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# COVID-19 lockdown measures and travel behavior: The case of Thessaloniki, Greece



TRANSPORTATION RESEARCH

INTERDISCIPLINARY PERSPECTIVES

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# ABSTRACT

In this paper, we investigate the travel behavior changes in Thessaloniki, Greece aiming to understand them and explore the factors that affect them under the COVID-19 mobility restriction measures. Socioeconomic and mobility data from two questionnaire surveys, one year before and during the COVID-19 lockdown of April 2020 (with 1462 and 196 responses respectively), were compared by utilizing a wide variety of inductive statistical tests. Ordinary Least-Squares regression models and Cox proportional hazards duration models were employed to explore any concurrent socioeconomic effect on travel behavior patterns. Results showed that the number of daily trips per person was on average decreased by 50% during the lockdown. This decrease was much greater for the non-commuting trips. Trips on foot were increased, private car was mainly used for commuting and public transport modal shares were heavily reduced. Trip durations were generally increased, as travelling was considered a recreational activity per se. The starting times of the first trips of the day were more evenly distributed throughout the day and many travelers only started their first trips late in the afternoon. Older travelers generally maintained their mobility behavior patterns despite their higher vulnerability to COVID-19 disease. Lower-income travelers were likely to make more daily trips. Male travelers tended to make higher-duration trips compared to their female counterparts. Since pandemics may become recurring events in the future, our findings provide for a better understanding of their influence on mobility and support the design of customized policies to fulfill sustainable mobility objectives during lockdown circumstances.

#### Introduction

After having been recognized as a "Public Health Emergency of International Concern", the COVID-19 disease was declared by the World Health Organization a pandemic in March 2020, with Europe being the epicenter of the pandemic at that time (Jiang et al., 2020). Since then, Coronavirus has infected several million individuals, with recent data (November 2020) reporting more than 53 million confirmed cases globally, including over 1 million deaths (WHO, 2020). Due to the lack of any effective therapeutics or vaccines and given the way of transmission of the virus, social distancing, along with other mobility restriction measures, emerged as key mitigation strategies. In this context, many governments across the world enacted stayat-home policies by closing educational establishments, office buildings, shops and restaurants, banning mass gatherings and encouraging remote working. The overall aim of these measures was to control the spread of the disease by reducing interactions between people and restricting mobility in order to mitigate the risk of healthcare system capacities being exceeded (Askitas et al., 2020; Klein et al., 2020a).

The mobility restriction policies imposed in response to the galloping COVID-19 pandemic have brought about radical changes in people's travel behavior, both at global and local level. In fact, transportation demand and traveler behavior are intrinsically linked to societal activity. Generally, changes related to the economy and societal shifts can heavily affect transport demand. The problem of correctly estimating transport elasticity has been widely explored by pertinent literature, as avoiding systematic bias can have extensive economic effects and can hinder developing a robust mobility ecosystem. Gross Domestic Product and economic activity have been found to directly influence transport demand (Libardo and Nocera, 2008), while economic crises have the potential to cause drastic changes in modal share (Efthymiou and Antoniou, 2017). At the same time,

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changes in the way of life can cause changes in the ways younger generations are travelling (McDonald, 2015). It is important to keep in mind that mean transport elasticities can be affected by a wide variety of factors. For instance, mean public transport elasticities have been found to be affected by data collection paradigms, the time of the day of the trip and the unit of analysis among others (Hensher, 2020). It becomes clear that shifts in transport demand and the mechanisms that affect them are a complex, multiparametric problem, that needs a delicate systematic approach to explore and one that will be heavily affected by global, society-altering events such as worldwide pandemics.

In the last few months, several studies have been conducted, with the aim of detecting how everyday mobility shifted during the pandemic period. While changes in transport activity (IEA, 2020), trip frequency in terms of daily/total trips (Aloi et al., 2020; Bucsky, 2020; de Haas et al., 2020; Katrakazas et al., 2020; Pepe et al., 2020), travelled distance (de Haas et al., 2020; Klein et al., 2020a; Pepe et al., 2020), modal share (Abdullah et al., 2020; Aloi et al., 2020; Bucsky, 2020; de Haas et al., 2020; Harrington and Hadjiconstantinou, 2020; Jenelius and Cebecauer, 2020; Pawar et al., 2020) and trip purpose (Abdullah et al., 2020; de Haas et al., 2020; De Vos, 2020; Klein et al., 2020a; Mogaji, 2020; Parady et al., 2020; Pawar et al., 2020) have already been explored, changes regarding other trip characteristics, such as trip duration, trip start time and car occupancy rate, have not been sufficiently researched yet. Moreover, agent-based models along with data science and machine learning techniques have been employed, in order to understand the interactions arising from people's mobility and to assess different changing design criteria for passenger transport hubs (Cavendish and Cousins, 2020). To the best of the authors' knowledge, no modelling attempts have been made so far in order to explore the relationship that trip frequency and duration had with socioeconomic and other trip characteristics, regarding both pandemic and pre-pandemic time periods. Specifically understanding the way distinct social groups (e.g. based on gender, income, age, etc.) have been differently affected by this pandemic, can lead to pinpointing policy implications and in turn ways of rendering societal structures more robust to future pandemics. Associating and modelling trip frequency and duration in relation to travelers' socioeconomic characteristics, would help identify whether or not COVID-19 measures equally affected all population groups (Major and Machin, 2020)

This paper explores and quantifies the effects of COVID-19 mobility restriction policies on citizens' travel behavior and mobility patterns, based on empirical evidence from the city of Thessaloniki, Greece. Thessaloniki is the second largest city in Greece and its functional urban area has a population of 973,997 residents, concentrating roughly 10% of total country's population (European Statistical Office (Eurostat), 2020). Population density of Thessaloniki is relatively high (16,505.4 inhabitants per km<sup>2</sup>) and denotes a heavily urbanized environment (Hellenic Statistical Authority (ELSTAT) (2020a)). The only currently available public transport mode is the bus. In the last decades, bus public transport use has been significantly decreased (-12%), while the modal share of private vehicles has been increased (+10%) and the shares of other travel modes are considered low (e.g. bicycle usage is less than 5%) (Thessaloniki Public Transport Authority (THEPTA) (2020)). A metro network is under construction, whose main line will consist of 13 stations and will go through the city's center. The city's urban transport network is considered widely congested. At the same time, car occupancy rates are traditionally low (Perra et al., 2017).

This research utilizes two (2) discrete datasets concerning the prepandemic and the pandemic period. The pre-pandemic dataset came from a revealed preference questionnaire survey conducted in 2019 (i.e. one year before the outbreak of the COVID-19 disease, from March 14th to May 23rd), while the pandemic dataset is derived from a tailor-made online questionnaire survey conducted during the COVID-19 lockdown event in Greece (April 6th–19th 2020). Both surveys were addressed to Thessaloniki's residents. Analyzing these two (2) datasets, the main objective of the current study is two-fold: Firstly, we seek to identify potential differences in mobility profiles before and during the pandemic period for the city of Thessaloniki, Greece, analyzing and comparing certain trip characteristics, such as trip frequency, mode choice, trip duration, trip starting time and car occupancy rates. In this respect, a customized setting of inferential statistical tests is employed. Secondly, we model trip frequency and duration, with the overall aim of capturing any differences in the relationships between those variables and certain socioeconomic and other trip characteristics before and during the lockdown period, for the same case study area. To this end, two (2) OLS (Ordinary Least-Squares) regression models and a Cox Proportional Hazards model are developed and further discussed.

On that basis, the research questions that this paper seeks to answer, are the following:

- 1. How did COVID-19 lockdown measures affect main travel behavior aspects, such as trip frequency, mode choice, trip duration etc.?
- 2. How did travelers' socioeconomic and trip attributes influence their mobility behavior during the pandemic?
- 3. How can the above observations help us form new policy regulations and have more robust and resilient mobility fail-saves in place in the event of future pandemics?

The rest of this paper is structured as follows: In Section 2, a brief report of the COVID-19 pandemic and lockdown characteristics in Greece and Thessaloniki is provided. In Section 3, a literature review is conducted, focusing on the major findings of studies that explored travel behavior changes during the pandemic period worldwide. In Section 4, the research methodology is presented, including the design of the questionnaire surveys, the datasets used, as well as the data analysis methods utilized. Section 5 presents the results of the statistical analyses performed in the framework of the current research, before moving to Section 6, which further discusses and concludes the paper.

