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Understanding the variability of daily travel-time expenditures using GPS trajectory data

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Transportation planning is strongly influenced by the assumption that every individual has for his daily mobility a constant daily budget of ≈ 1 hour. However, recent experimental results are proving this assumption as wrong. Here, we study the differences in daily travel-time expenditures among 24 Italian cities, extracted from a large set of GPS data on vehicles mobility. To understand these variations at the level of individual behaviour, we introduce a trip duration model that allows for a description of the distribution of travel-time expenditures in a given city using two parameters. The first parameter reflects the accessibility of desired destinations, whereas the second one can be associated to a travel-time budget and represents physiological limits due to stress and fatigue. Within the same city, we observe variations in the distributions according to home position, number of mobility days and a driver's average number of daily trips. These results can be interpreted by a stochastic time-consumption model, where the generalised cost of travel times is given by a logarithmic-like function, in agreement with the Weber-Fechner law. Our experimental results show a significant variability in the travel-time budgets in different cities and for different categories of drivers within the same city. This explicitly clashes with the idea of the existence of a constant travel-time budget and opens new perspectives for the modeling and governance of urban mobility.

Introduction

Recently, human mobility has been extensively studied using data on individual trips provided by the information-communication technologies [1–7]. In mobility-related decisions, travel time appears as a natural cost function, since it represents a limited resource used for performing daily activities [8]. The concepts of Travel-Time Expenditure (TTE, the daily amount of time spent traveling) and Travel-Time Budget (TTB, the average daily amount of time that people make available for mobility [9]) have been introduced by transportation planners to model the mobility demand and to explain some of the features characterising urban mobility [10]. Travel-Time Expenditure and Budget are more comprehensive quantities than the commuting time from home to work and back between home and work, and the related concept of Marchetti's constant [11, 12]. Indeed, this second perspective is limited to the journey-to-work mobility and thus exclude a large fraction of the individuals' mobility demand associated to amenities.

The existence of a Travel-Time Budget is assumed on the basis of the behavioural hypothesis that people spend a fixed amount of time available on traveling [13]. The extreme interpretation of Travel-Time Budget as an universal constant stable in space and time is still sustained and very influential in urban planning. Indeed, if Travel-Time Budget is constant, any investments in better infrastructure would not reduce daily travel times (and possibly, through that, polluting emissions) since it would only create new induced travel demand [14]. Most of the empirical results on Travel-Time Budget are determined as average values from large travel surveys. At a disaggregate level, however, Travel-Time Expenditures appear strongly related to the heterogeneity of the individuals, to the characteristics of the activities at destinations and to the residential areas [13]. Aggregated results suggest that the average amount of time spent traveling is constant both across populations and over time: approximately 1.0-1.1 hours per day [15]. Despite the gains in average travel speed due to infrastructural and technological advances in the past decades, Travel-Time Expenditures appear more or less stable or even growing [16–18]. This growth can be associated to the super-linear relationship between a city's population and the delays due to congestion [19].

In Italy, Global Positioning System (GPS) devices are installed in a significative sample of private vehicles for insurance reasons. The initial and the final points of each trajectory are recorded, together with the path length and some intermediate points at a spatial distance of 2 km or at a time distance of 30 seconds. These data allow a detailed reconstruction of individual mobility in different urban contexts [20] and measure the elapsed of time during mobility [21].

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In this paper, we explore the statistical features of Travel-Time Expenditures related to private mobility, both from an aggregate and individual point of view. Our goal is to point out some of the factors influencing travel demand by means of new specific measures, which describe differences among cities. The statistical analysis of empirical data points to the existence of a universal law underlying the distributions of Travel-Time Expenditures, which highlights the nature of time constraints in vehicular mobility. This result allows us to observe in detail the differences in daily travel demand for different cities, challenging the idea of a constant Travel-Time Budget and pointing out the important role of accessibility [22].

Quantity	Notation	Abbreviation
Daily travel-time expenditure	T	TTE
Daily travel-time budget	β	TTB
Accessibility time	α	-
Single trip travel-time	t	-
Function	Notation	Abbreviation
Probability density of x	$p(x)$	PDF
Cumulative density of x ($\int^x p(x')dx'$)	$P(x)$	CDF
Survival function ($1 - P(x)$)	$S(x)$	-
Hazard function ($dS(x)/dx$)	$\lambda(x)$	-
Conditional probability of x given y	$\pi(x y)$	-

TABLE I: List of notations.

Assumptions

Previous empirical observations on different data-sources [20, 23–26] have shown out that the TTE probability distribution $p(T)$, associated to a single mean of transportation, is characterized by an exponential tail

$$p(T) = \beta^{-1} \exp(-T/\beta), \quad \text{for } T > 1 \text{ hour.} \quad (1)$$

where β is a fit parameter. Our analysis confirms the universal character of the exponential behaviours for the TTE empirical distribution and points out relevant differences among the considered cities (see Fig. 1).

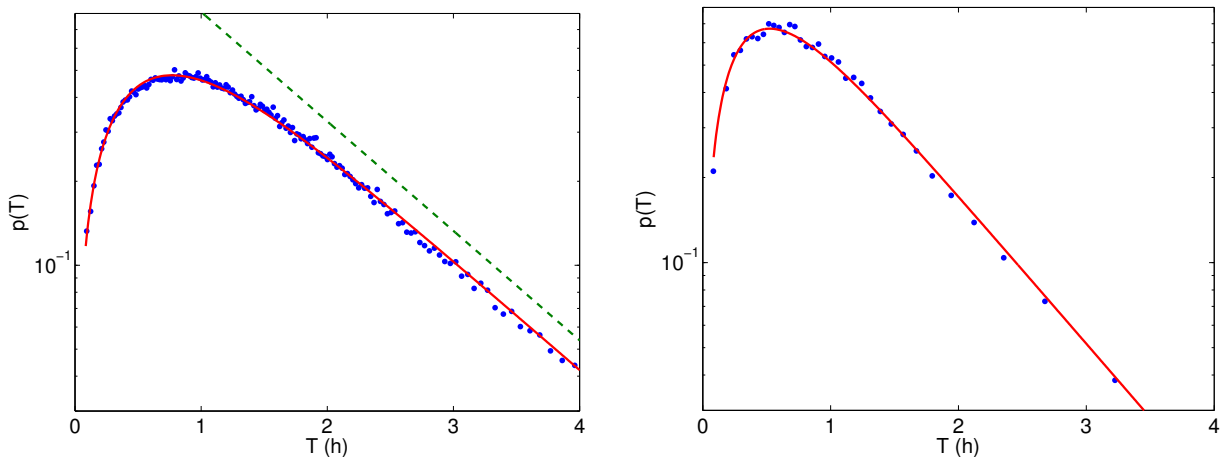


FIG. 1: **(Left) Travel Time Expenditure (TTE) distribution for the city of Naples (≈ 1 million inhabitants).** The empirical probability density $p(T)$ (dots) is correctly interpolated by the curve (6) (solid line) with $\alpha = 0.61\text{h}$, $\beta = 1.11\text{h}$ and $R^2 = 0.99$. The dashed line, shown as a guide to the eye, represents an exponential decay with a characteristic time β . **(Right) TTE distribution for the city of Grosseto ($\approx 80,000$ inhabitants).** The interpolation with the curve (6) is successful also for smaller cities like Grosseto: in this case the parameter values are $\alpha = 0.38\text{h}$, $\beta = 0.83\text{h}$ and $R^2 = 0.99$

As it is well known from Statistical Mechanics, the exponential distribution (1) can be derived from the Maximal Entropy Principle under some minimal assumptions [20]. More precisely, one assumes the existence of an average

finite TTE for the considered population and the independence of the individual behaviour: i.e. any microscopic configuration which associates a TTE to each individual with the constraint that the average TTE is finite, has the same probability to be observed. The parameter β defines the average time scale that limits the individual TTE and we will show that this is a characteristic of each city. Therefore, we propose to associate the concept of TTB to the value β which characterizes the exponential decay of the daily travel-time distribution. However, the eq. (1) does not give information on the dynamical processes underlying the human mobility which produces the distribution. We take advantage from the dynamical structure of the GPS data to propose a duration model (see Methods) that seems to be endowed with universal features with respect to the considered cities. The essential hypotheses at the bases of the duration model are: i) it exists a TTB; ii) the individual decision to continue the mobility for a time ΔT after a TTE T is the realization of a independent random event whose probability decrease proportionally to ΔT .

Results

The variability of Travel Time Expenditures

The average value of TTE does not give a sufficient insight on the statistical features of the distribution $p(T)$. For each city the statistical features of the distribution $p(T)$ turn out to be characterized by the two time scales α and β . In the duration model, after a characteristic time α , the choice of going back home or proceeding with further extra traveling is limited by the available TTB, whose average value is quantified by the time scale β . α therefore represents the average time under which the use of a private car seems to be not convenient.

