday and Sunday as starting days, i.e., 2/7 days. The share for the different ACFs is 4/7 for ACF2, 4/7 for ACF3, 3/7 for ACF4, 2/7 for ACF5, 2/7 for ACF6, and 0 for ACF7 as starting and end day are always within the same part of the week. Accordingly, ACF2 and ACF3 tend to be smaller and ACF7 tends to be larger. This explains why they are weakly negatively correlated.

In conclusion, the negative correlation between some higher lag autocorrelation functions can be understood by the differences in driving on different weekdays.

5. Discussion

Contrary to previous literature and common impression, our results show that car driving is less regular than commonly perceived. There might be several reasons for this. First, it is possible to achieve variability even in a habitual pattern. Huff & Hanson (1986) call it "systematic variability" being somewhere between completely stochastic and completely habitual. Schlich & Axhausen (2003) argue similarly. The view of travel habits being habitual is also influenced by the design of travel surveys that either sample a single "representative" day or ask for the most common behavior. Schwanen et al. (2012) argue that previous research on travel habits may be too simplistic and overstating the deterministic aspect of habits. Second, increasing the observation period increases the variability (Stopher et al 2008, Cherchi & Cirillo 2014; Järv et al., 2014). Third, we analyze a car and its driving distance, it might still be that the individual has more regular travel habits, especially when it comes to common destinations (Davis et al. 2018). While the car is still the dominant mode of travel in the US its share of daily person miles has been declining during the last years (McGucking & Fucci 2018). Also, within a household there might be several people using the same car. Elango et al. (2007) find that day-to-day variability is higher in households with higher income, more members, children and vehicles. In society as a whole, general constraints such as work times and business hours are declining in importance decreasing the share of identical trips and implying more complex travel patterns (Funke et al. 2019). Workdays still provide more structure and we do find, similar to previous studies (Kitamura & Van Der Hoorn 1987) that the variability during workdays is lower than during weekends. Previous studies also find that the habitual effect may differ depending on activity type, e.g. commuting is much more regular than leisure activities (Thomas et al 2019, Cherchi & Cirillo 2014, Järv et al 2014), partly explaining the lower variability during workdays. In our analysis we cannot distinguish between different activity types, which is a drawback. Still all types of trips need to be replaced if we are aiming at substituting the personal car either with an electric vehicle or with a combination of other modes. It is therefore important to also understand the overall picture of daily driving.

Our results are based on a large data set, however there are some drawbacks. The data set is not selected to be representative of the driving population of North America. All vehicles monitored are of the same make and brand: the Chevrolet Volt that is a Plug-in Hybrid Electric Vehicle. The owners are thus early adopters of a new technology and might have a different driving behavior than other groups, still PHEVs do not have any range limitations and thus are not expected to pose any limits on the driving behavior. The annual driving distance in our data is also comparable to the US national average (22,260 km annual driving distance for our sample compared to 21,700 km US average (FHWA 2020)) illustrating that in general these vehicles are driven the same amount as the average vehicle in the US. Furthermore, daily VKT as analyzed here, is most likely unaffected by the specific PHEV technology. Depending on the model year, the Chevy Volt vehicle has an all-electric range of 35 – 53 miles (or 56 – 85 km, acc. to EPA rating) plus 345 – 367 miles (555 – 590 km) gasoline range. Thus, the total vehicle range of 380 – 420 miles (or 611 – 676 km) is comparable to other vehicles of similar size and the Chevy Volt has no fundamental range limitation. Furthermore, there could be geographical differences in the share of electric driving as some regions in the US, e.g. California, have more public charging infrastructure. However, in the present work we only study total distances travelled irrespective of being powered from electricity or gasoline. Thus, there different public charger density can be expected to have a limited effect on total daily km travelled.

We also assume that the vast majority of vehicles in the sample are privately owned vehicles used for private purposes. First, the voltstats.net website is clearly intended for private individuals and the user sites show no indication of company owned vehicles. Second, we can with high likelihood exclude ride-hailing usage as the Chevrolet Volt is neither among the long list of suggested Uber or Lyft vehicles (gofar.co, 2021) nor among the most popular Uber cars (motorbiscuit, 2021; US news, 2021).

The long observation period for some users, raises the point of potential fundamental life changes during the observation time, potentially leading to change in cars usage and thus increased irregularity. While panel covers several years, the median observation period in the sample is 270 days (and 372 days in the full sample) and the 75% quantile is 460 days or 1.25 years. As fundamental live changes are exceptional, they are unlikely to occur during the typical observation period of less than two years but cannot be fully excluded. But this should not affect our main findings as fundamental live changes can be expected rare within the data.