#### The COVID-19 pandemic in Greece

In Greece, the first confirmed COVID-19 case was reported on 26 February 2020, while the first death on 12 March 2020. Until the end of the first pandemic wave in Greece (July 2020), the total number of confirmed cases and deaths were 3519 and 192 respectively (Worldometer, 2020). Reporting 328 and 18 total confirmed cases and deaths per million inhabitants for the aforementioned period, Greece recorded one of the lowest counts both in the EU and globally. More precisely, until the 5th of July 2020, Greece ranked 96th out of the 218 countries with confirmed COVID-19 cases and 21st out of the 27 countries of the EU (Fahmi, 2020).

This relatively successful performance of Greece is possibly attributed to the central government's quick response, imposing measures to control the spread of the disease while the number of confirmed cases was still low. The social distancing strategy implemented, escalated gradually from simple guidelines to strict measures, before countrywide level lockdown measures were imposed, between 23 March and 4 May 2020. The escalating measures, before the lockdown, included cancelling events and carnival festivities, encouraging citizens to avoid all unnecessary trips and crowded places, shutting down schools initially in hot zones and countrywide afterwards, providing working parents with special purpose leaves of absence and shutting down clubs, cinemas, theatres and gyms facilities (Alfavita, 2020; iEidiseis, 2020; Kathimerini, 2020; News247, 2020a, 2020b). During the national lockdown period, Greek citizens were allowed to move only for specific purposes, while they were required to send an SMS for each trip declaring their identity, their home address as well as

the purpose of their trip along with carrying their ID or passport documents. All the hotels and recreational facilities were closed, teleworking was heavily encouraged and the maximum number of passengers per vehicle was set to 3, including the driver. Moreover, intercity and international passenger trips were prohibited, while public transport services were limited. At the same time, the police were monitoring the proper implementation of the mobility restriction measures and the failure to comply was penalized with fines. The fines for "unjustified trips" were 150 Euros, but they were doubled for the weekend of 18th-19th April, in order to further deter unnecessary trips during Orthodox Easter (Greek Government, 2020). For comparison purposes, the corresponding fines in France, for infractions regarding COVID-19 (including being outside without proper justification and not respecting the local curfew), were €135 for the first offence but rose to  $\in$ 200 for repeat offenders, or up to  $\in$ 450 if the fine was not paid on time (Connexion, 2020). Italy, due to the heavier death toll of the virus, had higher fines for COVID-19 containment measures infractions, which were ranging between  $\notin$ 400 and  $\notin$ 3000 (from a previous maximum of €206) (Duncan, 2020). On the other hand, Germany did not implement the same kind of trip-restraining rules, but restricted public gatherings of more than two people, enforcing them with fines starting from  $\notin$  200 and going as high as  $\notin$  25,000 (The Local, 2020).

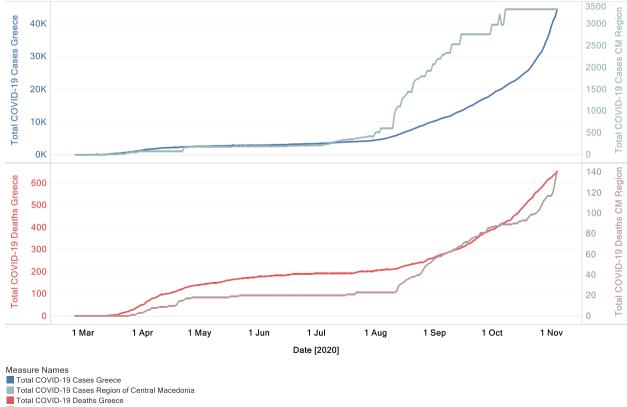
The performance of Thessaloniki in response to COVID-19 cannot be quantified in detail, since the National Public Health Organization does not collect data at city level. Nonetheless, at regional level, the Region of Central Macedonia, whose capital city is Thessaloniki, has confirmed 120 COVID-19 cases and 10.6 related deaths per million inhabitants, until the beginning of July 2020 (iMEdD organization (IMEDD) (2020)). Based on these, Central Macedonia was ranked 6th and 10th, respectively, out of the 13 Administrative Regions of Greece at the end of the first pandemic wave. Fig. 1 presents the evolution of the COVID-19 confirmed cases and deaths for both Greece and Central Macedonia between February 26th and November 4th, 2020, where it is evident that Thessaloniki's pattern was actually representative of the one which applied for Greece until the summer of 2020. Since then, COVID-19 cases started increasing in the whole country signaling the commencement of the second wave of the COVID-19 pandemic.

#### Literature review

The regulatory frameworks to ensure social distancing during trips, which were imposed by national and local authorities worldwide, were not received in the same manner or equally supported by all travelers. Maintaining social distancing protocols and decreasing trip frequencies have been deemed critical, as these factors have been directly linked to reduced COVID-19 transmission rates (Thakkar et al., 2020). Dzisi and Dei (2020), in their study regarding social distancing and wearing masks in Ghana, note that while most bus itineraries respected the reduced passenger capacity which was enforced, not all passengers wore masks on-board. Public acceptance and participatory planning can be invaluable assets in any ongoing changes and subsequent design of measures. Citizen engagement has been found to contribute significantly to the success of new services and changes in urban mobility (Marzano et al., 2019; Tesoriere and Campisi, 2020), since social groups with discreet characteristics (gender, age group, etc.) might show differentiated acceptance degrees for them (Campisi et al., 2020a).

#### Reduction of overall transport activity

The social distancing measures, enacted in response to the COVID-19 pandemic, have so far led to far-reaching changes in personal mobility patterns. Generally, travel demand decreased, and many



Total COVID-19 Deaths Region Of Central Macedonia

Fig. 1. The evolution of COVID-19 cases and deaths in Greece and in the Region of Central Macedonia (CM) (source: (iMEdD organization (IMEDD) (2020))).

countries have already witnessed sizeable drops in car traffic and public transport ridership. Along the same lines, the total number of trips as well as the distance travelled, also reduced considerably. According to IEA (2020), the global road transport activity by the end of March 2020 was 50% less than the 2019 average. Building different scenarios to model transport during the imposition of mobility restrictions, Bucsky (2020) calculated that COVID-19 measures decreased mobility by half in Budapest, Hungary, while the number of daily trips dropped from 10.1 to 4.3 million for the second half of March 2020, compared to 2018. Exploring the effects of COVID-19 lockdown event on urban mobility in Santander, Spain, Aloi et al. (2020) estimated an overall mobility reduction -in terms of number of total journeys- by 76% with variations throughout the day. Using anonymized, aggregated location data from mobile devices in the USA during the pandemic era, Klein et al. (2020a) observed an up to 60% reduction in people's daily mobility, while the average radius of gyration of users (a proxy for the travelled distance) decreased by 45-55% compared to a typical weekday. Seeking to detect changes in travel behavior and personal travel patterns in the Netherlands, De Haas et al. (2020) recognized that the total number of trips per person as well as the distance travelled for a period of three (3) days during the COVID-19 pandemic dropped by 55% and 68% respectively, compared to the fall of 2019. Focusing on mobility changes in Italy during the implementation of several COVID-19 restriction measures, Pepe et al. (2020) reported a 50% reduction in the total trips between Italian provinces and in the average users' radius of gyration, compared to the pre-pandemic averages. According to a worldwide questionnaire, deployed by Abdullah et al. (2020), trips became shorter and less frequent. The reduced trip frequency was also noted by Katrakazas et al. (2020) for Greece and the Kingdom of Saudi Arabia, using data collected by a smartphone application. The authors also linked the pandemic period with altered driving behavior (i.e. increased speeds and more frequent accelerating and braking) as well as a decrease in accidents. In terms of driving behavior, Stavrinos et al. (2020) also found that teens in Alabama, U.S.A., who were older, employed, part of a minority or had lower prosocial tendencies were less likely to reduce driving during COVID-19 restrictions' period.

## Changes in trip purposes

In broad terms, the above-mentioned reduction in the number of trips during the pandemic period, was observed across all the main trip purposes (i.e. Home-Based Work - HBW, Home-Based Other - HBO, Non-Home-Based - NHB). De Vos (2020) implied a reduction in the number of trips across all trip purposes as a result of the COVID-19 measures, stating that travel demand may be reduced due to the encouragement of teleworking and e-learning and the cancellation of public activities and events. In the Netherlands, De Haas et al. (2020) reported that all trip purposes, including commuting, education and leisure, decreased in absolute number of trips, with the only exception being the touring/walking trips. Analyzing changes over time of different activity frequencies during the COVID-19 pandemic in Japan, Parady et al. (2020) highlighted that a large percentage of their survey sample reported decreases in frequency for most activities, including commuting, grocery shopping and leisure. In an attempt to detect the impact of COVID-19 on the transport system in Lagos, Nigeria, Mogaji (2020) found that the disruption in transport services -as a result of the pandemic- affected people's social activities, depriving them of the chance to fulfill their everyday activities, such as shopping and visiting friends. Klein et al. (2020a) reported that the average commuting volume in terms of total number of commuters within twenty-four (24) hours in a given county across the USA, decreased almost by 65% compared to the typical daily values. Pawar et al. (2020) noted that 41% of commuters ceased travelling to work during the transition to lockdown. The worldwide research conducted by

Abdullah et al. (2020) showed that shopping became the primary purpose of travelling during COVID-19 pandemic period.