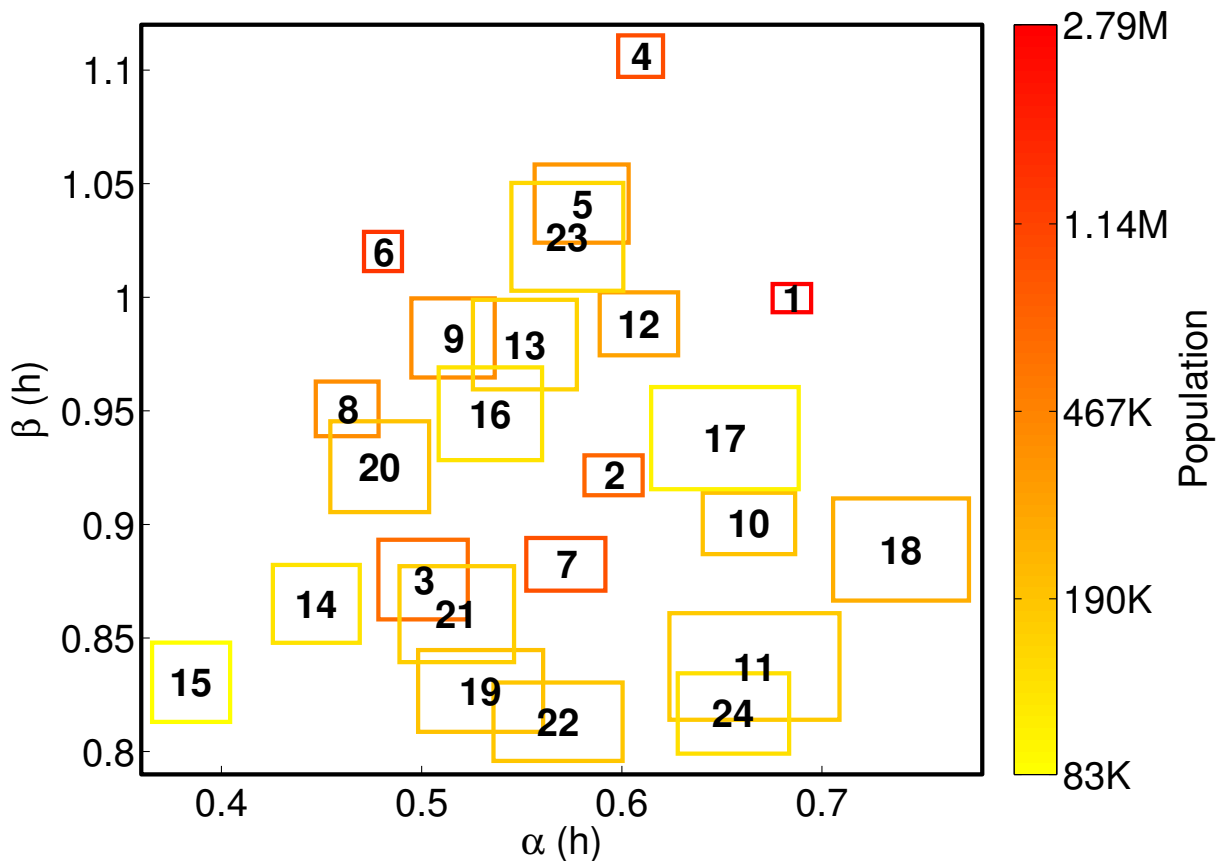


FIG. 2: Values of α and β for the 24 cities studied. The boxes represent 95% confidence intervals obtained with a bootstrap, for empirical best-fits for the model parameters. The differences we observe in the accessibility time α and in TTB β are thus significant and uncorrelated ($r = 0.09$). Both timescales are weakly correlated with the city's population ($r = 0.20$ for α and $r = 0.40$ for β .)

We focus our study on 24 Italian cities where we had a large statistic of users. The values of α and β are estimated from a bestfit for $S(T)$ with equation S5 (which is equivalent to fitting the CDF). The results are displayed in Fig. 2 and reported in the Table S1. Two examples are also proposed in Fig. 1. The two parameters are independent, with a Pearson correlation coefficient $r = 0.09$. β fall in the interval 0.8-1.1h, which is reasonably consistent with the values reported in the literature [15]. Nevertheless, the differences we observe among cities are statistically significant, as the 95% confidence intervals for the fits, estimated with a bootstrap, are ≤ 0.02 h. Therefore, our results clearly clash with the concept a constant TTB.

Since the values of β are moderately correlated with the number of inhabitants of the municipality ($r = 0.40$) or population density ($r = 0.49$), some of this variability is dependent on the city population [19, 27]. The accessibility time α is only weakly correlated with city population ($r = 0.20$) and not correlated ($r = 0.03$) with population density, and fall in the interval 0.3-0.8h. The confidence intervals for the fits are ≤ 0.04 h, granting that we have significant differences in accessibility time among cities. The general picture displayed in Fig. 2 shows that, if one has appropriate datasources to characterize the daily mobility of a single city, one needs the knowledge of both parameters. Under this lens, the variability of TTE is manifest and can be observed in both the ramping part (α) and the tail (β) of the distribution.

Disaggregate analysis: The case of Milan

Macroscopic statistical laws might depend on the details of the microscopic dynamics. Their extension down to the interpretation of the individual behaviour is therefore under debate [28]. Nevertheless, we believe that the universal character inherent to the concept of TTB could be an individual property. To support this statement, we consider here a disaggregate analysis of the GPS mobility data suggesting that our results might be extended to the individual level. A limitation of this analysis comes from the limited time considered in our dataset. Indeed, it refers only to a single month of mobility, a period probably too short to infer a definitive conclusion on our hypothesis.

We study the case of the city of Milan, the largest city in North Italy with ≈ 1.3 millions inhabitants (dash line in Fig. 5 left and labeled 6 in Fig. 2). We start with verifying that the shape of TTE distribution $p(T)$ is a property of each single individual. Using the GPS data, the heterogeneity of the population can be quantified by considering the distribution of the average individual TTE $\langle T \rangle$ empirically computed from the individual daily mobility. To compare different individuals, we normalize each TTE value by the corresponding individual average. In Fig. 3 (a), we show that the distribution of the normalised individual TTE $p(T/\langle T \rangle)$ is still very well fitted by the analytical curve (6). Therefore we conjecture that $\langle T \rangle$ contains the relevant information to explain the individual heterogeneity and the distribution (6) has an universal character that extends up to the individual level.

An individual disaggregation, according to the home location or characteristics of the mobility network, confirms the previous hypothesis (see Figs. 3 (b) and (c), and the Supplementary Information for further details). Thus, the heterogeneity is mainly determined by the average value $\langle T \rangle$ evaluated within each class. However, we find that $\langle T \rangle$ is longer for:

- i) people living in the city center ($\approx 8\%$ longer than for people living in the periphery), a result consistent with what was found in Ref. [29] for the city of Sydney; conversely, people in the periphery tend to make ≈ 0.5 trips more per day and ≈ 3.3 days more of mobility in average;
- ii) people performing many round trips (A-B-A patterns) not involving home.

The last criterium points to the existence of a second center of daily activity and allows to separate individual mobility networks into mono-centric and polycentric ones [30].

Our empirical data suggest that people with a polycentric mobility (who have more than one mobility hub) have greater $\langle T \rangle$ than people whose round trips start and end at home. However, if we classify the individuals according to the number of days in which they used the car, the TTE distributions differ when we consider small T values (see Fig. 3 (d)). Even if the exponential tail of the distributions does not change significantly, a tendency to suppress more short values of T is observed for users accustomed to regularly carry out their daily mobility by car. Our duration model associates this to a larger value of α and therefore the need in average of longer times to accomplish the necessary tasks of the day. In summary, people who take the car more often also need to drive more, yet maintaining a similar TTB. This is confirmed by considering the number of trips n that are accomplished in a day. The average value of n grows from 4.2, for people who drove 1-12 days up to the 7 for the class of users who drove all the 31 days (see Supplementary Information). This result clearly links the value of the accessibility time α to the need of accessing to the desired destinations by car. Drivers who experience better accessibility do not need to use the car every day, and when they do they can also drive less. In the following, we show that these differences can be linked to a different value of time for users performing more trips.

