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Relationship between COVID-19 and Community Mobility: Sample from Malatya Province

Veli Yilanci[1], Sami Akbulut[234], Huseyin Islek[5], Fatma Zeren[6], Ali Ozer[4], Recep Bentli[7]

[1]Canakkale Onsekiz Mart University, Faculty of Economics and Administrative Sciences, Department of Economics, Canakkale, Turkey
[2]Inonu University, Faculty of Medicine, Department of Surgery, Malatya, Turkey
[3]Inonu University Faculty of Medicine, Department of Biostatistics and Medical Informatics, Malatya, Turkey
[4]Inonu University Faculty of Medicine, Department of Public Health, Malatya, Turkey
[5]Alparslan University Faculty of Economics and Administrative Sciences, Department of Economics, Mus, Turkey
[6]Inonu University Statistics and Econometrics Research and Application Center, Turkey
[7]Inonu University Faculty of Medicine, Department of Internal Medicine, Malatya, Turkey

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Abstract

After the WHO defined the COVID-19 as a pandemic on March 11, 2020, measures such as wearing masks, keeping social distance, and staying at home were taken to reduce transmission worldwide. Community mobility is one of the important factors contributing to the uncontrolled spread of the epidemic. The aim of the study is to examine the relationship between the number of COVID-19 cases in the first half of 2021 in Türkiye's Malatya province and Google community mobility reports. The number of COVID-19 cases in Malatya between 01 January 2021 and 31 May 2021 was obtained from the Malatya Provincial Health Directorate. Community mobility data in the relevant period was obtained from Google community mobility. To examine the relationship between the number of COVID-19 cases and community mobility, wavelet coherence analysis was used. The Google mobility data used in the study consists of six different categories covering markets and pharmacies, parks, residential, retail, and recreational areas, public transport stops and workplaces. According to the results of wavelet coherence analysis, the increase in mobility in markets and pharmacies, retail and recreation areas, parks, workplaces, and transportation stations has increased the number of COVID-19 cases. The direction of the relationship between COVID-19 and residential mobility was found to be negative. In other words, the increase in the time spent in residences leads to a decrease in the number of COVID-19 cases. According to the results of wavelet coherence analysis, it was observed that in five of the six categories included in the study, there was a significant relationship between the number of cases and these categories, for the period examined at various frequencies. Depending on the degree of interactions at short- and long-term frequencies covered in the study, policy makers can determine short- and long-term policies to direct human mobility and thereby control the pandemic.

Keywords: COVID-19 pandemic, community mobility, wavelet coherence

Introduction

COVID-19, which emerged in December 2019 in Wuhan city of Hubei province of China, was declared a pandemic by the world health organization on March 11, 2020, as it spread very rapidly around the world [1]. This pandemic has had negative effects on both the health systems and economies of especially underdeveloped and developing countries. In order to combat the COVID-19 disease, the vaccine development studies were accelerated on one hand, while global measures were started to be taken to stop the uncontrolled progress of the pandemic on the other. The measures on which a general consensus has been achieved since the first day the pandemic was declared are wearing masks, hand washing, social distance, reducing mobility (stay at home), closing national and international borders, promoting online education and working from home [2]. Both the strict abidance by the rules and the initiation of vaccination programs caused a decrease in the number of COVID-19 cases, but with the emergence of new variants, this downward trend was replaced by a stagnation and a slight upward trend for a while [3].

The COVID-19 pandemic, along with the measures taken, has led to experiencing certain rare changes in many activities such as nutrition, education, transportation and mobility [4]. In this process, both the measures taken by the governments and the fact that people spend less time outside the home than before due to the fear of contracting the disease caused significant changes in

*Corresponding Author: Sami Akbulut, Inonu University, Faculty of Medicine, Department of Surgery, Malatya, Turkey
E-mail:sevda.akbulutsami@gmail.com

mobility patterns [5-8]. Understanding the relationship between human mobility and COVID-19 is essential, since the significant structural changes in mobility patterns and the modest impact of the Small World caused by restrictions have had a significant impact on the pandemic [9].

The aim of this study is to examine the relationship between the number of COVID-19 cases and community mobility, in the first half of 2021 in Turkey's Malatya province. For this purpose, the relationship between the variables will be analysed using the Wavelet Coherence model. The reason why this research is necessary is to analyse the relationship between mobility and pandemic, to contribute to the decision makers on whether or not to apply quarantine and restriction measures in this and similar pandemics and to evaluate the effectiveness of these measures taken about the course of the COVID-19 pandemic [10,11].