# Mode choice shifts

The aforementioned reduction of mobility did not appear to apply equally among all modes of transport. Bucsky (2020) recognized an 80% reduction in public transport demand in Budapest during the pandemic period, which led to a dramatic decrease of public transport modal share (from 43% to 18%). On the other hand, the car modal share increased from 43% to 65%, while bicycle usage experienced the greatest growth rate, by more than doubling its' share (from 2% to 4%). Analyzing the modal share between the pre-pandemic and pandemic period in the Netherlands, De Haas et al. (2020) found that the share of all transport modes -including car as a driver/passenger, public transport, 2-wheel vehicles and bicycle- was reduced during the pandemic, with the only exception being the walking trips that almost doubled their share. The same study also highlighted the significant drop in public transport use, as a result of the relative discouragement of the latter by both government authorities and public transport operators. Aloi et al. (2020) identified that the modal share during the pandemic period was significantly modifies for the city of Santander, Spain, as car modal share increased from 48% to 77% (despite the reduction in the number of the total car trips during the pandemic) and at the same time, public transport and walking trips showed a significant drop in their shares, from 8% to 2% and from 42% to 19%, respectively. Focusing on changes in commuting behavior due to COVID-19 pandemic in the UK, Harrington and Hadjiconstantinou (2020) reported that around 80% of the car commuters plan to continue travelling by car after the lifting of the restrictions, while 3.6% and 6.5% plan to shift towards walking and cycling, respectively. On the other hand, 48% of the public transport commuters plan to continue travelling by bus/rail, while the remaining 52% are likely to spread across different transport modes. Pawar et al. (2020) found that only 5.3% of commuters changed their mode of transport from public to private in India, but note that the probable reason for that was not preference or choice but the lack of available alternatives. Another interesting finding was that their safety perceptions was not found to significantly contribute to their decision-making. According to Jenelius' and Cebecauer's (2020) analysis of ticket validation data, public transport ridership decreased by 40-60% across Sweden, something that also caused passengers to use different terms of payments such as single tickets and travel funds. The worldwide research conducted by Abdullah et al. (2020) showed that trips by public transport are being replaced by private transport and non-motorized alternatives, and that the main motivator of that shift are pandemic related concerns. Those changes in transport mode preferences are characterized by an unprecedented shift of modern societies in favor of active mobility. As such, they have the potential to be the beginning of societies developing fundamentally healthier transport habits (Brooks et al., 2020).

Table 1 summarizes the COVID-19 related research findings which were presented in this Section.

## Methodology

## Data collection

This paper utilizes data from two (2) questionnaire surveys that took place in the city of Thessaloniki roughly one year apart; one during a typical period for the city (pre-pandemic) and one during the country-wide enforced lockdown due to the COVID-19 pandemic. Both questionnaire formats and survey procedures followed the GDPR rules and all collected data were anonymized.

#### Table 1

Summary of main findings from past related research.

| Research study                                  | Main Outcomes  | Country                                  |
|---|--|--|
| (Abdullah et al., 2020)                         | Shorter and less frequent trips;<br>Shopping became the primary<br>trip purpose; Public transport is<br>replaced by private means and<br>walking | Worldwide                                |
| (Aloi et al., 2020)                             | 76% mobility reduction; Increase<br>in car usage; Drop of public<br>transport and walking modal<br>shares  | Spain                                    |
| (Brooks et al., 2020)                           | The shift to more active mobility<br>can support fundamental changes<br>towards healthier transport<br>behavior                                  | UK                                       |
| (Bucsky, 2020)                                  | 50% mobility reduction; 80%<br>reduction in public transport use;<br>Increase of car and bicycle usage   | Hungary                                  |
| (de Haas et al., 2020)                          | 55% reduction of total trips;<br>Mobility reduction for all trip<br>purposes and for all transport<br>modes except touring /walking<br>trips     | Netherlands                              |
| (De Vos, 2020)<br>(Dzisi and Dei, 2020)         | Reduction of trips is expected<br>Reduced bus capacity was<br>respected but masks were not<br>always worn  | Worldwide<br>Ghana                       |
| (Harrington and<br>Hadjiconstantinou,<br>2020)  | 80% of the car commuters will<br>continue commuting by car after<br>the pandemic   | UK                                       |
| (IEA, 2020)                                     | Global road transport activity 50% down compared to 2019   | Worldwide                                |
| (Jenelius and Cebecauer, 2020)                  | 40–60% drop of public transport usage  | Sweden                                   |
| (Katrakazas et al., 2020)                       | Less frequent trips; Altered<br>driving behavior   | Greece and<br>Kingdom of<br>Saudi Arabia |
| (Klein et al., 2020a)                           | 60% mobility reduction; 65% commuting reduction  | U.S.A.                                   |
| (Mogaji, 2020)                                  | Reduced social activity due to<br>mobility restriction measures  | Nigeria                                  |
| (Parady et al., 2020)                           | Decreased activity for<br>commuting, grocery, shopping<br>and leisure purposes   | Japan                                    |
| (Pawar et al., 2020)                            | 41% of commuters stopped<br>travelling; Small Shift to private<br>modes due to lack of other<br>alternatives                                     | India                                    |
| (Pepe et al., 2020)<br>(Stavrinos et al., 2020) | 50% reduction of total trips<br>Teens that were older, employed,<br>part of a minority or had lower<br>prosocial tendencies were less            | Italy<br>U.S.A.                          |
| (Thakkar et al., 2020)                          | likely to reduce driving<br>Social distancing and decrease of<br>mobility are critical for the<br>reduction of COVID-19 cases                    | U.S.A.                                   |

The pre-pandemic questionnaire comprised 3 parts (Fig. 2). Parts A and B included questions regarding the respondents' household and personal characteristics respectively. Subsequently, the respondents were asked if they made a trip during the previous day and if they did not the survey ended. If they did, they were guided to answer the last part of the survey (Part C), where they were asked about the characteristics of the trip(s) they made during the previous day. The pre-pandemic questionnaires were completed on-field by trained personnel who performed face-to-face interviews with Thessaloniki's residents, at the city's points of interest, gathering places and main corridors. The locations that were chosen for the interviews were central locations with mixed land uses (services, leisure, shopping and residence) in all of Thessaloniki's greater area municipalities, in order to achieve the best possible population representativeness. Interviews took place from March 14th to May 23rd, 2019. In total, 1462 valid responses (i.e. completed questionnaires) were collected which referred to a total of 5431 trips. For the purposes of this study, the year 2019 was selected as a typical year, as no major events have been recorded which could have significantly altered the city's mobility characteristics. Hence, this sample is considered to display the typical non-pandemic travel behavior.

The pandemic questionnaire comprised 4 parts (Fig. 3). Parts A and B consisted of questions regarding the respondents' household and personal characteristics respectively. Subsequently, the respondents were asked if they made a trip during the previous day, and if not, the reasons they did not. If they did, they were asked about the characteristics of their trip(s) in Part C, such as the start and end time of the trip, the trip purpose and the mode of transport they used. Next, they were asked if they continued to another destination after having reached their first one or if they returned home and made any additional trips during the same day. This enabled us to map the specific trip chains of the respondents and the trip characteristics for each [i,j] trip segment, where i is the number of the trip chain and j is the number of each trip segment included in the trip chain. The survey ended with Part D that asked the respondents about aspects of scheduling and comfort of their daily trips. The data collection was conducted online. The survey was uploaded in the Limesurvey platform (Limesurvey, 2020) and then disseminated through a large number of nation-wide media. An online assistance service was activated to support the completion of the survey by the respondents. Data collection took place from 6th to 19th of April 2020, i.e. during the third and fourth week of the nationwide lockdown in Greece. In total, 1259 valid responses were collected, out of which 196 referred to the city of Thessaloniki and were further analyzed in this study. These 196 completed questionnaires referred to a total of 498 trips.

The sample of 1462 responses collected by the pre-pandemic questionnaire is considered adequate for the representation of a city with the population of Thessaloniki. More specifically, a sample of 1462 responses for a city with a population of 973,997 with a 95% confidence interval gives a margin of error of 2.56%. The sample of 196 responses, which was collected by the pandemic questionnaire, is on the lower side. However, given the exceptional circumstances of data collection during the lockdown period and the fact that pandemic responses refer to roughly the same months of the pre-pandemic survey period (previous year), the pandemic sample may also be considered appropriate. In practice, a sample of 196 responses for a city with a population of 973,997 with a 95% confidence interval gives a margin of error of 7%.