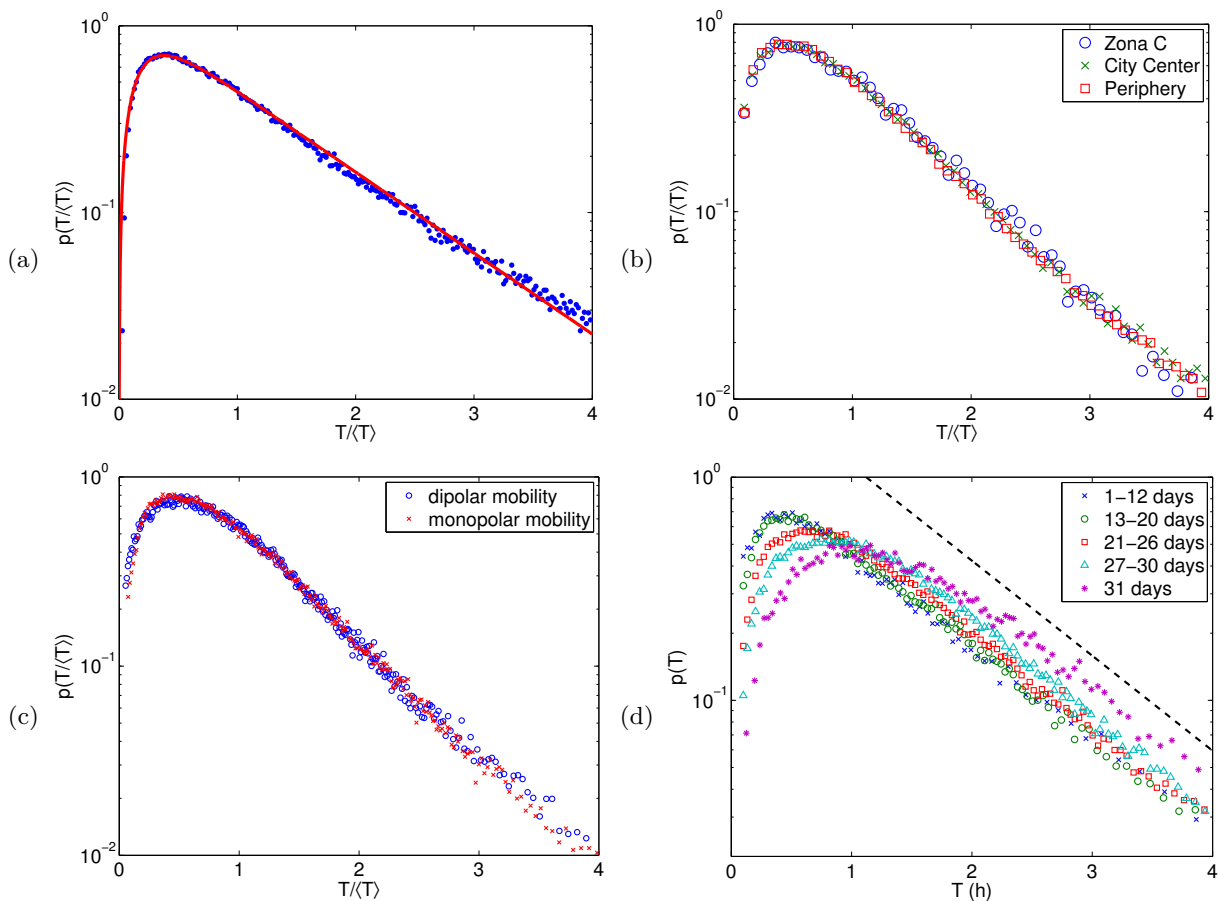


FIG. 3: **a) Distribution of the normalised individual TTE for the city of Milan:** the distribution of normalised individual TTE can be represented by the analytical distribution (6). The solid line is obtained by using the parameters $\alpha = 0.19$ and $\beta = 1.00$. **b) Normalised TTE distributions disaggregated according to home location:** the position of the main mobility hub (home) influences the average value of T but not the distribution scaled by that value. For the 'Zona C' we have $\langle T \rangle = 1.520 \pm 0.009\text{h}$, for the city center we have $\langle T \rangle = 1.482 \pm 0.004\text{h}$ while for the periphery we have $\langle T \rangle = 1.416 \pm 0.003\text{h}$ (errors correspond to the s.e.m); **c) Normalised TTE distributions disaggregated according to classification of the mobility network:** the role of home influences only the average value of T : selecting people whose mobility is characterised by more than one hub in their mobility network (we look for people with a percentage greater than 25% of round trips not starting and ending at home). Such people have $\langle T \rangle = 1.72\text{h}$, whereas people with a single mobility hub have only $\langle T \rangle = 1.24\text{h}$. **d) TTE distributions disaggregated according to the number of mobility days:** these disaggregated distributions have a similar decaying in the tails, i.e they have similar value of β (as a guide for the eye, the dashed line represents an exponential decay with the characteristic timescale β for Milan). Differences emerge instead in the behaviour of short TTE: people that use the car more regularly, have longer TTEs, since they perform more trips.

Evidence of a log-perception of travel-time costs

Finally, to link the duration model with the individual behavior and to shed light on the how individuals organize their mobility, we propose a time consumption model that allows for an interpretation of the empirical observations compatible with a logarithmic perception of the time cost of a trip. (See Methods). This model realizes a stochastic process for the individual decisions at the base of TTE, which is compatible with the assumptions of the duration model and with a possible logarithmic perception of the cost ΔT of a trip, analogous to the Weber-Fechner psychophysical law [31]. The same model does not reproduce the empirical observations, assuming a linear time perception. This result has been confirmed with a Montecarlo stochastic decision model based on the same premises (see Fig. 4 left and Supplementary Information). This model assumes a logit curve [32] in the decision model of the binary choice of interrupting the daily mobility after a certain trip, we could fit the TTE distributions in all cities with great precision ($R^2 > 0.986$).

The existence of simple universal dynamical models for empirical TTE distribution allows to introduce few ob-

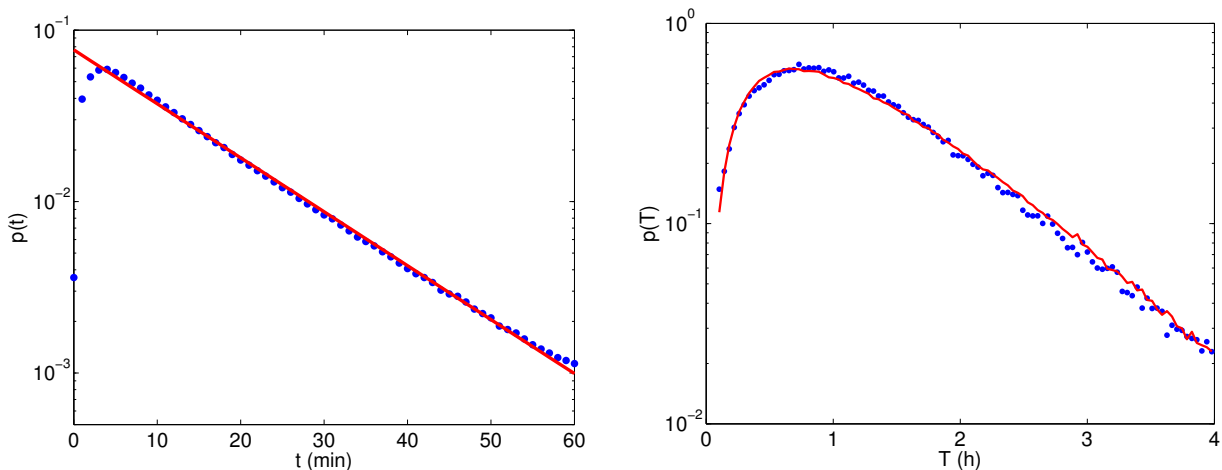


FIG. 4: **Travel-time distribution and stochastic decision model.** (Left) The travel-times distribution $p(t)$ in Milan (dots) compared with an exponential interpolation (solid line). The suppression for short travel-times, with $t < 4$ min could be a consequence of the characteristic GPS measurement time and does not affect the time scale $\langle t \rangle$. The results are consistent with the exponential fit of the tail. (Right) Comparison between the empirical TTE $p(T)$ distribution in Turin (dots) and the best fit distribution provided by our stochastic decision model, using a logistic threshold function (solid line, see Supplementary Information, $R^2 = 0.99$).

servables that point out relevant differences among cities and suggests relations between the presence of mobility infrastructures and/or the socio-economic indexes of a city, and the features of the empirical TTE distribution. These relations could be useful for urban planners to build governance policies for mobility.

Discussion

In our analysis, based on a large GPS database containing information on single vehicle trajectories in the entire Italian territory, we point out that the empirical distributions for the daily Travel-Time Expenditures in different cities can be modeled by a single distribution. This distribution is function of two parameters: α and β . The time scale α measures the characteristic mobility time associated to the use of private cars in a given city, whereas the limit value $1/\beta$ of the hazard function $\lambda(T)$ as $T \gg 1$, is associated to the concept of Travel-Time Budget. In our opinion, α is a good measure of the average accessibility [22] of a city. Lower values of α (i.e. higher accessibility) mean a better proximity to useful locations and faster mobility. We remark that if one considers Italian cities of different size and socio-economical conditions, the shape of the distribution appears to be endowed with an universal character only the values of Travel-Time Budget and suppression of short Expenditures changes.

