IT UNIVERSITY OF COPENHAGEN

Master's Thesis

The impact of COVID-19 lockdowns on the access to economic opportunities in the metropolitan areas of low and middle-income countries

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Abstract

This study investigates the impacts of COVID-19 lockdown measures conditioned on relative wealth by tracing changes in individual mobility in the metropolitan areas of Bogotá, Delhi, Jakarta, Lagos, and Mexico City. Our aim is to understand whether people are equally affected by mobility restrictions or if there is a disproportionately negative impact on the poorer communities. Our quantitative analysis is based on the recognition that mobility is important as a means of access to earning income and thereby influences personal wealth. Here we develop an Economic Access indicator (EA) that describes the access to the economic opportunities that can be reached from a community. By comparing the changes in EA due to mobility restrictions, we can analyze the economic impact of lockdowns on different wealth groups. The EA is built by combining mobility data from smartphones with lockdown strictness and micro-regional relative wealth indices. We anticipated that mobility patterns would change due to lockdown policies, and therefore we anticipated that the EA would change as well but it is possibly different for different wealth groups.

Using weighted linear regression, we find that lockdown measures have a disproportionately negative impact on the economic access of the poorest populations in all five cities. We also find that while in some cities (Delhi, Lagos) the poor have the largest decrease in mobility, in others (Mexico City, Bogotá, Jakarta), it is the richest, whose mobility is reduced the most. We thus show that reductions in mobility do not necessarily follow a universal pattern, which is likely to be due to complementing factors such as the unique socio-economic and urban infrastructure interplays in cities. However, our main findings highlight that while movement restrictions are applied equally to all, the pandemic is occurring in the context of existing social and economic inequalities. Understanding the impact of lockdown measures on the different communities, and how it varies across cities is important because it is the first step in the direction of developing public policy measures to address the unique realities in each of the urban populations i.e., to tackle income inequalities, facilitate the regaining of livelihoods during the recovery period, and create inclusive, resilient, and sustainable cities in line with the United Nations Sustainable Development Goals.

Abbreviations

CCDF	Complementary Cumulative Distribution Function
EA	Economic Access indicator
LMICs	Low and Middle-Income Countries
NPI	Non-Pharmaceutical Interventions
OLS	Ordinary Least Squares
OxCGRT	The Oxford COVID-19 Government Response Tracker
RWI	Relative Wealth Index
SI	Stringency Index
UN SDGs	United Nations Sustainable Development Goals
WLS	Weighted Least Squares (in our study referred to as weighted linear regression)

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1 Introduction

COVID-19 has caused an unprecedented social and economic disruption worldwide, which has radically changed the way people live and work. To slow the spread of the virus, and reduce the healthcare demand, governments have been implementing non-pharmaceutical interventions (NPIs), that include large-scale mobility restrictions, such as stay-at-home orders, travel bans, and quarantines. These measures are considered to be unparalleled in human history both in scale and in scope (Oh et al., 2021). The objective of this thesis is to investigate the economic impact of mobility restrictions on different wealth groups in the cities of low and middle-income countries (LMICs). We do this by tracing mobility pattern changes in response to COVID-19 lockdowns in the metropolitan areas of Bogotá, (Colombia), Delhi (India), Jakarta (Indonesia), Lagos (Nigeria), and Mexico City (Mexico). These five cities were carefully chosen based on the following inclusion criteria: (1) data availability – we had to have data for all the cities in our datasets; (2) geographic representation – cities needed to be geographically distributed across different continents; (3) size – the chosen cities are large capital cities with correspondingly large metropolitan areas.

Research has shown that mobility is important for access to economic opportunities (Boisjoly et al., 2017; Hidayati et al., 2021; Oviedo & Guzman, 2020), and our study is based on this recognition i.e., mobility is important as a means of access to earning income and thereby influences personal wealth. This means that the real value of living in a certain neighborhood is closely connected to mobility i.e., the value is not just about physically living in a place, but it is the value of all the places that can be reached from there to gain access to the economy of the city. Here we developed an Economic Access indicator (EA) that describes the access to the economic opportunities that can be reached from a specific location with a certain standard of living. By comparing the changes in EA as a result of mobility restrictions, we can analyze the economic impacts of lockdowns on different wealth groups based on where they live in i.e., in the low, middle, and high-income communities. When natural mobility is restricted such as during COVID-19 lockdowns, it is bound to impact the economic situation of people. Understanding the impact of lockdown measures on the poorest communities, and how it differs across cities is important because it is the first step in the direction of developing public policy measures to address the unique realities in each of the urban populations. This is crucial to tackle income inequalities, facilitate the regaining of livelihoods during the recovery period, and create inclusive, resilient, and sustainable cities in line with the United Nation's Sustainable Development Goals (UN SDGs) (United Nations, 2015b)

1.1 Background

The first publicly known cases of COVID-19 were confirmed in December 2019. Already in March 2020, it was declared a pandemic, and countries were urged to take immediate and aggressive action to control and contain the virus (World Health Organization, 2020). National governments quickly responded by adopting NPIs ranging from recommendations for social distancing to restricting all non-essential movements resulting in localized or national lockdowns. By April 2020, full or partial lockdown measures were affecting 2.7 billion workers, accounting for around 81 percent of the world's total workforce (International Labour Organization, 2020b). These are impressive figures, and while the measures introduced by governments applied equally to all, not everyone was equally affected.

Indeed, COVID-19 is believed to have exacerbated both economic and health inequalities around the world. Lockdown measures especially, while considered effective (Anderson et al., 2020), tend to disrupt normal lives and the functioning of economies, and there is a consensus that they disproportionately affect the most disadvantaged population groups (Dorn et al., 2020; Laajaj et al., 2021; Lewnard & Lo, 2020; Marmot & Allen, 2020; Nassif-Pires et al., 2020; Rawet et al., 2020). For example, lower-paid workers are more likely to have occupations that cannot be done remotely, because they require person-to-person contact and therefore commuting, and this also makes them more susceptible to the virus. Furthermore, many of them have lost their jobs, because they were in sectors that have been forced to suspend activities such as tourism, hospitality, and the food industry (Chen, 2020). When it comes to LMICs the hardest-hit sectors have a high proportion of people in the informal economy (International Labour Organization, 2018). Already before the pandemic, most of these workers lacked social protection and adequate working conditions, and for them stopping work, working remotely, or even physical distancing has often not been an option (International Labour Organization, 2020a).

Economic development and growth of cities are closely intertwined with cities providing many opportunities for higher incomes (Henderson, 2010). About two-thirds of people will be living in urban settings by 2050, and nearly 90 percent of this increase is concentrated in LMICs

(United Nations, 2018). This means that the future of humanity is largely centered around cities. However, during pandemics, cities, and particularly mega-cities in LMICs, because of their high population density, overcrowding and lack of access to basic services become the hotspots of the epidemic's spread (World Economic Forum, 2020). Therefore, it is crucial to learn the lessons from COVID-19 including through studies such as ours to be prepared for future pandemics.

1.2 Rationale

The starting point of our study is connected to the economic benefits of human mobility i.e., mobility is important as a means of access to earning income and thereby influences personal wealth. If people are confined to their homes, such as in the case of COVID-19 lockdowns, and their natural mobility is restricted, we would anticipate that their economic situation likely deteriorates as well. However, the impact might not be experienced equally by different wealth groups of the society for reasons related to inherent socio-economic inequalities such as income and occupation which determine what options are still available for people to continue accessing the economic opportunities of a city. This study aims to shed light on these notions.

On one hand, there is a growing body of research on human mobility networks and their application to study a range of different topics e.g., population densities (Ricciato et al., 2017), human mobility patterns (González et al., 2008; Hoteit et al., 2014), spread of diseases (Wesolowski et al., 2012), transportation modes (H. Wang et al., 2010), social events (Calabrese et al., 2010; H. Wang et al., 2010), and income segregation (Moro et al., 2021). On the other hand, COVID-19 has only been around for about two years, so research on how reduced human mobility caused by lockdown policies has impacted different income groups is relatively limited, and these studies mostly focus on the high-income countries such as Italy, Spain, USA, and UK (Bonaccorsi et al., 2020; Glodeanu et al., 2021; Hunter et al., 2021; Jeffrey et al., 2020). So, while inequalities related to COVID-19 have been discussed recently, to our knowledge the economic implications of lockdowns on the different income groups in LMICs using their pre-lockdown and lockdown mobility patterns have not been studied.

The purpose of our study is to provide insights into understanding the economic impacts of COVID-19 lockdowns on different income groups in LMCIs by using Bogotá, Delhi, Jakarta, Lagos, and Mexico City as case studies. These insights into economic inequalities are important because the most vulnerable populations face a high risk of increased poverty and will experience greater challenges in regaining their incomes during the recovery period (International Labour Organization, 2020b). The policy measures to adequately address the challenges imposed by the pandemic require accurate, quantitative data. We hope that our analysis can be part of the wider effort to help decision-makers and researchers in understanding the economic consequences of COVID-19 lockdowns on local communities in LMICs and thereby also prepare the cities and their populations for future infectious disease outbreaks.

1.3 Definitions

In the context of this study, we have defined the following terms (in alphabetical order):

a. **Cell** – refers to a specific micro-region (point h). The terms cell and micro-region are used interchangeably.
b. **City** – refers to a major city together with its surrounding primary commuter areas (see point f). The terms city and metropolitan area are used interchangeably.
c. **Economic Access indicator (EA**) – describes the access to the economic opportunities that can be reached from a specific micro-region.
d. **Flow** – refers to the number of trips between two micro-regions. It is used in the context of describing mobility;
e. **Lockdown** – refers to "lockdown-style" policies (also referred to as containment and closure policies), which have been proven to restrict the mobility of people incorporating both voluntary and involuntary measures to limit movement. It is based on the Strictness Index (SI) published by the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021).
f. **Metropolitan area** – refers to a major city together with its surrounding primary commuter areas (OECD, n.d.). In our study, we also refer to a metropolitan area as a city;
g. **Micro-region** – refers to the unique 2.4km regions that the Relative Wealth Index (RWI) data is calculated for (Chi et al., 2021). We also refer to a micro-region at times as cell, so these terms are used interchangeably;
h. **Mobility** – refers to the movement of people in space and time regardless of the transportation mean or purpose of the trip, and it is equivalent to human mobility;

i. **Mobility data** – refers to data obtained from smartphones. We use the terms mobile phones and smartphones interchangeably.
j. **Pre-lockdown** – refers to the period before the lockdown measures were implemented, and it is based on the SI values from OxCGRT.
k. **Relative Wealth Index (RWI)** – it is the micro-regional wealth relative to others in the same country, and we refer to it also as relative wealth (Chi et al., 2021). It is a proxy for relative standard of living, and we use this measure to discuss the distribution of poverty and wealth across the micro-regions in the metropolitan areas in our five cities and to differentiate between the poor and the rich income groups;
l. **Transition period** – it is the period between the end of pre-lockdown and the start of lockdown, where increasingly more measures to restrict movement started to be implemented by governments but it is not yet at the level to be considered a lockdown.

1.4 Research questions

This thesis investigates the effects of COVID-19 lockdown measures conditioned on micro-regional relative wealth by tracing changes in mobility in our chosen five cities. More specifically, the research questions (RQs) of this study are:

RQ1: How has the mobility of individuals been impacted by COVID-19 lockdown policies in the metropolitan areas in Bogotá, Delhi, Jakarta, Lagos, and Mexico City, and have people experienced a different impact based on their level of relative wealth?

RQ2: The real value of living in a place is connected to the mobility patterns, i.e., it is the value of all places one is able to reach to gain access to the economy of the city. Therefore, if mobility patterns changed because of lockdown policies, are all people equally affected in terms of their access to the economy, or is there a disproportionately negative impact for people living in low-income communities?

1.5 Methods & Data

To investigate the impacts of lockdowns on mobility for different wealth groups in the five cities, we utilize three datasets: 1) micro-estimates of wealth that provides the RWI (Chi et al., 2021); 2) the OxCGRT that provides the SI indicating the severity of lockdowns (Hale et al., 2021); and 3) mobility data that is obtained from smartphones and supplied by an unnamed company[1]. First, we define the pre-lockdown and lockdown periods, based on datasets (2) and (3). Secondly, we use dataset (1) to investigate changes in mobility for different wealth groups. Thirdly, we calculate the EA for each micro-region and for both the pre-lockdown and lockdown period and compute the difference between the two periods. Lastly, we model the difference as a function of RWI using linear regression.