In order to make the pre-pandemic and pandemic datasets comparable, all the respective variables were releveled so that they were coded with the same factor levels. Table 2 reports all the variables that were used in this study. The variables were divided into two (2) categories: (a) the socioeconomic variables pertain to personal characteristics of the respondents, such as gender, income, age and household size while (b) the mobility profile variables describe the key attributes of their trips (purpose, start time, frequency etc.). Table 2 shows some basic descriptive statistics of these variables in the pre-pandemic and pandemic datasets. Both pandemic and pre-pandemic samples are satisfactorily distributed against the main sociodemographic groups in Thessaloniki. More specifically, males represent the 50.2% of the pre-pandemic sample, the 46.9% of the pandemic sample and the 47.2% of Thessaloniki's population. Females represent the 49.8% of the pre-pandemic sample, the 53.1% of the pandemic sample and the 52.8% of Thessaloniki's population. Regarding age groups, there is a shift towards the economically active age groups in both samples, due to the older age groups' reluctance to take part both in the on-field interviews (pre-pandemic) and the increased difficulty for them to take part in the online survey (pandemic). In quantitative terms, the economically active age groups (15-60) represent the 94% of the prepandemic sample, the 90% of the pandemic sample and the 74% of Thessaloniki's population. The older age groups (60+) represent the

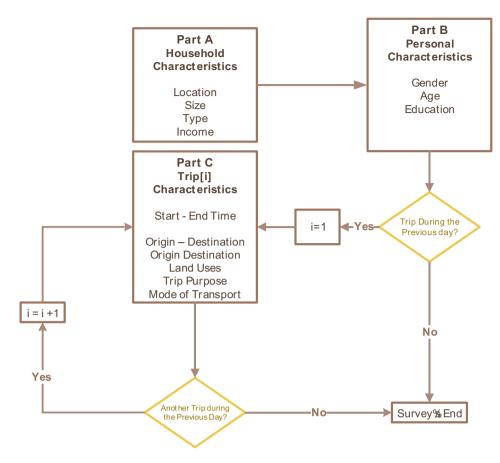


Fig. 2. Pre-Pandemic questionnaire survey structure (source: own elaboration).

6% of the pre-pandemic sample, the 10% of the pandemic sample and the 26% of Thessaloniki's population.

## Analysis setting

In order to explore our first research question and examine the pandemic's effect on trip behavior, we performed a series of statistical tests to understand whether six (6) typical mobility profile variables differed depending on the period where they were measured (prepandemic and pandemic) (Table 3).

These statistical tests were chosen, based on the type of the relevant variables of interest as well as their distribution. More specifically, in order to examine the pandemic's effect on trip frequency and car occupancy rate, both generally and per trip purpose, the Mann Whitney U test was utilized, as it was found the most fitting one to explore differences between two discrete independent samples. In order to check whether the pandemic had a significant effect on trip duration the Kaplan-Meier test was used, as it provides an easy way to assess the statistical difference between the duration curves of two or more groups (Juan and Xianyu, 2010). In order to test if the distribution of the start times of the first trips of the days significantly differs between the pre-pandemic and pandemic periods, the Granger Causality test was used. While this test's primary use is to determine if a timeseries distribution can be used towards forecasting another timeseries, its results can also be extended towards showing any similarities between the distributions. Table 3 summarizes all the statistical tests that were performed for the purpose of the current study.

For the second research question, we developed OLS models, where trip frequency was selected to be the dependent variable, while travelers' specific socioeconomic characteristics were used as potential explanatory variables (see Table 2). Utilizing the two (2) datasets, two (2) such models were built, in order to monitor any deviations between the pre-pandemic and pandemic circumstances. OLS regression is a widely used statistical technique for multivariate analysis that uses the minimum sum of squared residuals  $(\sum_{i=1}^{N} \varepsilon_i^2)$  to estimate the regression parameters. Even while OLS is commonly used in literature, attention should be paid to the necessary assumptions that need to be met, such as the expected value of the errors being 0, having no autocorrelation between the errors, homoscedasticity and having zero covariance between the errors and explanatory variables (Chumney and Simpson, 2006). In the case of trip duration, we employed a Cox Proportional Hazards model to explore the concurrent effect of travelers' socioeconomic characteristics and other trip characteristics (see Table 2) on trip duration (Raux et al., 2011). In this case, one (1) model was built that used data from both datasets in order to calculate the hazard ratio for the pandemic pseudovariable, while adjusting for the effect of the other variables affecting trip duration. The Cox Proportional Hazards model  $(h(t, X) = h_0(t)e^{\sum_{i=1}^p \beta_i X_i})$  is a semi-parametric technique of duration analysis, that accounts for the concurrent effect of multiple explanatory variables. It works by calculating the baseline hazard  $(h_0(t))$  and the effects of the variables on it  $(e^{\sum_{i=1}^p \beta_i X_i})$ . The model is applied under the assumption that the calculated hazard ratios are constant over time (proportional hazards assumption), as well as the assumption that, apart from the explanatory variables, all other effects on duration are considered equal (Clark et al., 2003; Kleinbaum and Klein, 2012). Based on this analysis settings' findings, our third research question is considered in Section 6, where we discuss how these radical changes in everyday mobility could guide us towards a more robust future mobility landscape.

The above-mentioned statistical tests (Table 3) as well as the Cox Proportional Hazards model were performed using the R programming software (R Core Team, 2020) and the packages survival (Therneau

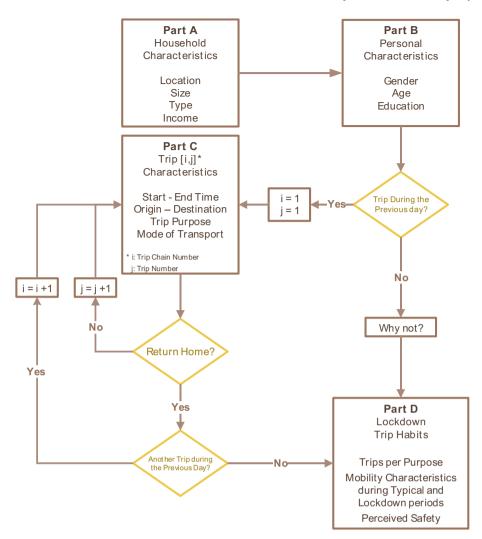


Fig. 3. Pandemic survey structure (source: own elaboration).

and Grambsch, 2000), Imtest (Hothorn et al., 2007) and dplyr (Wickham et al., 2020). The OLS models were developed in an IBM SPSS Statistics 25 environment (IBM Corpoperation, 2011).

#### Results

# COVID-19 lockdown impact on mobility profile variables

## Trip frequency (total number of daily trips per person)

Fig. 4 compares the percentage of travelers who made a particular number of daily trips between the pre-pandemic and pandemic periods, in the city of Thessaloniki. In general, a considerable reduction of 50% in the total number of daily trips per person before (Mean = 3.71 trips/person/day) and during (Mean = 2.51 trips/person/day) the pandemic was observed, regardless of the trip purpose. The Mann Whitney *U* test indicated that this difference was statistically significant (W = 82049, p < 0.001).

Mann Whitney U tests were also conducted for the total number of daily trips per person for all trip purposes (HBW, HBO, NHB) and the outcomes showed that there were statistically significant differences in all cases. In Fig. 5, the daily trip frequencies before and during the pandemic period for the three trip purposes (HBW, HBO, NHB) are presented. The largest decrease was observed for the HBO trips, which include travel purposes, such as shopping, education, leisure, etc. This outcome is in agreement with the temporary suspension of the retail and leisure establishments during the lockdown period, indicating at the same time a high sense of insecurity among citizens and a sense of compliance with the general restrictions imposed by the Greek authorities.

A slight decrease was observed for the HBW trip purpose. Generally, the COVID-19 pandemic gave rise to a significant increase in teleworking rates and at the same time, many enterprises remained closed during the lockdown (Hellenic Statistical Authority (ELSTAT) (2020b)). On the basis of the above, the reduction of the total number of HBW daily trips per person for the pandemic period, would be expected to be greater, as found in other relevant studies (de Haas et al., 2020; Klein et al., 2020a, 2020b; Reed and Henrickson, 2020). It should be noted that, the statistically significant decrease in the total number of daily NHB trips per person between the pre-pandemic and pandemic period is not further discussed, due to the low percentage of the NHB trips available at the pandemic dataset. As a result, while the NHB percentages are reported in charts throughout the paper, those results won't be commented on and aren't considered critical for the remainder of this analysis.