The distribution $p(T/\langle T \rangle)$ has an universal character. This suggests the existence of a behavioural model for the urban mobility that mimics the individual decision mechanisms. As a consequence, the statistical properties pointed out by the distribution (6) are traits of the individual behaviour and the aggregated probability distribution for a city is averaging over the individual heterogeneity in the values of α and β across the population. However, in the disaggregated analysis of GPS data at individual level, we find significant differences in the average Travel-Time Expenditure for different categories of drivers. In particular, drivers which use their car more often have higher values of α even if their β is approximatively the same (see Fig. 3 (d)). This is another confirmation of our interpretation of the parameter α as a measure of accessibility, because who has the worst accessibility to public transport facilities is forced to use the private vehicle over wider range of travel-times.

To interpret these results we propose a simple decisional model, which assumes the the existence of a *mobility energy* (the daily travel-time) and a log-time perception of the travel-time cost for a single trip. These results are also consistent with the Benford's empirical distribution of elapsed time during human activities [20] and Weber-Fechner psychophysical law [33]. Using a Statistical Mechanics point of view, the Travel-Time Expenditure T plays the role of energy in a model of the individual urban mobility based on a generalised utility function. However, one cannot simply define the trip duration ΔT as a mobility cost, because the data suggest that this perceived cost seems to decreases as the daily travel time T grows. A time consumption model that assumes a scaling cost $\propto \Delta T/T$ (i.e. a *law of relative effect* [34]) corresponding to a logarithmic preference scale [31]), is able to reproduce the statistical

properties of the empirical observations. As a direct application of this result, we are able to suggest the use of a non linear value of time for the activity-based modeling of human mobility.

At city-aggregate level, we observe that for every city the average Travel-Time Expenditure $\langle T \rangle$ is greater than the Travel-Time Budget β , because short values of T are statistically under-expressed [23]. This could reflect both the fact that the individual mobility demand is hardly satisfied after short travel-times, and the disadvantage using a private car for short times. Both α and β are needed to fully understand the Travel-Time Expenditures in a city. A straightforward application of the approach we propose permits to highlight the differences in the travel-time expenditures among cities and classes of individuals. In particular, we clearly observe a variability in the Travel-Time Budget β among cities. The dependency upon population density and the differences observed in the disaggregate analysis explicitly clashes with the idea of the existence of a fixed Travel-Time Budget.

Our results intend to nourish the discussion against this old paradigm of a constant Travel-Time Budget, which dangerously suggests that is not possible to reduce travel times, and therefore CO2 emissions, with improvements to the transportation infrastructures. The idea that travel time savings are not beneficial, because improving road infrastructures in cities will attract even more traffic, is not corroborated by the empirical data. Understanding the decision mechanisms underlying the individual mobility demand and the use of private vehicles in a city is a fundamental task to forecast the impact of new transportation infrastructures or of traffic restriction policies. On our opinion, it is thus clear the need of replacing constant the travel time budget and induced travel demand assumptions with new models, which should necessarily encompass both individual behaviour and city development.

Methods

GPS database

This work is based on the analysis of a large database of GPS measures sampling the trajectories of private vehicles in the whole Italy during May 2011. This database refers, on average, to 2% of the vehicles registered in whole Italy, containing traces of 128,363,000 trips performed by 779,000 vehicles. Records are always registered at engine starts and stops and every ≈ 2 km during the trips (or alternatively every 30 seconds in the highways). Each datum contains time, latitude-longitude coordinates, current velocity and covered distance from the previous datum directly measured by the GPS system using data recorded (but not registered) each second. We define a trip as the transfer between two locations at which the engine has been turned off. If the engine's downtime following a stop is shorter than 30 seconds, the subsequent trajectory is considered as a continuation of the same trip if it is not going back towards the origin of the first trajectory. We have performed filtering procedures to exclude from our analysis the data affected by systematic errors ($\approx 10\%$ of data were discarded). The problems due to signal loss is critical when the engine is switched on or when the vehicle is parked inside a building. In such cases we have used the information redundancy to correct 20% of the data by identifying the starting position of one trip with the ending position of the previous one. When the signal quality is good the average space precision is of the order of 10 m, but in some cases it can reach values up to 30 meters or more [35]. Due to the Italian law on privacy, we have no direct information on the owners or any specific knowledge about the social characters of the drivers sample.

The GPS data base is collected for insurance reasons using black boxes installed on vehicles, whose owners agreed with a special insurance contract. As a matter of fact, these contracts are more attractive for young people or are used on fleet of vehicles. This is a bias in our sample to study human mobility, since young people may use the private vehicle in a different way with respect to elder people. However our point of view is that the universal statistical properties of human mobility discussed in the paper are not affected, due to the large number trajectories and the different urban contexts. Some vehicles present in the database belong to private companies' fleets. In this case, employers who use the car for professional reasons might show a different behaviour, but they contribute to small percentage of all vehicles and therefore their statistical weight is small.

As the drivers's city of residence is unknown, it has been necessary to associate each car to an urban area using the available information. We have established that one driver lives in a certain city if the most part of its parking time is spent in the corresponding municipality area. For each driver, we have considered all the mobility performed in a day (in and out the urban area) to measure daily TTE T . In this way it is possible to measure the average value of T for over 1200 different municipalities, where we have at least 100 vehicles. Moreover, for a smaller number of cities we have sufficient data to analyse the shape of the probability density $p(T)$ or of the cumulative distribution $P(T) = \int_0^T p(T')dT'$, as done in [20] on a similar dataset.

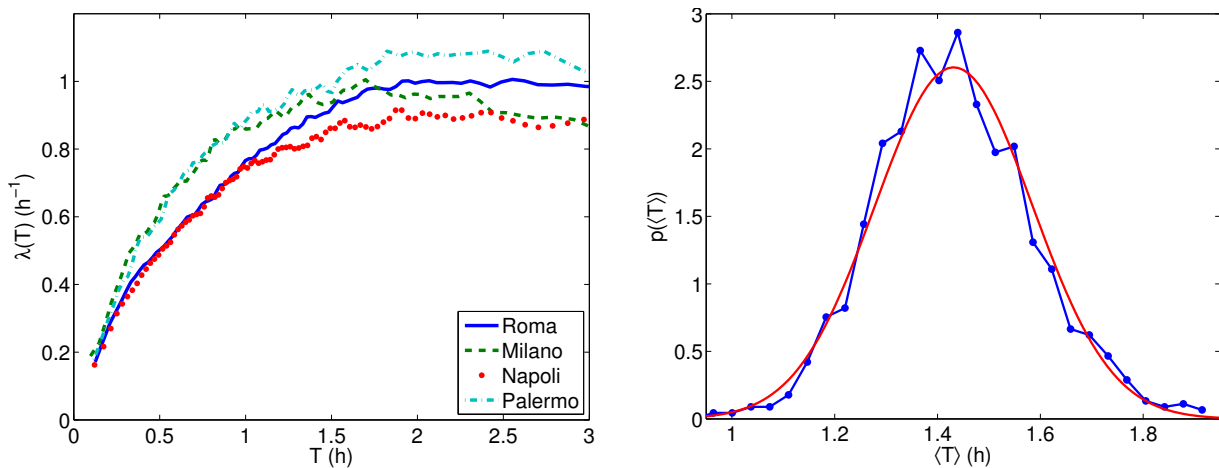


FIG. 5: **(Left) Different behaviours of the empirical hazard functions to model the mobility in a city.** Hazard functions $\lambda(T)$ for the cities of Milan in Northern Italy with 1.3 millions inhabitants (dash line), Rome, the capital, in Central Italy with 2.7 millions inhabitants (solid line), Naples in Southern Italy 1 million inhabitants (dot line) and Palermo in Sicily 700 thousand inhabitants (dot-dash line). We have significant differences, particularly in the height of the plateau ($1/\beta$) that is related to the TTB. **(Right) Average TTE in Italian cities.** The distribution of the average TTE for 1233 Italian municipalities where we have at least 100 GPS equipped vehicles (dots and lines) can be interpolated with a Gaussian with mean 1.43h and standard deviation 0.15h (solid line).

A duration model for Travel-Time Expenditures

An application of duration model to travel-time analysis has recently been proposed [36]. This type of model allows a mesoscopic description of the empirical data for a large range of human and animal temporal behaviours [37].

Using the GPS data base on single vehicle trajectories, it was possible to study the empirical TTE distribution for all cities that had at least a sample of 100 monitored vehicles (see Table S1). As example in Fig. 1, we show the TTE empirical distributions for Naples, the largest cities in the South of Italy (≈ 1 million inhabitants) and Grosseto, a small city in the center of Italy ($\approx 80,000$ inhabitants). This behaviour of the TTE distribution is observed in all the considered cities. The parameter β , computed by interpolating the empirical curves (see eq. (1)), defines the average time scale of individual daily mobility and it is a characteristic of each city. The distribution of the average TTE $\langle T \rangle$ for those cities is reported in Fig. 5 together with a normally distribution with mean 1.43h, and standard deviation 0.15h. Those values are thus significantly larger than the expected TTB of 1.1 hours [15].