1.6 Outline

This thesis is structured as follows: Chapter 2 outlines the literature review. Chapter 3 describes the datasets and the methodology used for the analysis. Chapter 4 is dedicated to the results, and Chapter 5 presents the discussion. Finally, a conclusion including limitations and future work are given in Chapter 6.

[1] The mobility data used in this thesis is highly aggregated in a spatial and temporal sense. It is provided by an undisclosed source in an anonymized and aggregated manner that preserves privacy through a GDPR compliant framework. For more information, please contact Vedran Sekara, Assistant Professor ITU, vsek@itu.dk

2 Literature Review

This literature review is structured based on a funnel approach i.e., we start with analyzing relevant studies first from the broader perspective to provide context and then focusing on the recent knowledge pertaining specifically to our topic. We do this by first discussing: (1) mobile phones and mobility data, and how they are used; (2) cities and interlinkages between urbanization and economic development. We then move on to discuss (3) how mobility is related to the potential access to the economy of cities, and thereby to the income of individuals. Once we have established this, we narrow our focus further to (4) put mobility research in the context of COVID-19 lockdowns and specifically discuss how these lockdown measures (by curtailing previously taken-for-granted mobility behaviors) have impacted different income groups. Our goal is to establish the relevance of our study in relation to the existing research, and we do this in the end by (5) identifying and summarizing gaps in relation to our proposed study. Finally, we also intend this chapter to be of great relevance when we discuss our results (Chapter 5) and show how they fit into prior research on the topic.

2.1 Data from mobile phones

In 2006 smartphones were defined as *next generation, multifunctional cell phones that facilitate data processing as well as enhanced wireless connectivity* (Zheng & Ni, 2006). The same year, the term mobile landscapes was introduced to describe the use of aggregated locational data for understanding urban systems (Ratti et al., 2006). Today, smartphones are essential and highly personal devices voluntarily carried by a significant number of people all around the world. In 2020, the global smartphone penetration rate is estimated to have reached 78% and this number is growing steadily (Statista, 2021c).

Mobile phones are a valuable tool for researchers because they can effectively capture human mobility i.e., the location of people in space and time (Grantz et al., 2020). These data are typically collected by private sector companies through Call Detail Records (CDRs) or through applications that use built-in GPS capabilities (The GovLab, 2021). In recent years, mobile phone data has been applied to research a range of different topics e.g., population densities (Ricciato et al., 2017), human mobility patterns (González et al., 2008; Hoteit et al., 2014), spread of diseases (Wesolowski et al., 2012), transportation modes (H. Wang et al., 2010), social events (Calabrese et al., 2010; H. Wang et al., 2010), and experienced income segregation by individuals (Moro et al., 2021). Mobility data is also an important proxy for social distancing, and it has effectively been used in the context of evaluating COVID-19 response policies as we will show in Section 2.4. However, since our focus is specifically on urban populations, we will first cover the socio-economic challenges in today's megacities, and how mobility data has been used in this context.

2.2 Urbanization and economic development

Cities are complex structures involving many interconnected communities, businesses, transportation networks, and people from all walks of life. The world has urbanized rapidly in the last 50 years, and today more than half of the global population are living in the cities (Buchholz, 2020). The major drivers for rural to urban migration are economic i.e., opportunities for increased incomes and growth, indicating that economic development and urbanization are closely connected (Henderson, 2010). It has been projected that by 2050 about two-third of the world's population will live in urban settings, and the majority of that increase (90 %) is concentrated LMICs (United Nations, 2018). This implies that the future of humanity is predominantly urban.

UN SDG 11 on creating sustainable cities and communities, states that economic benefits should be shared equally within the urban populations (United Nations, 2015a). The world's megacities, however, have increasingly been faced with segregation and inequalities, which affect the socio-economic situation (a combination of occupation, education, and income) of the people living in urban areas (Kuddus et al., 2020). Cities in LMICs, where most of the urbanization is predicted to happen, experience high income segregation, high informality rates, and often lack basic social protection for workers (ILO, 2021). This is a major area of concern because social cohesion and decreasing inequalities are considered crucial for sustainable urban development (Moro et al., 2021). Furthermore, research has shown that inequalities are an obstruction to poverty reduction, they can threaten peaceful societies, trigger conflicts, and are linked to negative environmental impacts (European Commission, 2019).

The concept of smart cities has been receiving a lot of attention in the context of technology-based sophisticated solutions, which enable the sustainable development of metropolitan areas, where cities can make better use of their resources (Neirotti et al., 2014), and thereby enhance the quality of life of their citizens. Considering that the future for most of the world's people is urban, reducing economic inequalities is crucial in LMICs to facilitate sustainable development. Here, mobility data can efficiently be used to facilitate the development of smart and sustainable cities and to understand and address inequalities in urban environments (A. Wang et al., 2021).

2.3 Urban mobility patterns

Cities are tightly connected with their primary social systems composed of people and their mobility patterns (Barbosa et al., 2021), and the mobility of people living in urban areas is a well-studied area of research (Barbosa et al., 2018, 2021; Boisjoly et al., 2017; González et al., 2008; Lenormand et al., 2015; Louail et al., 2017; Moro et al., 2021; W. Wang et al., 2015; Zhan et al., 2013). The connections between socio-economic status (i.e., related to a combination of occupation, education, and income) and human mobility patterns are diverse with studies showing that the rich and the poor in different countries and cities do not always exhibit the same mobility patterns (Barbosa et al., 2021). For example, a study done in Singapore and Boston showed that the poorer tend to travel less than the wealthy in Boston and more in Singapore, which led the researchers to conclude that such variability is likely driven by where the opportunities for employment, housing, and social activities were located in each city (Xu et al., 2018). Further examples, from the USA, South America, and Europe demonstrate variations in mobility patterns between rich and poor depending largely on the distinctive economic and sociodemographic circumstances of different cities (Barbosa et al., 2021).

Despite the heterogeneous nature of mobility patterns across cities, mobility is important for access to the economy: people in present-day large metropolitan areas undertake daily commutes to earn income (Barbosa et al., 2018). Furthermore, disadvantages driven by unequal access to the city's resources have been connected to mobility inequalities (Hidayati et al., 2021). Mobility patterns also reflect the choices people make and the opportunities available to them (Moro et al., 2021). An analysis of public transport in São Paulo, Brazil, showed that accessibility to employment is unevenly distributed, concentrating especially in the high-income areas and that mobility in the form of access to public transportation contributes to better access to formal jobs (Boisjoly et al., 2017). In fact, in the majority of city environments, shortcomings in access to urban mobility are positively correlated with lower income (Oviedo & Guzman, 2020). Spatial mismatches, whereby the employment opportunities for low-income individuals especially in the large urban areas are located far away from the areas where they live, are a major driver for mobility inequalities (Hidayati et al., 2021). The results from these studies indicate that the observed human mobility patterns are associated with access to opportunities for earning income i.e., access to the economy of the cities, and thereby mobility is directly connected with the overall economic situation of people, which is the underlaying principle of our study.

2.4 COVID-19 lockdowns and related inequalities

It has thus been shown that mobility is a crucial element in access to economic opportunities. So, what happens when mobility is restricted? Population mobility data is an important proxy for social distancing and is used effectively to evaluate COVID-19 response policies (Hunter et al., 2021; Jeffrey et al., 2020; Nouvellet et al., 2021; Tomori et al., 2021). For example, it has been used to explain the relationship between transmission patterns and the mobility of people (Nouvellet et al., 2021; Tomori et al., 2021), assess changes in physical mobility rates during lockdowns in the UK (Jeffrey et al., 2020) and study the effects of lockdowns on the walking behavior in metropolitan areas in the United States (Hunter et al., 2021).

To slow the spread of COVID-19, reduce healthcare demand, and protect those most susceptible to the virus, governments around the world have been implementing NPIs (Snoeijer et al., 2021) such as stay-at-home orders, quarantines, social distancing, and restrictions on social gatherings and travel (IMF, 2021). These measures, while considered effective (Anderson et al., 2020), present inherent risks and involve serious disruptions to the functioning of normal lives and economies, and there is a wide consensus that they disproportionately affect the most disadvantaged population groups (Dorn et al., 2020; Lewnard & Lo, 2020; Nassif-Pires et al., 2020). Specifically, lockdown and social distancing are believed to be prone to increasing inequalities in the social determinants of health (Bambra et al., 2020; Marmot & Allen, 2020), which include factors like income and social protection, unemployment, job security, and access to affordable housing (World Health Organization, n.d.).

A study based on the EU, Norway, and Switzerland has shown that the share of jobs directly threatened by the COVID-19 pandemic is strongly negatively correlated with regional GDP per capita e.g., a 10 percent decrease in regional GDP, is associated with a 0.5 percent increase in jobs at risk (Garrote Sanchez et al., 2020). This means that the poorer the region within a country, the more likely they are to have a higher number of jobs at risk. A study from Italy found that COVID-19 lockdowns hit the poorest municipalities with high-income inequality the hardest (Bonaccorsi et al., 2020). In Madrid, the low-income neighborhoods were hardest hit by lockdown policies as their residents are more likely to have in-person occupations, which require commuting (Glodeanu et al., 2021). LMICs are even harder hit than higher income countries because they typically have a higher share of jobs that cannot be done remotely and these occupations often pay significantly less (Dingel & Neiman, 2020). In India for example, unemployment has increased dramatically since COVID-19 started, and many temporary, and daily wage workers previously living in the densely populated urban areas, have lost their jobs, and have been forced to move back to the rural areas (Estupinan et al., 2021). Another report about the income of urban workers in India showed that the poorest suffered the biggest losses, and those in the top quartile of pre-COVID income actually saw an increase (Bhalotia et al., 2020). This is an interesting observation, and we hope that our analysis can shed further light on how the economic opportunities have been impacted for different wealth groups.

Income inequalities directly relate to different infection rates between socio-economic groups (Laajaj et al., 2021), which can also impact mobility patterns due to isolation requirements if tested positive. Low-income populations are much more exposed to COVID-19 because they do not have the same possibilities to quarantine, socially distance, or work from home, which are factors driven by informal employment and cramped living arrangements (Rawet et al., 2020). In the USA, differences in mobility were the sole driver of higher infection rates among the disadvantaged socioeconomic groups, because they were not able to reduce their mobility as easily and places that they visit tended to be more crowded (Chang et al., 2021). A country-level study comparing 118 countries based on mobility data from Google and the SI from OxCGRT in the period from March 2020 – May 2020 showed that as a result of lockdowns the overall mobility decreased the most in upper-middle and high-income countries and the least in low-income countries (Maire, 2020). The same research also showed that this was likely caused by extreme poverty, the share of vulnerable employment, and higher population density in the cities in LMICs. So, studies have demonstrated that the COVID-19 pandemic is occurring in the context of existing social and economic inequalities, and these examples further indicate that income inequalities are likely to both worsen the pandemic on one hand and are worsened by the pandemic on the other.

2.5 Gaps in existing research

On one hand, there is a growing body of research on human mobility networks and their application to study a range of different topics e.g., population densities (Ricciato et al., 2017), human mobility patterns (González et al., 2008; Hoteit et al., 2014), spread of diseases (Wesolowski et al., 2012), transportation modes (H. Wang et al., 2010), social events (Calabrese et al., 2010; H. Wang et al., 2010), and income segregation (Moro et al., 2021). On the other hand, COVID-19 has only been around for about two years, therefore research on how reduced mobility caused by lockdown policies has impacted different income groups is relatively limited (Bonaccorsi et al., 2020; Glodeanu et al., 2021; Hunter et al., 2021; Jeffrey et al., 2020). As the pandemic is still around us and most likely will stay in one form or another the socioeconomic impacts of containment and closure policies are an ongoing area of research.