#### Mode choice

A significant modal shift was observed in the pandemic period compared to the pre-pandemic one. These differences are visualized in Fig. 6. There was a moderate drop in car usage (37.86% pre-pandemic compared to 29.52% during the pandemic period), while

#### Table 2

Overview of the variables used in the study.

| Variables                                 |  | Options                            | Pre-Pandemic dataset |       |       |         | Pandemic dataset |       |       |         |
|---|--|------------------------------------|----------------------|-------|-------|---------|------------------|-------|-------|---------|
|   |  |                                    | n                    | %     | Mean  | St. Dev | n                | %     | Mean  | St. Dev |
| Socioeconomic variables                   | Number of Household Members                                |                                    | 1462                 | n.a.  | 3.04  | 1.33    | 196              | n.a.  | 2.43  | 1.29    |
|   | Gender   | Male                               | 734                  | 50.2% | n.a.  | n.a.    | 92               | 46.9% | n.a.  | n.a.    |
|   |  | Female                             | 728                  | 49.8% | n.a.  | n.a.    | 104              | 53.1% | n.a.  | n.a.    |
|   | Age Group  | 15–19                              | 171                  | 11.7% | n.a.  | n.a.    | 1                | 0.5%  | n.a.  | n.a.    |
|   |  | 20–29                              | 655                  | 44.8% | n.a.  | n.a.    | 27               | 13.8% | n.a.  | n.a.    |
|   |  | 30–39                              | 257                  | 17.6% | n.a.  | n.a.    | 61               | 31.1% | n.a.  | n.a.    |
|   |  | 40–49                              | 162                  | 11.1% | n.a.  | n.a.    | 51               | 26.0% | n.a.  | n.a.    |
|   |  | 50–59                              | 133                  | 9.1%  | n.a.  | n.a.    | 36               | 18.4% | n.a.  | n.a.    |
|   |  | 60–69                              | 61                   | 4.2%  | n.a.  | n.a.    | 16               | 8.2%  | n.a.  | n.a.    |
|   |  | 70+                                | 22                   | 1.5%  | n.a.  | n.a.    | 4                | 2.0%  | n.a.  | n.a.    |
|   | Monthly Average Household Income                           | ≤500€                              | 129                  | 8.8%  | n.a.  | n.a.    | 11               | 5.6%  | n.a.  | n.a.    |
|   |  | 500–1000 €                         |                      | 17.8% | n.a.  | n.a.    | 49               | 25.0% | n.a.  | n.a.    |
|   |  | 1000–2000 €                        | 333                  | 22.8% | n.a.  | n.a.    | 69               | 35.2% | n.a.  | n.a.    |
|   |  | ≥2000 €                            | 225                  | 15.4% | n.a.  | n.a.    | 49               | 25.0% | n.a.  | n.a.    |
|   |  | No Answer                          | 515                  | 35.2% | n.a.  | n.a.    | 18               | 9.2%  | n.a.  | n.a.    |
|   | Education Level  | Did not Graduate Elementary School | 18                   | 1.2%  | n.a.  | n.a.    | 0                | 0.0%  | n.a.  | n.a.    |
|   |  | Elementary School Graduate         | 13                   | 0.9%  | n.a.  | n.a.    | 0                | 0.0%  | n.a.  | n.a.    |
|   |  | Secondary School Graduate          | 60                   | 4.1%  | n.a.  | n.a.    | 1                | 0.5%  | n.a.  | n.a.    |
|   |  | Highschool/Technical School        | 789                  | 54.0% | n.a.  | n.a.    | 34               | 17.4% | n.a.  | n.a.    |
|   |  | Graduate                           |                      |       |       |         |                  |       |       |         |
|   |  | University Graduate                | 582                  | 39.8% | n.a.  | n.a.    | 161              | 82.1% | n.a.  | n.a.    |
| Mobility profile variables Transport Mode |  | Car                                | 2056                 | 37.9% | n.a.  | n.a.    | 147              | 29.5% | n.a.  | n.a.    |
|   |  | On Foot                            | 1642                 | 30.2% | n.a.  | n.a.    | 322              | 64.7% | n.a.  | n.a.    |
|   |  | Public Transport                   | 1195                 | 22.0% | n.a.  | n.a.    | 1                | 0.2%  | n.a.  | n.a.    |
|   |  | Bicycle                            | 59                   | 1.1%  | n.a.  | n.a.    | 10               | 2.0%  | n.a.  | n.a.    |
|   |  | Other                              | 479                  | 8.8%  | n.a.  | n.a.    | 18               | 3.6%  | n.a.  | n.a.    |
|   | Trip Duration (1st trip of the 1st trip chain, in minutes) |                                    |                      | n.a.  | 20.03 | 13.54   | 498              | n.a.  | 28.05 | 21.57   |
|   | Car Occupancy  | All trip purposes                  | 5431                 | n.a.  | 1.46  | 0.73    | 498              | n.a.  | 1.31  | 0.46    |
|   | , i i i i i i i i i i i i i i i i i i i                    | HBW                                | 663                  | n.a.  | 1.21  | 0.55    | 390              | n.a.  | 1.08  | 0.28    |
|   |  | HBO                                | 3749                 | n.a.  | 1.51  | 0.73    | 95               | n.a.  | 1.47  | 0.51    |
|   |  | NHB                                | 1019                 | n.a.  | 1.56  | 0.84    | 13               | n.a.  | 1.43  | 0.53    |
|   | Trip Frequency (per day)                                   | All trip purposes                  | 5431                 | n.a.  | 3.71  | 1.76    | 498              | n.a.  | 2.51  | 1.02    |
|   | 1 1 9 11 9 12  | HBW                                | 663                  | n.a.  | 0.45  | 0.57    | 390              | n.a.  | 0.49  | 0.87    |
|   |  | НВО                                | 3749                 | n.a.  | 2.56  | 1.47    | 95               | n.a.  | 1.98  | 1.20    |
|   |  | NHB                                | 1019                 | n.a.  | 0.70  | 1.15    | 13               | n.a.  | 0.01  | 0.07    |

Note 1: Trip Start Time (1st trip of the day) was also used as a variable in the study (see Fig. 9)

Note 2: The "Other" option of the "Transport Mode" variable refers to motorcycles, special buses, taxis, trucks or semi-trucks. The variable refers only to urban mobility mode choices.

## Table 3

Statistical tests performed for exploring COVID-19 lockdown (pandemic reference period) impact on trip-related variables.

## Car occupancy rate

Dependent Variables # Independent Variables Statistical Test Trip Frequency (total number of 1 Reference period (pre-Mann daily tips per person) pandemic:0, pandemic:1) Whitney U 2 Trip Frequency per Trip Purpose Car Occupancy Rate 3 Car Occupancy Rate per Trip 4 Purpose 5 Trip Duration (1st trip of the 1st Kaplan trip chain) Meier Trip Start Time (1st trip of the day) 6 Granger Causality

public transport trips were severely limited during the pandemic period (22% during the pre-pandemic period compared to 0.2% during the pandemic period). On the other hand, the modal share of trips on foot more than doubled (30.23% during the pre-pandemic and 64.66% during the pandemic period). Though initially small, there was also a substantial increase in bicycle trips (1.09% during the pre-pandemic and 2.01% during the pandemic).

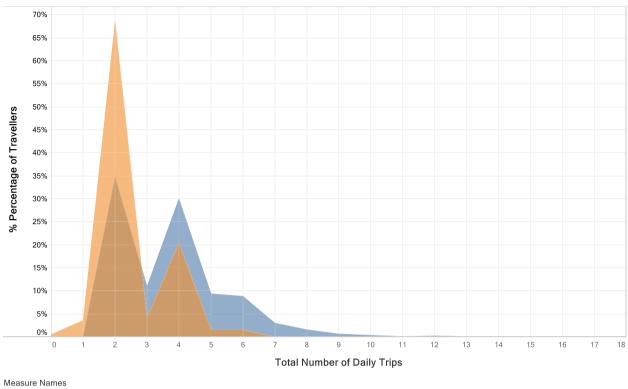
Fig. 7 shows the respective differences per trip purpose. Car trips were increased for HBW purposes during the lockdown but decreased for HBO trip purposes. On the other hand, trips on foot maintained about the same share for HBW trips and were greatly increased for HBO trips.

A Mann Whitney *U* test was performed in order to examine the relationship between car occupancy rate before (Mean = 1.46 persons/vehicle) and during (Mean = 1.31 persons/vehicle) the pandemic phase, regarding the city of Thessaloniki. The difference between these variables was not found to be statistically significant, as the aforementioned statistical test had a p-value of 0.167. Along the same lines, the differences between car occupancy of HBW and HBO trips before and during the pandemic were also not found to be statistically important. The observed reduction should be probably attributed to the car occupancy-related restrictions imposed by the Greek government for the lockdown event, allowing up to two (2) persons to travel by the same passenger car.