From the comparison of definitions of TTB for different modes of transportation, bodily energy consumption rates have to be taken into account to define a universal travel-energy budget [23]. The TTB β can be therefore interpreted as a physiological limit to daily mobility: it is the stress and fatigue accumulated while traveling that restricts the time an individual is willing to spend on mobility in a day. Let T the TTE of an individual, then we can introduce the *survival function* $S(T)$ as the probability that the TTE is greater than T . Assuming the Markov properties for the evolution of T , we have the relation

$$S(T + \Delta T) = [1 - \lambda(T)\Delta T]S(T) + o(\Delta T), \quad (2)$$

where $\lambda(T)$ is the *hazard function*, which is related to the conditional probability $\pi(T + \Delta T|T)$ to realize a TTE $T + \Delta T$ if one has spent a TTE T . The hazard function can be theoretically defined as

$$\lambda(T) = \lim_{\Delta T \rightarrow 0} \frac{1 - \pi(T + \Delta T|T)}{\Delta T}. \quad (3)$$

If we consider an ensemble of individuals, the hazard function has to be empirically defined as an average value

$$\lambda(T) = \left\langle \frac{1 - \hat{\pi}(T + \Delta T|T)}{\Delta T} \right\rangle_{\Delta T} \quad (4)$$

where $\hat{\pi}(T + \Delta T|T)$ refers to the conditional probability to observe a TTE $T + \Delta T$ of the individual dynamics and the average value is computed over the distribution of the possible increments ΔT in the considered population. $S(T)$

is related to the probability distribution $p(T)$ with $p(T) = -dS(T)/dT$. When the hazard function is constant, the underlying stochastic process is a stationary Poisson distribution. But the empirical hazard function, evaluated from GPS data (see Fig. 5 left), shows an exponential decay from the asymptotic uniform behaviour (see Fig. S1 and Supplementary Information), which can be analytically interpolated by

$$\lambda(T) = \beta^{-1}[1 - \exp(-T/\alpha)]. \quad (5)$$

We identify the parameter β with the TTB, whereas α may represent the typical average time associated the private car mobility, since the hazard function $\lambda(T)$ is small when $T \leq \alpha$. As a matter of fact, both quantities are characteristic of each city. The timescale α is associated to the accessibility of desired destinations in the city [22]. Indeed, it is interpreted as the average time necessary to satisfy the mobility demand using private cars. Larger values of α mean lower accessibility. Given $\lambda(T)$, we can compute the analytic form of the TTE probability distribution by explicitly solving Eq. (2) (see Supplementary Information)

$$p(T) = \beta^{-1} \exp(\alpha\beta^{-1}) (1 - \exp(-T/\alpha)) \exp(-\alpha\beta^{-1} \exp(-T/\alpha) - T/\beta). \quad (6)$$

According to Eq. (5), for $T \gg \alpha$ the dominant term is $\exp(-T/\beta)$ and we recover the exponential tail of the empirical TTE distributions. In the Fig. 1, we show two interpolations of the empirical distributions by using of the function (6). The associated fits for the hazard functions are displayed in Fig. S1. We have found a very good agreement considering cities of different size, importance, position and infrastructure development (see Table S1).

A time consumption model

To interpret the empirical results on an individual level, we formulate a time consumption model where each individual progressively accumulates travel-time according to a well defined strategy. This interpretation is based on three key aspects:

- i) the TTE is effectively a measure of the consumed *Energy* [23] during mobility;
- ii) there is a log-time perception of the trip durations as the TTE increases [34];
- iii) the trip durations are exponentially distributed [21].

The first item refers to a Statistical Mechanics interpretation of the TTE distribution function according to a Maxwell-Boltzmann distribution. The second item means that after a TTE of T , the perceived additional cost of a new trip by a driver is proportional to $\Delta T/T$, where ΔT is the new additional trip duration. The logarithmic scaling is a reflection of Weber-Fechner psychophysical law [31]. It is possible that the individual perception of weariness is at the origin of this logarithmic weighting of time, which has been proposed to explain the statistical properties of the duration of individual activities [20]. The third item is supported by empirical evidence: our data suggest that the travel-times cost t for a single trip has also predominantly an exponential probability density within the range $4 \leq t \leq 60$ minutes (see Fig.4 left)

$$p(t) \approx \langle t \rangle^{-1} \exp(-t/\langle t \rangle), \quad (7)$$

This result has been shown to be universal across different cities, with the characteristic decaying time $\langle t \rangle$ growing with city population [21]. In the Supplementary Information, we show that $\langle t \rangle$ also varies among the considered cities and might depend upon house prices, city surface and average travel speeds (See Fig. S2). In our model, each individual progressively accumulates travel-time to determine his TTE. According to our first assumption, a driver will accept a TTE of T with a probability

$$P(T) = \exp\left(-\frac{T}{\bar{\beta}}\right), \quad (8)$$

where $\bar{\beta}$ is the characteristic TTB of the population. Then the individual conditioned probability to accept a new trip of duration ΔT after a TTE of T is written

$$\hat{\pi}(T + \Delta T/T) = \frac{P(T + \Delta T)}{P(T)} \quad (9)$$

However the ΔT distribution for the new trip is not independent from the elapsed TTE T since users are reluctant to accept long trips when the TTE exceeds $\bar{\beta}$. Then we define a conditional ΔT distribution, which takes into account

the elapsed TTE, by using a threshold function $\theta_a(x)$

$$\theta_a(x) = \begin{cases} 1 & \text{if } x < a, \\ 0 & \text{otherwise.} \end{cases}$$

According to our assumptions, the distribution (7) is substituted by the conditional distribution

$$p(\Delta T/T) \approx \langle t \rangle^{-1} \exp(-\Delta T/\langle t \rangle) \theta_a(\Delta T/\gamma) \quad (10)$$

where the threshold a and the time scale γ depend on T or on other individual features: a is the acceptability threshold for a new trips, whereas γ defines the perceived measure unit of the cost of the new trip. The empirical observations suggest that the threshold a depends on the average number of activities $\langle n \rangle$ of an individual. This is illustrated by the correlation between the mobility timescale α (see eq. (5)) divided by $\langle n \rangle$ and $\langle t \rangle$ (see Fig. 6 left). To define γ , we assume a logarithmic perception of the trip time cost so that $\gamma \propto T$. Then we set the threshold $a = x_{max}/\langle n \rangle$ and $\gamma = T$, so that the threshold function is written in the form

$$\theta_{x_{max}/\langle n \rangle} \left(\frac{\Delta T}{T} \right) = \begin{cases} 1 & \text{if } \frac{\Delta T}{T} < x_{max}/\langle n \rangle, \\ 0 & \text{otherwise,} \end{cases}$$

where x_{max} turns out to be an *universal threshold*. Therefore Eq. (10) is based on the assumption that the propensity of a driver to accept a further trip of duration ΔT after having performed a TTE of T , scales as $\langle n \rangle/T$, where $\langle n \rangle$ is the average number of daily activities. In other words the individuals that perform more trips using private vehicles have a greater TTB: this could be also a consequence of the multi-modal mobility, which is not included in our database, and that allows individuals to divide their TTB according the different transportation means used. Moreover, an individual seems to organise the mobility using the TTB as a mobility energy (with the constraint of performing the compulsory daily activities), but keeping the percentage of TTE fluctuations constant. Using empirical values for the different quantities in the relation (11) we can estimate $x_{max} \simeq 2$ (see Fig. 6 left).

We compute the empirical hazard function for a population of drivers according to the definition (S2)

$$\lambda(T) = \langle t \rangle^{-1} \int_0^\infty \frac{1 - \exp(-\Delta T/\beta)}{\Delta T} \theta_{x_{max}/\langle n \rangle} \left(\frac{\Delta T}{T} \right) \exp(-\Delta T/\langle t \rangle) d\Delta T$$

An explicit calculation (see Supplementary Information) shows that the hazard function of the model has the same analytic form as the empirical interpolation (5), where the timescale of the short TTE suppression is

$$\alpha \simeq \langle n \rangle \langle t \rangle / x_{max}, \quad (11)$$

as one can see in Fig. 6 (right).

Competing interests

The authors declare that they have no competing interests.

Author's contributions

RG, AB designed and performed research and wrote the paper; RG, AB, SR performed research. RG prepared the figures.