There seems to be a consensus that COVID-19 has impacted the poorest communities the hardest (Dorn et al., 2020; Laajaj et al., 2021; Lewnard & Lo, 2020; Marmot & Allen, 2020; Nassif-Pires et al., 2020; Rawet et al., 2020), and some previous studies have assessed changes in mobility in response to COVID-19 lockdown measures (Bonaccorsi et al., 2020; Chang et al., 2021; Glodeanu et al., 2021). However, these studies have mostly focused on high-income countries such as Italy, Spain, the USA, and the UK (Bonaccorsi et al., 2020; Glodeanu et al., 2021; Hunter et al., 2021; Jeffrey et al., 2020).

So, while the overall inequalities related to COVID-19 have been much discussed recently, and changes in mobility have been studied in high-income countries, to our knowledge the economic implications of lockdowns on the different communities in LMICs, and specifically in our chosen five cities using their mobility patterns has not been explored. Our study focuses on specific cities, but our hope is that our findings could eventually be applied in the context of any large metropolitan area located in LMICs. We do, however, acknowledge, the importance of analyzing urban mobility in the context of local realities. The importance of studying each large metropolitan area separately lies in the recognition that mobility patterns between rich and poor are not universal, and they depend largely on the distinctive economic and sociodemographic circumstances of different cities i.e., while in some cities the poor travel more, in others they travel less (Section 2.3).

Our goal is to contribute to the research about changes in mobility due to COVID-19 lockdowns and its impacts on the different communities. We assess changes in mobility in the context of economic impact on different income groups in response to COVID-19 lockdowns by conducting our study using the same underlying datasets and a uniform methodology for all our chosen cities. We anticipate that this approach would enable us to potentially uncover greater insights into how mobility restrictions have impacted the different communities in terms of their potential access to the economy.

3 Methods

The objective of the chapter is to explain the three datasets and research methodology that we have chosen and consequently applied to the different metropolitan areas in order to address our research questions. We also provide justifications for our choices where appropriate.

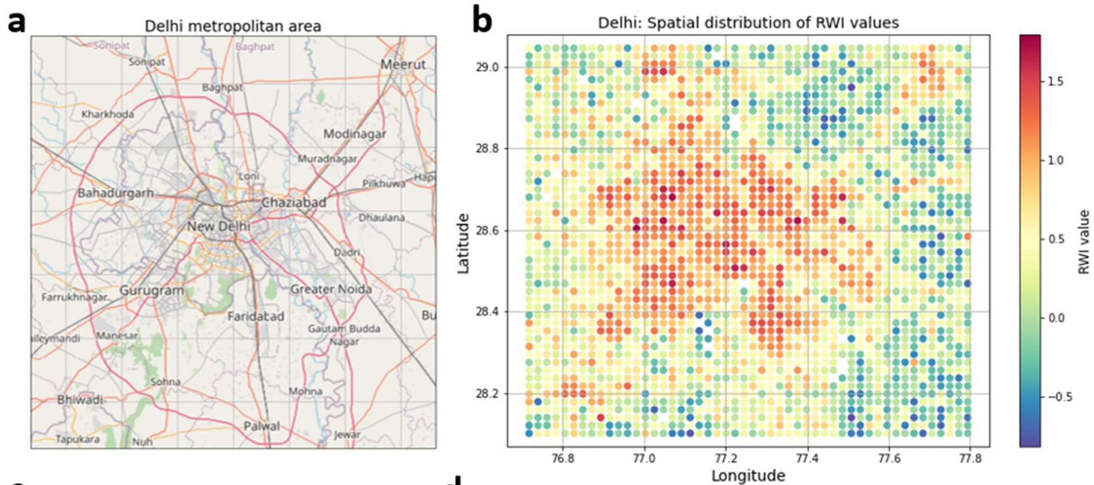
3.1 RWI data

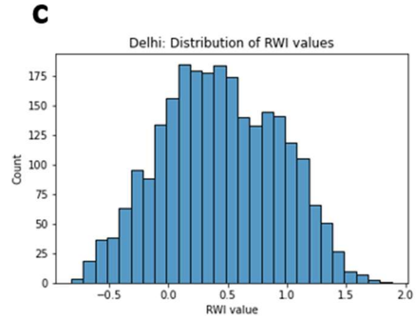
The RWI data are created by the University of California, Berkeley, and Facebook's Data for Good. These estimates have been built using data from mobile phone networks, satellites, topographic maps, and privacy protecting connectivity data from Facebook. The datasets cover LMICs at 2.4 km resolution and each such micro-region has an estimate of the relative wealth (relative to others in the same country) of the people living in the region (Chi et al., 2021). We use these data to distinguish in a spatial sense between poor, middle, and rich wealth groups in the five cities. The datasets were obtained from the Humanitarian Data Exchange, which is a publicly accessible platform managed by the United Nations Office for the Coordination of Humanitarian Affairs with the goal to facilitate open humanitarian data sharing (HDX, 2021).

In our study, we are using the RWI together with the longitude and latitude coordinates of the corresponding micro-regions to establish connections between the relative wealth of the place one lives and mobility from and to that place. To preserve the privacy of households, RWI values for micro-regions with fewer than 50 individuals are not reported. The dataset also contains a model error value for each RWI entry, but because it is unclear how these errors could be integrated into our analysis, they are therefore considered beyond the scope of this study. However, we do acknowledge that there is some uncertainty about the RWI values coming from the dataset.

3.1.1 Determining metropolitan areas

To define the boundaries i.e., obtain the longitude and latitude coordinates for the greater metropolitan areas of the five cities we made a bounding box using OpenStreetMap, which is an open geographic database covering the world (Fig. 1a) (OpenStreetMap, n.d.). As our cities vary in size and are shaped differently e.g., due to the mountain ranges surrounding them (Mexico City, Bogotá), being by the ocean (Lagos, Jakarta), or just being very large in terms of territory compared to others (Delhi) we could not just use the same size and shape bounding boxes. Instead, we defined the greater metropolitan area for each city based on the definition of the metropolitan area (Section 1.3) and used travel time estimates from the suburbs into the city centers based on information obtained from Google Maps. An alternative for defining the boundaries would have been to use shapefiles of the administrative borders covering the different metropolitan areas. However, because we were interested in the overall mobility of people in the greater metropolitan areas, and this transcends administrative boundaries, a bounding box approach was sufficient for the purposes of our study.





d

City	# micro-regions	Min	33%	Mean	66%	Max
Bogotá	841	-0.973	-0.167	0.128	0.316	1.568
Delhi	2484	-0.816	0.184	0.435	0.659	1.794
Jakarta	1521	-0.931	0.367	0.557	0.859	1.928
Lagos	838	-0.973	0.025	0.426	0.754	1.897
Mexico City	858	-0.711	0.516	0.743	1.063	2.257

Fig. 1 Overview of RWI data. (**a**) Map of our defined metropolitan area of Delhi (source: OpenStreetMap) (**b**) Map of the individual micro-regions with corresponding RWI values within the Delhi metropolitan area. Higher values seem to occur predominately in the city center, with lower values towards the outskirts. Note in Delhi there are a few white spots, where no micro-region is defined and thus no RWI value is available. This is either due to geographical constraints e.g., water bodies, mountain ranges, national parks, etc. Also, in micro-regions where population levels are < 50 individuals RWI values are not reported. Other cities have more of such areas (Appendices A – E subplot a). (**c**) Distribution of RWI values for Delhi (other cities: Appendices A – E subplot b). (**d**) Statistics of the RWI values from all five metropolitan areas. The 33% and 66% percentiles of RWI are used for defining poor, middle, rich communities (Section 3.4.1).

By means of example, the bounding box surrounding the metropolitan area of Delhi is shown in Fig. 1a. The corresponding RWI values in this region are shown in Fig. 1b and reveal the distribution of higher values mostly concentrated in the city centers and low values mostly on the outskirts. This pattern can also be observed in the other cities (Appendices A – E subplot a). The table in Fig. 1d shows the basic statistics of the RWI values for the different metropolitan areas, which are used to define three equal-sized groups to reflect poor, middle-income, and rich micro-regions. Note that there are differences between cities in where the absolute RWI boundaries (minimum and maximum values) are for each wealth group, which depend on the RWI data distributions in each metropolitan area.

3.2 Lockdown data

Lockdown data was obtained from the publicly available OxCGRT database. From the selection of available indices, we use the SI, because it specifically records the strictness of government policies, also defined as 'lockdown style' policies that are the primary methods for restricting people's behavior (Hale et al., 2021). It is calculated using nine different response metrics i.e., all containment and closure policy indicators and an additional indicator recording public information campaigns. The containment measures include closings of schools and universities, workplaces, canceling of public events, limits on gatherings, closings of public transport, orders to "shelter-in-place" and otherwise confine to the home, restrictions on internal movement between cities/regions, and restrictions on international travel. The SI is calculated as the mean score of these nine metrics, and it has a value between 0 and 100, with a higher score corresponding to a stricter response (Appendices A – E subplot g, red line). The index has been recorded from 1st January 2020 and it is being continuously updated. The SI is provided at the country level, and we are aware that across the world both national and sub-national or regional lockdowns of varying strictness have been implemented. However, in the absence of a similar well-established sub-national indicator, we use the country-level SI, as it allows us to define a consistent approach of what is considered a lockdown and make systematic comparisons between the changing strictness levels of government lockdown policies impacting the mobility of people in the five cities.

3.2.1 Defining lockdown dates

We used the SI to define lockdown dates for each city by identifying first when SI was low and started to increase, which constituted the end date of the pre-lockdown period. The start date of pre-lockdown was always 1st January 2020, which was determined by the constraints of the SI data (Section 3.2). It formed a natural start of the pre-lockdown period for every city, which is the time before the lockdown measures were implemented. When SI reached its highest levels, we defined it as the start of lockdown. When SI decreased significantly again, it constituted the end date of lockdown. We named the period between the end date of the pre-lockdown and the start of the lockdown a transition period, and it reflects a time where increasingly more measures to restrict movement started to be implemented by governments. However, since the SI is not yet at the level to be considered a lockdown, we decided to include this period from our analysis. Similarly, the period after the lockdown ("post-lockdown") does not show a return of mobility values to pre-lockdown levels since SI is still relatively high and rather reflects the 'new normal'. Therefore, this period is also excluded from the analysis. Since countries implemented lockdown measures of varying degrees of strictness by adapting to their local realities, we decided that assigning SI thresholds tailored to the unique circumstances in each country was reasonable and necessary in the context of our study (Table 1):

City	SI thresholds (end pre-/ start lock/ end lock)	End date pre-lockdown	Transition period	Start date lockdown	End date lockdown	Duration pre-lockdown/ lockdown (days)
Bogotá	20/80/70	11-03-2020	12 to 24-03-2020	25-03-2020	19-10-2020	71 / 209
Delhi	20/90/80	04-03-2020	05 to 21-03-2020	22-03-2020	01-10-2020	64 / 194
Jakarta	30/70/55	02-03-2020	03-03 to 09-04-2020	10-04-2020	12-10-2020	62 / 186
Lagos	20/80/55	17-03-2020	18 to 28-03-2020	29-03-2020	25-09-2020	77 / 182
Mexico City	20/80/70	23-03-2020	24 to 29-03-2020	30-03-2020	11-09-2020	83 / 166

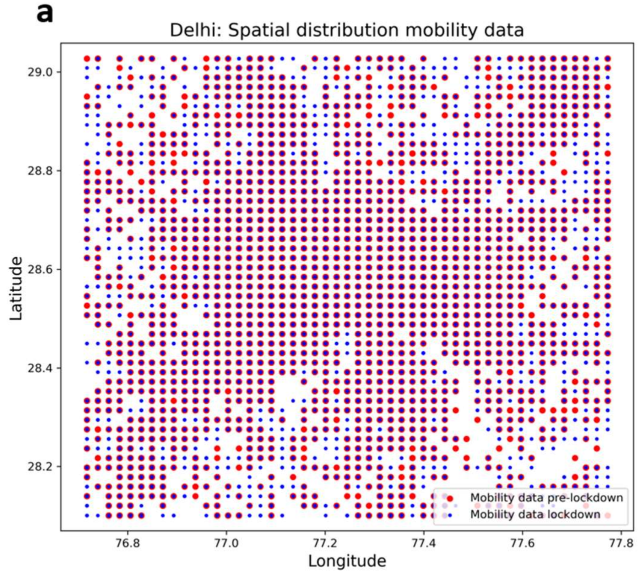
Table 1. Overview of the SI thresholds. The SI values are between 0 and 100 with a higher score indicating a stricter response. This value is used to define the dates of 1) the end of the pre-lockdown period (low SI value); 2) the start of the lockdown period (high SI value); 3) end of lockdown period (decreasing SI value) (Appendices A – E subplot g). Note that since countries have been different in how they have implemented lockdown policies e.g., in our case, only India reached SI level 90, so we have also tailored the SI thresholds to each countries' unique circumstances. The period between the end of pre-lockdown and the start of lockdown which we defined as a transition period where restrictions started to become implemented, has been excluded from our analysis. The post-lockdown period has also been excluded because the focus of this study is to specifically compare the pre-lockdown and lockdown periods.

