INEQUALITY IN MOBILITY DURING COVID-19: GLOBAL TO LOCAL ANALYSIS

A THESIS
SUBMITTED TO ABDULLAH GÜL UNIVERSITY
SOCIAL SCIENCES INSTITUTE
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF MASTER OF SCIENCE

By
Elif Gençaslan
June, 2022
Kayseri, Turkey

Elif Gençaslan INEQUALITY IN MOBILIYI DURING COVID-19: GLOBAL TO LOCAL ANALYSIS AGU 2022

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SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document has been obtained in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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M.Sc. thesis entitled “Inequality in Mobility During Covid-19: Global to Local Analysis” has been prepared in accordance with the Graduate Thesis Preparation Guidelines of the Abdullah Gül University, Social Sciences Institute.

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ABSTRACT

This thesis analyzes mobility patterns during the Covid-19 pandemic from a global and local perspective. The global framework includes 37 European countries and the local framework comprises 81 Turkish cities. The study follows the daily mobility trajectories of people from February 2020 to January 2022. The analyzes are conducted to understand the economic opportunities available in countries -at a macro scale- that facilitate or hinder the "proper" mobility behavior of individuals while focusing on the captive commuters, i.e., the share of the population who need to commute to the work despite the risk of infection and governmental policies. The results indicate that the workforce in regions with higher GDP per capita, education level, and life expectancy at birth was able to reduce their workplace mobility higher than commuters in areas with low income, education level, and life expectancy at birth. Therefore, unprivileged populations were exposed to higher health risks against rapid Covid-19 transmission in Europe and Turkish cities.

Keywords: Remote Work, Mobility, Covid-19, Equality of Opportunity

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ÖZET

Bu tez, Covid-19 pandemisi sırasındaki hareketlilik modellerini küresel ve yerel bir çerçeveden analiz etmektedir. Küresel çerçeve 37 Avrupa ülkesini ve yerel çerçeve 81 Türk şehrini içermektedir. Çalışma, Şubat 2020'den Ocak 2022'ye kadar insanların günlük hareketlilik kayıtlarını takip etmektedir. Analizler, bireylerin “uygun” hareketlilik davranışlarını kolaylaştıran veya engelleyen, ülkelerdeki mevcut ekonomik fırsatları -makro ölçekte- anlamak için yapılmıştır ve enfeksiyon riskine ve hükümet politikalarına rağmen çalışmak için işe gidip gelmesi gereken nüfusun payına odaklanmaktadır. Sonuçlar geliri, eğitim düzeyi ve doğumda yaşam beklentisi yüksek olan bölgelerdeki çalışanların işyeri hareketliliğini; geliri, eğitim düzeyi ve doğumda yaşam beklentisi düşük olan bölgelerdeki çalışanlara göre daha fazla azaltabildiklerini göstermektedir. Bu nedenle, Avrupa ve Türkiye şehirlerindeki ayrıcalıksız nüfuslar Covid-19’a karşı daha yüksek sağlık risklerine maruz kalmıştır.

Anahtar kelimeler: Uzaktan Çalışma, Hareketlilik, Covid-19, Fırsat Eşitliği

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LIST OF ABBREVIATIONS

GDP	Gross Domestic Product
HDI	Human Development Index
ICT	Information and Communications Technology
IOP	Inequality of Opportunity
LAC	Latin America and the Caribbean
OLS	Ordinary Least Squares
PIAAC	The Programme for the International Assessment of Adult Competencies
SME	Small and Medium-Sized Enterprises
UK	United Kingdom
UNDP	United Nations Development Programme
US	United States

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1 INTRODUCTION

When the first Covid-19 case was announced in Turkey, the government reacted with such measures as curfew, lockdowns, and many workplaces were forced to cease operations to tackle the new threat. At the same time, public and private institutions took urgent precautions to handle the spread of the virus. Institutions switched to the remote working model to keep employees away from the places at risk of the virus, which was new to most institutions' traditional working styles.

Although remote working has already been practiced as a way of working for some limited job types, it has become one of the necessary measures taken with the onset of the pandemic. To reduce the risk of infection by keeping people out of collective work environments, most public and private institutions tried to integrate and adapt the work-from-home model to their organizations. Due to recent advancements in digital connectivity, this model has accommodated well to some job types. Beňo (2021) discusses the advantages of recent developments in ICTs on remote working practices during Covid-19.

The work-from-home model amounts to carrying out work without the need to be present at a venue or co-locate with colleagues in an office. However, the jobs that require intensive face-to-face interaction have been deprived of this opportunity. Therefore, it is plausible to infer that the suitability for remote work has amplified inequalities in the labor market. This study aims to determine the inequality of opportunity that comes with this working style and analyze its impact. The opportunity, in this case, is considered as the opportunity of reducing workplace mobilities, therefore, reducing the risks of infection and corresponding health hazards. Because, mobility reduction is important to decrease infection rates (Cot et al, 2021).

In this thesis, mobility (especially workplace mobility) data provided by Google - Covid-19 Community Mobility Reports are used to determine countries' and cities' eligibility for remote work. Next, other socioeconomic indicators which represent wealth, health, and education levels are used to understand the reasons behind regional disparities in workplace mobility reduction. Analyzes are conducted in global and local frameworks. The global framework is studied at the country level and comprised of 37

European countries. The local framework is examined at the city level and included 81 cities in Turkey. The analyzes consist of graphs of average mobility percentage change by weekdays, before/after the first case, and socioeconomic indicators; simple regression models of mobility and random effect regressions between workplace mobility and socioeconomic indicators for waves; descriptive statistics and correlation matrix of independent variables (socioeconomic factors such as income and education level).

Global and local analysis put forth that workforce in regions with low wealth, education, and health level reduced their workplace mobility lower during the Covid-19 pandemic. Therefore, they were more exposed to health hazards.

This thesis is organized as follows: second chapter introduces literature on human mobility, mobility in the Covid-19, and equality of opportunity on mobility; third chapter explains the theoretical framework of this thesis; fourth chapter reveals methods used in the analysis; fifth chapter presents datasets used in analysis and visualizations; sixth chapter includes results of local and global analysis; seventh chapter discusses the finding and the study is concluded in eighth chapter.

2 LITERATURE REVIEW

2.1 Human Mobility

Previous literature shows that human mobility has a socioeconomic dimension, where class-based heterogeneities are often observed in commuting as well as daily mobility flows (Xu et al., 2018; Pappalardo et al., 2015; Hanson, S., & Hanson, P., 1981). For instance, a study conducted by Gonza´lez, Hidalgo, & Baraba (2008), which examines the individual human mobility pattern, reveals a spatial and temporal regularity in human mobility where individuals act in harmony with simple, reproducible patterns. They suggest that this natural harmony in individuals' mobility patterns allows us to understand and foresee all phenomena driven by human mobility. Song et al. (2010) also finds out that potential human mobility can be predicted at 93%. In this regard, examining the socioeconomic variation in human mobility patterns, Li et al. (2021) study the mobility behavior of different social classes. They argue that blue-collar workers commute longer distances than white-collar workers. Moreover, migrant workers live closer to work than local workers, irrespectively of their social class. Another study suggests that in disadvantaged regions characterized by weak job accessibility and low rent, workforce commute longer (Zhao & Cao, 2020). Similarly, Lotero, Hurtado, Floría, & Gómez-Gardeñes (2016) examine the uneven variation in spatial and temporal mobility patterns between different socioeconomic groups. They show a significant relationship between the mobility flows and socioeconomic conditions of groups. The study highlights that the early morning activities are delayed as the economic well-being of populations increases, and in wealthy regions, the spatial mobility pattern is more localized. Another study analyzing the association between the U.S. commuting patterns and local economic growth indicates a significant relationship between higher in and out commuting entropies and lower per capita income growth (Han, Findeis, & Brasier, 2010). In other words, there is higher mobility in places where income per capita is lower.

2.2 Mobility and Covid-19

The literature now offers a few papers studying the relationship between mobility and the Covid-19 period. For instance, a study examines human mobility in the first phase of the Covid-19 pandemic from a global perspective and the regional impacts of government policies and regulations against the epidemic (Mendolia, Stavrunova, & Yerokhin, 2021; Rapa, 2021). In the study, the stringency index is used to measure the government policies, and Google human mobility dataset is used to understand human mobility patterns during this period. The paper suggests that the information about the spread of pandemics (the speed and number of cases) are drivers of mobility patterns, and government interventions are responsible for the majority of the reduction in human mobility. Similarly, Sulyok & Walter (2020) highlights the negative correlation between mobility and Covid-19 case incidence in industrialized countries of Western Europe and the North Americas. Another study by Nouvellet et al. (2021) investigates the effectiveness of mobility restriction policies on virus transmission. They show that mobility is one factor that affects the spread of the virus. However, the study highlights that the model's predictive ability decreased after the relaxation of mobility restrictions. In other words, mobility becomes a poor predictor of viral transmission after returning to less strict measures against mobility. Engle, Stromme, & Zhou (2020) examine the association between Covid-19 infection levels, stay-at-home measures, and individual mobility in the U.S. states. The study reveals that the decline in human mobility is associated with local infection levels and official mobility interventions in the U.S. Additionally, Badr et al. (2020) indicates the relationship between declined Covid-19 case growth rates and mobility level. Moreover, Yilmazkuday (2021) put forth the impacts of mobility on Covid-19 deaths and cases.

A few papers study the long-term mobility trajectories as a response to public measures and the spread of the virus. For instance, Kim & Kwan (2021) analyze changes in human mobility during the Covid-19 pandemic. They incorporate such relevant factors as social, political, and policy interventions in their model. The findings indicate that while mobility decreased at the first pandemic stage (March – April 2020), it turned back to its pre-covid levels from April 2020 to June 2020. In their study of human mobility during Covid-19, Zhao et al. (2020) show that people have similar mobility patterns during the quarantine period despite a few differences across states. The study shows that after the first official closing, although none of the states announced the reopening, people showed a similar mobility pattern by increasing their mobility by the end of quarantine. The authors explain this behavior as “quarantine fatigue.” Another study discusses the term social distancing inertia. It declares that after the announcement of the pandemic, the level of Covid-19 cases has had a natural impact on the decrease of human mobility without a need for government intervention (Ghader, et al., 2020). However, they also observe that the decrease in human mobility slows down after two weeks despite increasing Covid-19 cases. The study that analyzes the human mobility dynamics in Colombia, Mexico, and Indonesia empirically shows that mobility restriction measures effectively reduce human movements (Fraiberger, et al., 2020).

2.3 Equality of Opportunity and Mobility

In this section, a literature review on the relationship between mobility and socioeconomic is provided. Several papers have shown that different social classes have had varying levels of health risks and opportunities during the pandemic (Levin et al., 2021; Matekenya et al., 2021). For example, a study conducted by Coven & Gupta (2020) investigates the demographic factors that play a role in mobility inequalities in response to the Covid-19 epidemic, especially sheltering options within cities. They found that in low-income residences, mobility to the workplace in low-income residences was high, and their level of staying at home was lower during non-work hours. On the other hand, people were more likely to leave cities for rich neighborhoods where the outbreak was intense. Additionally, Jay et al. (2020) found out that residents of high-income neighborhoods increased stay-at-homee level more than residents of low-income neighborhoods and individuals in low-income neighborhoods were more likely to work outside the home in the U.S.

Another study examines the effectiveness of stay-at-home orders among economic groups in the US. A county-level analysis of the impact of social distancing policies across economic groups shows that low-income communities are from 46% to 54% more mobile than high-income communities (Lou, Shen, & Niemeier, 2020). Their results also show that the policies don’t significantly reduce the mobility to work in low-income counties. Hatayama, Viollaz, & Winkler (2020) examines whether the level of economic development impacts the suitability of jobs for remote work. Their results show that since the jobs in developing countries require more manual tasks and less information technology usage, jobs are less amenable to remote work in economically less developed countries. The study also states that college graduates have jobs more suitable for remote work than their less-educated fellows and emphasizes the strong relationship between education level and amenability to remote work. Similarly, Do Lee et al. (2021) reveal the strong correlation between mobility reduction and socioeconomic status through occupation and income in England. In Turkey, the study conducted by Şeker, Özen, & Erdoğan (2020) analyzes the amenability of jobs for remote work among sectors. They find that while jobs in the ICT and finance sectors are more amenable to work from home, jobs in textile and apparel, accommodation and food, and leather sectors are less amenable. They also denote that only %10 percent of people can work from home in Turkey. Another study that discusses how many jobs are feasible for working from home indicates that countries with poor economies have less share of jobs suitable for remote work in their workforce (Dingel & Neiman, 2020).

Clearly, the industry and education level also determine remote working opportunities. A study (Gauvin et al., 2021) reveals that variation in mobility reduction is associated with educational attainment. Mongey, Pilossoph, & Weinberg (2020) investigate the characteristics of workers who work in jobs that are vulnerable to working from home and require physical proximity to other people. The study reveals that workers who are less educated and gain low wages are more economically vulnerable to social distancing policies. Few studies reveal that the job content of the same jobs differs across countries due to the level of development (Lo Bello et al., 2019; Hardy et al., 2018). Therefore, the same jobs may require higher face-to-face interaction or a high need for physical presence in countries where technology adoption is lower.

A study conducted by Pullano, Valdano, Scarpa, Rubrichi, & Colizza (2020) focuses on France during the Covid-19 pandemic and evaluates the impact of socioeconomic and demographic factors on human mobility. The study exposes that lockdown causes a 65 % decrease in general mobility. In association with workers in different sectors and variations in socioeconomic factors, mobility is disproportionately distributed in different regions. They also suggest that lockdown was beneficial to reducing human mobility; however, policy announcement timing impacted population mobility behavior. Therefore, their findings indicate that proper policies and policy communication should be considered while fighting the epidemic. Another study that analyzes changes in human mobility during the Covid-19 pandemic illustrates a significant relationship between mobility change and the strictness of the government's mobility restriction policies and poverty level (Kim & Kwan, 2021). The study includes survey results of 5000 working-age adults. It reveals that 35.2 % of the sample worked from home in May 2020 and the rate of remote work increased by 27-point by February 2020. Moreover, the survey also shows that high–income and well-educated individuals were much more suitable to shift remote working and had a lower risk of losing employment during the outbreak. Additionally, 71.7 percent of US workers could work from home effectively.

The study documented by Dueñas, Campi, & Olmos (2021) assesses how socioeconomic conditions affect mobility patterns. They emphasize the relation between socioeconomic factors and responses to restriction policies and reveal that while the mobility flow was higher in populations with better socioeconomic conditions before the outbreak, the decline in mobility was lower in populations with worse socioeconomic conditions. Another study that examines the socioeconomic gap in human mobility decline during the Covid-19 outbreak reveals that mobility reduction is associated with the wealth level of the population (Fraiberger, et al., 2020). The study stressed that mobility reduction in the top decile of wealth groups was higher than twice of the bottom decile of wealth groups.

3 THEORETICAL FRAMEWORK

As a normative framework of inequality, inequality of opportunity (IOP) argues that individuals should not be held responsible for the factors beyond their control and effort (Roemer, 1998). These factors are exogenous to individuals and include such circumstances as gender, race, ethnicity, and family background (Niehues et al., 2014; Türk and Östh, 2019). There have already been several studies estimating and revealing unfair inequalities in several countries and also across countries from a comparative perspective (Birdsall, 1998). The inequality of opportunity concept is quite popular, and there is great interest in the theory both in the scientific world and in politics. Even though the literature on IOP is still highly active and many new works are being produced, there may be little to explore from a theoretical perspective. However, the Covid-19 pandemic has brought about new inequalities, especially unfair inequalities that are not fully accounted for by even the most comprehensive theories, such as inequality of opportunity.

During the pandemic -despite governmental policies targeted to reduce human mobility- workers of specific industries and social classes had to commute to work. They, therefore, were subject to a greater risk than those who could work from home. Given the high risk of exposure and corresponding fatalities (almost 5.5 million worldwide total deaths at the end of the year 2021), it becomes clear that commuting has not been voluntary nor could be overcome by any effort. Therefore, it can be argued that the captive commuters (Jensen, 2009; Toger et al., 2021) have been subject to unfair health inequalities during Covid-19; hence, a new type of inequality of opportunities has emerged during the pandemic. A part of the inequality of opportunity may have been explained by income, where wealthier segments of the society could benefit from remote working opportunities and the level of education with a similar mechanism. This thesis focuses on the inequality of opportunity in health during the pandemic. The opportunity, in this case, is understood as the ability to reduce work mobility and commuting.

In the following chapters, the theoretical suggestion and hypothesis of the thesis are tested. The next two chapters introduce the methods and datasets, and the last two chapters discuss the results and provide conclusions.

4 METHODS

In this section, the empirical models are presented. The regression framework starts with simple models of the relationship between mobilities and socioeconomic variables. A univariate regression (simple model) can be specified as follows:

(Eq.1)

$$M_i = \beta_i + x_i + \varepsilon_i$$

where M_i denotes mobilities including general mobility, mobility towards workplaces, parks ,etc. in location i . x_i is a socioeconomic variable such as GDP per capita, mean years of schooling, life expectancy at birth, and human development index in location i. Finally, β_i and ε_i are intercept and error terms, respectively. Simple models are useful for understanding the interplay between mobilities and one explanatory variable. In this case, the regression coefficients are plotted to test the theoretical framework of the thesis and will be used as a benchmark for motivating the following more sophisticated model of mobilities.

To examine the determinants of mobility behavior in the Covid period, we specify the following full models of mobility:

(Eq.2)

$$M_{it} = \beta_i + \gamma_t + \sum_{a=1}^{m} \alpha_a SOC_{ait} + \sigma Pol_{it} + \sum_{b=1}^{n} \delta_b COV_{bit} \, \delta_b + \varepsilon_{it}$$

where M_{it} is the mobilities (to workplaces or other points of interest) in country (or city) i on day t, and β_i and γ_t are intercept and day of the week fixed effects, SOC_{it} are covariates for socioeconomic conditions in location i (GDP per capita, mean years of schooling, Gini index of inequality etc.), Pol_{it} indicate the policy stringency, COV_{it} are Covid-19 related variables such as daily cases, deaths and a count of days passed since the first recorded case, and governance index in location i. ε_{it} is the residuals of the model. Finally, α, σ and δ are parameters to be estimated. It is plausible to assume that the mobility behavior will differ between weekdays and weekends. This argument is especially relevant for analyzing workplace mobility and teleworking opportunities. Therefore, socioeconomic variables: GDP per capita, mean years of schooling, and human development index are interacted with the dummy variable indicating weekends. This way, the analyzes can predict whether the observed mobilities are behavioral or enforced by the needs of commuting. In affluent locations and locations with a high share of a highly educated population, the differences between weekday and weekend mobilities should be elevated owing to teleworking opportunities on weekdays so that the distinction regarding mobilities between working days and holidays disappears. Meanwhile, the differences between weekday and weekend mobilities should be more minor in cities and countries characterized by low income and education levels.