6. Conclusion

Based on observations from various measures of regularity of daily km travelled, we find that daily car driving, measured through daily driving distances, is mostly irregular and long-distance driving events are typically rare but play an important role in annual driving distances. By analyzing auto correlation functions, we find that the temporal correlation is low. Autocorrelation is significantly different from zero only for a minority of the observed vehicles for lags greater than one day. For a lag of one day, we find that slightly more than half of the vehicles have a significant, but weak (mean correlation ≤ 0.20), autocorrelation. Our results show a certain weekly pattern, still the autocorrelation is low. Similar to previous findings workdays show less variability than weekends (including Fridays), but overall 85% of the daily variability cannot be explained by external factors. Long-distance driving with more than 100 km of daily VKT is on average 19% of the driving days but 40% of annual VKT.

Our results have implications for several technologies and mobility services related to a decarbonization of the transport sector as well as travel surveys. First, existing research on electric vehicles overestimates the regularity of daily driving and thus the required all-electric range of these vehicles might be larger than previously thought. This is especially important for PHEVs were the driving pattern will affect the share of electric driving (Plötz et al. 2021). Specifically, long-distance driving reduces the electric driving share of PHEV and requires high power fast charging for BEV. Alternatively, irregular long-distance trips could be covered by other mobility services such as car sharing (Sprei and Ginnebaugh, 2018). Regularity of driving distances will also affect charging needs and consequently the interaction with the electric grid.

Second, the irregularity of driving illustrates that cars are used for many different types of trips and thus may need a combination of services and business models to be replaced. Becker et al. (2017) e.g., find the lowest vehicle ownership among members of both stationary and free-floating car sharing. Likewise, different types of services or types of car sharing might be used for different types of trips, e.g., a combination of bike sharing, station based car sharing, private vehicle usage or train rides.

Third, the emphasis on “typical” mobility of most of today’s mobility surveys could be misleading especially with respect to car mobility and long-distance travel is still not well covered in existing surveys (Mattioli & Adeel 2021). Likewise, existing studies on most commonly visited locations cannot directly be used to analyze the daily distances travelled. Accordingly, new mobility services including both personal and car mobility such as Mobility-as-a-Service or ride sharing and ride hailing, need to take this into account when planning for routing and design of their services. Less regular behavior entails the need for more flexible services. To consider irregularity will also be critical for the analysis of autonomous shared vehicles and their effect on energy use and carbon emissions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

This appendix contains the correlation Table for Fig. 3 and the figures for the full sample discussed in section 3.3.1.
Table A1 and Table A2
Fig. A1, Fig. A2, Fig. A3

Table A1
Correlation matrix between regularity measures.

	CV	CD	Gini	ACF1	ACF2	ACF3	ACF7	ACF14	ACF21	ACF28
CV	1.00	0.47***	0.87***	0.06***	0.13***	0.21***	−0.25***	−0.31***	−0.30***	−0.32***
CD		1.00	0.76***	0.13***	0.06***	0.02	0.09***	0.05**	0.05**	0.03
Gini			1.00	0.07***	0.12***	0.17***	−0.16***	−0.20***	−0.20***	−0.22***
ACF1				1.00	0.30***	0.07***	0.30***	0.22***	0.20***	0.18***
ACF2					1.00	0.49***	−0.05**	−0.13***	−0.13***	−0.18***
ACF3						1.00	−0.22***	−0.30***	−0.31***	−0.37***
ACF7							1.00	0.69***	0.71***	0.64***
ACF14								1.00	0.70***	0.73***
ACF21									1.00	0.71***
ACF28										1.00

$p < 0.001$ '***', $p < 0.01$ '**', $p < 0.05$ '*'; Abbreviations: CV = coefficient of variation, CD = Coefficient of D, Gini = Gini-index, ACF1 = $\mathrm{ACF}(l = 1)$, ACF 2 = $\mathrm{ACF}(l = 2)$, ACF 3 = $\mathrm{ACF}(l = 3)$, ACF 7 = $\mathrm{ACF}(l = 7)$, ACF 14 = $\mathrm{ACF}(l = 14)$, ACF 21 = $\mathrm{ACF}(l = 21)$, ACF 28 = $\mathrm{ACF}(l = 28)$.

Table A2
Correlation matrix for full sample.