3.3 Mobility data

The mobility data used in this thesis is highly aggregated in a spatial and temporal sense. It is provided by an unnamed source in an anonymized and aggregated manner that preserves privacy through a GDPR compliant framework. Mobility is given as a daily flow between two micro-regions and is spatially aggregated on the 2.4 km grid from the RWI dataset for each city (Fig. 2a). The data set covers the period from 01.01.2020 – 31.12.2020, and consists of five columns: start longitude, start latitude, end longitude, end latitude, and the flow, the latter is a proxy for the number of trips between the two points. To further preserve the privacy of the mobility flows in the dataset, the data for all metropolitan areas are processed in the same way: (1) rescaled between the same minimum and maximum values, (2) noise is added, and (3) edges with small flow values are omitted. Because these operations are similar for all metropolitan areas, the original flow patterns are preserved and data remains comparable between cities, and thus do not significantly affect our results. These mobility data make it possible for us to detect variations in mobility flows before and during lockdowns across the five cities.

Importantly, it can be seen in Fig. 2a that the mobility dataset for Delhi does not have a flow value for every RWI micro-region (the white spots), or that it has only a flow value for either the pre-lockdown or lockdown period (only red circle and only blue dot, respectively, Appendices A – E subplot c for other cities). To calculate ΔEA (Section 3.5) for a micro-region (hereinafter we will also refer to it as a cell), we must have mobility data in the cell for both the pre-lockdown and lockdown periods (both a red circle and blue dot on top of one another, Fig. 2a). The proportion of cells that have both a flow value for the pre-lockdown and lockdown periods in Delhi is 63.1% (1568 out of 2484 cells) of the total defined RWI micro-regions (Fig. 2b). The proportion in the other cities is between 52.0% and 86.5% (Fig. 2b).

a



b

City	# cells RWI data	# cells pre- & lockdown mobility data	Proportion of RWI cells
Bogotá	841	521	62%
Delhi	2484	1568	63.1%
Jakarta	1521	1054	69.3%
Lagos	838	436	52.0%
Mexico City	858	743	86.5%

Fig. 2 Available aggregated mobility data in pre-lockdown and lockdown periods. (**a**) The map shows which cells (defined by the 2.4 km cell grid from the RWI dataset, Fig. 1b) mobility data is available during the pre-lockdown (red circles) and lockdown periods (blue dots). The white spots are cells where no mobility data is available for either period, red circles indicate availability only for the pre-lockdown period, and blue dots indicate data availability in only the lockdown period. Places that have a red circle and blue dot on top have data for both periods. For calculation of the ΔEA (Section 3.5), mobility data is required for both periods, and therefore only the cells with both a red circle and blue dot are included in that analysis (for other cities see Appendices A – E subplot c). For Delhi, cells with both mobility data in the pre-lockdown and lockdown period amount to 63.1% of the RWI micro-regions. (**b**) The number of defined cells (from the RWI dataset) within the city, and the number and proportion (relative to the defined RWI cells) of cells with mobility data for both pre-lockdown and lockdown periods.

3.3.1 Converting mobility flow values

The raw flow values in the mobility dataset were scaled using a natural logarithm, so we calculated the exponential to make our flow values correspond to the non-logarithmic scale, and these values were used in subsequent data manipulations. Daily flow averages between cells were calculated by aggregating the flow values by the individual cells and dividing this sum by the number of days in the pre-lockdown and lockdown periods, respectively. We are using a Complementary Cumulative Distribution Function (CCDF) to show the estimated distributions of the average daily flow values for the Delhi metropolitan area in the pre-lockdown and lockdown periods (Fig 3).

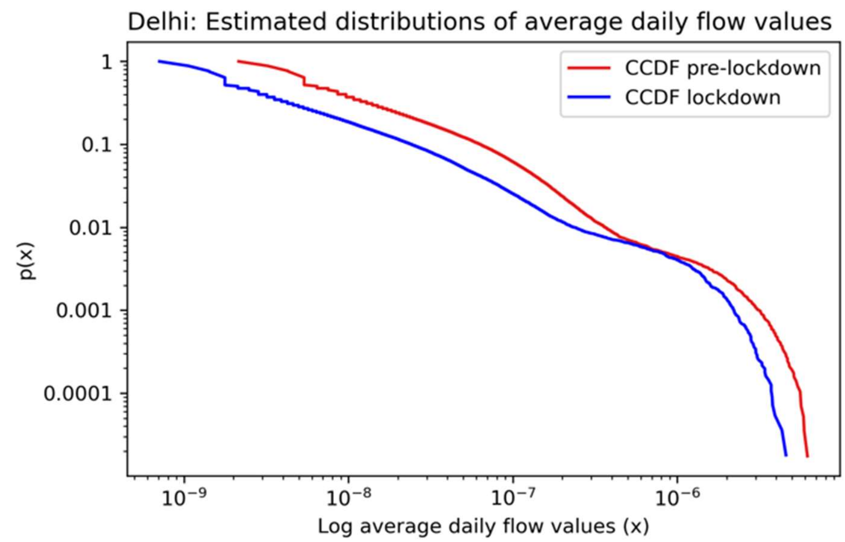


Fig. 3 Complementary Cumulative Distribution Function (CCDF) of the estimated distributions of average daily flow values for the pre-lockdown and lockdown periods using a log-log scale for Delhi. It is showing an almost uniform decrease in mobility in the lockdown period. The same pattern is observed in the other cities (Appendices A – E subplot e).

From the CCDF it can be seen that the likelihood of a given flow value decreases almost uniformly during the lockdown (shifted to the left, to lower probability), reflecting that the daily number of trips made within Delhi decreased almost uniformly during the lockdown period. This pattern can also be observed in the other cities (Appendices A – E subplot e). There is a narrow range of higher flow values (around $10^{-6.3}$), where the likelihood was similar to the pre-lockdown period.

3.3.2 Calculating different flow values

To analyze and visualize mobility flow values, we are using different flow values in specific contexts. For clarity and reproducibility, we will be explaining these shortly in the following sections (3.3.2.1 and 3.3.2.2). We will also be providing references to figures or tables where these values have been used, so it is further made explicit how we obtained the values that are being presented.

3.3.2.1 City-wide operations

(a) **Total daily flow per city** – total number of trips per day in a city. Obtained by summarizing all flow values by day, and used to show how city-wide mobility changes throughout the year (Fig. 6a, Appendices A – E subplot g)

(b) **Average daily flow per city, pre-lockdown period** - average total number of trips per day within the city. Obtained by summing the total daily flow for the pre-lockdown period and dividing by the number of days the period lasts (black solid line, pre-lockdown in Fig. 6a, Appendices A – E subplot g).

(c) **Average daily flow per city, lockdown period** – average total number of trips per day within the city. Obtained by summing the total daily flow for the lockdown period and dividing by the number of days the period lasts (black solid line, lockdown in Fig. 6a, Appendices A – E subplot g).

(b) and (c) are used to quantify the decrease in the average daily number of trips between pre- and lockdown periods for the entire city.

3.3.2.2 Cell-based operations

To investigate the micro-regional differences in daily flow during pre-lockdown and lockdown periods, and to prepare our mobility data to calculate the EA value (Section 3.5), we applied several cell-based operations (Table 2).

Start cell id	End cell id	Total flow start to end cell	Duration in days	Average daily flow start to end cell	Total flow start cell	Proportion flow start to end
2	1	250	50	5	400	250/400
	2	150	50	3		150/400

Table 2. Example of mobility data table structure generated in preparation for EA calculation. Cell ids are unique identifiers created for each micro-region in the RWI dataset and used to match locations in the mobility dataset. For simplicity, longitude and latitude coordinates for the start and end cells are omitted in this example. For both pre-lockdown and lockdown periods such a table is made, based on the defined lockdown dates as described in Section 3.2.1.

First, we divide the mobility dataset into two subsets, one covering the pre-lockdown and the other the lockdown period. Then, we perform the following cell-based operations:

(d) **Total flow from a start to an end cell** e.g., from 2 to 1 or from 2 to 2 – the total number of trips within the period from a start to an end cell. This value is obtained by summing the flow values from a start cell to each individual end cell.

(e) **Total flow from a start cell** e.g., from 2 to 1 and from 2 to 2 summed – total number of trips originating from cell 2. This value is obtained by summing the total flow values from a start cell. It is used to calculate the probability of flow from cells 2 to 1 and 2 to 2 etc.

(f) **Proportion of flow from start to end cell** – the probability that flow from cell 2 to 1 or 2 to 2 occurred. This is calculated by dividing (d) by (e). This probability is used to calculate the proportion of EA from the end cell that is accessed from the start cell.

(g) **Average daily flow from start to end cell** – average daily number of trips from cell 2 to cell 1, cell 2 to cell 2, etc. This is calculated by summing the flow values and dividing by the number of days in the pre-lockdown (or lockdown) period to obtain the average daily flow for the period. These values are used to visualize the spatial differences in daily flow values for pre-lockdown and lockdown periods, and to find average daily flow values for different wealth groups (Figs. 3, 7, 8).

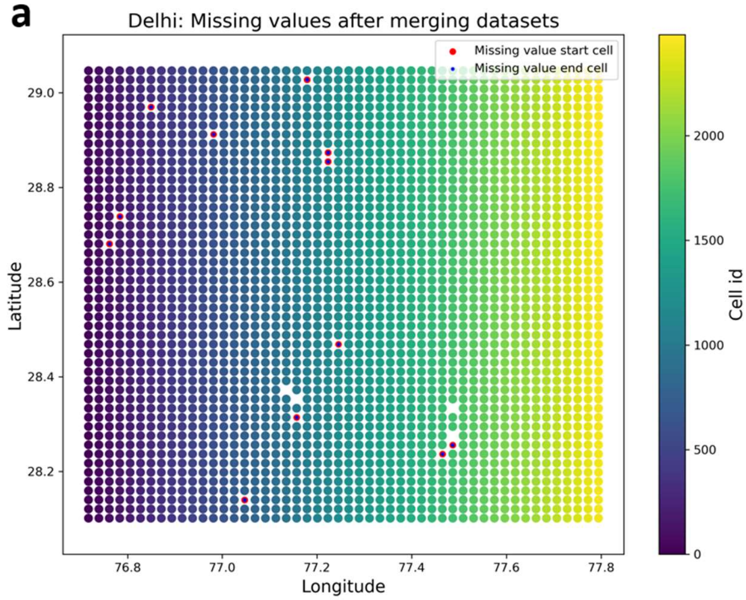
3.4 Adding RWI values to the mobility dataset

To prepare for the calculation of the EA, we combined the RWI values with the pre-lockdown and lockdown mobility datasets by matching the cell locations in the two datasets. We did this by first assigning cell ids for unique longitude and latitude combinations in the RWI dataset (Fig. 4) and subsequently mapped these cell ids to the same latitude and longitude pairs for the start and end points in the mobility dataset. Next, we assigned the corresponding RWI values to the cell ids in the mobility dataset.