Material and Methods

Data Set

This research was designed as a cross-sectional empirical study. In this study, the relationship between the number of COVID-19 cases detected between 01 January 2021 and 31 May 2021 in Malatya province and community mobility was examined. While the number of COVID-19 cases was obtained from Malatya Health Directorate, community mobility data were obtained from Google community mobility reports. The mobility data obtained from Google consists of six different categories covering markets and pharmacies, parks, residential, retail and recreational areas, public transport stops and workplaces [12]. Google mobility data has been prepared to demonstrate how visits to different places and the duration of stay in these places vary according to a certain reference value, taking into account location information. The reference value represents the median value for the relevant day of the week during the five-week period from January 3 to February 6, 2020 [12].

Transformations

In the literature, transformations such as Fourier, Hilbert and Wavelet are frequently used to reach information that is not available in a series. Although the Fourier transform is the most frequently used among these transforms, it does not give satisfactory results if the series have a stationary or non-periodic structure [13]. Compared to the Fourier transform, Wavelet transforms can capture movements such as trends and sudden changes and gives stronger results than the Fourier transform when the data creation process is in a non-linear or non-stationary structure. In this study, continuous wavelet transform (CWT) was used to examine the dynamics of variables over time, and Wavelet coherence approach was used to examine the relationship between variables over time.

Continuous Wavelet Transform

While the discrete wavelet transform (DWT) allows the analysis of series only at certain time scales, there is no such restriction in CWT [14]. The interpretation of the graphs obtained from the CWT, which provides the transformation of a time series as a function of time and frequency, is easier than the interpretation of the graphs obtained from the DWT. The following integral is used to obtain the CWT (15):

$$W(u,s)=\int_{-\infty}^{\infty} x(t)\psi_{u,s}(t)\,dt$$

The *x(t)* here shows the related time series. $\psi_{us}(t)$ on the other hand, is the wavelet function as defined below:

$$\psi_{u,s}(t)=\frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)$$

Here, t represents the time, s represents the scale parameter indicating the wavelet time, and u represents the translation parameter that indicates the position of the wavelet in time. With the change of s and u , the magnitudes of a series at different scales, as well as the variation of this magnitude over time, can be detected [16].

In this study, one of the most popular wavelet filters, the Morlet wavelet (MD) transform, which maintains a balance between time and frequency accuracy, is used [17]. The MD has both real and imaginary parts, which allows to separate the periods and magnitudes of the time series [18]. MD may be defined as follows:

$$\psi(t)=\pi^{-1/4}e^{-iw_0 t}e^{-\frac{t^2}{2}}$$

Here i and w_0 represents a complex number and a central frequency, respectively (15). For ease of interpretation, following the studies of Aguiar-Conraria and Soares [17], and Grinsted and colleagues [19], $w_0=6$ is chosen.

Wavelet Coherence

Wavelet coherence, which is one of the tools for examining the relationship between two or more variables, can be considered as a measure of correlation between variables at different frequencies. Torrence and Webster [20] define wavelet coherence as an exact representation of the covariance between variables. The wavelet coherence between the two variables such as *Y* and *X* can be defined as follows [21]:

$$R(Y,X)=\frac{S(W(Y,X))}{\left(S[W(Y)]S[W(X)]\right)^{1/2}}$$

Here *R(Y,X)* represents the wavelet coherence between the variables. R represents the cross-correlation between two series as a function of frequency, taking values between 0 and 1. The square of the coherence measure which takes a value in the $0\leq R^2\leq 1$ range, shows the strength of the coherence. If this value is close to 1, it indicates that the coherence between the series is high, while a value close to 0 indicates that the coherence is low. W (.) represents the wavelet transformation, while *S* represents the corrective operator in both time and scale.

It would be very useful to treat wavelet coherence as a built-in correlation coefficient in the time-frequency space [19]. If the corrector is not used here, the coherence value will be 1 at each scale and time. S for MD in time and scale can be represented as:

$$S_{time}(W)=\left(W_n(s)*c_1^{-t^2/2s^2}\right);\ S_{scale}(W)=\left(W_n(s)*c_2\prod(0,6s)\right)$$