## Trip duration

Regarding trip duration, due to the different questionnaire's format in the pre-pandemic and pandemic periods, only the first trip of each trip chain was taken into consideration for comparison purposes. Furthermore, only trips with a duration of 80 min or less were accounted, because the trips with a greater duration accounted for only 1.3% of the sample.

Trip duration was considerably increased between the prepandemic (mean trip duration = 20 min) and pandemic phases (mean trip duration = 28 min) in Thessaloniki. A possible explanation for that is that the SMS scheme did not put any limitations on trip duration and therefore an important share of travelers might have extended the duration of their trips so as to perform the same



pandemic period
pre-pandemic period

Fig. 4. Percentage of travelers who made a particular number of daily trips for the pre-pandemic and pandemic period in Thessaloniki (source: own elaboration).

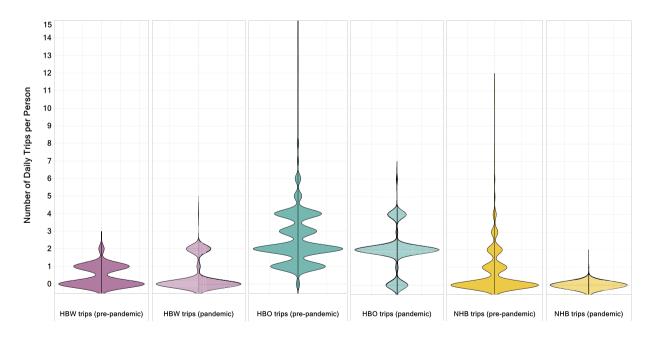
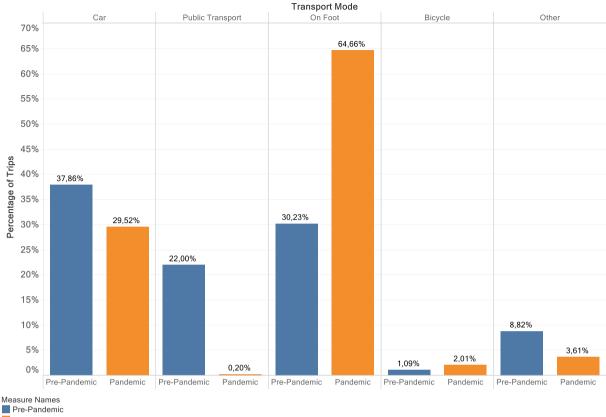


Fig. 5. Daily trip frequencies before and during the pandemic period per trip purpose (HBW, HBO, NHB) in Thessaloniki (source: own elaboration).

activities under a more strict monitoring of number of trips per person. Amassing extra amounts of time outside could have acted like a coping mechanism against the social encumbering effects of the social distancing measures. The Kaplan Meier test indicated that the difference between the pre-pandemic and pandemic trip durations was statistically significant (p < 0.0001). The survival curves for the prepandemic and pandemic periods are displayed in Fig. 8. The survival probability (i.e. the probability of the trip not ending at a specific point in time during its duration) is mostly increased for the pandemic period for trip durations between 20 and 60 min. For shorter durations the probability of the trip ending is much more similar between the two periods.



Pandemic

Fig. 6. Modal share comparison between the pre-pandemic and pandemic periods in Thessaloniki (source: own elaboration).

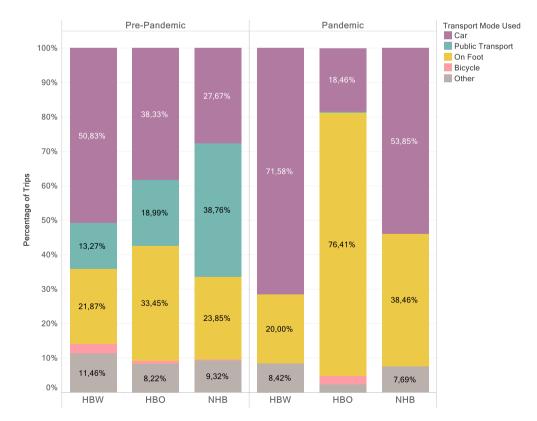
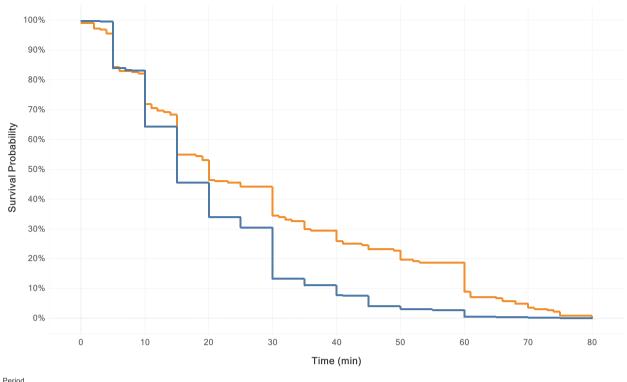


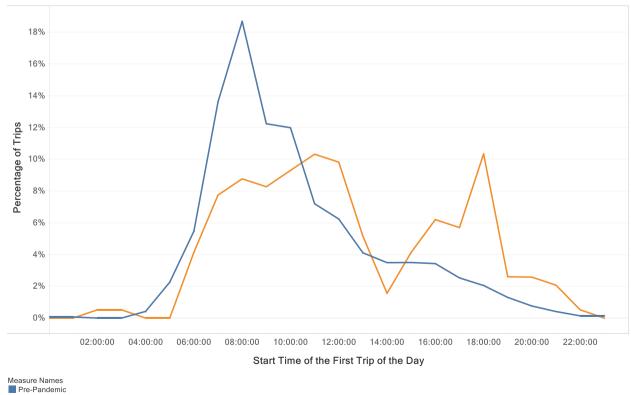
Fig. 7. Modal share comparison per trip purpose (HBW, HBO, NHB) between the pre-pandemic and pandemic periods in Thessaloniki (source: own elaboration).





Pandemic

Fig. 8. Kaplan Meier curve comparing pre-pandemic and pandemic trip durations in Thessaloniki (source: own elaboration).



Pre-Pandem

Fig. 9. Comparison of trip starting times for the first trip of the day between the pre-pandemic and pandemic periods in Thessaloniki (source: own elaboration).

#### Trip starting time

Fig. 9 shows the distribution of the starting time of the first trip of the day between the two periods under consideration. A Granger causality test was conducted testing whether one timeseries can be predicted using the other and the results were not statistically significant (p = 0.243), rejecting the null hypothesis. This indicates that there is a significant difference between the two timeseries. In fact, during the pre-pandemic period a considerable percentage (almost 18%) of the first trips started at the morning peak hour (around 08:00 am). In the pandemic period, while an important share of the distribution is still concentrated around 08:00 am, a lot of the trips have shifted towards the afternoon and evening hours and there is a second peak concentrated around 18:00. A possible explanation is that due to teleworking, non-overlapping shifts and other measures that supported social distancing, a lot of the employees who previously used to leave home during the morning peak hour started going out later than morning.

#### Modeling socioeconomic effects on mobility

## Impact on trip frequency

Table 4 summarizes the OLS regression model results, which associate the total number of daily trips per person against the socioeconomic variables in both the pre-pandemic and pandemic datasets. The statistically significant variables are flagged with asterisks (\*/\*\* statistical significance at the alpha = 0.05/0.01 level). The goodness-of-fit statistics showed a good fit of the proposed OLS models for both periods. The R-squared (R<sup>2</sup>) values appeared to be 0.77 and 0.84 respectively, suggesting that the regression models fit well the observed data. The p-values (Sig.) associated with the F-values (Anova) appeared to be smaller than the alpha level (0.000 < 0.01), for both models, indicating that the group of the explanatory variables included in the OLS models can reliably predict the dependent ones.

The number of household members presented statistically significant coefficients for both the pre-pandemic and pandemic OLS models. Therefore, being a member of a large sized household increases an individual's probability of making more daily trips during both the examined periods. However, the estimated regression coefficient appeared to be much higher for the pre-pandemic situation (i.e. 0.512 against 0.170). This may be attributed to peoples' greater reluctance to spread the household activities (and therefore the trips) across many family members in order for the COVID-19 exposure risk to be confined to as few household members as possible.