3.4.1 Handling missing values

We do not have mobility data for all the RWI micro-regions as discussed in Section 3.3 (Fig. 2a), and therefore cannot use every micro-region in subsequent analyses. We also have cells where we have mobility data, but there are no corresponding RWI values available, which resulted in missing cell ids for these mobility data (Fig. 4a, red and blue dots, Appendices A – E subplot d for other cities). However, the share of these missing values for the different cities was relatively small i.e., between 1.63 and 0.05%, with an average of 0.51%, and we, therefore, decided to discard these mobility entries (Fig. 4b). There are two main overall reasons for this type of missing values (i.e., mobility data within undefined RWI cells). Firstly, for privacy concerns, the wealth estimates in the RWI dataset are not reported for small populations containing fewer than 50 individuals (Chi et al., 2021). Secondly, certain areas have topographic constraints e.g., water bodies, mountain ranges, national parks, which means that there are either no people or a very small number of people living there. We could still capture mobility into some of those areas, and this can be explained for example people being able to go to these places, but not physically living there.

a



b

City	Missing values (%)
Bogotá	1.63
Delhi	0.02
Jakarta	0.05
Lagos	0.42
Mexico City	0.42

Fig. 4 Cells with mobility data but missing RWI values. (**a**) Map of missing value locations after merging the mobility and RWI datasets. The white spots are areas where no micro-region has been defined and no corresponding RWI value is provided, and thus this location is not assigned a cell id. The red dots are start cell locations and blue dots are end cell locations where we have mobility data but no RWI data. For other cities see Appendices A – E subplot d. (**b**) Statistics of the missing values in the different cities. We decided to delete the missing values and thus not consider them further in our analysis, because they make up a small portion of the mobility data (average 0.51%), meaning that not much information is lost.

3.4.2 Determining the relationship between RWI and mobility

To investigate the effects of lockdown restrictions on the mobility of different wealth groups, we first assigned three equal-sized groups based on the RWI values, which we interpreted as the poor, middle, and rich communities. We then calculated their corresponding average daily flow values for the pre-lockdown and lockdown periods (Appendices A – E subplot f). To allow for a 1:1 comparison of average daily flow values between the same three wealth groups, we used the same RWI value ranges for both periods.

3.5 Calculation of EA and ΔEA

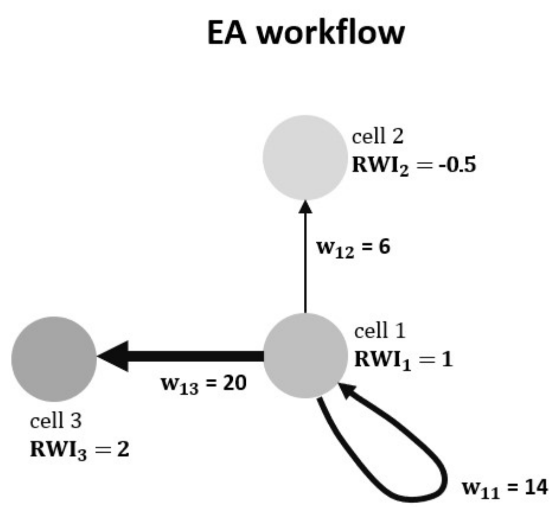
We characterize the EA of a cell according to all of the economic value that can be reached from it. For each cell i its EA can be computed as:

$$EA_i = \sum_j RWI_j \cdot \frac{w_{ij}}{\sum_k w_{ik}}$$

where:

i, j, k = indicate any cells in our dataset
EA_i = Economic Accessibility in cell i
RWI_j = RWI value of cell j
w_{ij} = Total flow from cell i to j (including self-loops) for pre-lockdown or lockdown period
$\sum_k w_{ik}$ = Sum of total outgoing daily flow from starting cell i

We calculate the EA both for pre-lockdown and lockdown periods. By means of example, we show a mobility network (Fig. 5) between three cells (1, 2, and 3) and run through the calculation of the EA value of cell 1 (EA_1). In short, the EA_1 calculation is the sum of the proportionally accessed RWI from cell 1, and it is meant to reflect the economic value that can be reached from that location.



(a) $\sum_k w_{ik} = w_{11} + w_{12} + w_{13} = 14 + 6 + 20 = 40$

(b) $EA_1 = RWI_1 \cdot \frac{w_{11}}{40} + RWI_2 \cdot \frac{w_{12}}{40} + RWI_3 \cdot \frac{w_{13}}{40} = 1 \cdot \frac{14}{40} + (-0.5) \cdot \frac{6}{40} + 2 \cdot \frac{20}{40} = 1.275$

Fig. 5 Calculation of EA Example of calculating the EA for cell 1.

The RWI values of the three cells are indicated ($RWI_1 = 1$, $RWI_2 = -0.5$, $RWI_3 = 2$). The daily flow values from cell 1 to its destination cells 1, 2 and 3 are shown next to the black arrows ($w_{11} = 14$, $w_{12} = 6$, $w_{13} = 20$) and also include a self-loop of cell 1 (w_{11}).

The first step is to calculate the total outgoing flow ($\sum_k w_{ik}$) during pre-lockdown or lockdown (depending on which period we calculate the EA for) from cell 1 as can be seen in Fig. 5 calculation (a). The subsequent calculation (b) includes the following steps: computing the proportions from total flow (e.g., for cell 1 to 2 this is $\frac{w_{12}}{40} = 6/40 = 0.15$) and multiplying it with the RWI value of the destination cell (e.g., for cell 1 to 2 this is $RWI_2 \cdot 0.15 = -0.5 \cdot 0.15 = -0.075$). By doing this, we get the mobility weighted RWI for each destination cell of cell 1. Finally, we sum up all the individual weighted RWI values, which gives us EA_1 i.e., the total EA value people can potentially access from cell 1. These calculations are done both for the pre-lockdown and the lockdown period, based on the generated two subsets of the mobility dataset (Section 3.3.2.2).

The final step is to calculate the difference between the lockdown and pre-lockdown EA value for each cell, resulting in ΔEA, which indicates the changes in accessed economic opportunities for each cell. It is calculated as follows:

$$\Delta EA_i = EA_{Li} - EA_{Pi}$$

where:

i = indicates any cell in our dataset

ΔEA_i = Delta Economic Accessibility for cell i

EA_{Pi} = Economic Accessibility for the pre-lockdown period for cell i

EA_{Li} = Economic Accessibility for the lockdown period for cell i

Choosing this method to calculate the EA values relates to the economic benefits of human mobility i.e., mobility is important as a means of access to the economy of the cities to earn income and thereby influences personal wealth (Section 2.3).

3.6 Weighted Linear Regression

To investigate if there is a dependency of ΔEA on the RWI value of the start cell i.e. if changes in economic access potentially depend on the wealth of a specific region, we initially decided to use a Linear Regression (OLS). However, cells with relatively low total flow values caused large variance in ΔEA, which can be interpreted as an artifact of mobility patterns of a smaller number of individuals rather than generic mobility patterns. These cells are thus outliers rather than real variation in ΔEA which would influence the OLS, and ideally should be weighted less. We, therefore, decided to use a Weighted Linear Regression (WLS) where observations from cells with larger populations are weighted more than others. As we did not have population data for the micro-regions, we chose to use total outgoing flow summed for both pre-lockdown and lockdown periods as a proxy and therefore as weights (Section 4.2).

4 Results

This chapter outlines our main findings in relation to our proposed RQs. To answer RQ1, we show the impact of the COVID-19 lockdown measures on overall mobility in the five cities and by the RWI group. In answering RQ2, we outline our results regarding the changes in EA. In this section, we present the results using primarily the examples from Delhi's metropolitan area, the detailed data about the other four cities, where not explicitly provided in the text, are referenced accordingly to direct towards corresponding appendices.

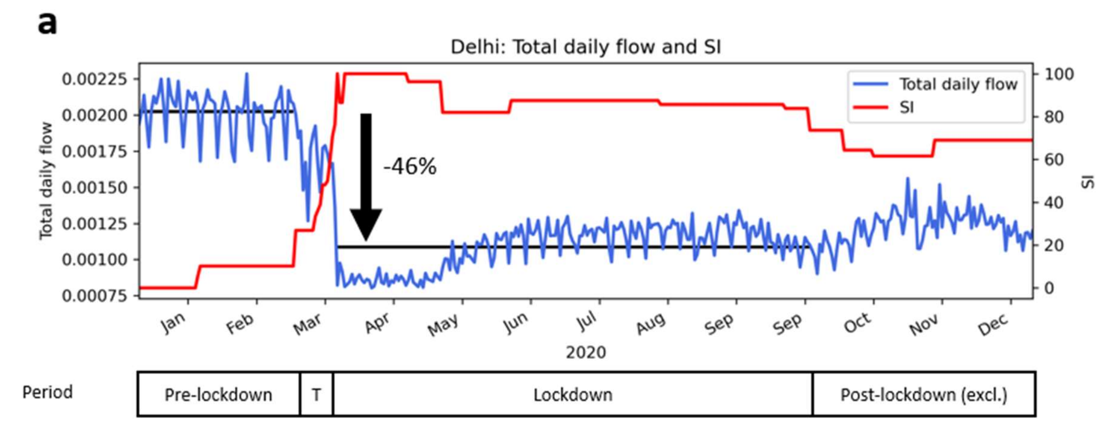
4.1 RQ1: Effects of lockdown measures on mobility

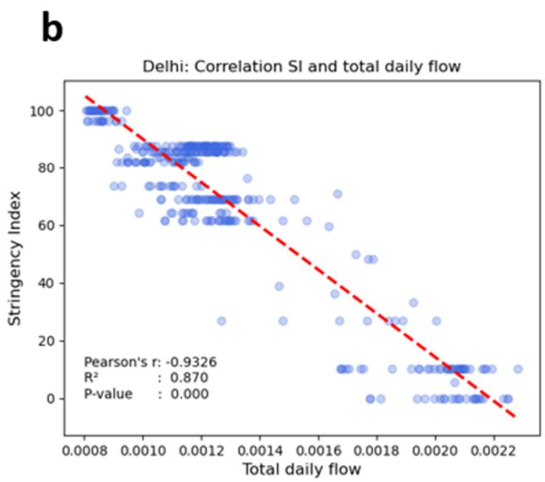
4.1.1 Changes in city-wide mobility

The exact date that the COVID-19 lockdown measures came into effect differed slightly between Bogotá, Delhi, Jakarta, Lagos, and Mexico City. However, for all of them, this happened within the month of March 2020 as reflected in the substantial increase of SI, which meant that in this period mobility became much more restricted (Appendices A – E subplot g).

In Fig. 6a we can see the total daily number of trips (black line) for Delhi for the year 2020, plotted together with the SI (red line). A clear decrease in the daily number of trips can be observed in the middle of March, followed by a dramatic drop at the end of March. This coincides with SI levels moving rapidly up from the beginning of March to the end of March. The pre-lockdown period is therefore defined from January 1st until the SI is above 20 (March 4th, 2020) (Fig. 6c). The start of the lockdown is defined where the SI reaches 90, which is on March 22nd, 2020. We interpreted the time between pre-lockdown and lockdown as a transitional period, which is excluded from further analysis (Section 3.2.1).

Fig. 6b shows a strong anti-correlation between the daily number of trips and SI levels (coefficient of correlation: -0.9326; R^2: 0.870, P-value: 0.000), which suggests that mobility is strongly dependent on the SI level. As we can see in Fig. 6c, mobility decreased significantly in Bogotá (-69%), Delhi (-46%), Jakarta (-58%), Lagos (-47%), and Mexico City (-69%).





c

City	SI thresholds (end-pre/ start-lock/ end-lock)	City-wide decrease average daily flow (%)
Bogotá	20/80/70	-69%
Delhi	20/90/80	-46%
Jakarta	30/70/55	-58%
Lagos	20/80/55	-47%
Mexico	20/80/70	-69%

Fig. 6. Decreases in mobility during the lockdown. (**a**) City-wide total daily flow for Delhi and SI levels for India for the year 2020, showing a dramatic drop in daily mobility after SI levels rose. The pre-lockdown, transition (T), lockdown, and post-lockdown periods are indicated. Note that the transition and post-lockdown periods are excluded from analysis (Section 3.2.1). (**b**) Relationship between SI and total daily flow, showing a strong anti-correlation (Pearson's r: -0.9326, R^2 = 0.870, P-value = 0.000), which is clearly observed in (a). (**c**) In all investigated cities we observed similarly large decreases in mobility as a result of increasing SI. However, there is a 33-percentage point difference between the lowest (Delhi) and largest drop (Bogotá).