Eq.1 and Eq.2 will be estimated with OLS regression. More specifically, by a random-effects model as suggested by the Hausman test. The following section presents the dataset used in the analysis.

5 DATASETS

This section presents data sources and corresponding descriptive statistics. Community Mobility Reports include daily human mobility changes for regions since the date when Covid-19 cases started to appear. The data consists of mobility trends of 135 countries, their cities, and districts. Mobility change is presented from six different aspects: retail and recreation percent change, grocery and pharmacy percent change, parks percent change, transit stations percent change, workplaces percent change, and residential percent change. The data shows how visit volume and stay duration changed in regions and specified place categories compared to baseline days. Baseline day is determined as the median value from January 3, 2020, to February 6, 2020, and daily percent changes of mobility to categorized places are calculated based on the baseline. The data used in the analyzes show the mobility change between February 15, 2020, and December 26, 2021. Additionally, average mobility is calculated by taking the mean of the aforementioned six categories of mobility to be used in the analysis.

The Oxford Covid-19 Government Response Tracker (OxCGRT) collects data on measures that governments take in response to the Covid-19 pandemic. The data includes policy measures across 20 indicators. These are school closing, workplace closing, canceling public events, restrictions on gatherings, closing public transport, stay-at-home requirements, restrictions on internal movement, international travel controls, income support, debt/contract relief, fiscal measures, international support, public information campaigns, testing policy, contact tracing, emergency investment in healthcare, investment in vaccines, facial coverings, vaccination policy, protection of elderly people. Aggregating the 20 indicators, five common indices are constituted to state level of government responses with numbers from 1 to 100.

The stringency index evaluates the strength and strictness of measures taken by governments of 184 countries, limiting citizens' behavior and state level of government responses with numbers from 1 to 100. It is calculated by considering nine topics of measures and presented daily. The nine metrics policies include school closing, workplace closing, canceling public events, restrictions on gatherings, closing public transport, stay-at-home requirements, restrictions on internal movement, international travel controls, and public information campaigns. The data stringy index calculations start from the dates when governments started to take measures for the fight against the Covid-19 pandemic separately for each country. To be used in the analysis, the stringency index is re-calculated by excluding workplace closing measures and following Oxford Covid-19 Government Response Tracker's method of stringency index calculation.

The complete Covid-19 dataset is a collection of the Covid-19 data maintained by Our World in Data. It consists of 67 different variables for several countries, including total cases, new cases, new deaths, population, etc. Case records start for each country from the release date of the first case confirmation and are updated daily. Variables such as population consist of the most recent values for countries. Our World in Data collects the Covid-19 cases data from Covid-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University; population data from the United Nations, Department of Economic and Social Affairs, Population Division, World Population Prospects 2021.

The human development index with its indicators, life expectancy at birth, and mean year of schooling are taken from the UNDP Human Development Reports in 2020. Human Development Index measures the average achievement of human development in three dimensions: standard of living, health, and education. Life expectancy at birth is the number of years a newborn will expect to live. Gini index and GDP per capita are extracted from The World Bank, and their values consist of the available values of the most recent year for each country. The Gini index represents the wealth inequality within social groups or nations. It takes a value between 0 corresponds to perfect equality, and 100 corresponds to perfect inequality.

The Life Index in Provinces dataset published by the Turkish Statistical Institute in 2015 is used in the local analysis. The dataset covers eleven dimensions of life and consists of 41 indicators. It includes income and wealth, education, working life, civic engagement, health, social life, security, housing, environment, access to infrastructure services, and life satisfaction. The index takes a value between 0 and 1, and the closer it is to 1, the better the life level is. The indicators used in the analysis are employment rate, life expectancy at birth, income wealth index, education index, and civic engagement. The city population dataset is taken from the Turkish Statistical Institute and belongs to 2020. Additionally, HDI is calculated for cities of Turkey by taking the geometric mean of three-dimensional indices; life expectancy at birth for health, income wealth index for the standard of living, and education index for education.

The Governance Score is explained as the framework given by government investments and policies and consists of physical indicators like infrastructures and non-physical attributes like exposure to financial risks, business legislation, etc. The data is from the Global Sustainability Competitiveness Index, 2020, prepared by Solability.

In addition to all these datasets, case day count dummy, weekend dummy, wave dummy, cases dummy, metropolis dummy, and new deaths/population lag variables are composed. Wave dummy determined separately for global and local analysis based on the trend of daily new cases as shown in Figure 6.1.1 and Figure 6.2.2. The peak point of the new cases is determined as the separation points of waves. A Metropolis dummy is used in local analysis to show whether the city is a metropolis or not. The cases day count variable counts the days from the day the first Covid-19 case is announced for all countries. Cases dummy shows whether there is a confirmed Covid-19 case for each country. The new deaths/population lag variable is composed by dividing the number of new deaths by population and taking a seven days lag of it.

Descriptive statistics of global analysis' independent variables are shown in Table 5.1. While the average HDI is 0.88 in Europe, the mean years of schooling vary between 9.26 and 14.15 across European countries. There are also substantial differences in the governance index with a standard deviation of 4.99.

Table 5. 1 Europe Descriptive Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
HDI	0.88	0.06	0.75	0.85	0.89	0.93	0.96
Mean Year of Schooling	11.99	1.10	9.26	11.36	12.31	12.69	14.15
Governance Score	60.69	4.99	50.47	56.96	60.75	63.92	69.36
New Deaths/Population Lag	0.32	0.52	-4.10	0.01	0.10	0.41	10.46
GDP per Capita	10.11	0.91	8.20	9.61	10.07	10.80	12.11
Life Expectancy at Birth	79.35	3.46	71.90	76.05	80.90	82.25	83.78
Recalculated Stringency Index	51.39	20.54	0	39.6	51.0	66.7	100
Gini	31.21	4.06	24.60	27.60	30.80	34.70	41.30

The correlation matrix of global analysis' independent variables is shown in Table 5.2. The matrix shows that the HDI and daily Covid-19-related mortality are negatively and significantly correlated. Additionally, there is a significant and positive correlation between Gini and Covid-19-related mortality. On the other hand, GDP per capita, life expectancy at birth, and mean years of schooling are considered the components and have a positive significant correlation to the 0.001 significance level.

Table 5. 2 Europe Correlation Matrix of Independent Variables

	HDI	Mean Year of Schooling	Governance Score	New Deaths/Population Lag	GDP per Capita	Life Expectancy at Birth	Recalculated Stringency Index	Gini
HDI		0.556^{***}	0.364^{***}	-0.192^{***}	0.788^{***}	0.845^{***}	0.215^{***}	-0.140^{***}
Mean Year of Schooling	0.556^{***}		0.351^{***}	-0.123^{***}	0.427^{***}	0.088^{***}	0.041^{***}	-0.279^{***}
Governance Score	0.364^{***}	0.351^{***}		0.032^{***}	0.198^{***}	0.244^{***}	0.083^{***}	-0.068^{***}
New Deaths/Population Lag	-0.192^{***}	-0.123^{***}	0.032^{***}		-0.188^{***}	-0.154^{***}	0.135^{***}	0.085^{***}
GDP per Capita	0.788^{***}	0.427^{***}	0.198^{***}	-0.188^{***}		0.701^{***}	0.107^{***}	-0.018^{**}
Life Expectancy at Birth	0.845^{***}	0.088^{***}	0.244^{***}	-0.154^{***}	0.701^{***}		0.220^{***}	-0.054^{***}
Recalculated Stringency Index	0.215^{***}	0.041^{***}	0.083^{***}	0.135^{***}	0.107^{***}	0.220^{***}		0.026^{***}
Gini	-0.140^{***}	-0.279^{***}	-0.068^{***}	0.085^{***}	-0.018^{**}	-0.054^{***}	0.026^{***}	

Computed correlation used pearson-method with listwise-deletion.

Descriptive statistics of local analysis' independent variables are shown in Table 5.3. While the average HDI is 0.67 in Turkey; the income/wealth index varies between 0.02 - 0.88, the education index varies between 0.10 - 0.75, and life expectancy at birth varies between 74.95 - 80.5 across cities in Turkey. There are also substantial differences in employment rate with a standard deviation of 6.15.

Table 5. 3 Turkey Descriptive Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
HDI	0.67	0.25	0.00	0.58	0.77	0.85	1.00
Income/Wealth Index	0.40	0.17	0.02	0.31	0.44	0.52	0.88
Education Index	0.53	0.14	0.10	0.48	0.57	0.63	0.75
Life Expectancy at Birth	78.14	1.03	74.95	77.54	78.00	78.70	80.50
Civic Engagement	0.42	0.11	0.10	0.38	0.43	0.47	0.80
Employment Rate	46.20	6.15	27.80	43.50	47.20	49.90	59.10
Recalculated Stringency Index	61.17	17.25	0.00	52.08	65.10	72.92	85.42

The correlation matrix of local analysis' independent variables is shown in Table 5.4. The matrix shows that the HDI and employment rate are positively and significantly correlated. Additionally, there is a significant and positive correlation between the employment rate and civic engagement. On the other hand, income/wealth index, life expectancy at birth, and education index are considered as the components of HDI and they have a positive significant correlation on the 0.001 significance level.

Table 5. 4 Turkey Correlation Matrix of Independent Variables

	HDI	Income/Wealth Index	Education Index	Life Expectancy at Birth	Civic Engagement	Employment Rate	Recalculated Stringency Index
HDI		0.937***	0.887***	0.290***	0.596***	0.473***	-0.005
Income/Wealth Index	0.937***		0.704***	0.236***	0.543***	0.440***	-0.005
Education Index	0.887***	0.704***		0.343***	0.567***	0.437***	-0.004
Life Expectancy at Birth	0.290***	0.236***	0.343***		0.083***	-0.022***	-0.001
Civic Engagement	0.596***	0.543***	0.567***	0.083***		0.308***	-0.004
Employment Rate	0.473***	0.440***	0.437***	-0.022***	0.308***		0.002
Recalculated Stringency Index	-0.005	-0.005	-0.004	-0.001	-0.004	0.002	

Computed correlation used pearson-method with listwise-deletion.

6 FINDINGS

6.1 Global Framework

The global analysis is divided into three parts by considering the change in the number of daily new cases in Europe. The dataset used in the global analysis consists of 37 European countries. Initially, the analysis is conducted for a full period from February 15, 2020, to the end of the year 2021. Following that, the analysis separated into two from the first peak point, which corresponds to November 02, 2020, as shown in Figure 6.1.1.

Figure 6.1. 1 Europe Daily New Cases

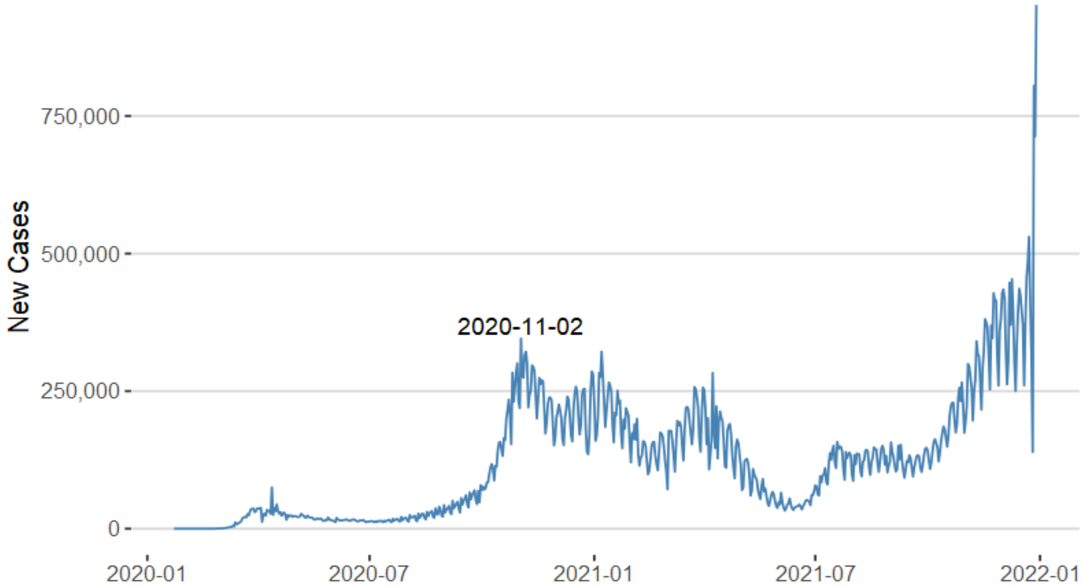


Figure 6.1.2 presents Europe's country-level distribution of mobility, wealth, health, and education indicators. It explicates the negative relation between socioeconomic indicators (GDP per capita, mean years of schooling, life expectancy at birth, and HDI) and workplace mobility during the Covid-19 pandemic. We see that the workforce in countries with high levels of the aforementioned socioeconomic indicators such as the U.K., France, Germany, Norway, Sweden, and Finland was able to reduce their workplace mobility higher.

Figure 6.1. 2 Europe Maps for Mobility Variables and Education, Wealth and Health Indicators

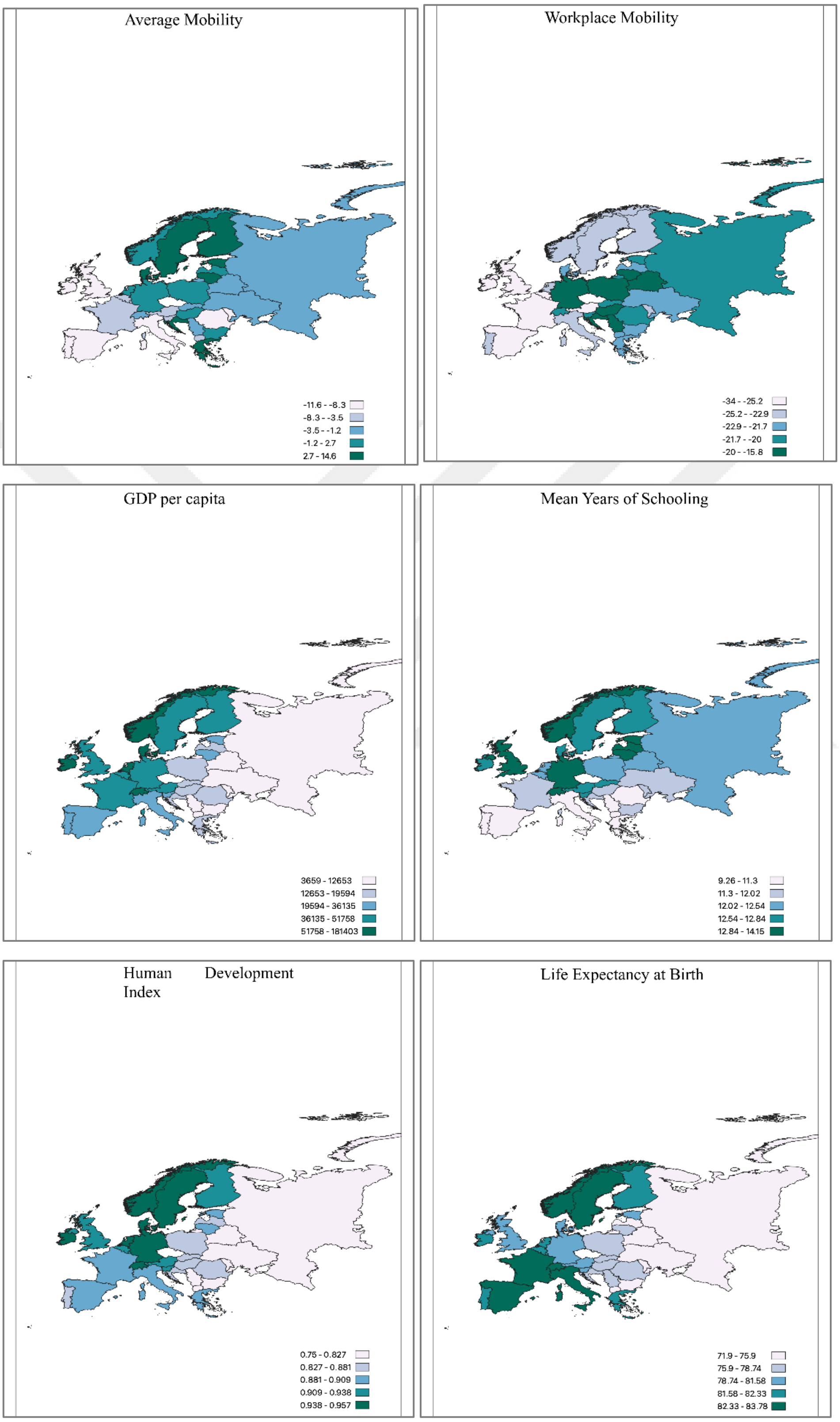


Figure 6.1.3 shows the average mobility percent change by weekdays and income levels in Europe. Y-axis values are the arithmetic means of mobility for the period from the date the first Covid-19 case is announced to the end of the year 2021. Level 5 refers to the highest, and level 1 refers to the lowest range. The graph shows that high-income countries in Europe decreased their workplace and transit station mobility higher than low-income countries on weekdays. In contrast, their parks and residential mobility rose higher based on the baseline month of January 2020 on both weekdays and weekends. On the other hand, while low-income groups' weekend parks and residential mobility exceed weekdays, high-income groups' weekday parks and residential mobility exceed the level of weekends.