In respect to the monthly average household income, all income groups were found statistically significant for the pre-pandemic OLS model and were more likely to perform more daily trips, compared to the reference income group of "1000–2000 $\in$ ". In the pandemic model, the " $\leq$ 500 $\in$ " was the only income group that was found to be associated with more daily trips compared to the reference income group of "1.000–2.000 $\in$ ". This fact is possibly explained by the nature of the occupations which are often related to the different income groups. People belonging to low-income households are more expected to have manual labor jobs and thus continued to commute even during the pandemic period. On the contrary, people belonging to high-income households are more likely to follow careers that require computer skills which in turn enable them to shift to teleworking during the lockdown period. Furthermore, considering that online shopping has proliferated during the COVID-19 period and income is positively associated with the frequency of online shopping (Cao et al., 2012; Saphores and Xu, 2020), low-income groups were less likely to shop online and more likely to make actual trips to cover such need.

Results also showed that being a male traveler increases the probability of performing more daily trips during both the pre-pandemic and pandemic terms. This probability is comparatively lower under pandemic circumstances (i.e. coefficient value of 0.644 against 0.382). The effect of travelers' age on trip frequency is not considerably different between the two periods. Since no significant change was observed for the "60–69" age group, it could be argued that the government's intention to protect the elderly by targeting them as vulnerable group and encouraging them to heavily reduce their daily trips, did not probably lead to the desired results. It should be noted that the relatively high estimated regression coefficients for the "70+" age group - stemming from both the pre-pandemic and pandemic OLS models - are largely due to the few respondents belonging to the aforementioned age group (1.5% and 2% of the total number of the respondents, respectively).

Out of the education level variables, the "University Graduate" was the only category where a statistically important positive correlation with trip frequency was found. This finding, however, can be attributed to various sociodemographic reasons, since this educational group, compared to other ones examined, generally represents a greater variance of employment, income and gender backgrounds.

## Impact on trip duration

In order to quantify the lockdown effect on trip duration, while taking into account the simultaneous effect of other socioeconomic and trip related factors, a Cox Proportional Hazards model was fitted. The hazard ratios and their confidence intervals that were derived from the model are displayed in the forest plot of Fig. 10. The forest plot displays the variables that were included in the model in the first column, and their levels in the second column. The third column shows the hazard ratios, as these were calculated by the model. Next to them their confidence intervals are displayed graphically (it is important for the confidence interval not to include the "0" value that is displayed by a dotted vertical line). Finally, at the right side of the forest plot the p-values of the variable levels are shown. A hazard ratio of less than 1 means that the corresponding variable's factor level increases the expected trip duration compared to the reference level, as it reduces the "hazard" of the trip ending sooner. A hazard ratio of more than 1 means that the corresponding variable's factor level reduces the expected trip duration compared to the reference level, as it increases the "hazard" of the trip ending sooner. The model's concordance index (also displayed on Fig. 10) is 0.64, which is considered acceptable.

Fig. 10 shows that the pandemic variable had a hazard ratio of 0.38, something that indicates that the trips during the pandemic were much more likely to last longer. This finding was also confirmed by our Kaplan Meier test results and discussed in Section 5.1.4. Fig. 10 highlights a hazard ratio of 0.90 for men, which indicates that men take somewhat longer trips compared to women.

Trips by public transport seem more likely to last significantly longer than trips with cars (hazard ratio of 0.56), while trips made on foot, by bicycle or by other modes of transport are more likely to have a shorter duration compared to car trips (hazard ratios of 1.49, 1.94 and 1.15 respectively). Noticeably, age, trip start time, trip purpose and number of household members were not found to be significant determinants of trip duration.

# Discussion and concluding remarks

In this study we investigated the impact of the COVID-19 lockdown measures on the travel behavior patterns in Thessaloniki, Greece. We carried out two discrete tailored questionnaire surveys, before and during the lockdown, to collect socioeconomic and trip related data. We then employed appropriate statistical tests and modelling techniques to compare key mobility profile variables between the prepandemic and pandemic periods along with highlighting the effect of socioeconomic attributes on the trip frequency and duration figures. The methodological framework we developed can be applied to explore similar research questions in settings and periods where

# Table 4

OLS regression results of total number of daily trips per person in the pre-pandemic and pandemic periods.

| Regressors   |                                       | Pre-Pandemic  |            |                           |        |         | Pandemic   |            |                              |        |         |  |
|--|---------------------------------------|---|------------|---------------------------|--------|---------|--|------------|------------------------------|--------|---------|--|
|  |                                       | Unstandardized<br>Coefficients  |            | Standardized Coefficients | t      | Sig.    | Unstandardized<br>Coefficients   |            | Standardized<br>Coefficients | t      | Sig.    |  |
|  |                                       | В   | Std. Error | . Error Beta              |        |         | В  | Std. Error | Beta                         |        |         |  |
| Number of Household Members<br>(including yourself)<br>Monthly Average Household |                                       | 0.512   | 0.031      | 0.414                     | 16.712 | 0.000** | 0.170  | 0.065      | 0.172                        | 2.613  | 0.010*  |  |
| Income:  |                                       |   |            |                           |        |         |  |            |                              |        |         |  |
| ≤500€  | Reference: 1000-                      |   |            |                           |        |         |  |            |                              |        |         |  |
| 20000  | 2000€                                 |   |            |                           |        |         |  |            |                              |        |         |  |
| 1000–2000€   | 20000                                 | 1.852   | 0.187      | 0.133                     | 9.927  | 0.000** | 0.805  | 0.393      | 0.071                        | 2.048  | 0.042*  |  |
| 500-1000€  |                                       | 1.515   | 0.145      | 0.156                     | 10.443 | 0.000** | 0.208  | 0.203      | 0.039                        | 1.024  | 0.307   |  |
| ≥2000€   |                                       | 1.094   | 0.168      | 0.105                     | 6.527  | 0.000** | 0.109  | 0.225      | 0.020                        | 0.485  | 0.628   |  |
| No answer  |                                       | 1.064   | 0.125      | 0.154                     | 8.480  | 0.000** | -0.237   | 0.320      | -0.025                       | -0.742 | 0.459   |  |
| Gender:  |                                       |   |            |                           |        |         |  |            |                              |        |         |  |
| Male   | Reference: Female                     | 0.644   | 0.099      | 0.111                     | 6.482  | 0.000** | 0.382  | 0.166      | 0.097                        | 2.309  | 0.022*  |  |
| Age Groups:  |                                       |   |            |                           |        |         |  |            |                              |        |         |  |
| 15–19  | Reference: 20-29                      | 0.606   | 0.189      | 0.050                     | 3.215  | 0.001** | 1.040  | 1.188      | 0.027                        | 0.875  | 0.383   |  |
| 30–39  |                                       | 0.659   | 0.148      | 0.067                     | 4.445  | 0.000** | 1.330  | 0.232      | 0.274                        | 5.722  | 0.000*  |  |
| 40–49  |                                       | 0.515   | 0.178      | 0.042                     | 2.898  | 0.004** | 1.011  | 0.249      | 0.190                        | 4.060  | 0.000*  |  |
| 50–59  |                                       | 0.859   | 0.190      | 0.063                     | 4.523  | 0.000** | 1.223  | 0.274      | 0.194                        | 4.460  | 0.000** |  |
| 60–69  |                                       | 0.943   | 0.266      | 0.047                     | 3.549  | 0.000** | 0.863  | 0.347      | 0.091                        | 2.490  | 0.014*  |  |
| 70+  |                                       | 2.093   | 0.454      | 0.063                     | 4.610  | 0.000** | 1.222  | 0.602      | 0.064                        | 2.028  | 0.044*  |  |
| Education Level:   |                                       |   |            |                           |        |         |  |            |                              |        |         |  |
| Did not Graduate   | Reference:                            | 0.168   | 0.488      | 0.004                     | 0.344  | 0.731   | -  | -          | -                            | -      | -       |  |
| Elementary School  | Highschool/                           |   |            |                           |        |         |  |            |                              |        |         |  |
|  | Technical School                      |   |            |                           |        |         |  |            |                              |        |         |  |
|  | Graduate                              |   |            |                           |        |         |  |            |                              |        |         |  |
| Primary School   |                                       | -0.320  | 0.579      | -0.007                    | -0.553 | 0.580   | -  | -          | -                            | -      | -       |  |
| Secondary School   |                                       | -0.226  | 0.289      | -0.011                    | -0.783 | 0.434   | 1.415  | 1.245      | 0.037                        | 1.137  | 0.257   |  |
| University   |                                       | 0.627   | 0.111      | 0.096                     | 5.622  | 0.000** | 0.852  | 0.189      | 0.285                        | 4.502  | 0.000*  |  |
|  | Model Summary-Goodness                |   |            |                           |        |         | Model Summary-Goodness   |            |                              |        |         |  |
|  | of Fit Metrics                        |   |            |                           |        |         | of Fit Metrics   |            |                              |        |         |  |
|  | , , , , , , , , , , , , , , , , , , , | .768, Adjusted R <sup>2</sup> : 0.765<br>Error of the Estimate: 1.988 |            |                           |        |         | R <sup>2</sup> : 0.836, Adjusted R <sup>2</sup> : 0.824<br>Std. Error of the Estimate: 1.137 |            |                              |        |         |  |
|  |                                       |   |            |                           |        |         |  |            |                              |        |         |  |
|  | F-value (Anova): 298.3                | 374, Sig.: 0.000  | )**        |                           |        |         | F-value (Anova): 65.756, Sig.: 0.000**   |            |                              |        |         |  |

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Note 1: Dependent Variable: Total Number of Daily Trips per Person in Pre-pandemic and Pandemic Eras.