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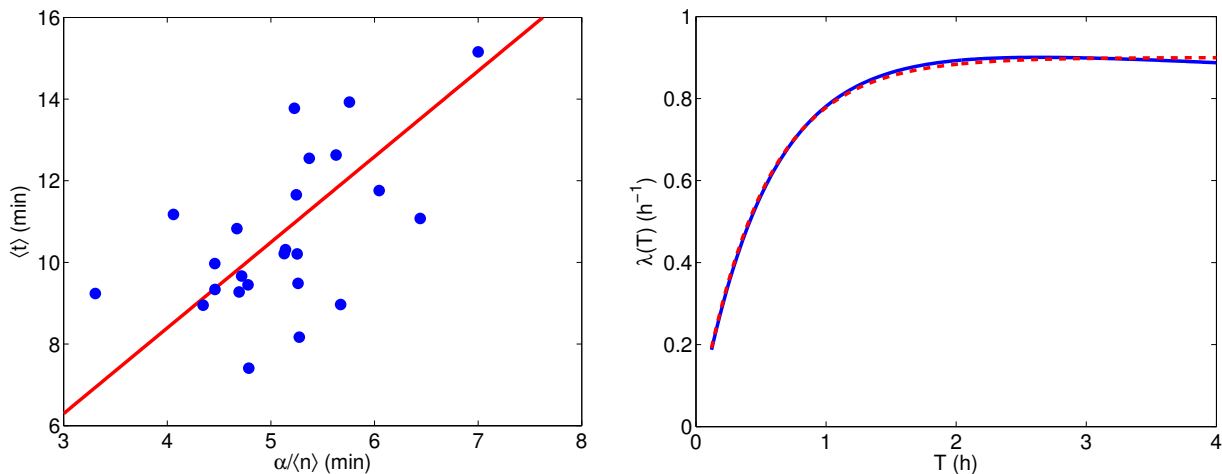


FIG. 6: **(Left)** Correlation between the time of a single trip duration $\langle t \rangle$ and the ratio between the short travel-time expenditures and the average number of activities $\alpha/\langle n \rangle$: each dot refers to a different city ($r = 0.57$); the straight line has a slope $x_{max} = \langle t \rangle \langle n \rangle / \alpha = 2.1 \pm 0.1$ (error is s.e.m.). **(Right)** Comparison between the hazard function (5) inferred from our empirical data and the hazard function computed using the decision model: the hazard function derived from the decision model (solid blue line), using realistic parameters values $\langle t \rangle \simeq .2$ h, $\bar{\beta} = 1$ h, $\langle n \rangle = 5$ and $x_{max} = 2$ is compared with the empirical hazard function (5) (dashed red line) with $\beta = 1.08 \times \bar{\beta}$ and $\alpha \simeq 0.5$ h.

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SUPPLEMENTARY INFORMATION

List of analyzed cities

#	Name	Pop.	Area	v	$\langle t \rangle$	$\langle n \rangle$	$\langle T \rangle$	α	β	R^2
1	Roma	2786034	1285.3	26.87	0.253	5.87	1.52	0.69±0.01	1.00±0.01	0.99
2	Palermo	653522	158.9	23.00	0.170	6.80	1.39	0.60±0.01	0.92±0.01	0.99
3	Genova	606978	243.6	23.17	0.211	5.34	1.29	0.50±0.02	0.88±0.02	0.98
4	Napoli	957012	117.3	24.47	0.232	6.35	1.58	0.61±0.01	1.11±0.01	0.99
5	Bari	340355	116.0	31.03	0.172	6.77	1.52	0.58±0.02	1.04±0.02	0.99
6	Milano	1345890	181.8	24.35	0.230	5.52	1.44	0.48±0.01	1.02±0.01	0.99
7	Torino	905780	130.3	24.17	0.196	5.68	1.36	0.57±0.02	0.88±0.01	0.97
8	Bologna	383949	140.7	29.22	0.180	5.94	1.37	0.46±0.02	0.95±0.01	0.97
9	Firenze	373446	102.4	25.93	0.209	5.76	1.40	0.52±0.02	0.98±0.02	0.95
10	Reggio Calabria	186273	236.0	24.79	0.123	8.32	1.42	0.66±0.02	0.90±0.01	0.99
11	Perugia	169290	449.9	35.22	0.149	7.05	1.36	0.67±0.04	0.83±0.02	0.98
12	Catania	289971	180.9	23.95	0.170	7.12	1.48	0.61±0.02	0.99±0.01	0.99
13	Foggia	152181	507.8	24.20	0.149	7.61	1.45	0.55±0.03	0.98±0.02	0.99
14	Forlì	118968	228.2	33.30	0.186	6.61	1.27	0.45±0.02	0.87±0.02	0.99
15	Grosseto	82616	474.3	31.80	0.154	6.98	1.19	0.39±0.02	0.83±0.02	0.99
16	Latina	120526	277.8	31.32	0.156	7.19	1.40	0.53±0.03	0.95±0.02	0.99
17	Lecce	96274	238.4	31.46	0.155	8.33	1.46	0.65±0.04	0.94±0.02	0.98
18	Messina	240858	211.2	23.13	0.185	6.89	1.43	0.74±0.03	0.89±0.02	0.98
19	Modena	186289	183.2	32.09	0.158	6.65	1.30	0.53±0.03	0.83±0.02	0.97
20	Parma	189833	260.8	33.87	0.166	6.45	1.37	0.48±0.02	0.93±0.02	0.98
21	Ravenna	159404	244.2	38.18	0.161	6.58	1.31	0.52±0.03	0.86±0.02	0.98
22	Reggio Emilia	172317	231.6	32.00	0.158	6.48	1.29	0.57±0.03	0.81±0.02	0.97
23	Salerno	138284	59.0	28.16	0.194	6.55	1.49	0.57±0.03	1.03±0.02	0.99
24	Siracusa	123517	204.1	24.43	0.136	7.46	1.30	0.66±0.03	0.82±0.02	0.99

TABLE S2: The different columns are: # = id number in the figures, Name = municipality where the driver spent most of his parking time, Pop. = Municipality Population, Area = Municipality Area (km²), v = speed (km/h), $\langle t \rangle$ = average travel-time per trip (h), $\langle n \rangle$ = average number of daily trips, $\langle T \rangle$ = average daily travel time expenditure (h), α = accessibility measure (h), β = travel-time budget (h), R^2 = coefficient of determination. Errors represent the 95% confidence intervals for the fit the parameters, estimated using a bootstrap method with 100 repetitions.

Duration Model

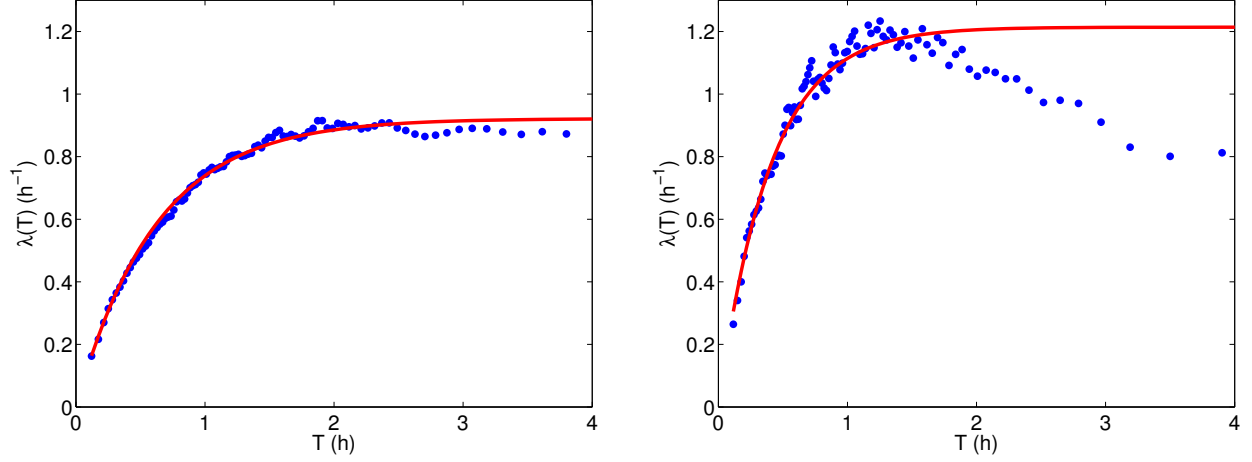


FIG. S1: **(Left) Hazard function in Naples.** The empirical hazard function $\lambda(T)$ (dots) is found to be exponentially converging to a constant value. **(Right) Hazard function in Grosseto.** We remark that the lack of data in the TTE distribution tail does not allow an accurate numerical evaluation of the hazard function. Therefore, in this case to estimate of α and β in some cities, we exclude the decreasing behaviour of the empirical hazard function. In both figures, the values of the parameters obtained by the exponential fit of $\lambda(T)$ (solid line) define the solid line in Fig. 1.