Figure 6.1. 3 Average Mobility Percentage Change by Weekdays and Income Levels in Europe

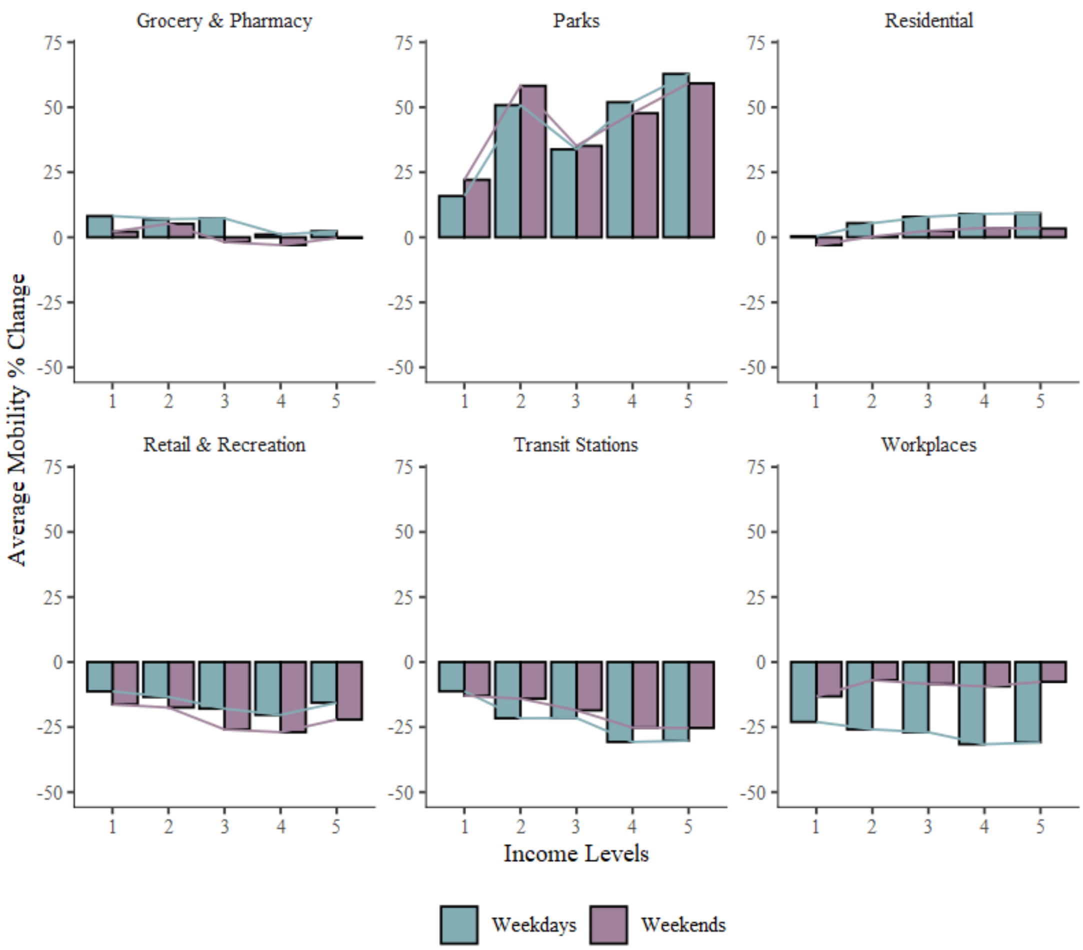


Figure 6.1.4 shows the average mobility percentage change by before/after Covid-19 and income levels in Europe and indicates that while people who live in countries with high GDP per capita start declining their workplace mobility before Covid-19's first case announcement, in countries with lower GDP per capita people have higher workplace mobility compared to the baseline month of the pandemic. Additionally, high-income groups decreased their transit station mobility and increased parks and residential mobility much higher after the first case. These results support the idea that economically privileged populations had the flexibility of working from outside of the workplace, either at home or park.

Figure 6.1. 4 Average Mobility Percentage Change by Before/After Covid-19 and Income Levels in Europe

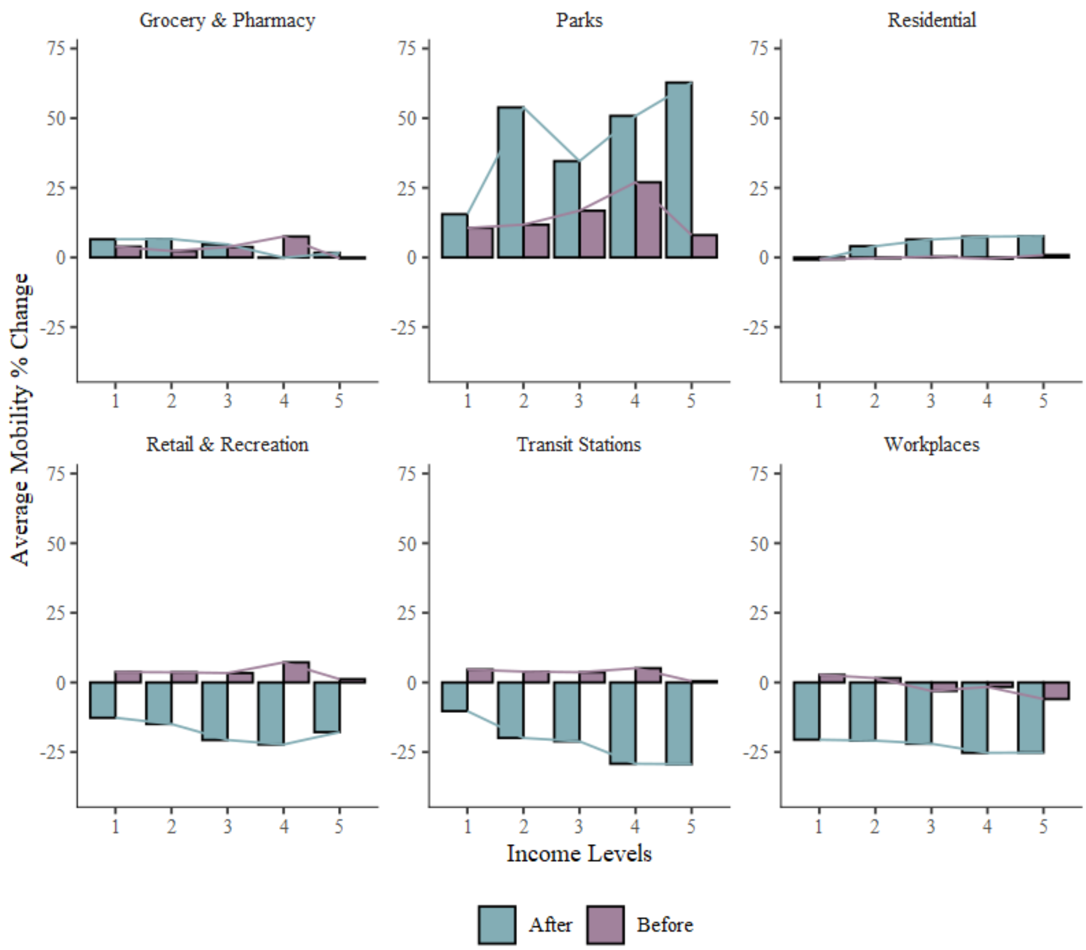


Figure 6.1.5 shows the average mobility percent change by weekend/weekdays and education levels in Europe. Similar to income levels, in countries with high mean years of schooling, people decreased their workplace and transit station mobility higher on weekdays. It can be inferred that highly educated people have suitable jobs for teleworking (Hatayama, et al., 2020). Additionally, their mobility toward parks and residential areas increased higher than in countries with lower mean years of schooling.

Figure 6.1. 5 Average Mobility Percentage Change by Weekend and Education Levels in Europe

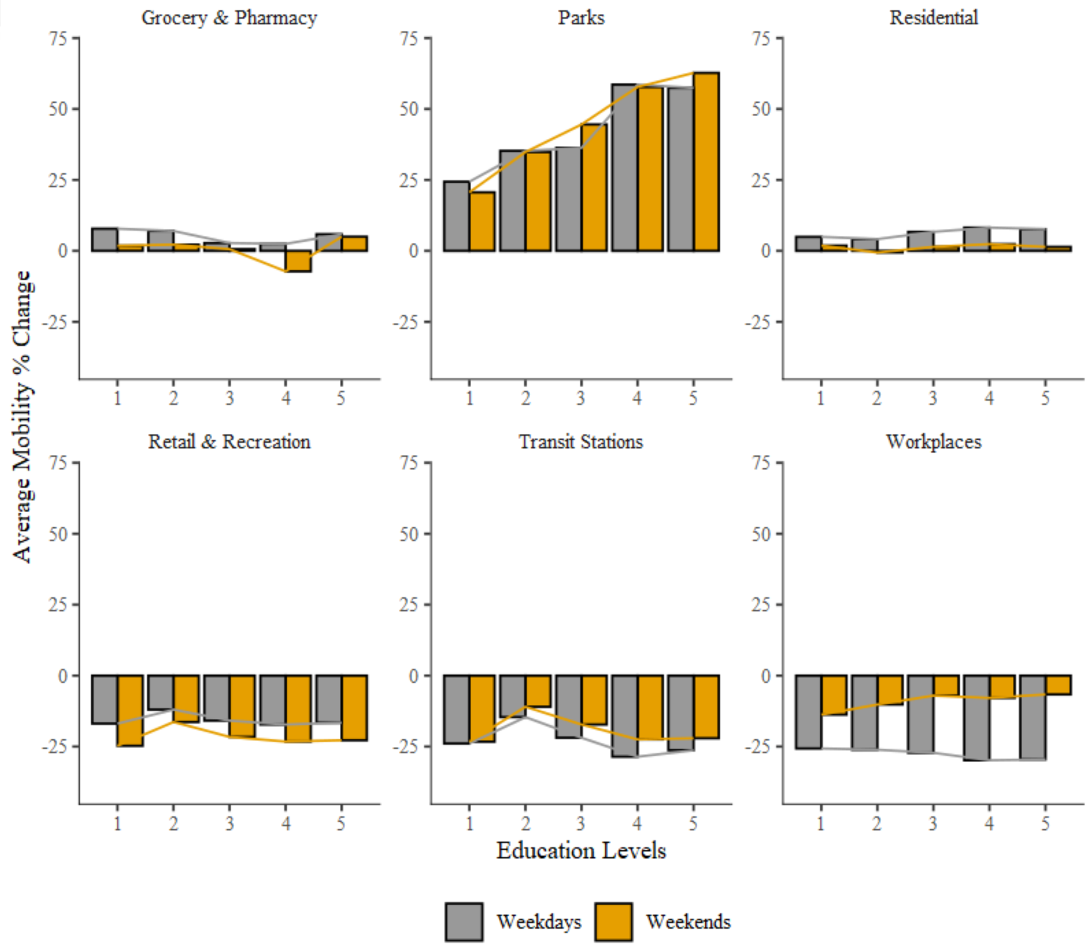
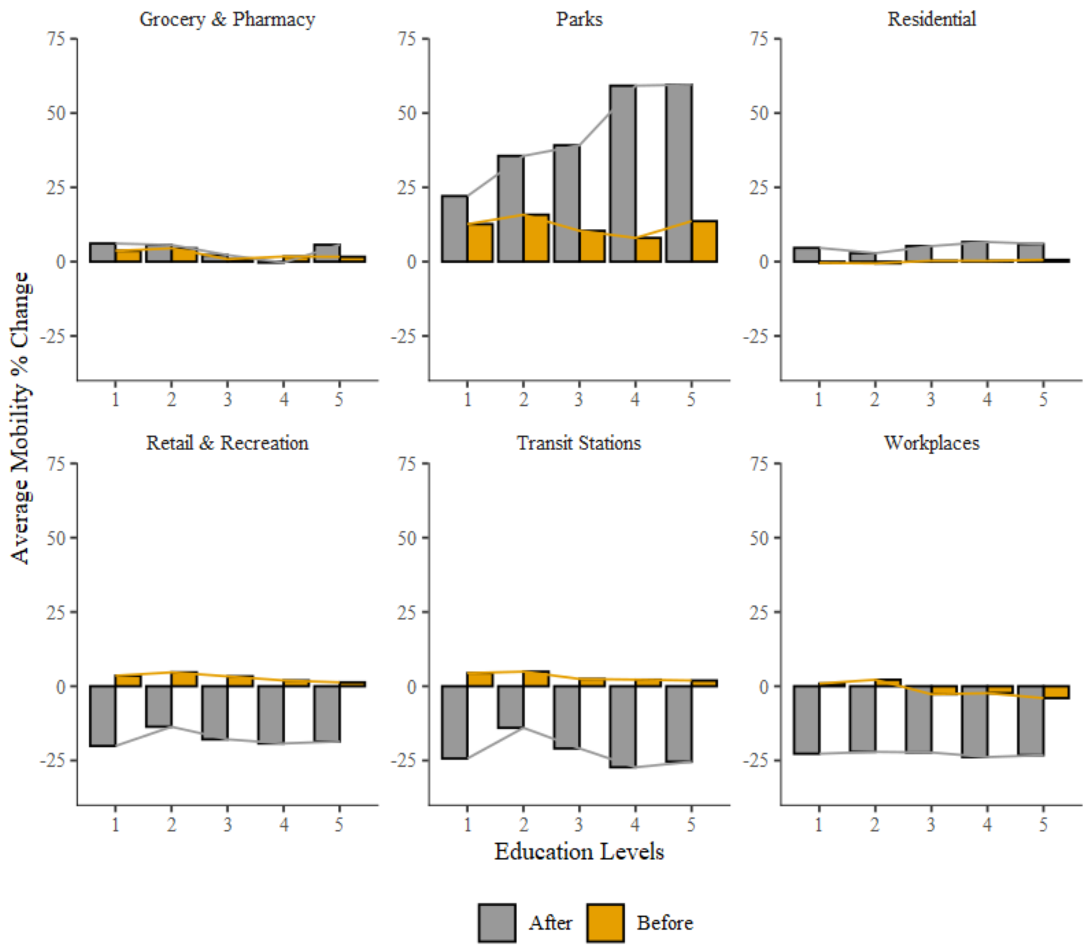


Figure 6.1.6 shows the average mobility percentage change by before/after Covid-19 and illustrates especially in countries with high mean years of schooling, park mobility goes up after the first case of Covid-19. We see that, albeit, by a small margin, they change their transit stations and residential and workplace mobility more than those with low mean years of schooling.

Figure 6.1. 6 Average Mobility Percentage Change by Before/After Covid-19 and Education Levels in Europe



Overall, the findings support the theoretical framework put forth by this thesis in that while high-income countries and countries with higher human capital were able to reduce their mobility, countries that are characterized by low income (and low education) did not experience the same opportunity. Therefore, a degree of inequality of opportunity in health emerged due to the heterogeneous availability of teleworking opportunities. In particular, the highest income countries could reduce their mobilities toward workplaces by 24.8 %, whereas the lowest quantile could reduce mobilities only by 20.2 %.

6.1.1 *Simple Models of Mobility*

In this section, the output of the estimation results from Equation 1 is plotted and interpreted. The human development index is composed of three dimensions: education, the standard of living, and health. In this section, the relation between mobility trends and the human development index is examined. Secondly, each of the three dimensions is studied separately. At the same time, mean years of schooling are associated with the educational dimension, GDP per capita is determined by the standard of living, and life expectancy is analyzed for the health dimension. Figures 6.1.7, 6.1.8, 6.1.9, and 6.1.10 visualize the relation between mobility and human development index, GDP per capita, life expectancy, and mean year of schooling from a global perspective. Before graphing the relations, first, the mobility is calculated by taking the arithmetic mean of mobility of six given mobility categories for each country for the given date range. Next, the relationship between them is plotted. The exact process is applied to all indexes whose effect on human mobility is examined.

Graphs follow similar human mobility patterns and regression results for the four indexes, and human mobility categories arise in the same direction. Graphs show that as the education level, standard of living, and wealth level is improved in countries, mobility to workplaces and transit stations is reduced. On the other hand, residential and park mobility rise conversely. In detail, a 1% increase in logarithm of GDP per capita causes a 2.09% decline in workplace mobility, a 6.27% decline in transit transition mobility, a 13.7% rise in parks mobility, and a 3.55% rise in residential mobility. A 1 unit increase in the mean year of schooling explains a 0.35% decrease in workplace mobility (there seems to be a negative and weak relation), 1.46% decrease in transit station mobility, 11% increase in parks mobility, and 0.83% increase in residential mobility. A 1 unit increase in life expectancy at birth is associated with a 0.5% decrease in workplace mobility, 1.7% decrease in transit station mobility, 2.47% increase in parks mobility, and 0.83% rise in residential mobility. Overall, as the composition of these three indicators, 1 unit rise in the human development index corresponds to a 29.8% decline in workplace mobility, 104%

decline in transit stations mobility, 250% increase in parks mobility, and 51.7% increase in residential mobility.

It can be inferred from these relations that in countries that are advanced in education, health, and standard of living, the majority of the workforce has jobs suitable for remote work. Consequently, workplace mobility decreases, and residential mobility increases. The study conducted by Hatayama, Viollaz, & Winkler (2020) shows that jobs in economically less developed countries are less amenable to remote work since jobs in developing countries require more manual tasks and less information technology usage.