\* Significance at 5%.

\*\* Significance at 1%.

| Pandemic                                      | Pre-Pandemic<br>(N=2155)            | reference             |     |     | -           |            |
|---|-------------------------------------|-----------------------|-----|-----|-------------|------------|
|   | Pandemic<br>(N=224)                 | 0.38<br>(0.32 - 0.44) | ⊢∎→ |     |             | <0.001 *** |
| Gender  | Female<br>( <i>N</i> =1171)         | reference             |     |     |             |            |
|   | Male<br>(N=1208)                    | 0.90<br>(0.82 - 0.97) |     | ۲   | <b>8</b> -1 | 0.01 **    |
| Transport Mode                                | Car<br>(N=903)                      | reference             |     |     |             |            |
|   | Public Transpor<br>( <i>N=433</i> ) | 0.56<br>(0.49 - 0.63) |     | ⊢∎⊣ |             | <0.001 *** |
|   | On Foot<br>(N=829)                  | 1.49<br>(1.35 - 1.64) |     |     | ⊢∎⊣         | <0.001 *** |
|   | Bicycle<br>(N=27)                   | 1.94<br>(1.32 - 2.85) |     |     | <u>ب</u>    |            |
|   | Other<br>(N=187)                    | 1.15<br>(0.99 - 1.35) |     |     | <b>.</b>    | 0.075      |
| # Events: 2379; Globa<br>AIC: 31918.22; Conco |                                     |                       |     | .5  | 1           | 2          |

Hazard Ratios for Trip Duration

Fig. 10. Forest Plot of the Hazard Ratios and their confidence intervals, as derived from the duration model fitted (source: own elaboration).

unprecedent or sudden events (such as extreme weather, civil disorders, terrorism and national emergencies etc.) bring about the imposition of general mobility restrictions. In this context, we also demonstrated the employment of duration modelling techniques as a promising tool for comparing duration-related variables of datasets which belong to dissimilar time periods.

Empirical findings showed that in Thessaloniki, Greece, during the COVID-19 lockdown, the number of daily trips per person was reduced while the respective trip durations were increased. The number of commuting trips was the least affected compared to the trips with other purposes. In the lockdown period, the starting time of the first trips of the day used to spread from the early morning hours throughout the day and a new spike formed in the late afternoon hours. An increased number of those trips was made on foot. Additionally, private car became the main travel mode for commuting. Lower-income groups and men were associated with increased trip frequencies during the pandemic. The latter group of travelers also tend to perform trips with comparatively greater duration. No significant travel behavior differentiations were observed between pandemic and prepandemic phases due to the age status of trip makers.

These findings demonstrate a new mobility landscape and since such pandemics may be recurring events in the future, they emphasize the need for designing and implementing appropriate policies which will be in line with sustainable mobility objectives while fulfilling wider community goals under such circumstances. Depending on the stakeholders they concern, we categorize those policies to transport operators', national and local authorities' related ones. More specifically:

Transport operators' related policies

• Our results showed that the private car was widely used during the pandemic period for commuting trips while public transport shares, for the same trip purpose and generally, almost disappeared. A possible explanation for that is that the private car emerged as the easy, intuitive solution to social distancing obligations. Having your own protective anti-COVID bubble possibly presented itself as a desirable solution, even for travelers that would have preferred more sustainable modes of transport during the pre-pandemic period. However, private car remains a relatively unsustainable transport mode for long term commitment. On the other hand, public transport cannot operate at full capacity over a pandemic, but

improvements can be made towards upgrading both safety and level of service. Technologies like electronic ticketing can be used to improve contact tracing of public transport passengers. The internal design of public transport vehicles can be enhanced to accommodate dividers and larger distancing as passengers boarding or alighting from them. Alternative or complementary services, such as micromobility sharing can be further improved and promoted (Campisi et al., 2020b; Li et al., 2020).

National authorities' related policies

- Though that the starting times of trips are more evenly distributed over the lockdown daytime periods, considerable concentrations of them continue to appear during the morning and late afternoon hours. This fact, combined with the increased trip durations which were observed, may still create crowding situations. Further adjusting work schedules and shopping hours, can help with further spreading trips throughout the day.
- The age group of a traveler was found to similarly affect the number of daily trips she/he makes in both the pre-pandemic and pandemic periods. However, older age groups are at a greater risk of suffering from serious COVID-19 symptoms, so minimizing their exposure to the virus should be a priority. But even when they are in a high-risk age group, these potential travelers may still have jobs they need to get to, primary necessities they need access to, and social needs they need to cater to. At the same time, it is often harder for older citizens to fulfill those needs remotely. Teleworking, online deliveries, and online socializing have been found not to be as accessible for older generations and physically getting outside of the house becomes the only viable alternative (Bulut et al., 2020; Lian and Yen, 2014; Monahan et al., 2020). In order to remedy this, online services need to become more accessible and more approachable by older users. Also, more inclusive alternative tools, like helplines and psychological assistance services, should be implemented and promoted.
- Production facilities, primary necessity stores, health care facilities, sanitation departments, delivery services, etc. had to stay open during the lockdown as they provided vital services to societies. Generally, employees at those facilities kept having to travel to work and come into contact with colleagues or customers. In fact, our findings showed that the lower-income groups performed an

increased number of daily trips when compared to the other income groups during this period. While societies recognize the valuable contribution of those employees, it is also important that more tangible measures are taken as well. Those could be in the form of reduced working hours, by compensating employers to hiring extra staff, and increased work benefits or intensified preemptive health protection measures.

Local authorities' related policies

• Male travelers appeared to have made both more and longer trips during the lockdown period. Along with respecting COVID-19 mobility restriction measures, female travelers would probably have been more reluctant to travel due to their anxiety of being involved in physical attack incidents, which could have been more frequent under reduced traffic conditions (research has shown that women have increased fear of walking alone to home, a fear that is made more intense by empty streets (García-Carpintero et al., 2020)). Awareness campaigns, increased patrolling and public space safety improvement measures are policies that could constitute an effective response to such safety concerns.

A basic limitation of this study is that our two datasets (prepandemic and pandemic) were not collected in identical ways. One was collected on-field, while the other was collected online, since onfield interviews were not possible due to the social distancing measures. This fact explains the samples' differentiations between the two datasets as well as the fact that we were able to analyze trip duration figures only for the first trips of each trip chain, since the duration of subsequent trips were not available in the pandemic dataset. Moreover, the face-to-face interviews that were utilized to collect the data for the pre-pandemic dataset can be prone to interviewer related bias, meaning that certain responses might be inadvertently promoted. In order to mitigate that effect, the interviewers who conducted the interviews were carefully trained. At the same time the online survey, which was deployed to collect data for the pandemic dataset, could include bias that was caused by poor understanding of the questions. In order to lessen the chances of that happening, the survey thoroughly explained less-known terms and used easily understood language along with providing an online assistance service. Furthermore, the pandemic dataset includes a smaller number of responses compared to the prepandemic dataset. While a larger sample size would have been preferred, the challenges of data collection during the lockdown and the need to contain (as much as possible) the data collection period during the same time frame as the pre-pandemic survey, severely limited our capacity to collect a larger amount of data. Further research should also employ more personalized survey methods for determining travel behavioral changes during lockdown events. Focus group discussions with specific socioeconomic and employee groups could be a successful way to capture in more detail their preferences and perceptions against lockdown impacts on both personal mobility and well-being aspects.

## CRediT authorship contribution statement

**Ioannis Politis:** Conceptualization, Methodology, Validation, Investigation, Writing - original draft, Supervision. **Georgios Georgiadis:** Conceptualization, Methodology, Validation, Writing - original draft, Writing - review & editing. **Efthymis Papadopoulos:** Formal analysis, Software, Writing - original draft, Writing - review & editing, Visualization. **Ioannis Fyrogenis:** Methodology, Software, Writing original draft, Writing - review & editing, Visualization. **Anastasia Nikolaidou:** Formal analysis, Investigation, Validation. **Aristomenis Kopsacheilis:** Formal analysis, Investigation, Data curation. **Alexandros Sdoukopoulos:** Formal analysis, Investigation, Visualization. **Eleni Verani:** Formal analysis, Investigation, Writing - original draft.

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