This substantial drop in mobility is also visualized in map view for the city of Delhi using the average daily flow values between the start and end cells for the pre-lockdown and lockdown periods, showing a significant reduction in connections (Fig. 7a, b). For example, it can be seen that connections between suburbs and the city center disappear largely during the lockdown. The reduction can also be observed when plotting the average daily number of trips made from the start cell for the pre-lockdown period (Fig. 7c) and the lockdown period (Fig. 7d) and keeping the same color scale. Values significantly decrease between the two.

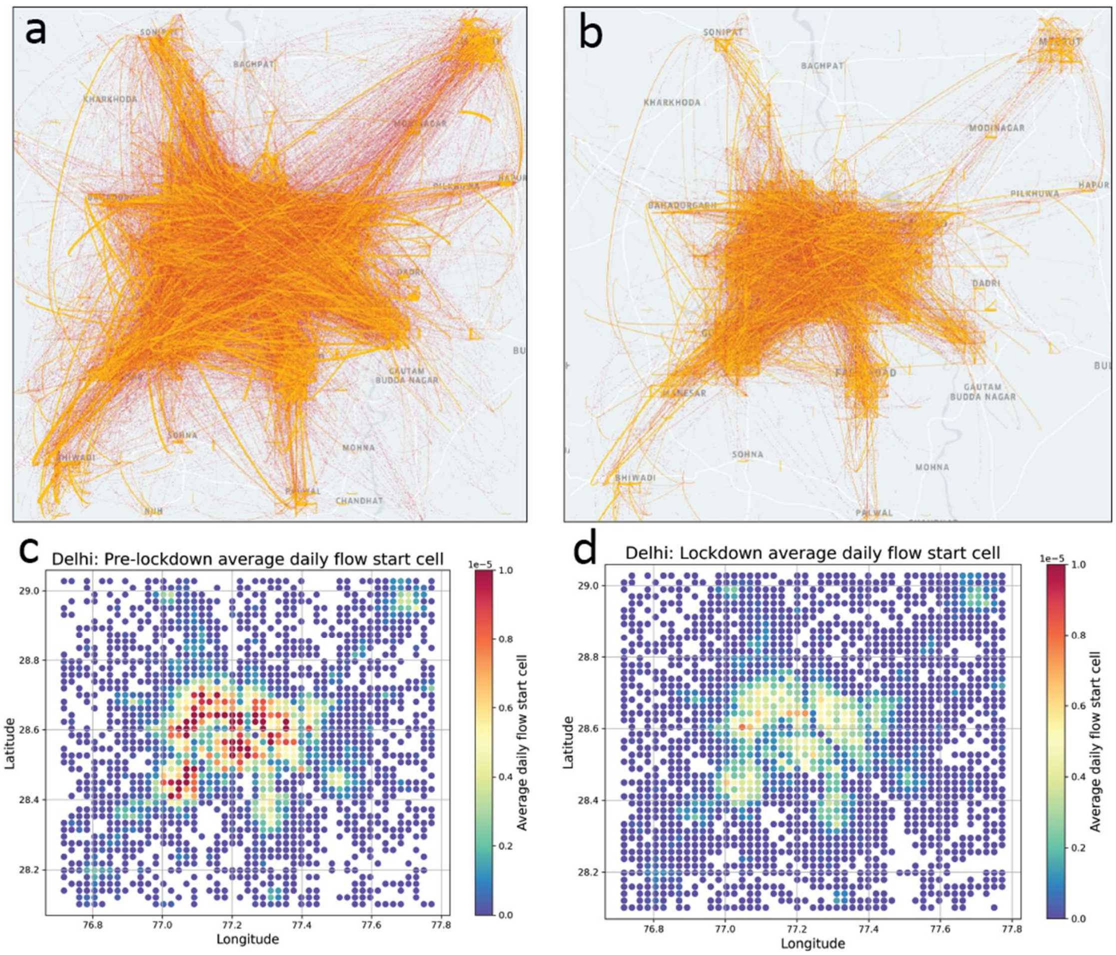


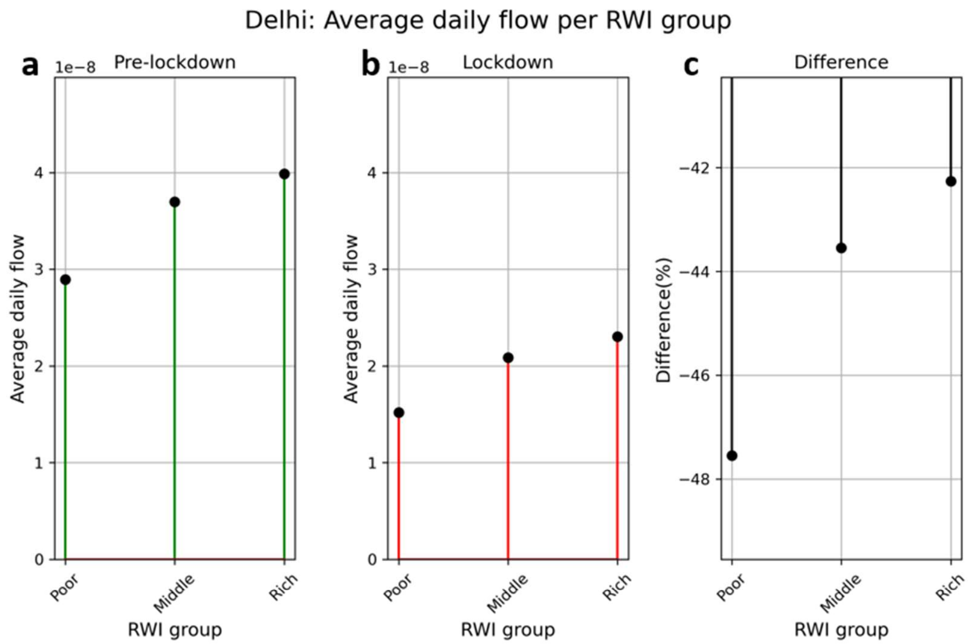
Fig. 7 Spatial visualization of the impact of lockdowns on mobility in Delhi. (**a**) Map showing the average daily flow during the pre-lockdown period. Arcs reflect the flow between the start and end cells. The colors are based on the average daily flow values, with yellow high and red low values. The thickness of the arc is linearly dependent on the average daily flow value. Note the many and dense connections between cells and between suburbs. (**b**) Map showing the average daily flow during the lockdown period. Note the much-reduced number of connections. Made in Kepler.gl. Due to technical limitations in Kepler, scales and stroke thickness cannot be set on absolute scales for 1:1 comparison. However, we can still observe a reduced number of connections between cells, and therefore we decided to use it as a spatial representation of Fig. 6a. (**c**) Spatial distribution of average daily flow in the start cell for the pre-lockdown period. Note the concentration of large values in the city center and suburbs. (**d**) Spatial distribution of average daily flow in the start cell for the lockdown period, using the same color-scale as in (c). Note the much-reduced average daily flows on average, but still a concentration of higher values in the city center.

Furthermore, a comparison of the CCDFs of the average daily flow values between the pre-lockdown and lockdown periods shows an almost uniform decrease, except within a small range of larger flow values (Fig. 3, Section 3.3.1). This reflects that average daily mobility decreased relatively uniformly. This pattern is observed in all of our five cities (Appendices A – E subplots e).

4.1.2 Changes in mobility by RWI values

Next, we want to investigate how much people can move depending on their RWI, i.e., how much flow originates from a cell with a particular RWI value (as visualized in Fig. 7a-d). Fig. 8 shows the city-wide average daily flow during pre- and lockdown periods (a and b) and the difference (c, in percentage), using three equal-sized groups based on RWI values in Delhi. The RWI value ranges for the groups are consistent across the periods. We can see that before the lockdown period, the poorest had the lowest average daily flow values, and the richest had the highest average daily flow values (Fig. 8a). This means that on average the poorest made the fewest number of trips, and the richest the most. After the lockdown measures were put in place, the same pattern seems to occur i.e., poorest making the fewest number of trips and richest the highest number of trips (Fig. 8b).

City-wide average daily flow in Delhi decreased by 46% (Fig 6a), but when we focus specifically on the three wealth groups, we can see that the poorest show the highest decrease of 47.5%, the middle group decreased by 43.5%, and the richest by 42.3% (Fig. 8c). Thus, the data show a disproportional decrease in mobility for the poorest (-47.5 %) in comparison to the richest (-42.3 %), which means that people living in areas with the lowest RWI values, experienced a larger decrease in mobility compared to those living in areas with higher RWI values. This leads us to conclude that the mobility of the different RWI groups has not been equally affected by the lockdown policies.



d

Group	RWI ranges	Pre-lockdown average flow	Lockdown Average flow	Absolute difference	Relative difference (%)
Poor	(-0.81, 0.938]	$2.89 \cdot 10^{-8}$	$1.52 \cdot 10^{-8}$	$-1.37 \cdot 10^{-8}$	-47.54
Middle	(0.938, 1.153]	$3.70 \cdot 10^{-8}$	$2.09 \cdot 10^{-8}$	$-1.61 \cdot 10^{-8}$	-43.55
Rich	(1.153, 1.794]	$3.99 \cdot 10^{-8}$	$2.30 \cdot 10^{-8}$	$-1.69 \cdot 10^{-8}$	-42.26

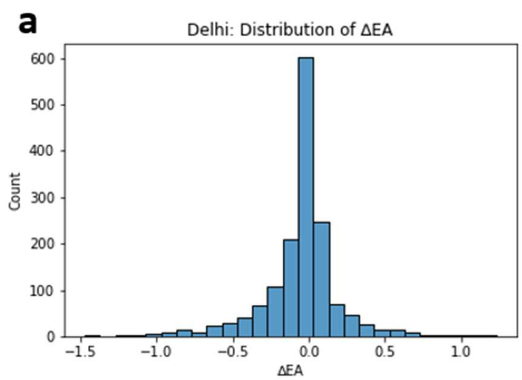
Fig. 8 The impact of lockdowns on average daily flow values by RWI group in Delhi. The RWI values were assigned into three equal-sized groups based on the RWI values in the pre-lockdown dataset and the ranges are the same for both pre-lockdown and lockdown periods (Section 3.4). (**a**) Pre-lockdown average daily flow values. Note that the poorest RWI group travels the least, the richest the most. (**b**) Lockdown average daily flow values. Across all three RWI groups, average daily flow values decrease dramatically. (**c**) The difference between (b) and (a) expressed in percentage. Note that the poorest RWI group showed the largest relative decrease in average daily flow while having the smallest absolute decrease. The richest showed the least relative reduction in mobility. (**d**) Details on the RWI value ranges and observed flow values for each RWI group. Details on the other cities can be found in Appendices A – E subplot f.

However, a comparison to other cities shows that this is not a universal pattern (Appendices A – E subplot f). For example, in Mexico City, the mobility for the poorest RWI group decreased by 55.8%, whereas the middle and richest groups decreased by 62.3% and 64.3%, respectively, showing the opposite pattern compared to Delhi (Appendix E subplot f). For Lagos, the middle group decreased the most, by 48.2%, followed by the poorest with 45.6%, and the richest with the least decrease of 41.8% (Appendix D subplot f). Therefore, it might be difficult to find a universal answer to RQ1, since there might be other factors that control who is traveling and how far, which can differ between cities (e.g., public transport infrastructure, access to a private vehicle, etc.). These possible reasons and implications will be discussed in Chapter 5.

4.2 RQ2: Changes in EA

We know from the mobility data analysis for Delhi that, as a result of lockdowns, the poorest people had the most significant relative decrease in mobility (Fig. 8c). When we compare the EA values between the pre-lockdown and lockdown periods, calculated as ΔEA (Section 3.5), we see that the majority (60.5%) of the values are below zero, meaning that in these micro-regions the EA value in the lockdown was lower than in the pre-lockdown period (Fig. 9a). However, for 38.8% of the cells, the ΔEA is positive, and the remaining 0.7% stayed the same. The mean ΔEA for Delhi is -0.056 and the standard deviation 0.272, the other cities are indicated in Fig. 9b.