Figure 6.1. 7 The Relation Between GDP per Capita and Average Mobility Percent Change of Countries in Europe

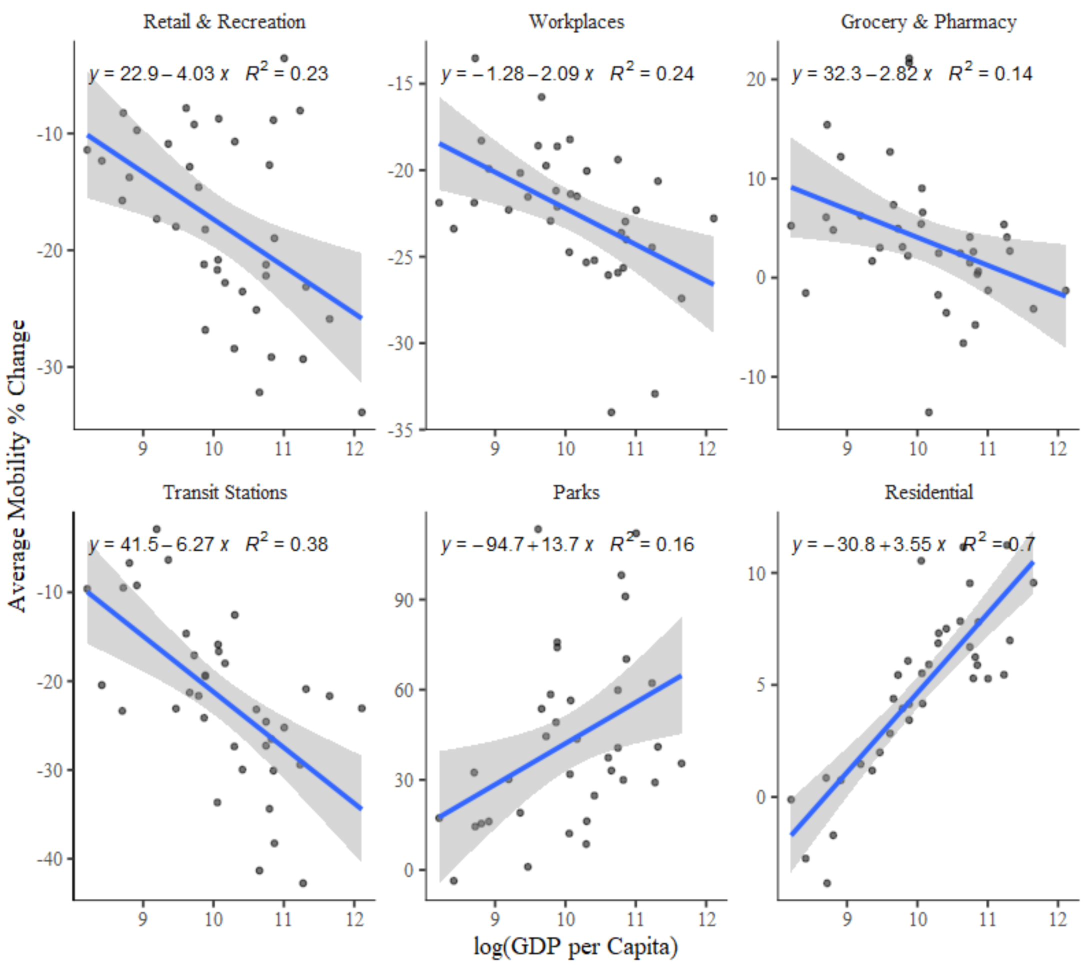


Figure 6.1. 8 The Relation Between Mean Year of Schooling and Average Mobility Percent Change of Countries in Europe

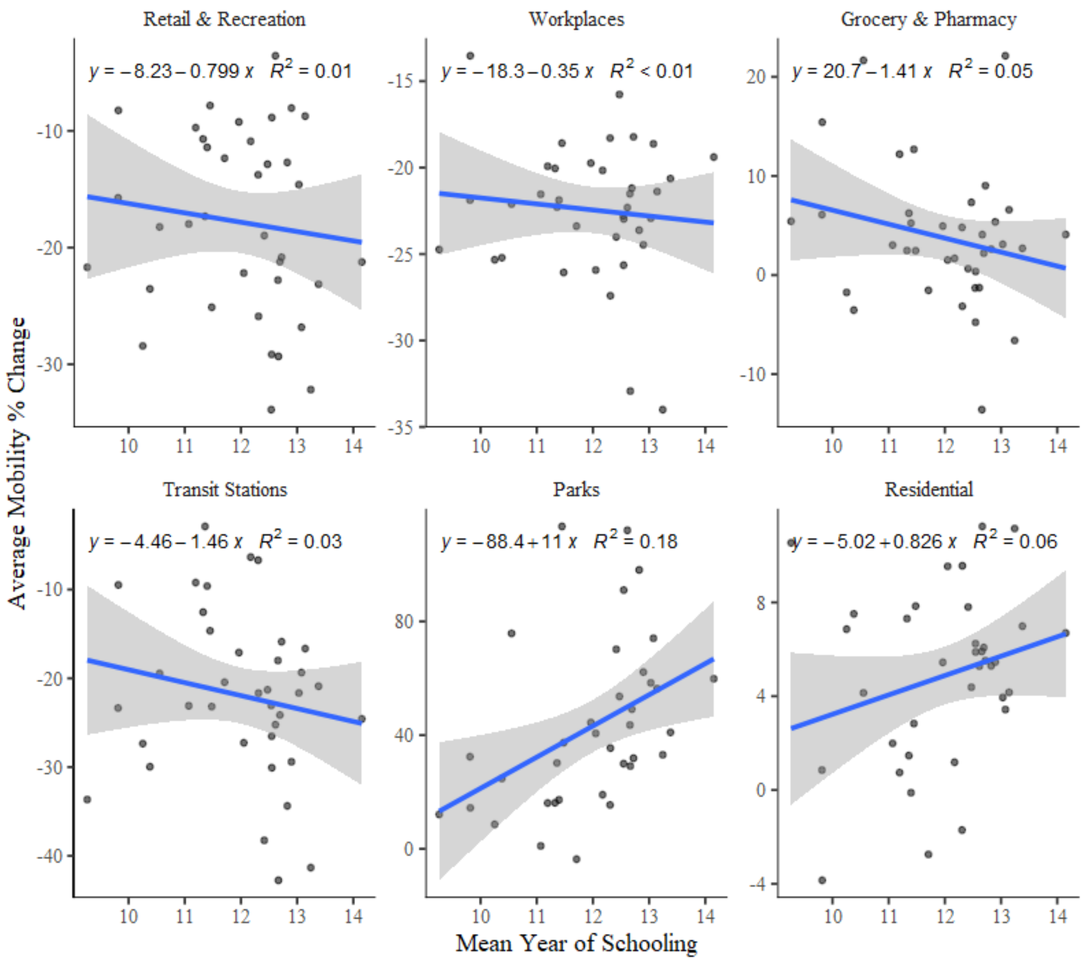


Figure 6.1. 9 The Relation Between Life Expectancy at Birth and Average Mobility Percent Change of Countries in Europe

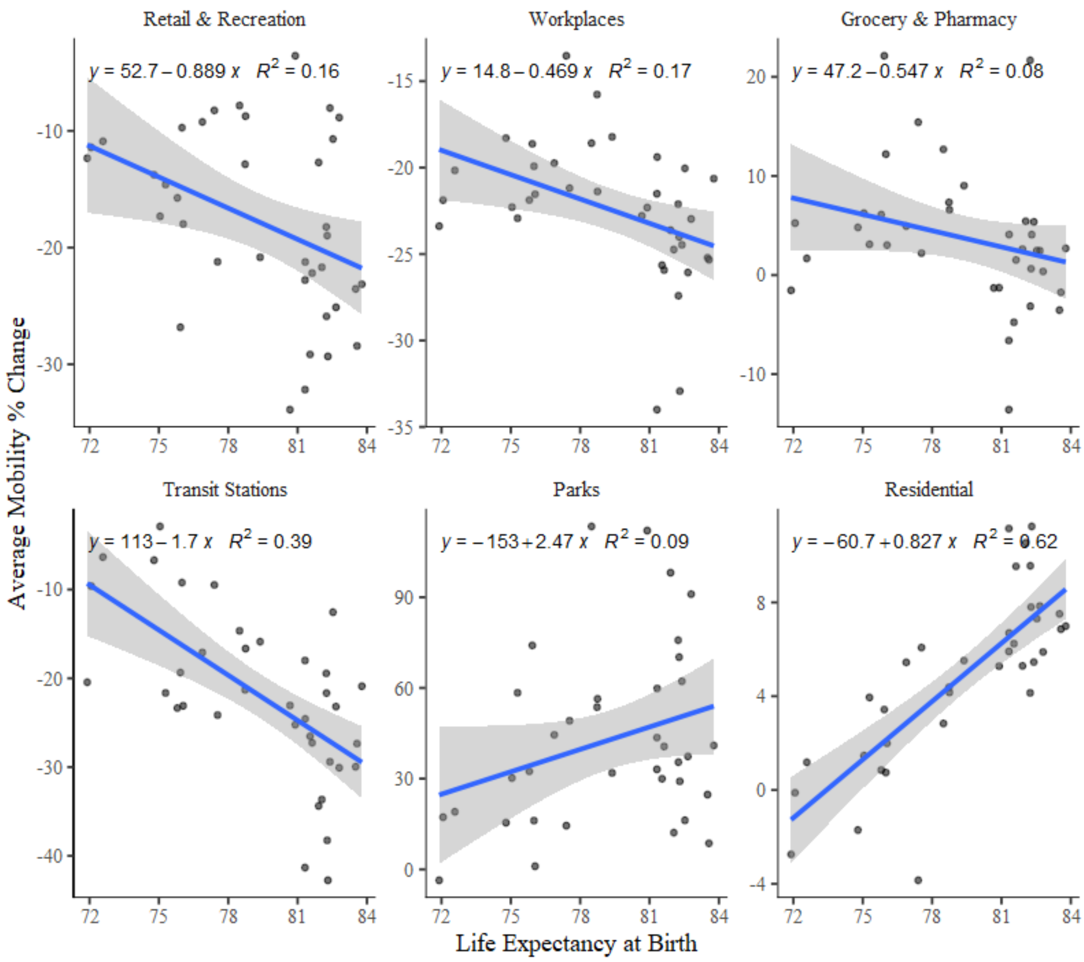
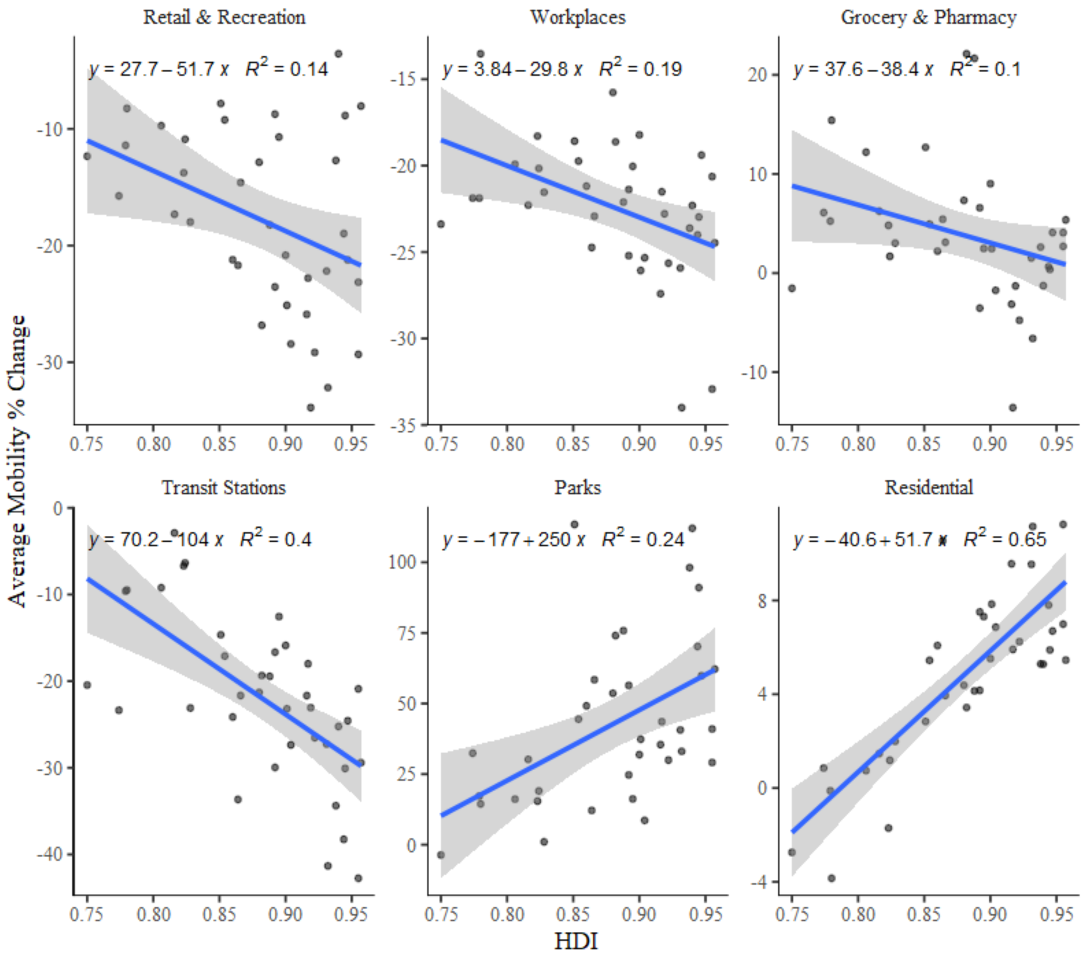


Figure 6.1. 10 The Relation Between HDI and Average Mobility Percent Change of Countries in Europe



6.1.2 *Regression Models*

In this section, the estimation results of Equation 2 are presented. The first output of the full model in Table 6.1.1 shows the negative relationship between GDP per capita and workplace mobility. In other words, people who live in countries with higher GDP per capita were able to decrease their workplace mobility higher. One unit increase in logarithm of GDP per capita is associated with a 2.74 % decrease in workplace mobility. Meanwhile, the poor segment of society was more exposed to the Covid-19 virus. This supports the hypothesis of this thesis and puts forth the uneven effect of the Covid-19 crisis on economically unprivileged populations from February 2020 to the end of the year 2021.

On the other hand, the workforce in human-developed countries declined to commute higher. A 1% rise in the human development index corresponds to a %36.76 decrease in mobility toward the workplace. The human development index gives a generic idea about the effects of the population's income, education, and health level. Therefore, this study examines its indicators' impacts separately to understand their level of influence.

Similarly, in countries with high mean years of schooling, the workforce decreased its workplace mobility and, therefore, was more amenable to remote work, as shown in Table 6.1.1. So, a 1-year increase in European countries’ mean year of schooling has resulted in a %1.49 decrease in commute percent. Life expectancy at birth shows a similar effect on workplace mobility to the mean year of schooling. There is a negative and significant relationship between workplace mobility and life expectancy at birth during the period from February 2020 to the end of the year 2021. Namely, a 0.37% decline in workplace mobility is explained by a 1-year increase in countries’ life expectancy at birth at a 0.95 confidence level. Consequently, the mean year of schooling and life expectancy at birth were not as strong as the impact of GDP per capita and HDI. On the other hand, we don't observe a significant impact of Gini and Governance Score on workplace mobility for the given period.

Table 6.1. 1 Workplace Mobility Full Model

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**
Predictors	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Intercept	0.05	22.57	7.92	15.74	35.72 *	29.68 *
	(10.46)	(18.27)	(12.85)	(10.67)	(17.00)	(12.79)
Cases Day Count	0.02 ***	0.02 ***	0.02 ***	0.02 ***	0.02 ***	0.02 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Governance Score	0.14	0.14	0.12	0.14	0.15	0.13
	(0.13)	(0.14)	(0.14)	(0.13)	(0.13)	(0.14)
New Deaths/Population Lag	-3.15 ***	-3.15 ***	-3.15 ***	-3.25 ***	-3.34 ***	-3.31 ***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
log(GDP per Capita)	-2.74 ***			-4.31 ***		
	(0.78)			(0.79)		
Recalculated Stringency	-0.27 ***	-0.27 ***	-0.27 ***	-0.27 ***	-0.27 ***	-0.27 ***
Index	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gini	-0.05	-0.16	-0.11	-0.05	-0.16	-0.11
	(0.15)	(0.17)	(0.16)	(0.15)	(0.15)	(0.16)
Weekend 1	19.27 ***	19.27 ***	19.27 ***	-35.49 ***	-25.44 ***	-56.27 ***
	(0.19)	(0.19)	(0.19)	(2.28)	(2.16)	(3.06)

Mean Year of Schooling		-1.49 *			-2.56 ***	
		(0.67)			(0.63)	
Life Expectancy at Birth		-0.36			-0.37 *	
		(0.19)			(0.18)	
HDI			-36.76 **			-61.66 ***
			(12.42)			(12.38)
log(GDP per Capita):Weekend 1				5.42 ***		
				(0.22)		
Mean Year of Schooling:Weekend 1					3.71 ***	
					(0.18)	
HDI:Weekend 1						85.41 ***
						(3.46)
Observations	22518	22518	22518	22518	22518	22518
R^2 / R^2 adjusted	0.430 / 0.430	0.430 / 0.430	0.430 / 0.430	0.444 / 0.444	0.441 / 0.441	0.445 / 0.445

* p<0.05 ** p<0.01 *** p<0.001

Table 6.1.2 includes the results of the aforementioned indicators' impacts for the first wave which is the period between February 2020 and November 2020, and Table 6.1.3 is consists of regression results of the second wave which is the period between November 2020 to the end of the year 2021 (separation point of the waves is shown in Figure 6.1.1). We see that the impact of GDP per capita, mean year of schooling, life expectancy at birth, and human development index are strongest in the first wave. Besides, a 1% increase in workplace mobility is explained by a 4.04% decrease in the logarithm of GDP per capita, a 1.65-year decrease in the mean year of schooling, 0.71 unit decrease in life expectancy at birth, and a 55.34 unit decrease in human development index.

Table 6.1. 2 Workplace Mobility First Period

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**
Predictors	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Intercept	24.56 *	64.84 **	37.00 *	34.56 **	73.24 ***	50.11 ***
	(11.21)	(20.56)	(14.44)	(11.29)	(19.95)	(14.73)
Cases Day Count	0.07 ***	0.07 ***	0.07 ***	0.07 ***	0.07 ***	0.07 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Governance Score	0.00	-0.01	-0.02	0.00	-0.01	-0.02
	(0.14)	(0.16)	(0.15)	(0.14)	(0.16)	(0.16)
New Deaths/Population Lag	-9.42 ***	-9.43 ***	-9.43 ***	-9.36 ***	-9.47 ***	-9.35 ***
	(0.54)	(0.54)	(0.54)	(0.54)	(0.54)	(0.54)
log(GDP per Capita)	-4.04 ***			-5.03 ***		
	(0.83)			(0.84)		
Recalculated Stringency Index	-0.39 ***	-0.39 ***	-0.39 ***	-0.39 ***	-0.39 ***	-0.39 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gini	-0.12	-0.26	-0.21	-0.12	-0.26	-0.21
	(0.16)	(0.19)	(0.18)	(0.16)	(0.18)	(0.18)
Weekend 1	22.94 ***	22.94 ***	22.94 ***	-11.95 ***	-6.36 *	-22.52 ***
	(0.28)	(0.28)	(0.28)	(3.39)	(3.18)	(4.55)

Mean Year of Schooling		-1.65 *			-2.35 **	
		(0.76)			(0.74)	
Life Expectancy at Birth		-0.71 **			-0.71 ***	
		(0.22)			(0.21)	
HDI			-55.34 ***			-70.21 ***
			(13.93)			(14.23)
log(GDP per Capita):Weekend 1				3.45 ***		
				(0.33)		
Mean Year of Schooling:Weekend 1					2.44 ***	
					(0.26)	
HDI:Weekend 1						51.37 ***
						(5.14)
Observations	7853	7853	7853	7853	7853	7853
R^2 / R^2 adjusted	0.627 / 0.627	0.627 / 0.627	0.627 / 0.627	0.632 / 0.632	0.631 / 0.631	0.632 / 0.632

* p<0.05 ** p<0.01 *** p<0.001

Table 6.1. 3 Workplace Mobility Second Period

	Model1	**Model2**	**Model3**	**Model4**	**Model5**	**Model6**
Predictors	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Intercept	-18.85	3.79	-9.28	-0.27	20.16	17.07
	(10.81)	(17.51)	(12.93)	(10.84)	(17.53)	(12.97)
Cases Day Count	0.03 ***	0.03 ***	0.03 ***	0.03 ***	0.03 ***	0.03 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Governance Score	0.17	0.18	0.16	0.18	0.18	0.17
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
New Deaths/Population Lag	-2.76 ***	-2.74 ***	-2.76 ***	-2.92 ***	-3.05 ***	-3.03 ***
	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)
log(GDP per Capita)	-2.60 **			-4.47 ***		
	(0.80)			(0.81)		
Recalculated Stringency	-0.08 ***	-0.08 ***	-0.08 ***	-0.07 ***	-0.07 ***	-0.07 ***
Index	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gini	-0.03	-0.15	-0.09	-0.03	-0.15	-0.09
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Weekend 1	17.34 ***	17.34 ***	17.34 ***	-47.27 ***	-36.15 ***	-73.15 ***
	(0.24)	(0.24)	(0.24)	(2.76)	(2.63)	(3.71)
Mean Year of Schooling		-1.48 *			-2.77 ***	