The proposed TTE model is based on the Markov property for the evolution of the survival distribution $S(T)$ (see def. (2) in the main paper). Assuming a regular character for the decision stochastic process, we have

$$S(T + \Delta T) = \pi(T + \Delta T|T)S(T) + o(\Delta T), \quad (\text{S1})$$

where the likelihood $\pi(T + \Delta T|T)$ defines the conditioned probability for the representative individual of performing a daily mobility $T + \Delta T$ given the elapsed time T from the beginning of the daily mobility. Then, we introduce the *hazard function* $\lambda(T)$ (i.e. the probability of ending the mobility after a time the interval ΔT knowing that the user was still driving at time T) according to

$$\lambda(T) = \lim_{\Delta T \rightarrow 0} \frac{1 - \pi(T + \Delta T|T)}{\Delta T}, \quad (\text{S2})$$

However the definition (S2) cannot be used if we consider a microscopic stochastic dynamics that mimics the individual decisions, so in the paper , we propose an alternative definition which link the individual behaviour with the average property of the population

$$\lambda(T) = \left\langle \frac{1 - \hat{\pi}(T + \Delta T|T)}{\Delta T} \right\rangle_{\Delta T} \quad (\text{S3})$$

where $\hat{\pi}(T + \Delta T|T)$ is the conditional probability to observe a TTE $T + \Delta T$ of the individual dynamics and the average value is computed over the distribution of the possible increments ΔT in the considered population. In the limit $\Delta T \rightarrow 0$ from (S1) we get the differential equation:

$$dS(T)/dT = -\lambda(T)S(T). \quad (\text{S4})$$

In a stationary situation, the hazard function $\lambda(T)$ is constant ($\lambda(T) = h_0$) and the differential equation (S4) leads to an exponential solution $S(T) = h_0 \exp(-h_0 T)$ which corresponds to an exponential probability density ($p(T) = -dS(T)/dT$) for the TTE. Under this point of view the exponential tail of the empirical distribution $p(T)$ can be associated to a constant probability of ending the daily mobility, independently from the elapsed daily travel-time T as expected for a Poisson process. However, the observed under-expressed short travel-times implies an increasing trend for the hazard function $\lambda(T)$: i.e. when the TTE is short, the probability to stop the daily mobility is lower than the asymptotic value. This observation suggests that it is unlikely for an individual to consider his daily mobility

concluded after a very short cumulative travel-time T , because some daily duties have still to be accomplished. A more suitable shape of the function $\lambda(T)$ can be extrapolated from GPS data (see Supplementary Fig. S1). We perform an analytical interpolation of the empirical data by

$$\lambda(T) = -\frac{dS(T)/dT}{S(T)} = \beta^{-1} (1 - \exp(-T/\alpha)) , \quad (\text{S5})$$

where the parameters β is the TTB, characteristic of a particular city, and α is the timescale of the short travel time expenditures suppression. According to our point of view α could be interpreted as the average time necessary to satisfy the daily mobility demand using private cars. After a time α , the choice of going back home is only due to the limited TTB constraint, quantified by the time scale β . Given $\lambda(T)$, we integrate analytically the differential equation (S4) obtaining an analytical form for the survival function

$$S(T) = C_N \exp(-\alpha\beta^{-1} \exp(-T/\alpha) - T/\beta) , \quad (\text{S6})$$

Imposing $S(0) = 1$ (thus neglecting null TTEs), the normalisation constant can be fixed at $C_N = \exp(\alpha\beta^{-1})$. Consequently, the probability density function for the TTE distribution reads

$$p(T) = \beta^{-1} \exp(\alpha\beta^{-1}) (1 - \exp(-T/\alpha)) \exp(-\alpha\beta^{-1} \exp(-T/\alpha) - T/\beta) . \quad (\text{S7})$$

Analytical solution for the time consumption model

Let us consider a driver who has carried out a daily mobility T and he has to decide if to perform or not a further trip whose duration is ΔT . According to our Statistical Mechanics point of view, the exponential decay of the empirical TTE distribution (see eq. (1) and Fig. 1 in the paper), suggests that the mobility time plays the role of the *energy*. As a consequence we expect that the probability to accept a TTE T is

$$P(T) = \exp\left(-\frac{T}{\bar{\beta}}\right) , \quad (\text{S8})$$

where $\bar{\beta}$ is the expected value of TTE. In the model, to evaluate the probability of performing a new trip the drivers considers the possibility to accept the cost ΔT of the new trip using a threshold function

$$\theta_{x_{max}/\langle n \rangle} \left(\frac{\Delta T}{T} \right) = \begin{cases} 1 & \text{if } \frac{\Delta T}{T} < x_{max}/\langle n \rangle , \\ 0 & \text{otherwise} , \end{cases} \quad (\text{S9})$$

where $\langle n \rangle$ is the average number of performed daily activities and x_{max} is an universal threshold (see Fig. 5 left). Then according to empirical observations (see. eq. (9) in the text) we introduce the conditional distribution for the time cost ΔT of the single trips

$$p(\Delta T/T) \approx \langle t \rangle^{-1} \exp(-\Delta T/\langle t \rangle) \theta_{x_{max}/\langle n \rangle} \left(\frac{\Delta T}{T} \right) \quad (\text{12})$$

The presence of the threshold function $\theta_{x_{max}/\langle n \rangle}$ means that, as the TTE increases, the individual gets used to be driving and he has a propensity to accept longer trips (compatibly with his TTB and the number of activities he has to perform). Since the perceived cost of a new trip in the model is set $\propto \Delta T/T$, we correlate this choice with the existence of a *log-time* perception. To reproduce the macroscopic statistical laws of human mobility, the drivers are considered as *independent particles* and we average on the cost ΔT of the individual trips using the empirical distribution (12) (Supplementary Fig. S2 (a)). According to the TTB existence assumption, a rational driver evaluates the probability to perform the new trip after having used a TTE T , as

$$\pi(T + \Delta T|T) = \frac{P(T + \Delta T)}{P(T)} = \exp\left(-\frac{\Delta T}{\bar{\beta}}\right) . \quad (\text{S10})$$

and using the definition (S3) of the hazard function, we set

$$\lambda(T) = \left\langle \frac{1 - \pi(T + \Delta T|T)}{\Delta T} \right\rangle = \int_0^\infty \left(\frac{1 - \exp(-\Delta T/\bar{\beta})}{\Delta T} \right) \theta_{x_{max}/\langle n \rangle} \left(\frac{\Delta T}{T} \right) d\Delta T , \quad (\text{S11})$$

and using the definition (S9) we derive an analytical expression for the hazard function

$$\lambda(T) = \frac{1}{\alpha} \int_0^{x_{max}} \exp\left(-\frac{Tx}{\langle n \rangle \alpha}\right) \frac{1 - \exp(-Tx/(\langle n \rangle \bar{\beta}))}{x} dx, \quad (\text{S12})$$

where we introduce the timescale α (see eq. (S5))

$$\alpha \simeq \langle n \rangle \langle t \rangle / x_{max}. \quad (\text{S13})$$

The time scale (S13) is consistent with the empirically evaluated timescale for the short TTE suppression (see Fig. 5 left) with $x_{max} \simeq 2$. A numerical integration of eq. (S12) provides a hazard function which has the same behaviour as the interpolation (S5) derived from the empirical GPS data. In the Fig. 5 right, we show a comparison between the integral (S12) and the empirical hazard function where $\beta = 1.08\bar{\beta}$ and α computed from the previous relation. We remark the presence of a scaling factor between the empirical evaluated β and the theoretical expected value $\bar{\beta}$. More precisely β proves to be an overestimate of $\bar{\beta}$ since the incremental ratio in the integral (S11) decreases as the cost ΔT becomes large. In other words, according to the time consumption model, the empirical data bestow a greater TTB to individuals with respect to the theoretical value, due to the reduced perception of the trip cost when the TTE increases.

Properties of the average trips' duration $\langle t \rangle$ and average number of trips $\langle n \rangle$.

We consider the correlation between the parameters α and β with the average travel-time $\langle t \rangle$ for a single trip. The results show that $\langle t \rangle$ has a positive correlation of 0.57 with β and no correlation with α . But $\langle t \rangle$ is strongly correlated with the average house costs per square meter (Supplementary Fig. S2 (b)) and negatively correlated with the municipalities surface (Supplementary Fig. 3 (b)). This empirical observation could be a consequence of the activities sprawling in the larger cities, whereas they are concentrated inside the historical center for the smaller cities. The relationship between $\langle t \rangle$ and the average trip's speed seems instead not trivial (Supplementary Fig. (d)). As a matter of fact an almost constant average trip length of ≈ 5.3 km is observed in the majority the cities, independently by the municipality area. Therefore one expect a relation $\langle t \rangle v = const$ among the cities, where v is the average travel speed characteristic of the different road networks. Indeed, if we exclude Rome, whose spatial scale is much larger than that of all the other cities, the cities with an average speed greater than 25 km/h verify this relation, whereas we observe a strong deviation from the theoretical curve in the cities with average speed < 25 km/h. We interpret this effect as the result of a different dynamic regime in the road network: when the average travel speed is low the stochastic effects due to the stops at crossings or to congestion effects could strongly influence the vehicle dynamics, so that the proportionality between covered distance and time is lost. On the contrary a high average travel speed suggests that the free flow is dominant and the vehicle dynamics can be described in a deterministic way.