The spatial distribution of ΔEA can be seen in Fig. 9c. We can see that for the majority of the cells in the central part of Delhi, ΔEA is close to zero. Towards the outskirts, the largest differences seem to occur (both increase and decrease). However, a comparison of Fig. 9c and d shows that cells with large ΔEA values occur in cells with low total outgoing flow, which could be interpreted that these cells have fewer inhabitants and could be prone to causing outliers that might not reflect a reliable ΔEA observation. While the spatial plots reveal some interesting patterns, the ΔEA values in relation to the RWI values should be investigated together with the total outgoing flow (summed for both pre-lockdown and lockdown periods), to ensure data robustness.



b

City	μ ΔEA	σ
Bogotá	-0.097	0.268
Delhi	-0.056	0.272
Jakarta	-0.017	0.221
Lagos	-0.028	0.257
Mexico City	-0.057	0.182

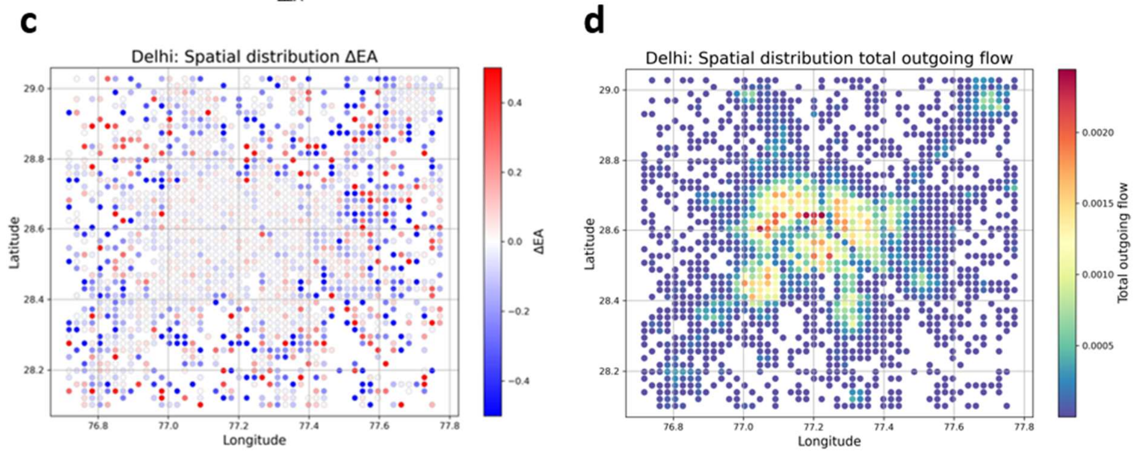


Fig. 9 The impact of lockdowns on access to economic opportunities in Delhi. Results of the calculation of ΔEA (lockdown EA – pre-lockdown EA) for Delhi and other cities. For other cities see Appendices A – E subplots h, i, and j. (**a**) Distribution of ΔEA in Delhi, reflecting the impact of the lockdown and restrictions in access to economic opportunities. Negative values reflect a decrease in EA as a result of lockdown measures, positive values an increase in EA. (**b**) Mean (μ) and standard deviation (σ) of ΔEA for the other cities. All cities have similar means slightly below zero, and standard deviations of a similar order of magnitude, indicating that, on average, people have slightly lost economic access in the cities. (**c**) Spatial distribution of ΔEA, showing more positive and negative values in the outskirts, close to zero in the city center (Fig. 1a-b). Color-scale set between 0.5 and -0.5 for visualization purposes. (**d**) Spatial distribution of total outgoing flow (pre-lockdown and lockdown aggregated), used as a proxy for population and data robustness. Note that most of the large ΔEA values occur in areas with relatively low total outgoing flow values, which we interpreted as areas with fewer inhabitants and thus more likely prone to causing outliers. White areas are cells where we did not have mobility data for both the pre-lockdown and lockdown periods (Section 3.3), which are needed to compute ΔEA (Section 3.5).

We, therefore, continued the analysis by investigating if there is a possible dependency of ΔEA on the RWI values (Fig. 10). We initially ran an OLS regression on these data and found a positive slope (0.1222), but a relatively low R-squared value (0.047) (Appendix B subplots m and n). The low R-squared value can be explained by the two variables showing a funnel shape from low to high RWI values, whereby at lower RWI a larger spread is observed in ΔEA (Fig.

10, Appendices A – E subplot k for other cities). Towards higher RWI values, the ΔEA becomes more consistent and seems to show less negative or even positive ΔEA values. The funnel shape may be understood by color-coding the points by total outgoing flow (pre-lockdown and lockdown combined), showing that the high variance in ΔEA occurs in cells with low total outgoing flow values (Fig. 10). These cells thus cause relatively large variance because they may reflect the movement of a relatively small number of individuals and are thus prone to causing outliers rather than reflecting the real variation of ΔEA in the data. Therefore, if we want to suppress outliers and detect generic trends between ΔEA and RWI of the starting cell using linear regression, we want to weigh the observations by the population in that cell, i.e., use a WLS regression.

In the absence of population data for our micro-regions, we chose to use the total outgoing flow from a cell to approximate population numbers for that cell (see also 3.6 and 5.3 for a discussion). We assumed that higher flow values would signal higher population numbers and would result in more consistent travel patterns that indicate where people access economic opportunities and thus reflect more reliable ΔEA estimates. It would therefore be more appropriate to make cells with low total outgoing flow more transparent (less trustworthy), while cells with high total outgoing flow opaquer (more trustworthy) (Fig. 10, transparency of the points). In the WLS, the ΔEA observations are thus weighted by the total outgoing flow for data robustness.

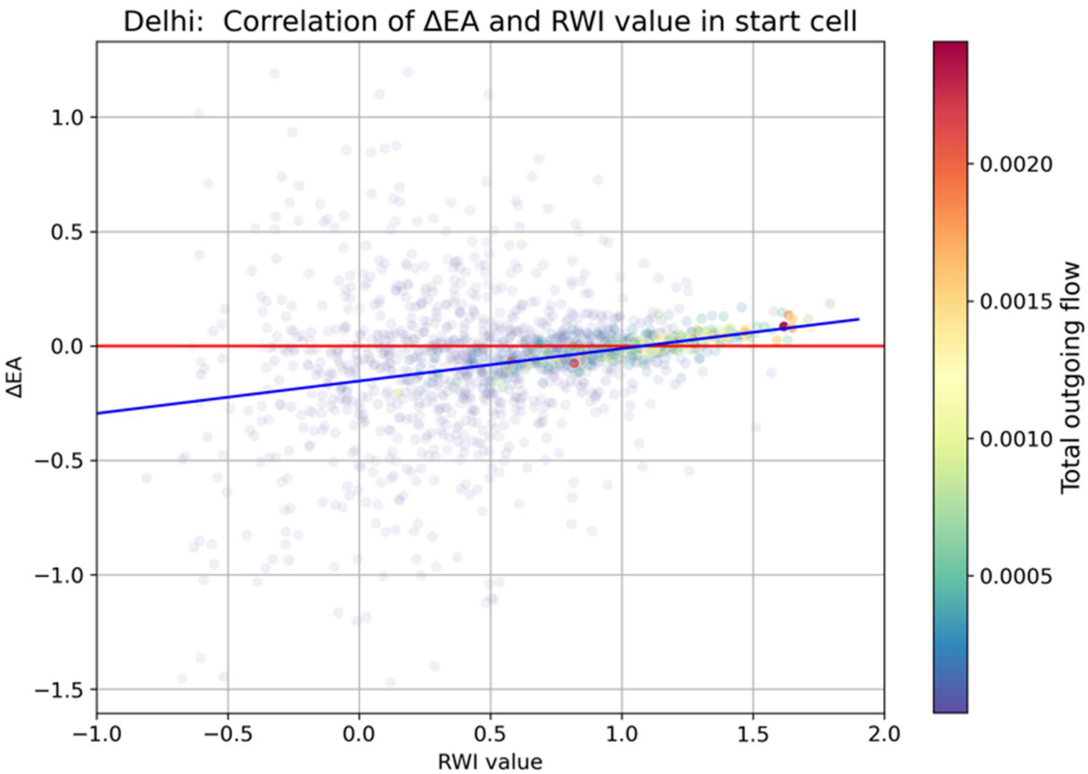


Fig. 10 A statistically significant dependence of ΔEA on RWI value: the poor lost EA and rich won EA. Correlation of RWI values and ΔEA observed within the start cells that were active both in the pre-lockdown and lockdown periods for Delhi (see Fig. 9c and d). The colors indicate the total number of trips made from a start cell during both periods, which are interpreted as an indication of the population and robustness of the observation. To further reflect this robustness, the transparency of the points is set dependent on total outgoing flow (see Appendix A – E subplot m for all data without transparency). Note the highly transparent purple points, which are cells with the largest variability in ΔEA, but have very low total outgoing flow. The blue line reflects the linear trendline from WLS, whereby the total outgoing flow is used as weights. Note the positive slope (0.1418) which has p-values smaller than 0.001 and thus is of statistical significance, which is observed for all investigated cities (Table 3, plots for the other cities in Appendices A – E subplots l). This means that the poorer you are to start with, the larger the decrease in your EA will be (blue line under the red line). The richest, however, gained EA during the lockdown period, reflected by positive EA (blue line above the red line).

The WLS for Delhi shows a statistically significant positive slope of 0.1418 ($\sigma = 0.004$) and an R-squared value of 0.418 (Fig. 10, the blue line is the trendline from WLS). The much larger R-squared value (e.g., R-squared OLS: 0.047) indicates that using the total outgoing flow as weights has helped to suppress the large variance in ΔEA in small cells. The positive slope suggests a significant dependence of ΔEA on RWI, i.e., depending on starting level of wealth, groups are disproportionately affected by lockdown measures. In Delhi, the EA decreased in neighborhoods with RWI lower than 1 (ΔEA is negative, the blue line below the red line in Fig. 10), whereas neighborhoods with RWI above 1 gained in EA, as a result of mobility restrictions (blue line above the red line in Fig. 10).

City	# micro-regions	R^2	Slope	σ
Bogotá	521	0.420	0.1053***	0.005
Delhi	1568	0.418	0.1418***	0.004
Jakarta	1054	0.228	0.0658***	0.004
Lagos	436	0.388	0.1157***	0.007
Mexico City	743	0.478	0.0766***	0.003

Table 3. WLS regression results: statistically significant slope between ΔEA and RWI value of the starting cell. Statistics of WLS were performed on the five cities. All cities show a positive slope (0.0766 – 0.1418), significant (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$), and a positive t (16.591 – 33.511).

For all investigated cities, a statistically significant positive slope is found with a value between 0.0766 and 0.1418, with R-squared values between 0.228 to 0.478. This suggests that within the investigated cities, individuals living within lower starting RWI neighborhoods (i.e., poorer neighborhoods) are disproportionately more disadvantaged by the lockdown than individuals living in high starting RWI neighborhoods (i.e., rich neighborhoods). The starting RWI value where the effect goes from negative to positive is within a narrow range between 1 and 1.25 for these cities (Appendix A – E subplots k). To summarize, our results thus show that the poorer one is to start with, the larger the decrease in EA will be. Conversely, the richer one is to start with, less EA is lost, or one might even gain EA. We will be discussing these findings and some of the possible implications in the next Chapter (Section 5.3).

5 Discussion

By combining data from mobile phones with relative wealth and lockdown strictness indices, we were able to gain useful insights into how changes in mobility impact different income groups in our chosen five cities. In this section, we explain what our results mean and attempt to put them in a wider context of economic inequalities within urban environments while relating them to previous research.

5.1 Differences in the relative decrease in the recorded number of trips between cities

Our findings reveal that in all the five cities investigated, the number of trips decreased dramatically as a result of government lockdown policies. We observed relatively large differences between the cities, with mobility decreasing significantly in Bogotá and Mexico City (-69%), the least in Delhi (-46%) and Lagos (-47%), with Jakarta (-58%) falling in the middle (Fig. 6c, Appendices A – E subplot g). This is an interesting observation, and it is not straightforward to provide a one-size-fits-all explanation for these differences.