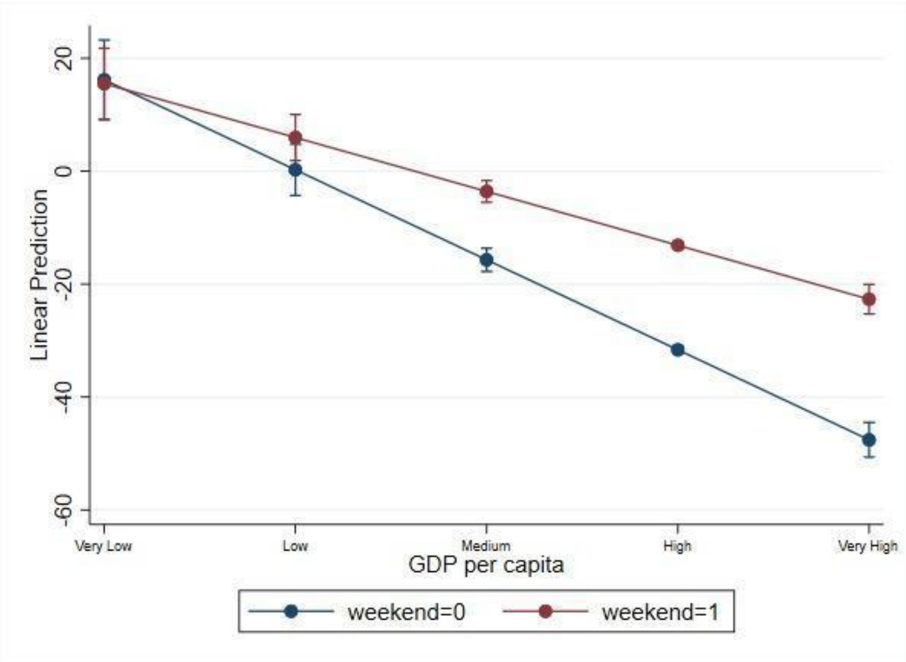
		(0.64)			(0.65)	
Life Expectancy at Birth		-0.35			-0.37 *	
		(0.19)			(0.19)	
HDI			-37.86 **			-68.20 ***
			(12.52)			(12.58)
log(GDP per Capita):Weekend 1				6.40 ***		
				(0.27)		
Mean Year of Schooling:Weekend 1					4.44 ***	
					(0.22)	
HDI:Weekend 1						102.35 ***
						(4.19)
Observations	14665	14665	14665	14665	14665	14665
R^2 / R^2 adjusted	0.356 / 0.355	0.356 / 0.355	0.356 / 0.355	0.379 / 0.379	0.374 / 0.373	0.381 / 0.381

* p<0.05   ** p<0.01   *** p<0.001

In addition, the recalculated stringency index is associated with a decrease in commute. To be used in the analysis, the stringency index is re-calculated by excluding workplace closing measures and following Oxford Covid-19 Government Response Tracker's method of stringency index calculation. Meanwhile, it can be inferred that governments' policies and restrictions (except workplace closings) conducted against the Covid-19 pandemic also resulted in a decrease in workplace mobility. And its effect was strongest in the first wave.

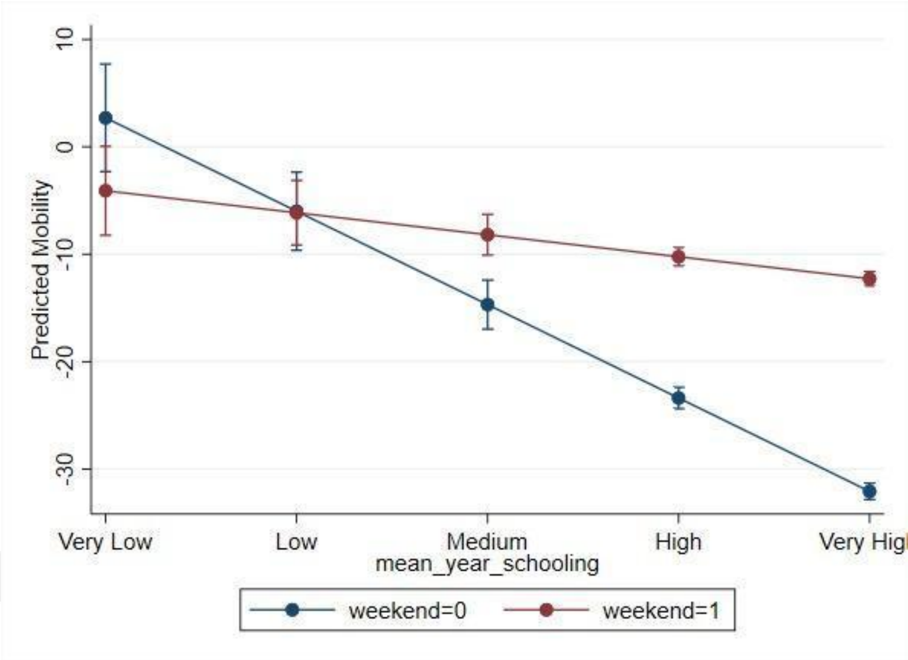
Figures 6.1.10 and 6.1.11 show the predicted mobilities from the regression model. The first graph illustrates a similar mobility change predicted on weekdays and weekends when income is low. However, as income increases, the number of people working from home on weekdays increases, and workplace mobility decreases in European Countries.

Figure 6.1. 11 Marginal Effect of Mean Years of Schooling on European County's Workplace Mobility



Similar to GDP per capita, as the mean year of schooling in European countries increases, workplace mobility decreases more, and the difference in mobility between weekends and weekdays decreases as predicted by the mobility model specification.

Figure 6.1. 12 Marginal Effect of Mean Years of Schooling on European County's Workplace Mobility



The extensive analysis of mobilities in European countries supports the theoretical framework of this thesis. While several factors were associated with the observed mobilities during the pandemic, especially socioeconomic differences between the countries generated unfair inequalities in health. In the following analysis, the thesis hypothesis is tested by a local framework focusing on Turkish cities.

6.2 Local Framework: Mobility in Turkey

After the rapid spread and rising mortality rate of the Covid-19 virus, the Government took urgent precautions like workplace closures, lockdowns, and curfew in Turkey. Many institutions switched to the remote working model to reduce the risk of infection by keeping people out of collective work environments. The study conducted by Hatayama, Viollaz, & Winkler (2020) indicates that Turkey is the most vulnerable country to remote work among LAC region countries in the PIAAC sample. Another study reveals that the Covid-19 epidemic negatively affects four in every five SMEs in Turkey (Business for Goals, 2020). Moreover, Şeker et al. (2020) examine the sectoral employment vulnerability levels and emphasize how amenability to remote work has concretized the inequality in the labor market. Consequently, it is essential to determine the subjects of this inequality and to investigate the reasons behind it on a regional scale comparatively. Maps in Figure 6.2.1 include city-level distribution of mobility, wealth, education, and health indicators and show that especially people in cities in southeast Turkey reduce their workplace mobility less. Moreover, these cities have the lowest education, income-wealth, and human development index during the period between the beginning of the Covid-19 pandemic and the end of the year 2021. Similarly, the average mobility in the same region has decreased less, although not as much as workplace mobility. Briefly, maps visualize the negative relationship between workplace mobility - human development index and the education – wealth/income index indicators.

Figure 6.2. 1 Turkey Maps for Mobility Variables and Education, Wealth and Health Indicators

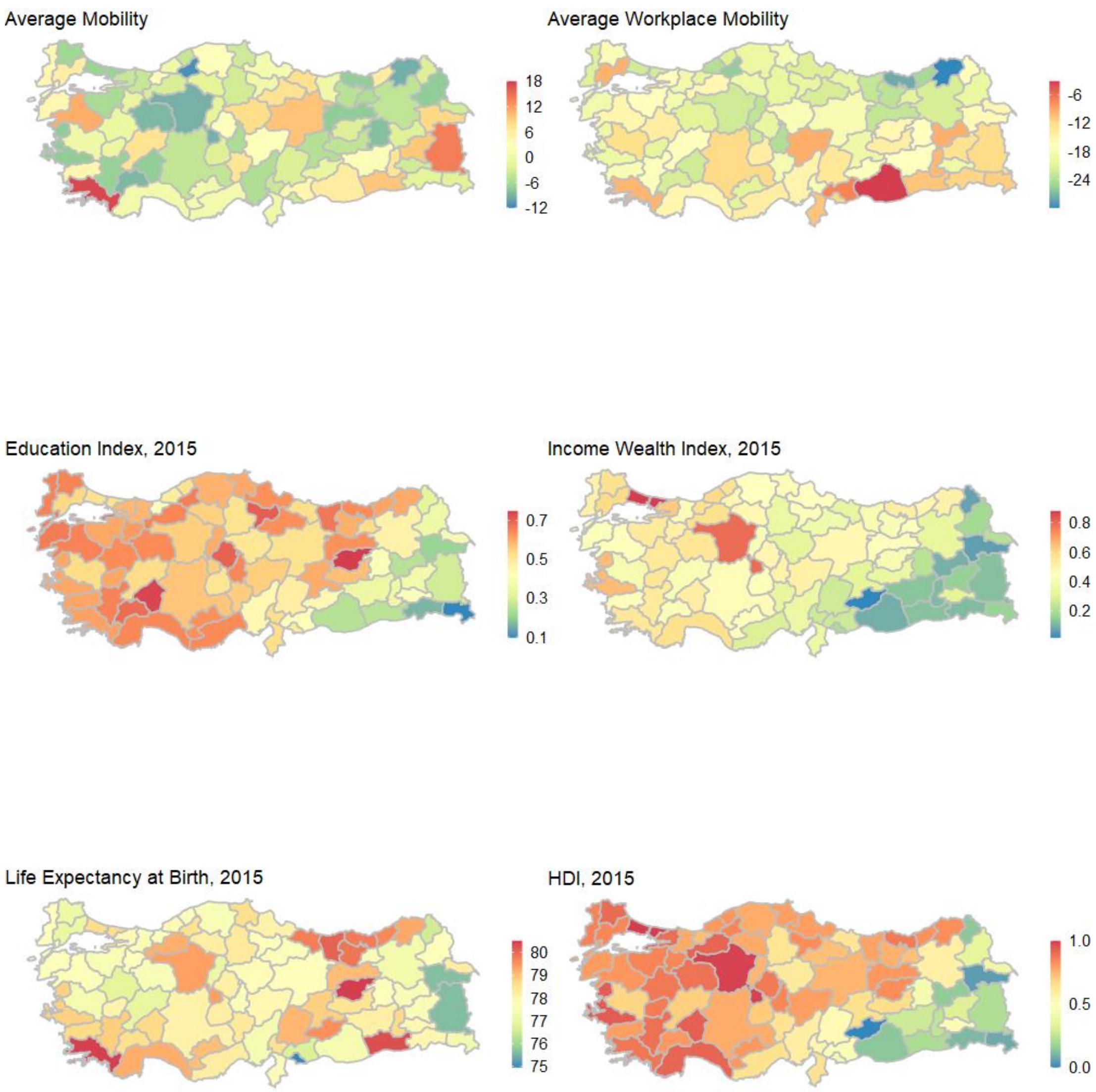


Figure 6.2.2 shows the daily change for average mobility patterns and new cases/1000 in Turkey. Daily general mobility is calculated by taking the average of six mobility indicators. Following that, daily new cases are divided by 1000 to be able to follow the trend between two lines daily. Considering the relationship between the average mobility curve and the curve of the new case, the first wave is determined as of November 27, 2020, and the second wave is determined as of April 16, 2021, for Turkey. The negative relationship between the number of cases and average mobility is also seen in the graph. While there is an upward trend in the number of new cases, average mobility decreases.

Figure 6.2. 2 Daily Change in Average Mobility and Number of New Cases in Turkey

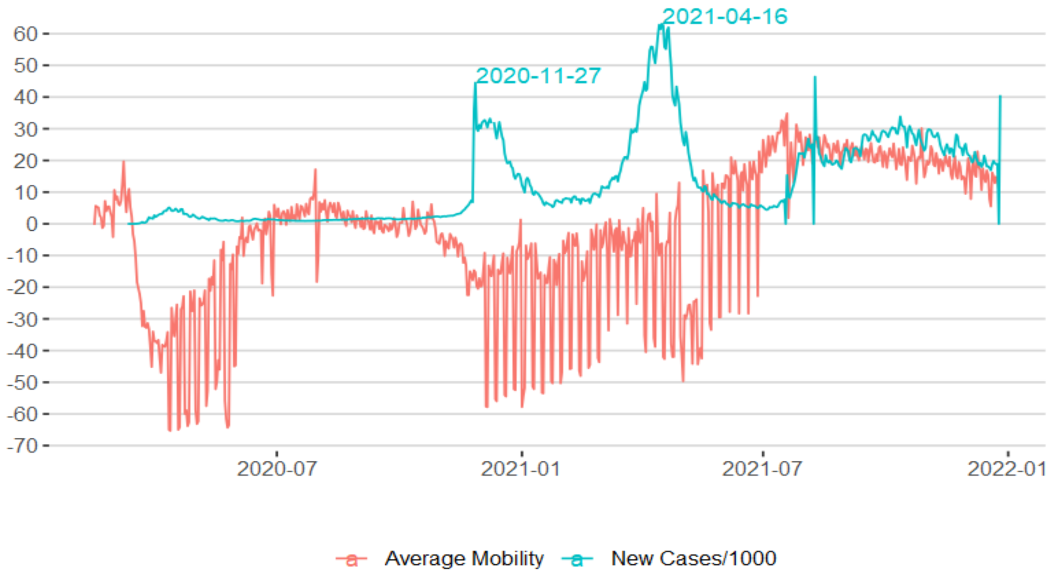


Figure 6.2. 3 Daily Change in Average Mobility, Workplace Mobility, and Stringency Index in Turkey

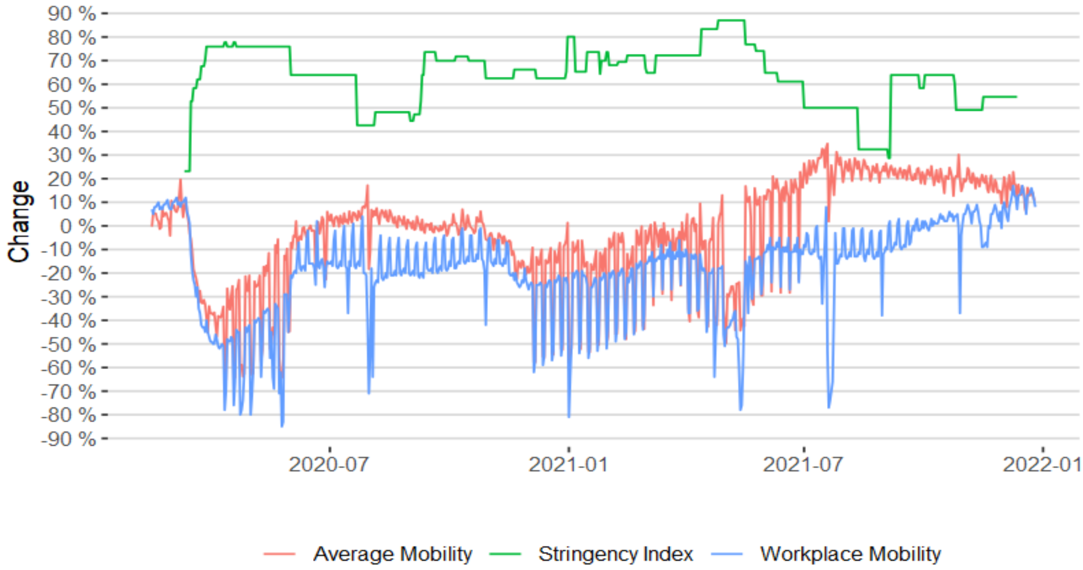


Figure 6.2.4 shows the average mobility percent change by weekdays and income levels in Turkey. Y-axis values are composed by taking the arithmetic mean of mobility for the period from the date the first Covid-19 case is announced to the end of the year 2021. And level 5 refers to the highest, and level 1 refers to the lowest range. The graph shows that as the income level increases, people can decrease workplace mobility higher on weekdays. On the other hand, high-income people increased park mobility more than low-income people. This means that jobs with high income allow remote working, and people have free time to work anywhere on weekdays. We can also infer that people with high income were able to decrease transit station mobility more on both weekdays and weekends. These findings highlight the inequality in mobility between different income level groups and reveal that low-income people are more at risk of Covid-19 virus transmission.