If one computes the number of daily trips n , whose empirical distribution $p(n)$ shows an exponential tail [20], we see that the limiting average values of $\langle n \rangle$ are strongly anti-correlated (correlation coefficient -0.78) with the average trip length $\langle t \rangle$, suggesting a tradeoff consistent with the concept of TTB. This seems confirmed by the negligible correlation (correlation coefficient -0.17) between $\langle n \rangle$ and β , whereas between $\langle n \rangle$ and α the correlation is 0.40, reflecting the role of α as a measure of the time needed for the necessary mobility. Finally, we have a remarkably low correlation (correlation coefficient 0.13) between the average number of daily trips $\langle n \rangle$ and the average trip's speed, which confirms that mobility induced by travel-time savings is not due to a larger number of trips but to longer trips [15].

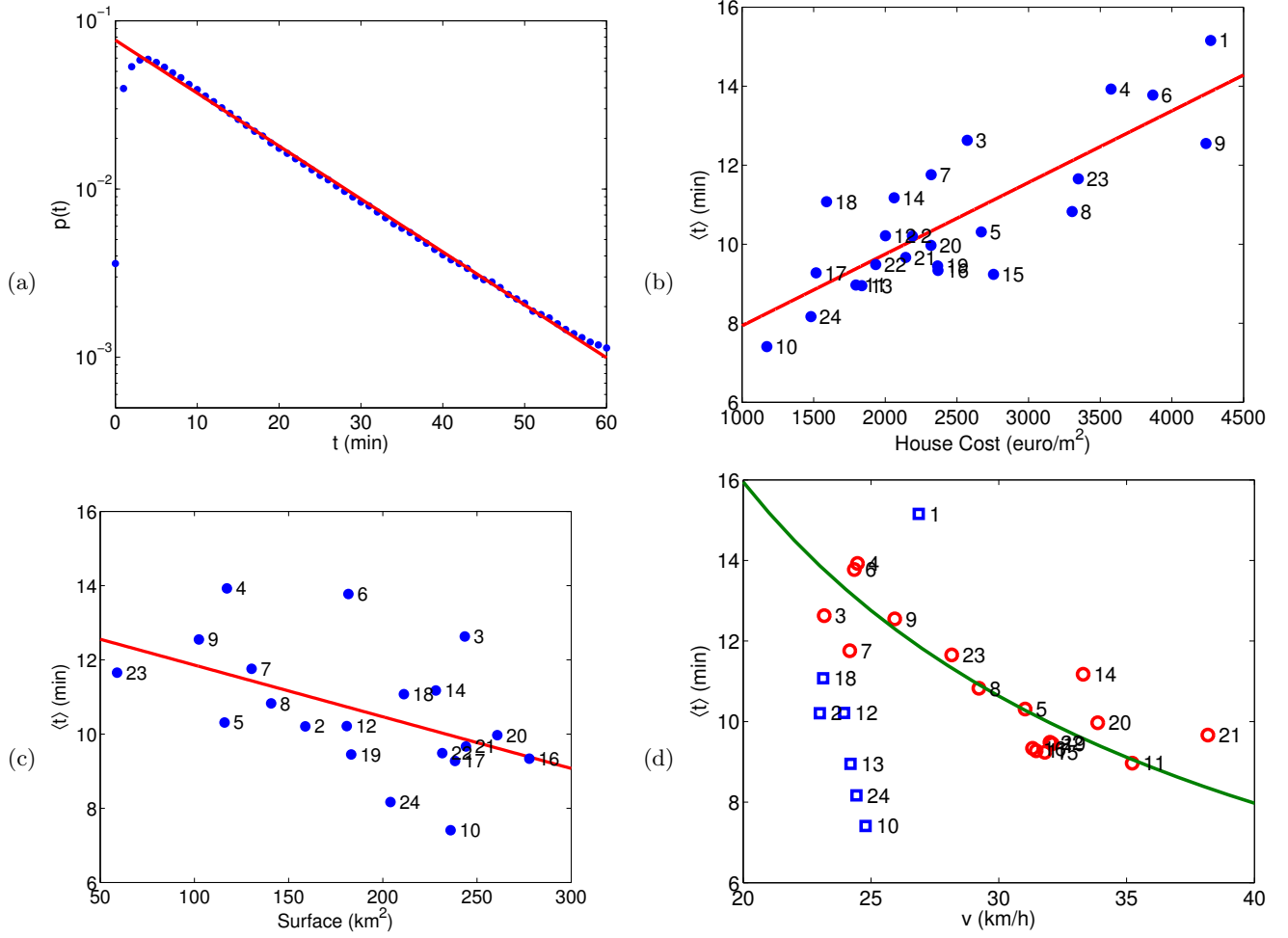


FIG. S2: **Properties of the average trips' duration $\langle t \rangle$** (a) **Exponential distribution.** The $p(t)$ distribution (dots) for Milan and exponential interpolation of its tail (solid line) with $\langle t \rangle = 13.8\text{min}$; (b) **Growth with house prices.** Travel-times grow significantly in cities where housing is more expensive (correlation coefficient 0.83, source: www.immobiliare.com); (c) **Decrease with the city surface.** Travel-times tend to be reduces in ider cities (correlation coefficient -0.49); (d) **Decrease with travel speed.** A part of the cities lie approximatively on an hyperbole (solid line), representing a constant average length of $\approx 5.3\text{km}$.

Disaggregated analysis for the city of Milan

To study the effect of individual heterogeneity we have disaggregated the empirical data into different classes of drivers. This analysis has been performed for the city of Milan. Due to the absence of any metadata the features to characterize the individuals have been extracted from the GPS data according to:

- home location, identified by the parking place where the cumulative parking time is the longest one [24];
- number of days in which the individual have used the car during the month;
- structure of the mobility network: mono-centric or polycentric [30].

To identify differences in TTE dependence from home location we have divided the Milan municipality in three concentric areas, according to the central structure of the city. We have chosen circular boundaries that we can approximatively associate with:

- i) the area within the inner ring road (Cerchia dei Bastioni) identified as the *Zona C*, the name that identifies the congestion charge area;
- ii) the area between the inner and the outer ring road (Cerchia dei Navigli), that we call *city center* in Fig. 3 (b);
- iii) the *periphery*, outside the outer ring road.

Among the drivers identified as citizens of Milan, 7% live in the *Zona C*, 27% live in the city center and 63% live in the periphery. The remaining 3% are individuals whose home locations we found outside the city area and they were excluded from the analysis. To point out differences in the home's role, we take into account all the mobility performed in and out the municipality area of Milan, evaluating the percentage rt of round trips involving home as origin or destination. When $rt > 75\%$ we define the individual mobility network as mono-centric: 58% of the drivers in Milan have this property. Conversely, if $rt < 75\%$, we can introduce a second hub in the individual mobility network [30], which has a significative role in the organization of the individual mobility.

Numerical formulation of the time consumption model

Each individual accumulates progressively the travel times into the total travel-time $T_n = \sum_{i=1}^n t_i$, where n is the number of daily trips. From the other hand each trip is associated to a performed activity and it is possible to introduce an utility function U [34], representing in some preference scale the satisfaction and/or the advantages derived by performing that activity. Without any further information, our null hypothesis is that the activity utility U is a random variable uniformly distributed in the interval $(0, 1)$ (arbitrary units). To define a behavioural model we assume that this utility is counter-balanced by a cost due to the time already spent driving until that moment.

Each trip represents an increment of total travel time $\Delta T = t$. Travel-times t are distributed exponentially with average fixed at the experimental values of table S1. The total cost associated to travel is not to be quantified not proportionally to T , but to its logarithm $\log(T)$ plus a certain constant to exclude negative values. Then the cumulative utility \mathcal{U} is given by the linear combination:

$$\mathcal{U} = c_1(c_2U - \log(T)) \quad (13)$$

The parameter c_2 represents the cost/benefit ratio, which could be associated to a value of time), while c_1 is the unit measure of the utility scale which is associated to the shape of the logistic threshold. T is the individual TTE distributed according to eq. (S7).

If we evaluate the probability of performing a daily activity according to the logistic model [32]

$$p(U) = \exp(\mathcal{U}) / (1 + \exp(\mathcal{U})) \quad (14)$$

using Monte-Carlo simulations, the related TTE distribution turns out to be very similar to the empirical one (see Fig. 3 right). For all considered cities, the best fits have a $R^2 > 0.986$. Similarly to what observed in the main text, this correspondence does not happen assuming costs proportional to T .