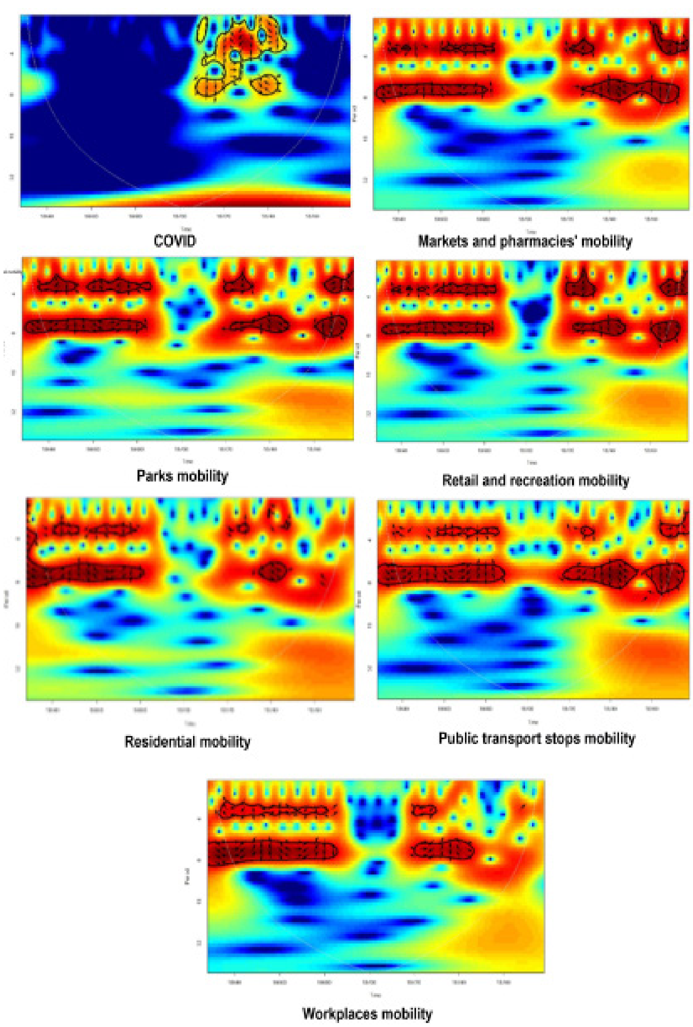
Here, "Stime" represents the corrective parameter in the wavelet scale axis, while "Sscale" indicates the corrective parameter in time. Here C^1 and C^2 represent the normalization constants. A value of 0.6 represents the empirically determined de-correlation length of the Morlet wavelet [16]. Π on the other hand, represents the rectangular function. The significance of the estimated wavelet coherence is tested with Monte Carlo simulations.

Study Protocol and Ethics Committee Approval

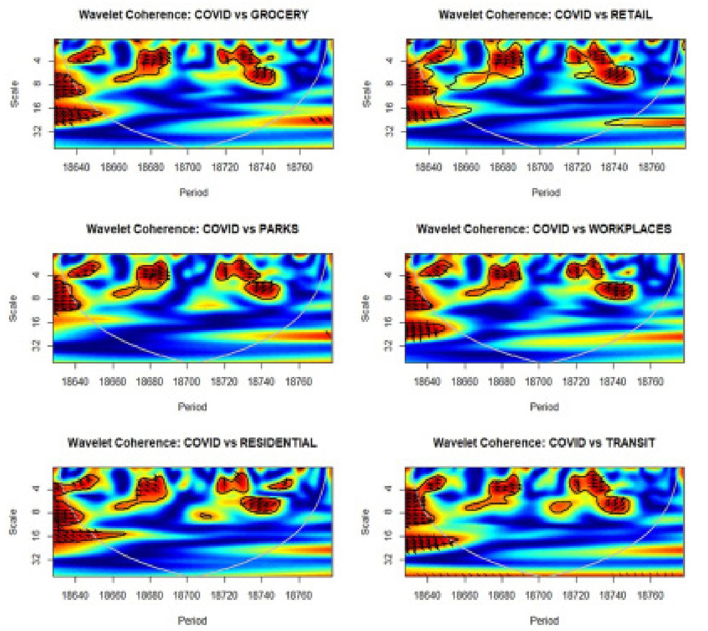
This cross-sectional study involving human participants was by the ethical standards of the institutional and national research committee and the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Data on the number of COVID-19 patients in the specified date range in Malatya were obtained from Malatya Provincial Health Directorate. Ethical approval was obtained from the Inonu University Institutional Review Board (IRB) for non-interventional studies (2022/3246).

Results

In the first stage of the study, the dynamism of the variables over time and the expression of the original data as a function of time and frequency were examined using the CWT method. CWT charts show the variability of a variable over time. The islets in Graphic 1 show that the variability of the variables is statistically significant. Also, blue areas are interpreted as low variability, while red areas are interpreted as high variability.