Figure 6.2. 4 Average Mobility Percent Change by Weekdays and Income Levels

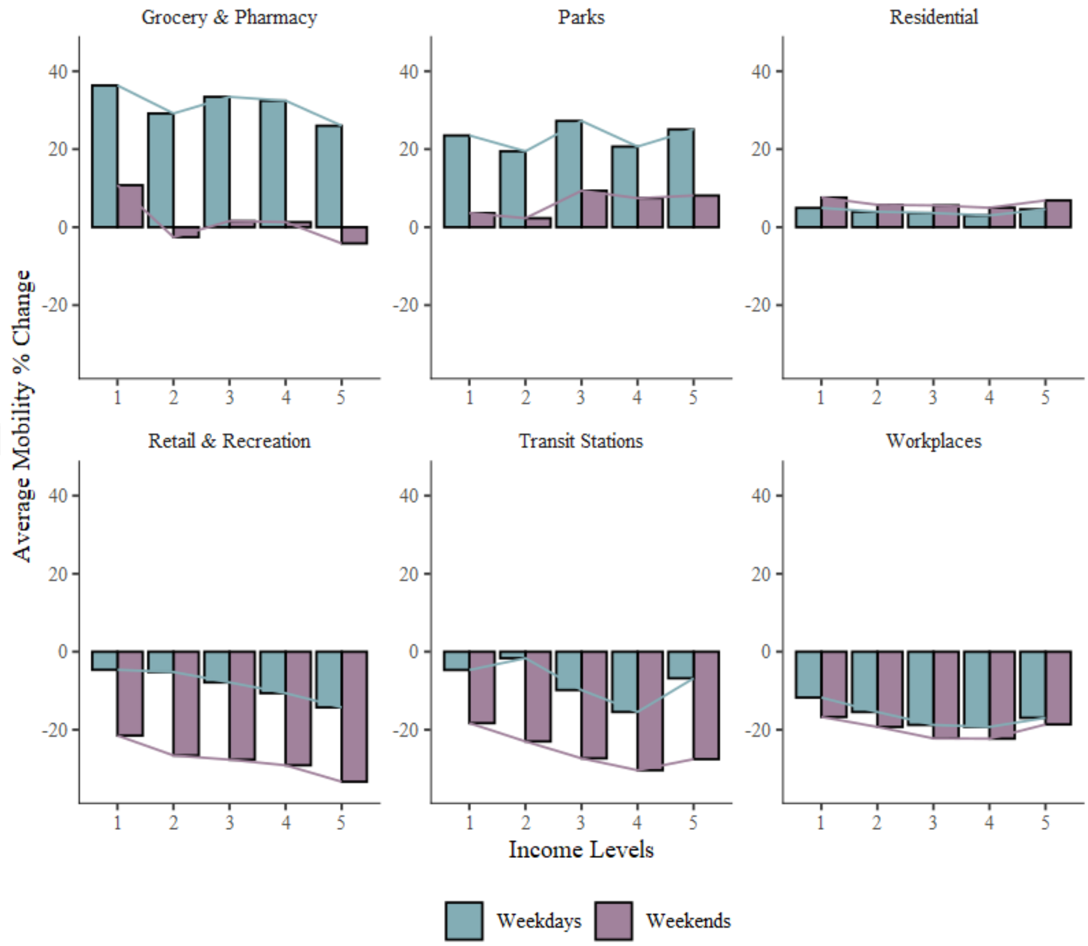


Figure 6.2.5 shows the average mobility percent change before/after Covid-19 and income levels in Turkey. Besides, people with high income reduced their workplace mobility more after the first Covid-19 case; their workplace mobility was lower before the Covid-19. On the other hand, the change in transit mobility before and after Covid-19 is also considerable. It is seen that while the high-income segment decreased their transit mobility level less before the pandemic, they were able to reduce mobility much more after the pandemic. Additionally, mobility to parks for all income levels was higher after the pandemic.

Figure 6.2. 5 Average Mobility Percent Change by Before/After Covid-19 and Income Levels

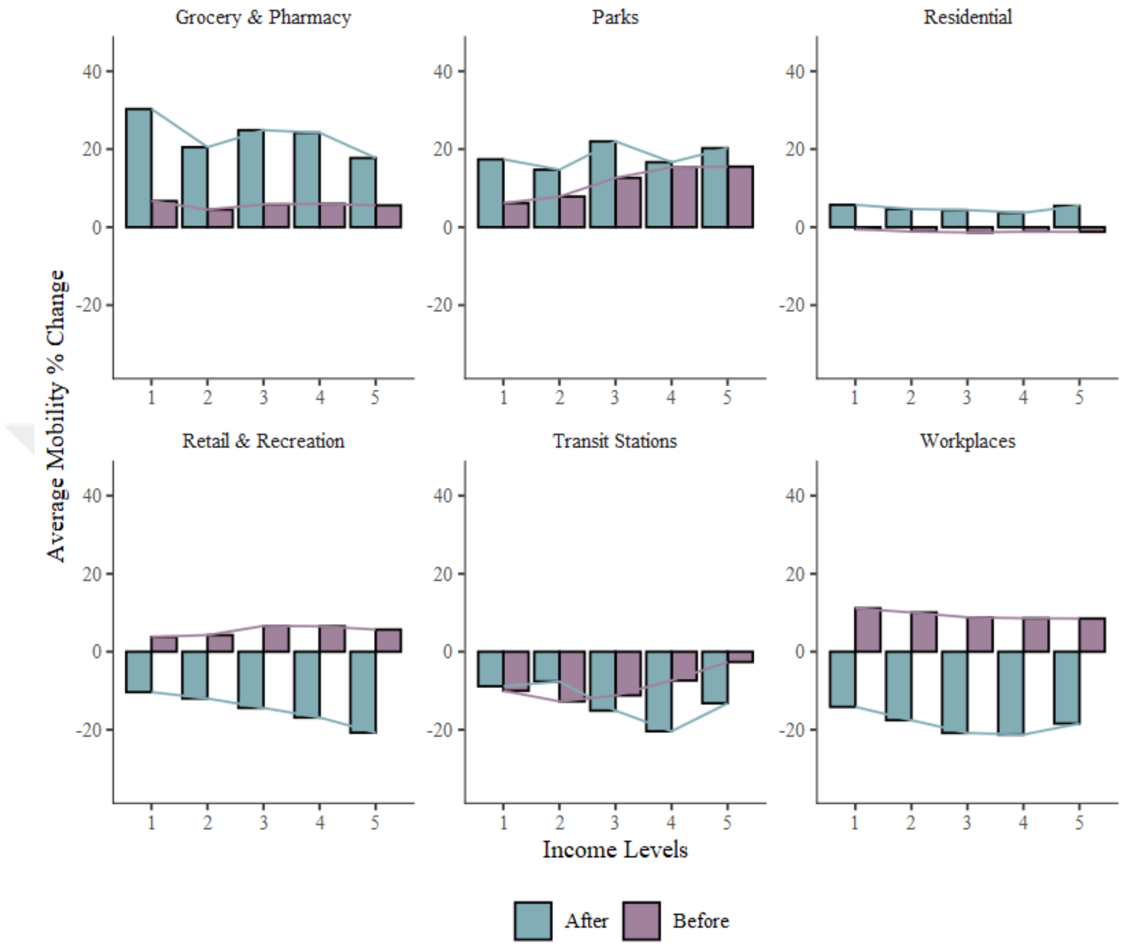
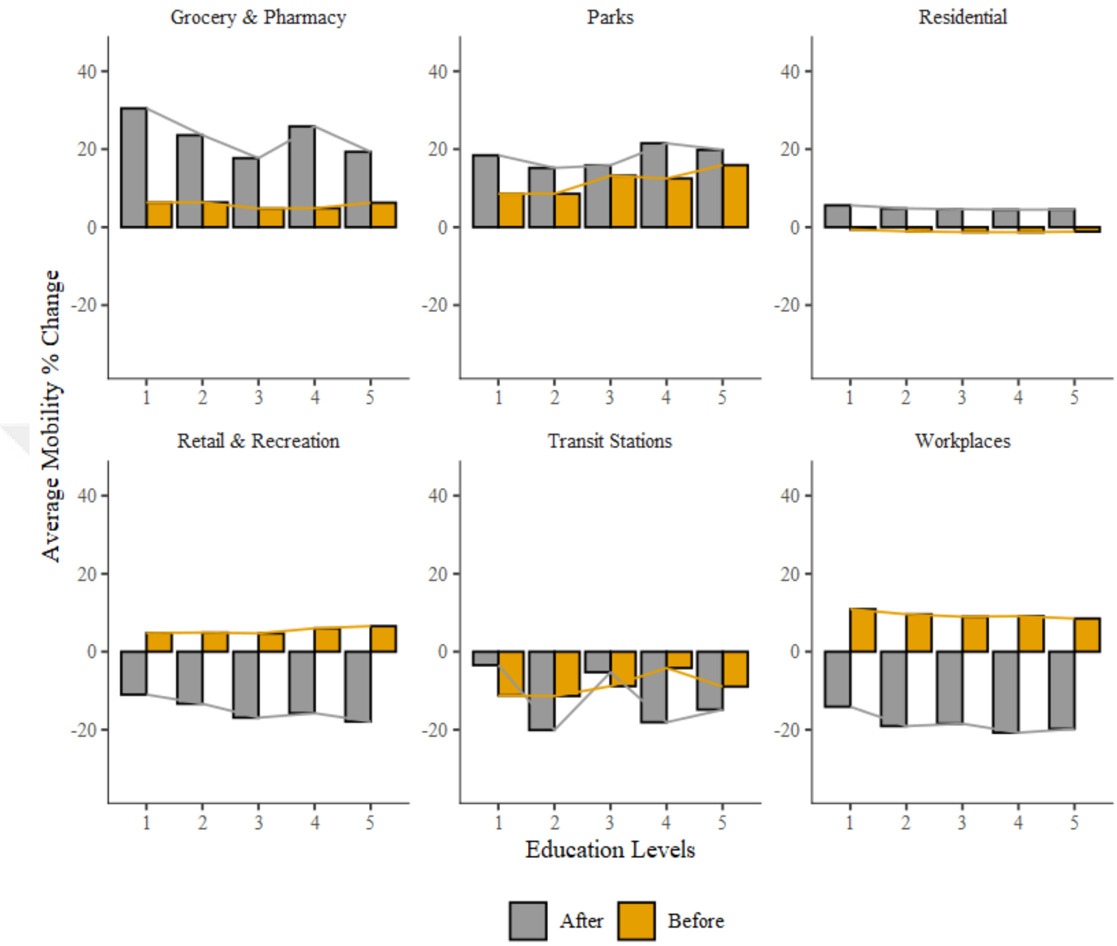
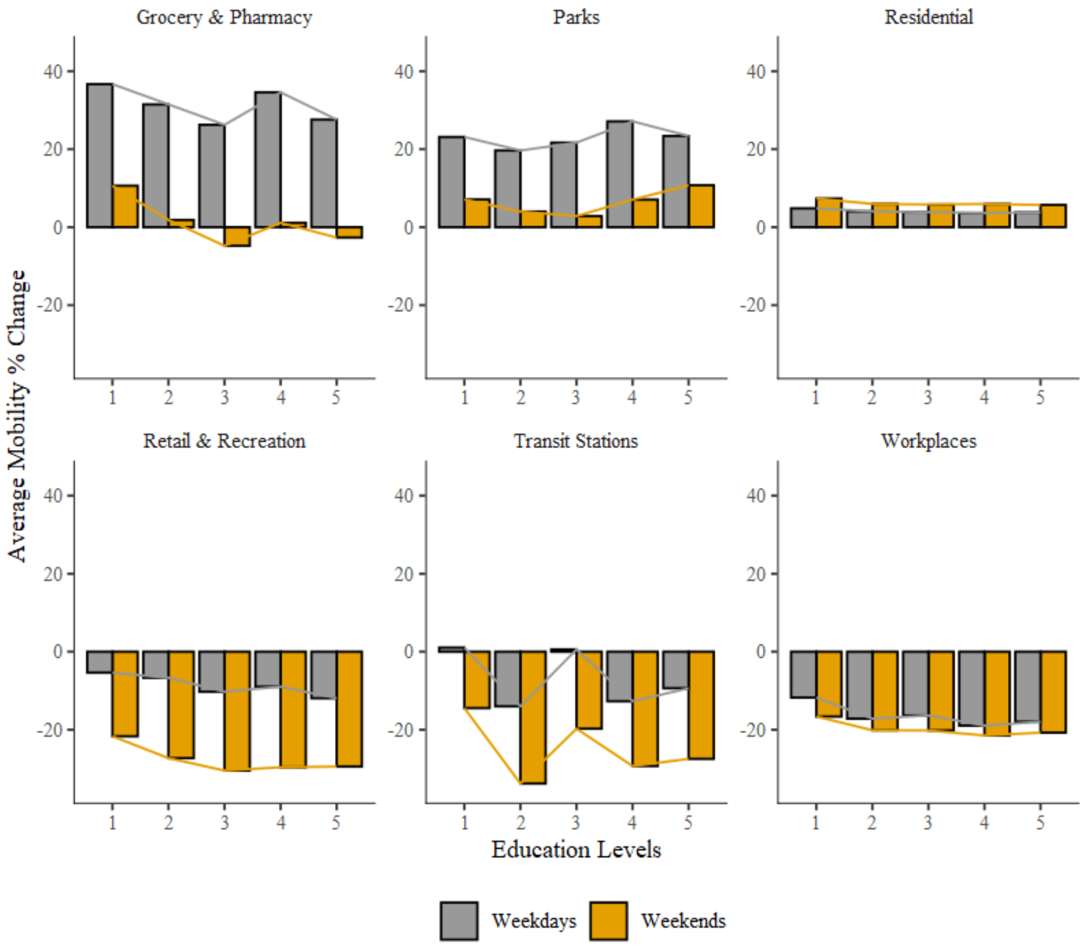


Figure 6.2. 6 Average Mobility Percent Change by Before/After Covid-19 and Education Levels



The highly educated population follows a similar mobility pattern to the wealthy population, as seen in Figure 6.2.7, which shows the average mobility percent change by weekend/weekdays and education levels in Turkey. We also see from Figure 6.2.7 that in cities with high education levels, people were able to decrease their workplace mobility on weekdays. Meanwhile, their park visits were higher on weekdays.

Figure 6.2. 7 Average Mobility Percentage Change by Weekdays and Education Levels



6.2.1 *Simple Models of Mobility*

Average mobility change follows a similar pattern between all six mobility categories and four independent indicators, but their potency varies. We see from Figure 6.2.8, Figure 6.2.9, Figure 6.2.10, and Figure 6.2.11 that wealth, education, life expectancy, and human development levels of cities have a negative impact on workplace mobility. However, the education index has the strongest (R2 = 0.24), and life expectancy at birth has the weakest influence (R2 = 0.07) on workplace mobility. While a 1% change in the education index causes % a 17.3 percent decrease in average workplace mobility, a 1% change in life expectancy at birth decreases average workplace mobility by 1.3%. Additionally, it seems that the four indexes mentioned above have a positive but weak impact on mobility to parks and transit stations; 'y' cannot explain the 'x'.

Figure 6.2. 8 The Relation Between Income Wealth Index and Average Mobility Percent Change of Cities in Turkey

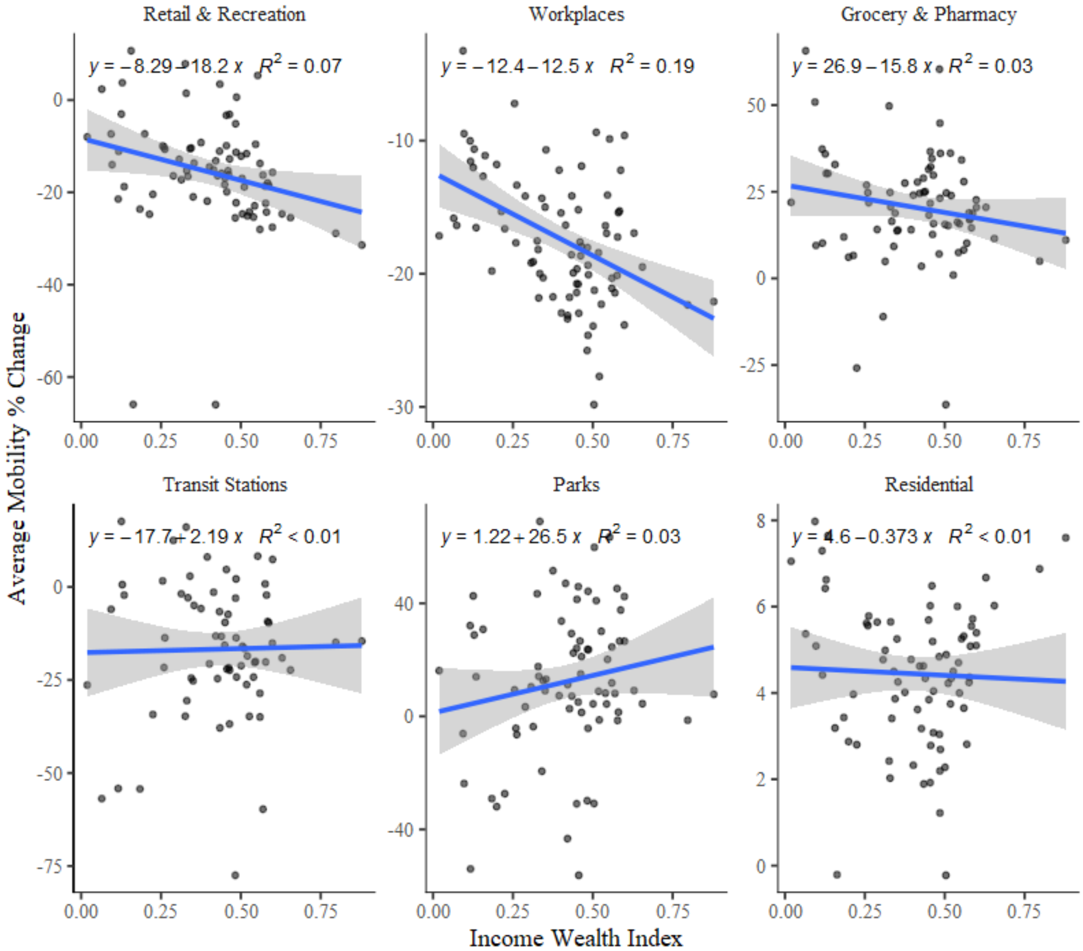


Figure 6.2. 9 The Relation Between Education Index and Average Mobility Percent Change of Cities in Turkey

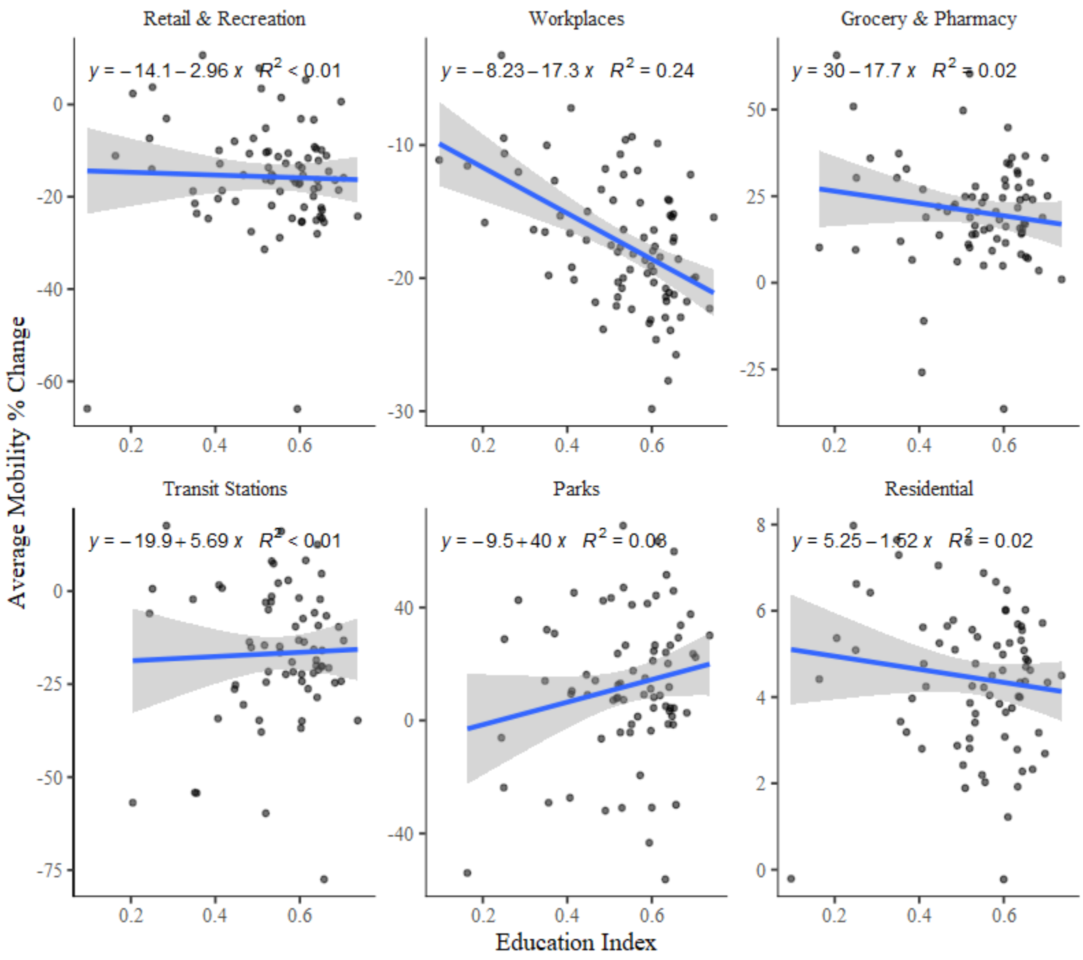


Figure 6.2. 10 The Relation Between Life Expectancy at Birth and Average Mobility Percent Change of Cities in Turkey