	CV	CD	Gini	ACF1	ACF2	ACF3	ACF7	ACF14	ACF21	ACF28
CV	1	0.48***	0.86***	0.09***	0.16***	0.22***	−0.24***	−0.28***	−0.27***	−0.29***
CD		1.00	0.76***	0.18***	0.12***	0.09***	0.12***	0.10***	0.09***	0.08***
Gini			1.00	0.11***	0.17***	0.20***	−0.13***	−0.17***	−0.17***	−0.19***
ACF1				1.00	0.36***	0.15***	0.29***	0.23***	0.20***	0.19***
ACF2					1.00	0.51***	−0.00	−0.08***	−0.09***	−0.11***
ACF3						1.00	−0.13***	−0.20***	−0.22***	−0.25***
ACF7							1.00	0.70***	0.70***	0.66***
ACF14								1.00	0.73***	0.73***
ACF21									1.00	0.73***
ACF28										1.00

$p < 0.001$ '***', $p < 0.01$ '**', $p < 0.05$ '*'

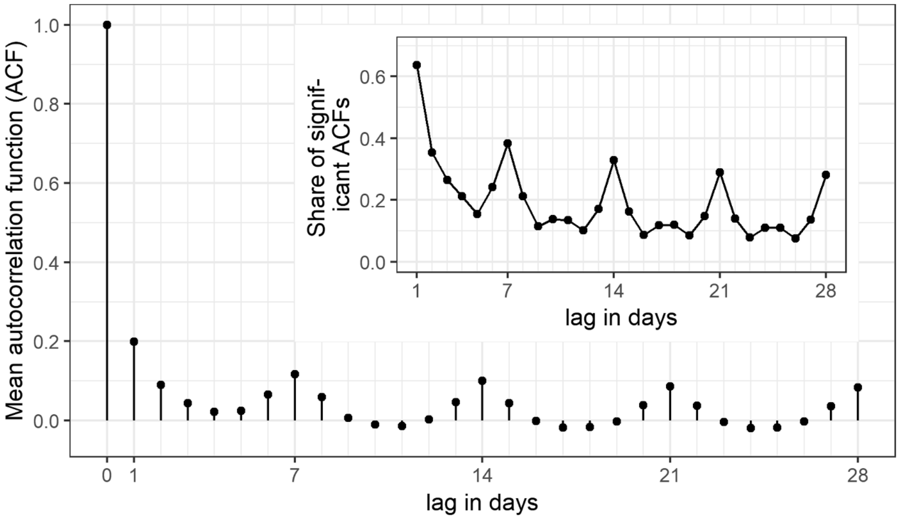

Fig. A1. Mean of the autocorrelation functions for all vehicles versus time lag. The inset shows the share of vehicles with autocorrelation different from zero (p < 1 %).

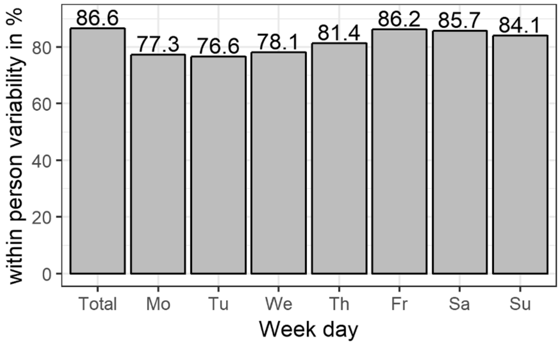

Fig. A2. Within-person variability of daily travelled distances. The Figure shows the within-person variability for all daily VKT and for the daily VKT of individual weekdays only.

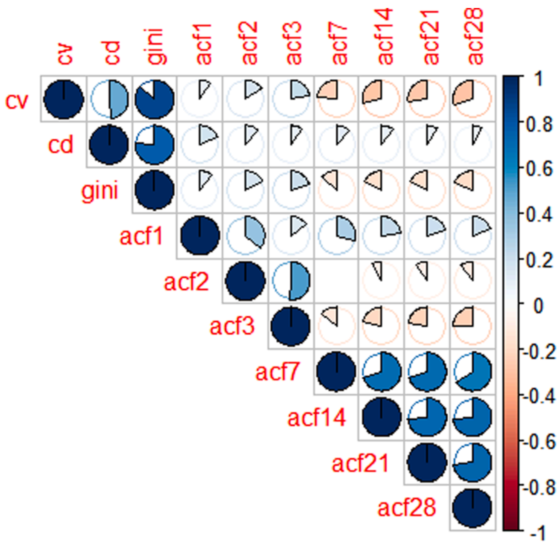

Fig. A3. Correlation matrix for measures of regularity. Positive correlation in blue and negative correlation in red. Strength indicated by angle. Insignificant (p greater than 0.01) correlations omitted. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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