Graphic 1. Continuous wavelet transform of COVID-19 case numbers and mobility variables



Graphic 2. Relationship Between Number of COVID-19 Cases and Types of Mobility

As can be seen in Graphic 1, the variability in the number of COVID-19 cases is statistically significant and high, at frequencies of 0-8 days, between March 15 and April 30. The variability in market and pharmacy mobility is statistically significant and high at the frequency level of 2-4 days, except for March and the period between 10 April-10 May. In addition, the variability in market and pharmacy mobility at 6-8-day frequencies is statistically significant and high in all periods except March. The variability in park mobility is statistically significant and high, similar to the variability in market and pharmacy mobility at 2-4-day frequencies, except for March and the period between April 10 and May 10. At the 6-8-day frequency level, it is statistically significant and high in all periods except March and 1-10 May. For retail and recreational mobility, the variability is statistically significant and high in all periods except March and 10 April-10 May at 2-4-day frequencies. The variability in retail and recreational mobility also shows a statistically significant and high variability similar to the variability in park mobility in all periods except March and 1-10 May at the 6-8-day frequency level. On the other hand, the variability in residential mobility is statistically significant and high at 0-8-day frequencies, in the first days of January and until the last 10 days of February, at 0-2 and 6-8-day frequencies. In addition, it is seen that there is variation in 6-8-day frequencies for a short period in mid-April. For the mobility at the transportation stations, the variability is statistically significant and high in all periods except March at 6-8-day frequencies. It is seen that the variability is statistically significant and high in the 2–4-day frequencies in February and May. The variability in workplace mobility, on the other hand, displays a similar image to residential mobility. The similar pattern of variability in residential and workplace mobility corresponds to post high volatility period in the number of COVID-19 cases. This can be interpreted as a preliminary inference that changes in the number of COVID-19 cases reduce residential and workplace mobility.

Wavelet coherence analysis, on the other hand, is used to evaluate the relationship between two or more variables in the context of time and frequency. In the wavelet coherence analysis, the arrows in the islets give information about the direction of the relationship between the variables. While "→" indicates the positive relationship between variables, "←" indicates the negative relationship. In addition, the right upwards and left downwards arrows indicate that the first variable is the cause of the second variable, and the left upwards and right downwards arrows indicate that the second variable is the cause of the first variable.

Graphics of wavelet coherence analysis between COVID-19 and six mobility types for Malatya province are shown in Figure 2. The relationship between COVID-19 and market and pharmacy mobility shows a statistically significant and positive view at different frequencies until 20 January. Between February 10 and February 30 and throughout April, the positive correlation continues at 2-8-day frequencies. While market and pharmacy mobility played a leading role on the number of COVID-19 cases until January 20, this relationship reversed in April and started to play a leading role on the market and pharmacy mobility of COVID-19. Similar findings were obtained for the relationship between COVID-19 and other types of mobilities other than residential mobility. These results show that the increase in mobility in markets and pharmacies, retail and recreation areas, parks, workplaces, and transportation stations increase the number of COVID-19 cases. The relationship between COVID-19 and residential mobility was found to be negative at similar frequencies and times as in other types of mobilities. In other words, the increase in the time spent in residences leads to a decrease in the number of COVID-19 cases

Discussion

This study is expected to contribute to the literature in three different ways. First, it is the first study to examine the relationship between the number of COVID-19 cases and mobility for the province of Malatya. Second, it makes more specific inferences, taking into account different types of mobility. Finally, it uses the wavelet transforms, which takes into account the time-frequency approach as an analysis method. By using this approach, the relationships between the variables can be analysed more comprehensively.