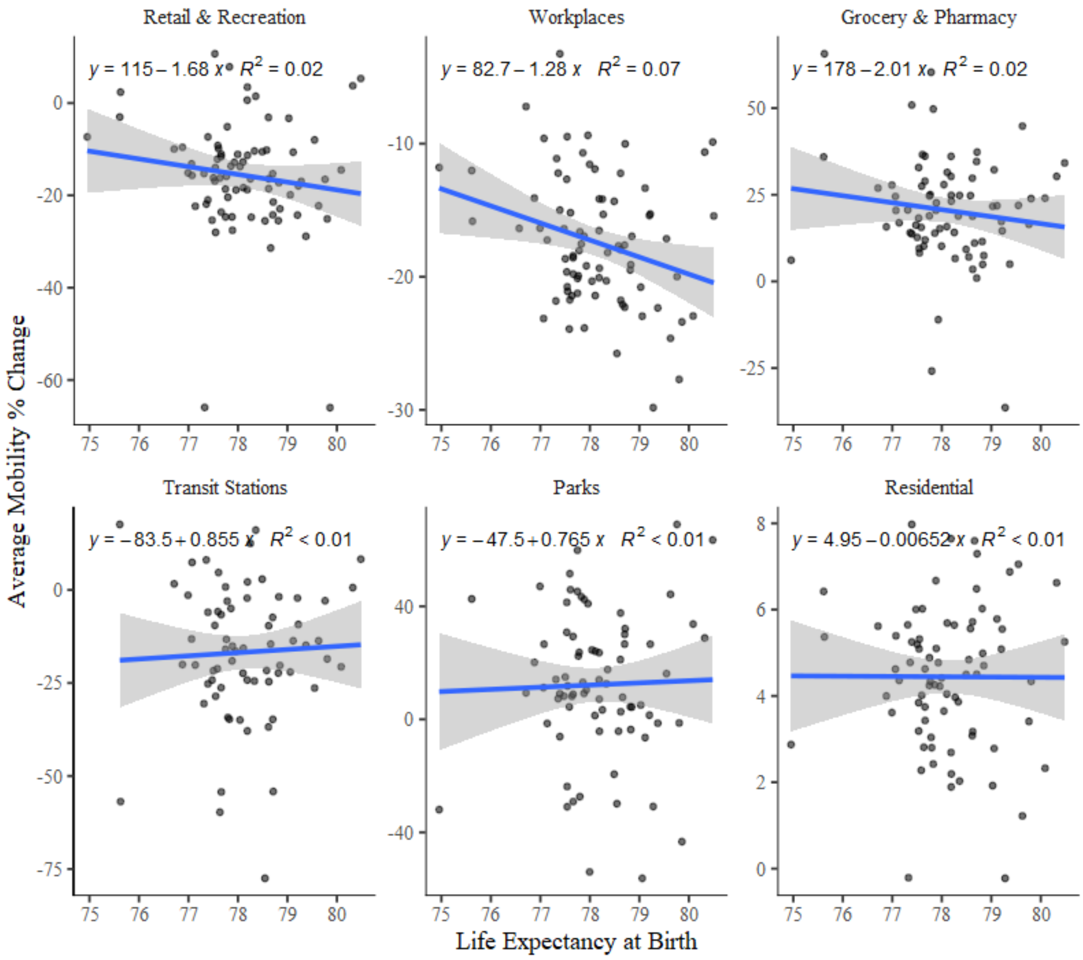
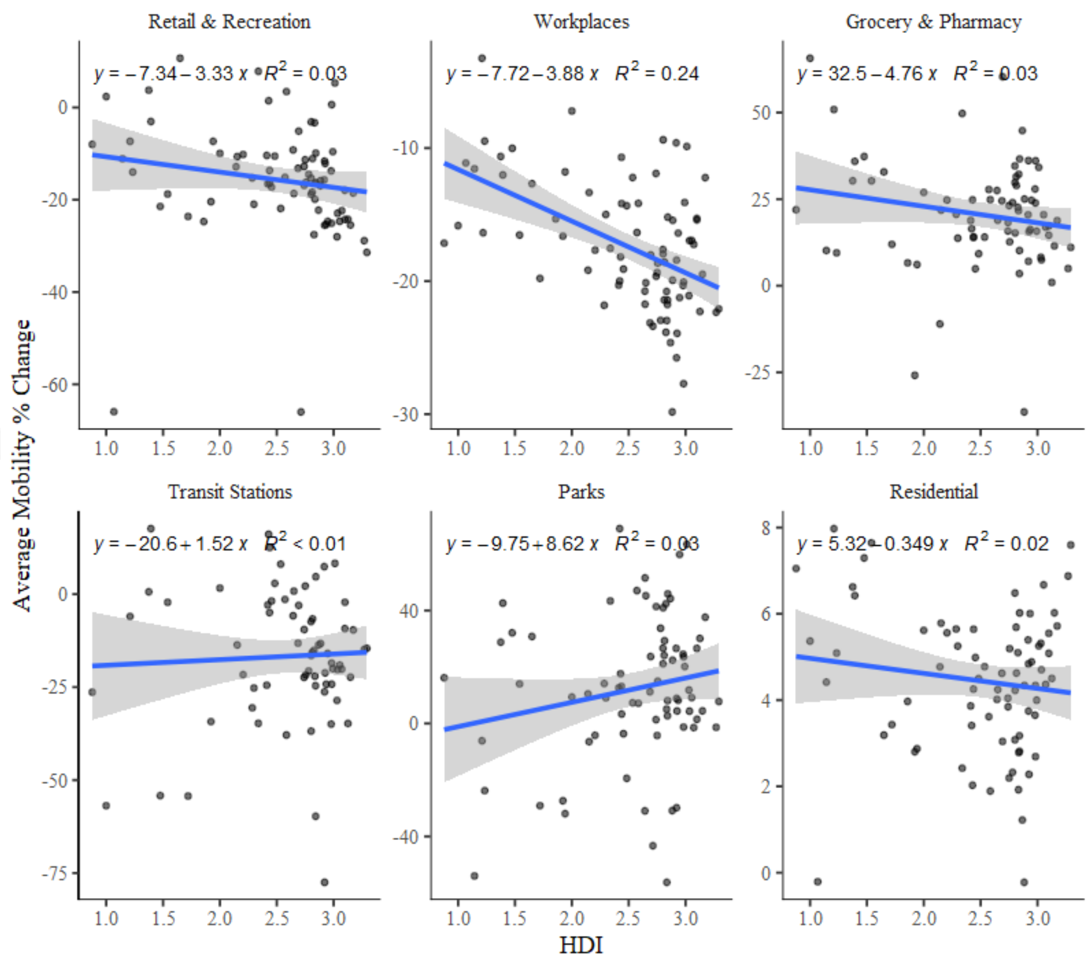


Figure 6.2. 11 The Relation Between HDI and Average Mobility Percent Change of Cities in Turkey



6.2.2 *Regression Models*

The local analysis is divided into four parts by considering the change in the number of daily new cases in Turkey. Firstly, the analysis is conducted for an entire period from the date of the first Covid-19 to the end of the year 2021. Next, the period between the starting date of Covid-19 cases and the first peak point (27 November 2020) is defined as the first wave. The period between the first (27 November 2020) and second peak points (16 April 2021) is determined as the second wave: the period between the second peak point (16 April 2021) and the end of the year 2021 is defined as the third wave as shown in Figure 6.2.2.

The first column of Table 6.2.1 (full model) shows that cities with high income (per person) have experienced a higher workplace mobility decline concerning the baseline month of January 2020. This means that -as the hypothesis of this thesis suggests- high-income groups were able to decrease their workplace mobilities and, therefore, they were less exposed to Covid-19.

Meanwhile, poor segments of the society were more vulnerable to the pandemic. Indeed, Table 6.2.1 quantifies that a 1% increase in the share of top income earners in a city is associated with a 10.94% decrease in mobility toward workplaces from the date the first case in Turkey was announced to the end of the year 2021. Similarly, cities with high concentrations of highly educated individuals decreased their mobility toward workplaces. So that 1% rise in the level of education index of a city corresponds to a 13.04% decline in workplace mobility. On the other hand, model 3 puts forth that there is a significant negative relationship between civic engagement and change in workplace mobility. In other words, in cities where participation in activities of public interest is high, workplace mobility has decreased much more. Meanwhile, as the level of civic engagement in a city increases by 1%, workplace mobility decreases by 15.13%. While income and education level may pick up mobility trajectories in relation to teleworking opportunities, civic engagement picks up a degree of mobility behavior that may be attributable to behavior. In cities with high civic engagement (and social capital), people might have followed the rules and policy suggestions to higher degrees. Life expectancy is explained as the lifetime that a newborn in the region is expected to have. It also has a negative significant impact in the 0.95 confidence interval but it is not as strong as the above-named indicators. Finally, the human development index gives a brief idea of the effects of the aforementioned indicators as their composition. The index gives a general insight to understand the level of human development for different aspects of cities. Therefore, it is important to find out the impact and its indicators on amenability to remote work for different social groups and cities. Model 4 confirms the negative substantial effect of the human development index on workplace mobility. Namely, a 1% increase in the human development index causes an 8.12% decrease in workplace mobility.

Table 6.2. 1 Workplace Mobility Full Model

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Predictors	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Intercept	107.38 ** (35.64)	96.21 ** (37.28)	135.31 *** (34.24)	95.00 ** (36.07)	108.06 ** (35.17)	97.04 ** (36.35)	136.40 *** (34.11)	95.76 ** (35.26)
Recalculated Stringency Index	-0.60 *** (0.00)	-0.60 *** (0.00)	-0.60 *** (0.00)	-0.60 *** (0.00)	-0.60 *** (0.00)	-0.60 *** (0.00)	-0.60 *** (0.00)	-0.60 *** (0.00)
Income Wealth Index	-10.94 *** (3.05)				-12.61 *** (3.02)			
Life Expectancy at Birth	-1.00 * (0.45)	-0.82 (0.48)	-1.30 ** (0.44)	-0.84 (0.46)	-1.00 * (0.45)	-0.82 (0.46)	-1.30 ** (0.43)	-0.84 (0.45)
Employment Rate	-0.11 (0.08)	-0.12 (0.08)	-0.17 * (0.08)	-0.09 (0.08)	-0.11 (0.08)	-0.12 (0.08)	-0.17 * (0.08)	-0.09 (0.08)
Metropolis 1	3.32 *** (0.95)	2.70 ** (0.94)	2.92 ** (0.93)	3.15 *** (0.93)	3.32 *** (0.94)	2.70 ** (0.91)	2.92 ** (0.93)	3.15 *** (0.91)
Weekend 1	-3.37 *** (0.15)	-3.37 *** (0.15)	-3.37 *** (0.15)	-3.37 *** (0.15)	-5.76 *** (0.39)	-6.44 *** (0.61)	-7.08 *** (0.60)	-5.95 *** (0.43)
Education Index		-13.04 *** (3.96)				-14.67 *** (3.87)		
Civic Engagement			-15.13 *** (4.31)				-17.66 *** (4.31)	

HDI				-8.12 *** (2.12)				-9.20 *** (2.08)
Income Wealth Index:Weekend 1					5.93 *** (0.88)			
Education Index:Weekend 1						5.76 *** (1.11)		
Civic Engagement:Weekend 1							8.83 *** (1.38)	
HDI:Weekend								3.84 *** (0.60)
Observations	54443	54443	54443	54443	54443	54443	54443	54443
R^2 / R^2 adjusted	0.304 / 0.304	0.304 / 0.304	0.304 / 0.304	0.304 / 0.304	0.305 / 0.305	0.305 / 0.305	0.305 / 0.305	0.305 / 0.305

* p<0.05 ** p<0.01 *** p<0.001

On the other hand, Table 6.2.2 reveals that the effect of income, education, civic engagement, and human development levels of cities in the first wave (from the starting date of the Covid-19 pandemic in Turkey to 27 November 2020) is higher than the whole period. The first and second waves are the periods in which curfews are enforced, schools are closed, and switching to remote work inconvenient jobs is started in Turkey; although some restrictions are relaxed from time to time. Following that, while we observe the effect of the income level and civic engagement level in the first wave is strongest among waves, the impact of education level and human development level of the population is strongest in the second wave. However, the effect of restrictions was reversed in the second wave. Table 6.2.2 and Table 6.2.3 show that while there is a negative relationship between recalculated stringency index (recalculated by excluding workplace closing measures in stringency index calculation of Oxford Covid-19 Government Response Tracker) and workplace mobility in the first period, there is a positive relationship in the second period between workplace mobility and income level of cities. In the third wave which recalculated stringency index has a negative impact on workplace mobility, civic engagement remains an affecting indicator in the 0.95 confidence interval but the income/wealth index, education index, and human development index don't have a significant impact on workplace mobility. Meanwhile, in the third period, the recalculated stringency index starts to decline as seen in Figure 6.2.3. The controlled normalization process started in Turkey on March 2, 2021, and Figure 6.2.2 visualizes its effect on both average and workplace mobility change, especially in the third period.

Table 6.2. 2 Workplace Mobility First Period

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Predictors	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Intercept	78.44 ** (29.15)	73.71 * (32.22)	110.25 *** (29.06)	69.20 * (30.23)	78.66 ** (29.04)	74.44 * (32.11)	111.05 *** (29.25)	69.60 * (29.89)
Recalculated Stringency Index	-0.66 *** (0.01)	-0.66 *** (0.01)	-0.66 *** (0.01)	-0.66 *** (0.01)	-0.66 *** (0.01)	-0.66 *** (0.01)	-0.66 *** (0.01)	-0.66 *** (0.01)
Income Wealth Index	-12.17 *** (2.50)				-12.65 *** (2.51)			
Life Expectancy at Birth	-0.64 (0.37)	-0.54 (0.41)	-0.99 ** (0.37)	-0.52 (0.38)	-0.64 (0.37)	-0.54 (0.41)	-0.99 ** (0.37)	-0.52 (0.38)
Employment Rate	-0.06 (0.07)	-0.09 (0.07)	-0.13 * (0.06)	-0.05 (0.07)	-0.06 (0.07)	-0.10 (0.07)	-0.13 * (0.07)	-0.05 (0.07)
Metropolis 1	-0.73 (0.77)	-1.43 (0.81)	-1.20 (0.79)	-0.96 (0.78)	-0.73 (0.77)	-1.43 (0.81)	-1.20 (0.80)	-0.96 (0.77)

Weekend 1	5.05 *** (0.22)	5.05 *** (0.22)	5.05 *** (0.22)	5.05 *** (0.22)	4.35 *** (0.56)	2.45 ** (0.88)	2.25 ** (0.86)	3.80 *** (0.62)
Education Index		-12.38 *** (3.42)				-13.75 *** (3.44)		
Civic Engagement			-15.35 *** (3.66)				-17.24 *** (3.73)	
HDI				-8.28 *** (1.78)				-8.79 *** (1.77)
Income Wealth Index:Weekend 1					1.74 (1.27)			
Education Index:Weekend 1						4.87 ** (1.60)		
Civic Engagement:Weekend 1							6.66 *** (1.98)	
HDI:Weekend								1.86 * (0.87)
Observations	22568	22568	22568	22568	22568	22568	22568	22568
R^2 / R^2 adjusted	0.377 / 0.376	0.376 / 0.376	0.377 / 0.376	0.377 / 0.376	0.377 / 0.376	0.377 / 0.376	0.377 / 0.377	0.377 / 0.377

* p<0.05 ** p<0.01 *** p<0.001

Table 6.2. 3 Workplace Mobility Second Period

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Predictors	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Intercept	124.52 ** (43.44)	85.72 * (42.09)	155.86 *** (41.87)	98.91 * (42.36)	125.43 ** (43.44)	86.85 * (42.09)	157.31 *** (41.88)	99.89 * (42.36)
Recalculated Stringency Index	0.14 *** (0.02)	0.14 *** (0.02)	0.14 *** (0.02)	0.14 *** (0.02)	0.14 *** (0.02)	0.14 *** (0.02)	0.14 *** (0.02)	0.14 *** (0.02)
Income Wealth Index	-12.29 *** (3.72)				-14.55 *** (3.74)			
Life Expectancy at Birth	-1.73 ** (0.55)	-1.17 * (0.54)	-2.06 *** (0.53)	-1.40 ** (0.54)	-1.73 ** (0.55)	-1.17 * (0.54)	-2.06 *** (0.53)	-1.40 ** (0.54)
Employment Rate	-0.35 *** (0.10)	-0.29 ** (0.09)	-0.41 *** (0.09)	-0.29 ** (0.10)	-0.35 *** (0.10)	-0.29 ** (0.09)	-0.41 *** (0.09)	-0.29 ** (0.10)
Metropolis 1	5.52 *** (1.15)	4.83 *** (1.06)	5.08 *** (1.14)	5.45 *** (1.09)	5.52 *** (1.15)	4.83 *** (1.06)	5.08 *** (1.14)	5.45 *** (1.09)
Weekend 1	-22.90 *** (0.23)	-22.90 *** (0.23)	-22.90 *** (0.23)	-22.90 *** (0.23)	-26.08 *** (0.60)	-26.88 *** (0.94)	-27.96 *** (0.93)	-26.34 *** (0.66)
Education Index		-21.88 *** (4.47)				-24.01 *** (4.49)		
Civic Engagement			-17.06 ** (5.27)				-20.51 *** (5.31)	

HDI				-11.08 *** (2.48)				-12.54 *** (2.50)
Income Wealth Index:Weekend 1					7.92 *** (1.36)			
Education Index:Weekend 1						7.47 *** (1.71)		
Civic Engagement:Weekend 1							12.07 *** (2.14)	
HDI:Weekend								5.13 *** (0.93)
Observations	11340	11340	11340	11340	11340	11340	11340	11340
R^2 / R^2 adjusted	0.460 / 0.460	0.461 / 0.461	0.460 / 0.460	0.461 / 0.460	0.462 / 0.462	0.462 / 0.462	0.462 / 0.461	0.462 / 0.462

* p<0.05 ** p<0.01 *** p<0.001

Table 6.2. 4 Workplace Mobility Third Period

	Model1	Model2	Model3	Model4	Model5	Model6	Model7	Model8
Predictors	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Intercept	98.34 (50.88)	94.88 (53.00)	120.71 * (48.67)	89.30 (51.93)	71.28 (50.88)	67.58 (53.00)	93.49 (48.68)	62.30 (51.93)
Recalculated Stringency Index	-0.50 *** (0.01)	-0.50 *** (0.01)	-0.50 *** (0.01)	-0.50 *** (0.01)				
Income Wealth Index	-9.08 * (4.36)				-11.32 ** (4.38)			
Life Expectancy at Birth	-0.99 (0.64)	-0.92 (0.68)	-1.23 * (0.62)	-0.88 (0.66)	-0.99 (0.64)	-0.92 (0.68)	-1.23 * (0.62)	-0.88 (0.66)
Employment Rate	-0.03 (0.12)	-0.06 (0.12)	-0.07 (0.11)	-0.02 (0.12)	-0.04 (0.12)	-0.06 (0.12)	-0.07 (0.11)	-0.02 (0.12)
Metropolis 1	6.55 *** (1.35)	6.03 *** (1.33)	6.24 *** (1.33)	6.40 *** (1.34)	6.55 *** (1.35)	6.05 *** (1.33)	6.25 *** (1.33)	6.41 *** (1.34)
Weekend 1	-1.90 *** (0.24)	-1.90 *** (0.24)	-1.90 *** (0.24)	-1.90 *** (0.24)	-5.40 *** (0.74)	-4.73 *** (1.16)	-5.68 *** (1.14)	-5.13 *** (0.82)
Education Index		-9.22 (5.63)				-10.55 (5.66)		
Civic Engagement			-14.09 * (6.13)				-16.49 ** (6.18)	
HDI				-6.53 * (3.05)				-7.74 * (3.07)

Income Wealth Index:Weekend 1					8.31 *** (1.68)			
Education Index:Weekend 1						5.04 * (2.11)		
Civic Engagement:Weekend 1							8.64 ** (2.63)	
HDI:Weekend								4.58 *** (1.14)
Observations	20535	20535	20535	20535	20535	20535	20535	20535
R^2 / R^2 adjusted	0.285 / 0.285	0.285 / 0.285	0.285 / 0.285	0.285 / 0.285	0.005 / 0.005	0.004 / 0.004	0.005 / 0.004	0.005 / 0.004

* p<0.05 ** p<0.01 *** p<0.001

These findings point out the heterogeneity in mobility reduction by socioeconomic groups and in particular by social class. Consequently, in cities where the income level per person is high people were able to decrease their mobility level more than in cities with low-income communities. Since the less paying jobs are less favorable for work-from-home (Mongey et al., 2020) low-income people were more exposed to the risks of the Covid-19 crisis.

7 DISCUSSION

Society's unprivileged part is negatively and disproportionately affected by the Covid-19 crisis (Huang et al., 2020). While this population commonly consists of frontline workers, the wealthy part of the society has jobs suitable for remote work on weekdays. On the other hand, mobility to parks was higher for the wealthy part of society on both weekends and weekdays. This points out the disproportional impacts of the pandemic, where teleworking opportunities were readily available for the rich segment of the society along with opportunities to engage in recreational activities.

People who are able to work remotely have the flexibility to limit their outdoor physical presence. Besides, the low-income part of the society was exposed to higher health risks against rapid Covid-19 transmission due to their essentially onsite work activities. Therefore, it may be proper to say that wealth inequalities have a remarkable role because of this uneven distribution of exposure to health risks. In other words, the low-income population faces the disproportionate burden of Covid-19 crises since they were not able to reduce their mobility higher (Chang et al., 2021). Additionally, Drefahl et al. (2020) state that individuals with low income and education face a higher risk of death from COVID-19.

Besides the unequal exposure to health risks, this outbreak caused negative disproportioned employment outcomes. Workers who cannot work from home undertake the uneven adversity of exposure to the risk of losing their jobs due to workplace closures, especially in sectors that require high face-to-face interaction.

Governments have been implementing restrictions and measures to handle the rapid spread of the Covid-19 outbreak. However, the outcomes of these regulations depend on the heterogeneous socioeconomic conditions of the society, especially in low and middle-income areas. Therefore, authorities should ensure healthy commuting conditions for the workers whose jobs require physical presence at workplaces during the pandemic to mitigate their high exposure risk to the virus. This certainly requires new city planning, including introducing additional transportation opportunities and means between residential locations and workplaces. The extensive literature on the spatial mismatch theories (Gobillon, 2007) suggests that the asymmetric distribution of job opportunities and residential areas becomes apparent for lower segments of society, especially for low-skill workers. This means that potential policies must take into account the spatial mismatch experienced by the low-skilled workers who have also been captive commuters during the pandemic. The top five European countries in which commuters reduced their workplace mobility least were Bosnia and Herzegovina, Poland, Czech Republic, Belarus, and Croatia. On the other hand, the top five cities where workers decreased workplace mobility least in Turkey were Şanlıurfa, Gaziantep, Kayseri, Muş, and Tekirdağ.

8 CONCLUSIONS

With the spread of Covid-19 and its increasing lethality, countries and organizations have started to take stricter measures like curfew, lockdowns, and workplace closures. Many institutions switched to the remote working model, which was a new phenomenon for those accustomed to the traditional on-site working style. Although remote work has already been practiced for some limited job types, it has become a necessary precaution to reduce the risk of infection by keeping people out of collective work environments. However, jobs that require high face-to-face interaction had to bear the disproportionate burden of Covid-19 crises. Meanwhile, amenability to remote work has concretized the inequality in the labor market. Consequently, it is crucial to determine the subjects of this inequality and to investigate the reasons behind it on a regional scale comparatively.

This thesis analyzes the inequality behind the amenability of remote work by examining workplace mobility patterns and explores the impact of socioeconomic factors from a global and local perspective. The global framework includes 37 European countries, and the local framework comprises 81 cities in Turkey. Mobility data is taken from Google - Covid-19 Community Mobility Reports and follows daily mobility trajectories from February 2020 to January 2022. The analysis is divided into parts by considering peak points of daily new cases for both global and local analyzes, and defined as pandemic waves (Figure 6.1.1).

Global analysis results prove that economically unprivileged populations were more exposed to the Covid-19 virus in Europe. In countries with higher GDP per capita, the workforce was able to decrease their workplace mobility at higher rates. Similarly, in countries with high mean years of schooling, people declined commuting levels higher. Briefly, while countries with higher human capital were able to reduce their mobility toward the workplace, countries with lower GDP per capita, and education levels did not experience the same opportunity. On the other hand, the wealthy segment of Europe decreased their transit station mobility and increased parks and residential mobility much higher than the low-income segment during the period. Moreover, they were able to reduce their workplace and transit station mobility higher than the low-income segment on weekdays, and their parks and residential mobility increased higher. While people in countries with high GDP per capita started to decrease workplace mobility before the first Covid-19 case was detected in their country, people living in countries with lower GDP per capita had higher workplace mobility compared to baseline month of mobility. And countries with high mean years of schooling followed a similar mobility pattern with the GDP per capita. Overall, as the education level, standard of living, and wealth level is improved in countries, mobility to workplaces and transit stations decreases, and residential and park mobility increases.

The local analysis indicates that poor segments of the society were more vulnerable to the pandemic and were more exposed to Covid-19. Like global analysis, people in cities with high human capital had the chance of decreasing their workplace mobility and avoiding the risk of getting infected in a collective workplace environment. Moreover, people living in cities with high incomes reduced their transit station mobility and increased park mobility. To sum up, people living in cities with high education, high life expectancy at birth, and increased civic engagement followed similar mobility patterns. Additionally, cities in the southeast of Turkey have the lowest education, income-wealth, and human development index, also the workforce located there decreased workplace mobility less during the period.

Overall, these results indicate that jobs with high income allow remote work and people have free time to work anywhere on weekdays and the inequality in mobility between different income level groups reveal that low-income people are more at risk of Covid-19 virus transmission in Europe and Turkey.

9 REFERENCES

[1] Badr, H. S., Du, H., Marshall, M., Dong, E., Squire, M. M., & Gardner, L. M. (2020). Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study. *The Lancet Infectious Diseases*, *20*(11), 1247-1254.

[2] Baum, C. F., & Henry, M. (2020). Socioeconomic factors influencing the spatial spread of COVID-19 in the United States. *Miguel, Socioeconomic Factors influencing the Spatial Spread of COVID-19 in the United States (May 29, 2020)*.

[3] Beňo, M. (2021). The advantages and disadvantages of E-working: An examination using an ALDINE analysis. *Emerging Science Journal, 5*, 11-20.

[4] Bick, A., Blandin, A., & Mertens, K. (2020). Work from home after the COVID-19 Outbreak.

[5] Birdsall, N. (1998). Life is unfair: Inequality in the world. *Foreign Policy*, 76-93.

[6] Chang, S., Pierson, E., Koh, P. W., Gerardin, J., Redbird, B., Grusky, D., & Leskovec, J. (2021). Mobility network models of COVID-19 explain inequities and inform reopening. *Nature*, *589*(7840), 82-87.

[7] Cot, C., Cacciapaglia, G., & Sannino, F. (2021). Mining Google and Apple mobility data: Temporal anatomy for COVID-19 social distancing. *Scientific reports*, *11*(1), 1-8.

[8] Coven, J., & Gupta, A. (2020). Disparities in mobility responses to COVID-19. *New York University*, 150.

[9] Demir Seker, S., Nas Ozen, E., & Acar Erdogan, A. (2020). Jobs at Risk in Turkey.

[10] Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home?. *Journal of Public Economics*, *189*, 104235.

[11] Do Lee, W., Qian, M., & Schwanen, T. (2021). The association between socioeconomic status and mobility reductions in the early stage of England's COVID-19 epidemic. *Health & place*, *69*, 102563.

[12] Drefahl, S., Wallace, M., Mussino, E., Aradhya, S., Kolk, M., Brandén, M., ... & Andersson, G. (2020). A population-based cohort study of socio-demographic risk factors for COVID-19 deaths in Sweden. *Nature communications*, *11*(1), 1-7.

[13] Dueñas, M., Campi, M., & Olmos, L. E. (2021). Changes in mobility and socioeconomic conditions during the COVID-19 outbreak. *Humanities and Social Sciences Communications*, *8*(1), 1-10.

[14] Engle, S., Stromme, J., & Zhou, A. (2020). Staying at home: mobility effects of covid-19. *Available at SSRN 3565703*.

[15] Fraiberger, S. P., Astudillo, P., Candeago, L., Chunet, A., Jones, N. K., Khan, M. F., ... & Montfort, A. (2020). Uncovering socioeconomic gaps in mobility reduction during the COVID-19 pandemic using location data. *arXiv preprint arXiv:2006.15195*.

[16] Gauvin, L., Bajardi, P., Pepe, E., Lake, B., Privitera, F., & Tizzoni, M. (2021). Socio-economic determinants of mobility responses during the first wave of COVID-19 in Italy: from provinces to neighbourhoods. *Journal of The Royal Society Interface*, 18(181), 20210092.

[17] Ghader, S., Zhao, J., Lee, M., Zhou, W., Zhao, G., & Zhang, L. (2020). Observed mobility behavior data reveal social distancing inertia. *arXiv preprint arXiv:2004.14748*.

[18] Gobillon, L., Selod, H., & Zenou, Y. (2007). The mechanisms of spatial mismatch. *Urban studies*, *44*(12), 2401-2427.

[19] Goetz, S. J., Han, Y., Findeis, J. L., & Brasier, K. J. (2010). US commuting networks and economic growth: Measurement and implications for spatial policy. *Growth and Change*, *41*(2), 276-302.

[20] Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A. L. (2008). Understanding individual human mobility patterns. *nature*, *453*(7196), 779-782.

[21] Hanson, S., & Hanson, P. (1981). The travel-activity patterns of urban residents: dimensions and relationships to sociodemographic characteristics. *Economic geography*, *57*(4), 332-347.

[22] Hardy, W., Lewandowski, P., Park, A., & Yang, D. (2018). THE GLOBAL DISTRIBUTION OF ROUTINE AND NON-ROUTINE WORK. *Institute for Structural Research Working Paper*, *5*, 2018.

[23] Hatayama, M., Viollaz, M., & Winkler, H. (2020). Jobs' amenability to working from home: Evidence from skills surveys for 53 countries. *World Bank Policy Research Working Paper*, (9241).

[24] Huang, X., Li, Z., Lu, J., Wang, S., Wei, H., & Chen, B. (2020). Time-series clustering for home dwell time during COVID-19: what can we learn from it?. *ISPRS International Journal of Geo-Information*, *9*(11), 675.

[25] Jay, J., Bor, J., Nsoesie, E. O., Lipson, S. K., Jones, D. K., Galea, S., & Raifman, J. (2020). Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. *Nature human behaviour*, *4*(12), 1294-1302.

[26] Jensen, A. M. (2009). Mobile children: Small captives of large structures?. *Children & Society*, *23*(2), 123-135.

[27] Kim, J., & Kwan, M. P. (2021). The impact of the COVID-19 pandemic on people's mobility: A longitudinal study of the US from March to September of 2020. *Journal of transport geography*, *93*, 103039.

[28] Levin, R., Chao, D. L., Wenger, E. A., & Proctor, J. L. (2021). Insights into population behavior during the COVID-19 pandemic from cell phone mobility data and manifold learning. *Nature Computational Science*, *1*(9), 588-597.

[29] Li, Y., Geertman, S., Hooimeijer, P., Lin, Y., & Yang, H. (2021). Do migrants and locals differ in commuting behavior? A case study of Xiamen, China. *Transport policy*, *108*, 1-10.

[30] Lo Bello, S., Sanchez Puerta, M., & Winkler, H. (2019). From Ghana to America: The skill content of jobs and economic development.

[31] Lotero, L., Hurtado, R. G., Floría, L. M., & Gómez-Gardeñes, J. (2016). Rich do not rise early: spatio-temporal patterns in the mobility networks of different socio-economic classes. *Royal Society open science*, *3*(10), 150654.

[32] Lou, J., Shen, X., & Niemeier, D. (2020). Are stay-at-home orders more difficult to follow for low-income groups?. *Journal of transport geography*, *89*, 102894.

[33] Matekenya, D., Espinet Alegre, X., Arroyo Arroyo, F., & Gonzalez, M. (2021). Using mobile data to understand urban mobility patterns in Freetown, Sierra Leone.

[34] Mendolia, S., Stavrunova, O., & Yerokhin, O. (2021). Determinants of the community mobility during the COVID-19 epidemic: The role of government regulations and information. *Journal of Economic Behavior & Organization*, *184*, 199-231.

[35] Mongey, S., Pilossoph, L., & Weinberg, A. (2021). Which workers bear the burden of social distancing?. *The Journal of Economic Inequality*, *19*(3), 509-526.

[36] Niehues, J., & Peichl, A. (2014). Upper bounds of inequality of opportunity: theory and evidence for Germany and the US. *Social Choice and Welfare*, *43*(1), 73-99.

[37] Nouvellet, P., Bhatia, S., Cori, A., Ainslie, K. E., Baguelin, M., Bhatt, S., ... & Donnelly, C. A. (2021). Reduction in mobility and COVID-19 transmission. *Nature communications*, *12*(1), 1-9.

[38] Pappalardo, L., Pedreschi, D., Smoreda, Z., & Giannotti, F. (2015, October). Using big data to study the link between human mobility and socio-economic development. In *2015 IEEE International Conference on Big Data (Big Data)* (pp. 871-878). IEEE.

[39] Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020). Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: a population-based study. *The Lancet Digital Health*, *2*(12), e638-e649.

[40] Rapa, N. (2021). *Mitigation measures, prevalence response and public mobility during the COVID-19 emergency* (No. WP/03/2021). CBM Working Papers.

[41] Roemer, J. E. (1998). Equality of opportunity. In *Equality of Opportunity*. Harvard University Press.

[42] Song, C., Qu, Z., Blumm, N., & Barabási, A. L. (2010). Limits of predictability in human mobility. *Science*, *327*(5968), 1018-1021.

[43] Sulyok, M., & Walker, M. (2020). Community movement and COVID-19: a global study using Google's Community Mobility Reports. *Epidemiology & Infection*, *148*.

[44] Toger, M., Kourtit, K., Nijkamp, P., & Östh, J. (2021). Mobility during the covid-19 pandemic: A data-driven time-geographic analysis of health-induced mobility changes. *Sustainability*, *13*(7), 4027.

[45] Türk, U., & Östh, J. (2019). How much does geography contribute? Measuring inequality of opportunities using a bespoke neighbourhood approach. *Journal of Geographical Systems*, *21*(2), 295-318.

[46] UNDP (2020). Survey on Impact of Covid-19 on Enterprises and Needs. Retrieved May 01, 2022, from https://www.undp.org/turkey/press-releases/four-every-five-smes-substantially-impacted-covid-19-crisis

[47] Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). Human mobility and socioeconomic status: Analysis of Singapore and Boston. *Computers, Environment and Urban Systems*, *72*, 51-67.

[48] Yilmazkuday, H. (2021). Stay-at-home works to fight against COVID-19: International evidence from Google mobility data. *Journal of Human Behavior in the Social Environment*, *31*(1-4), 210-220.

[49] Zhao, J., Lee, M., Ghader, S., Younes, H., Darzi, A., Xiong, C., & Zhang, L. (2020). Quarantine fatigue: first-ever decrease in social distancing measures after the COVID-19 pandemic outbreak before reopening United States.

[50] Zhao, P., & Cao, Y. (2020). Commuting inequity and its determinants in Shanghai: New findings from big-data analytics. *Transport policy*, *92*, 20-37.