One of the measures taken to reduce the spread of infectious diseases such as COVID 19 is to reduce human mobility. There are many scientific studies that have been conducted showing that reducing mobility causes a decrease in the number of cases. Maloney and Taskin [22] demonstrated with Google mobility data that staying at home in the US is voluntary. Wang and Yamamato [23] have predicted the number of COVID-19 cases using Google mobility data for the Arizona region. Using the data between January 21, 2020 and September 2, 2020 in the USA, Yilmazkuday [24] has investigated the impact of those staying in the same county on the county-level COVID-19 cases and deaths, and found that the number of cases and deaths is lower in counties with less travel to other counties. In their study, Kraemer and colleagues [25] investigated the relationship between human mobility and control measures for China by using spatial analysis methods. The findings of the study show that the correlation between the number of cases and mobility decreases with the implementation of control measures. This shows that the restrictions applied in China have reduced the COVID-19 pandemic. In their study, Badr and colleagues [26] examined the relationship between phone mobility data and COVID-19 cases for US states using daily mobility data from January 1, 2020 to April 20, 2020. Analysis results were obtained using mathematical modelling, which developed a social distance scale based on the change in mobility data. According to these results, it was observed that the correlation coefficient of 20 out of 25 states was above 0.7. Gatalo and colleagues [27] developed three different social distance scales using phone mobility data and conducted a similar study with Badr and colleagues [26]. According to their analysis using data from March 27, 2020, to April 20, 2020, a strong correlation was found between decreased mobility and decreased COVID-19 cases for all three social distance scales. In the analyses they conducted for later times, there is a weak relationship. In their study, Nouvellet and colleagues [11] examined the relationship between mobility and COVID-19 cases with time series methods, using 2020 Google and Apple data for 52 countries. The findings of the study show that with the decrease in mobility, contagion of the disease has decreased in 73% of the countries, and with the relaxation of restrictions, mobility and contagion have diverged in 80% of the countries. Using 2020 Google and Apple data for Turkey, Kartal and colleagues [10] have investigated the relationship between COVID-19 cases and different types of mobilities using causality analysis. According to the results of the study, a long-term relationship and causality relationship was reached between pandemic cases and some mobility types. ın their study, Yilmazkuday and colleagues [28] have investigated the relationship between mobility and COVID-19 cases and deaths using the difference in differences method, using the data of February 15, 2020 and May 2, 2020 for 130 countries. The results of the study show that less mobility is associated with lower COVID-19 cases and deaths. In their study, Askitas and colleagues [29] have investigated how lockdown policies for 135 countries affected COVID-19 contagion and population mobility. They used a dynamic analysis based on events using data from January 3, 2020 to February 6, 2020. The results of the analysis, on the other hand, show statistically significant findings that policies restricting mobility reduce cases originating from the pandemic. In their study, Xiong and colleagues [30] have analysed the relationship between mobile device location mobility data and COVID-19 in the US states by the dynamic panel method, using the data between March 1, 2020 and June 9, 2020. According to the results, there is a strong and positive relationship between mobility and COVID-19 in US states.

In this study, the relationship between the daily number of COVID 19 cases and various Google mobility data for Malatya province was examined with the wavelet coherence analysis approach. Mobility data were analysed in 6 categories. With wavelet coherence analysis, the interaction or co-movement between COVID-19 and Google mobility variables was measured at different frequencies and over time. According to the results of continuous wavelet transform, COVID-19 cases show significant variability at 8-day frequencies between the end of March and the end of April. Google mobility data shows volatility at 2-4 and 6-8 frequencies, except for March. In residential and workplace mobility data, a stable situation was also observed in May. According to the results of wavelet coherence analysis, it was observed that there was a significant relationship between market and pharmacy mobility and the number of cases for the period examined at various frequencies. Similarly, the interaction between other types of mobilities and the number of cases was revealed by this analysis. Obtained findings support the studies of Nouvellet and colleagues [11], Yilmazkuday [24], Kraemer and colleagues [25], Yilmazkuday and colleagues [28], Askitas and colleagues [29] and Xiong and colleagues [30].

Conclusion

In this study, the relationship between the mobility in six different locations in Malatya province including markets and pharmacies, parks, residences, retail and recreation areas, public transportation stops and workplaces, and the number of COVID-19 cases was analysed by wavelet method for the period of 01 January - 31 May 2021. The findings show that the mobility experienced in markets and pharmacies until January 20 played a leading role on COVID-19 cases, and in April, the direction of this relationship changed, and COVID-19 started to play a leading role on market and pharmacy mobility. In other words, it is possible to state that with increasing cases, people frequently visit these locations especially for protective measures. Reaching similar findings for other types of mobilities other than residential mobility shows that the increase in mobility in markets and pharmacies, retail and recreation areas, parks, workplaces and transportation stations, especially in the first period of the analysis, has an increasing effect on the number of COVID-19 cases. The negative relationship between COVID-19 and residential mobility shows that the increase in the time spent in residents leads to a decrease in the number of COVID-19 cases. Therefore, these obtained results show that decision makers can control the pandemic by directing human mobility during pandemic periods.

Conflict of interests
The authors declare that there is no conflict of interest in the study.

Financial Disclosure
The authors declare that they have received no financial support for the study.

Ethical approval
Ethics committee approval was obtained from Inonu University institutional review board (IRB) for non-interventional studies (Approval No: 2022/3246) and performed according to the ethical (Declaration of Helsinki) and legal standards in Turkey.

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