These results can be influenced by the limitations within the mobility dataset. Making extensive inferences based on this data source is complicated due to considerable ownership biases associated with different socioeconomic and geographical factors (Wesolowski et al., 2013). For example, not everyone owns a smartphone, in particular people in lower income groups, and the elderly are less likely to own smartphones (Coston et al., 2021). Smartphone ownership also varies widely between countries depending on their level of development – emerging economies have a much lower smartphone ownership rate than developed countries (Statista, 2021b). Also, all forms of smartphone-based tracking essentially track a specific device rather than an actual person, so mobile phones in reality capture proxies of movement (Grantz et al., 2020). These limitations mean that data sets might be missing inputs from parts of the population, especially those with access to the least number of resources, or it is not representative enough (Statista, 2021a)[2]. This skews the recorded number of trips towards the

[2] e.g., 54% of Indians had a smartphone in 2020, likely the richest rather than the poorest

wealthier population, who are more likely to be able to work from home during lockdowns than their poorer counterparts (Section 2.4).

Furthermore, depending on distinctive economic and sociodemographic circumstances, mobility patterns can differ significantly between rich and poor, whereby either the poorest or richest travel the most, which can further complicate interpreting the general decrease – exemplified by the different decreases in mobility per RWI group (poor, medium, and rich) discussed in Section 5.2. Lastly, we used different SI levels to define pre-lockdown and lockdown dates, which were dependent on the observed SI levels for a given country. Indeed, due to the differences in absolute SI levels observed in each country we used the relative scale to define pre-lockdown and lockdown periods, i.e., defining lockdown start date where the SI value was highest, and end where it significantly dropped. This means that the strictness of the lockdowns differed between the five cities, which can hinder a 1:1 comparison between the cities.

Furthermore, each country had its own ways of implementing and enforcing restrictions, which can vary in effectiveness. Patrolling by police or soldiers and fines, curfews, freedom of movement (e.g., restricted to a specific radius from home), etc., could result in a significantly different total decrease in mobility. For example, Bogotá had very strict enforcement of lockdown measures by police and military (The Washington Post, 2020), which might explain the large drop in mobility (-69%, Fig. 6c, Appendix A subplot g). Mexico City did not enforce lockdown policies by force due to a 70-year long complex history of law enforcement under authoritarian rule and did not want to provoke social unrest (The Washington Post, 2021), however, the average daily number of trips decreased still the same as in Bogotá (-69%, Appendix E subplot g). In the particular case of Mexico City, we suspect an issue with the underlying mobility dataset, where we see a decrease in SI around 1st of June, meaning loosening of restrictions, but mobility is further reduced after which it follows a fairly static pattern until the end of the year. In Delhi, the city with the lowest decrease (-46%), lockdown policies were also enforced with fines. However, statistics collected by Hindustan Times showed that 86% of the 200.000 fines given out between April to May 2021 could not be recovered, which might indicate that people in Delhi, in general, have been able to get away with not honoring lockdown policies (Hindustan Times, 2021).

Another factor that might contribute to different decreases in mobility is the proportion of jobs where work from home was feasible. The Gross Domestic Product (GDP) per capita is a good indication of material wealth and a proxy for the standard of living (Alexis, 2017) (Appendix F). Perhaps in Delhi, where the GDP per capita (USD 1900.70) is 4.4 times lower than in Mexico City (USD 8346.70) (The World Bank, 2020), a comparatively larger proportion of the population was not able to start working from home and had to continue commuting to their workplace (Appendix F subplots a, f). In contrast, it may have been possible for a larger proportion of the population in Mexico City to work from home due to a higher overall standard of living, leading to a larger decrease in the number of trips.

Lastly, how people travel might impact the decrease in the daily number of trips. If a large portion of the population travels with public transport, any disruption to this system might highly impact how many trips people are making. This can relate to limited service, scaled back seating capacities (e.g., 50% for Delhi) (Sify, 2021), fear of infection in public transport, or complete halting of services like school buses (The Indian Express, 2020). In contrast, cities with larger private car penetration numbers might show a lower decrease in the number of trips since people can travel independent of disruptions in the public transport system and have lower risks of getting infected during traveling and therefore feel safer to continue to travel. While this is beyond our current dataset, future work could focus on coupling such details to the mobility reduction patterns and may add clarity to variations between cities.

5.2 Differences between different socio-economic populations within cities

The analysis of the mobility data by wealth group, has revealed some interesting patterns within Delhi, and variations between the different cities (Fig. 8, Appendix F). Here we are reporting both the absolute and relative change in mobility for each wealth group i.e., to provide the full information and reach a more balanced discussion on how the indicators have changed in each wealth group. For all cities, the poorest communities made on average the lowest daily number of trips both during pre-lockdown and lockdown periods, whereas the richest had the highest average daily number of trips in all cities (except during pre-lockdown in Lagos, where the middle wealth group was marginally the highest). However, for Delhi, the relative decrease was largest for the poorest communities (-47.5%) and lowest for the richest (-42.3%). Part of this might come from the fact that the absolute number of trips was lowest for the poor communities, and thus a similar absolute reduction in mobility will result in a larger relative decrease (Fig.

8a-c). The larger decrease for poorer communities could have several explanations and without further information, it can be difficult to pinpoint the underlying reasons and requires further integration with other datasets. Indeed, studies have shown that the rich and the poor in different countries and cities do not always exhibit the same mobility patterns, and such variability is likely driven by where the opportunities for employment, housing, and social activities were located in each city (Xu et al., 2018). Further examples, from the USA, South America, and Europe demonstrate variations in mobility patterns between rich and poor depending largely on the distinctive economic and sociodemographic circumstances of different cities (Barbosa et al., 2021).

A recent study conducted in the European Union investigated what jobs were most at risk as a result of COVID-19 and found that non-essential jobs that required intense person-to-person interactions (and therefore generally required commuting) were most prone to termination (Garrote Sanchez et al., 2020). They also found that there was a strong negative correlation between the proportion of these jobs and the regional GDP per capita, meaning that with lower GDP per capita a larger proportion of the jobs are at risk. Bringing this concept to our study, the poorer communities may thus have had the largest share of non-essential jobs that required person-to-person interactions, while richer communities would have had a smaller proportion. So, on the one hand, a larger share of jobs that require person-to-person interaction could keep mobility up during lockdowns, but on the other hand are also more prone to be made redundant, resulting in a reduction in mobility. It is, amongst other contributing factors, thus also a balance between the two that will influence the relative decrease in mobility and ultimately the ΔEA.

In Delhi, where the poorest communities (lowest GDP per capita) show proportionally the largest mobility reduction, it could indicate that their job loss and the resulting decrease in mobility has been more important than still having to continue commuting because of a job that requires person-to-person interaction (Fig. 8c). Furthermore, without a stable income, commuting is possibly less feasible for the poorest group. In contrast, richer communities (higher GDP per capita) show proportionally the smallest reduction, which could indicate that a smaller portion of the jobs was at risk. Furthermore, while a larger proportion of people had the possibility to work from home, which would result in a larger decrease in mobility, they also still could undertake trips. Without further data on unemployment rates for the periods, this remains naturally speculative.

The mobility reduction patterns differ between the cities and the per capita GDP might partially explain the observed variations (Appendix F). Differences in per capita GDP in the five cities (up to 4.4 times between the highest, Mexico City and Delhi, the lowest) might mean that the proportion of jobs that are non-essential and require intense person-to-person contact might be much higher in Delhi and Lagos than in Mexico City and Bogotá. Therefore, the poorer communities in Delhi and Lagos might have experienced many more layoffs than Mexico City and Bogotá, resulting in a much larger drop in mobility in the poorest communities. Similarly, the share of jobs that can be done remotely might have been much higher in Mexico City and Bogotá and therefore can explain why the largest drop in mobility occurs in the richer communities (Appendix F).

There might be other reasons for the variations between the cities that can be attributed to the distinctive economic and sociodemographic circumstances of different cities e.g., the location of employment opportunities, schools, public transport infrastructure, car penetration rate, etc. (Barbosa et al., 2021; Xu et al., 2018). Future work could add these attributes to the analysis to further investigate socio-economic boundary conditions for different communities and their relation to changing mobility patterns.

5.3 A disproportional disadvantage for poor communities

One of the key concepts of this study is that the real value of living in a place is connected to the economic opportunities one can access from their place of residence (Boisjoly et al., 2017; Hidayati et al., 2021; Oviedo & Guzman, 2020). The WLS showed that there is a statistically significant dependence of ΔEA on the starting RWI of the neighborhood since the ΔEA can be modeled by a linear function of starting RWI with a positive slope (Table 3, Fig. 10, Appendices A – E subplots k). This means that the poorer the individual is to start with, the larger the negative economic effect is as a response to the mobility restrictions. Significantly, we find a positive slope for all of the studied cities, which suggests that the poorer communities have been impacted more by the mobility restrictions and lost disproportionally more access to important economic opportunities, compared to their richer counterparts. This is in line with the findings of Sanchez et al. (2020) and also in line with the study done in India, where those in the top quartile of pre-COVID income actually saw an increase in total income in the period from May to July 2020 (Bhalotia et al., 2020). The richest cells in each city showed a positive ΔEA, and the poorest cells a negative ΔEA, but it might reflect a limitation in our calculation of EA. Namely, it might not account for all the nuances of human mobility related to accessing economic opportunities. For example, if some people from a rich neighborhood travel to a poor community during the pre-lockdown period (for example NGO workers commuting to work in a poor area), but due to lockdown cannot travel there anymore and now commute only around the rich neighborhoods, ΔEA will become positive, meaning that they have gained from lockdowns. However, in reality, they might have lost their job. Alternatively, it could indicate that people from these neighborhoods were, on average, able to access cells with even higher RWI values than before the lockdown (Appendices A – E subplot k). Because our analysis does not distinguish between work-related commutes and recreational or social trips, it could also indicate that the type of trips made between the two periods is different e.g., less work-related trips and more recreational mobility. As an example, recreational walking patterns increased compared to pre-pandemic levels and especially in the richer areas (Hunter et al., 2021).

In contrast, even though the poor communities did not always experience the largest relative decreases in the number of trips (e.g., Fig 8c, Appendices A – E, subplots f), the WLS shows consistently negative ΔEA for these groups. This might indicate that these communities have consistently been cut off from access to economic opportunities found in wealthier RWI cells during the lockdown. This can reflect that this group is more prone to have jobs at risk of termination that require person-to-person interaction and thereby commuting, which causes them to lose access to pre-pandemic economic opportunities (Section 5.2) (Garrote Sanchez et al., 2020).

Our findings have provided evidence of the disproportionate economic impact of COVID- 19 lockdowns on the poorest populations. However, we cannot claim universality from these results. While economic inequalities are a global phenomenon, differences in mobility patterns can be observed between high-income countries and LMICs (Barbosa et al., 2021). Further, these results are specific to local realities in Bogotá, Delhi, Jakarta, Lagos, and Mexico City, and we cannot expect to see the same patterns occurring in other cities based solely on our research. This is because, mobility patterns between rich and poor are not universal, and they depend largely on the distinctive economic and sociodemographic circumstances of different cities i.e., while in some cities the poor travel more, in others they travel less (Barbosa et al., 2021; Hidayati et al., 2021; Oviedo & Guzman, 2020).

6 Conclusions, limitations, and future work

We investigated, for the first time, the impact of the COVID-19 lockdown measures on the access to economic opportunities for different income groups in Bogotá, Delhi, Jakarta, Lagos, and Mexico City by integrating mobility data from smartphone records with relative wealth data and lockdown strictness indicators. While the overall inequalities related to COVID-19 lockdowns have been much discussed recently, to our knowledge these studies have mostly focused on high-income countries. In this chapter, we will summarize our main findings, acknowledge the limitations in our study and present our suggestions for future research.

Our analysis has been based on the recognition that mobility is important as a means of access to the economy of the city for earning income and it thereby influences personal wealth. Our main findings show that, for all investigated cities, COVID-19 mobility restrictions have disproportionately negatively impacted the poorer communities in access to economic opportunities, while the richest communities had even better access to economic opportunities than before the lockdown. This discovery highlights that while the conditions of lockdowns are applied equally to all, they are likely to further expose and exacerbate existing economic inequalities thereby making the poorest people and communities even more vulnerable than they were before. Our results also show that reductions in mobility by wealth groups do not necessarily follow a universal pattern. While in some cities (Delhi and Lagos) the poor experienced the largest reduction in mobility, in others (Mexico City, Bogotá, and Jakarta), it is the richest, whose mobility had been reduced the most due to lockdowns.

Our research also has its limitations, which point towards topics that can be addressed in the future. Firstly, there are specific limitations in the datasets used in our analysis. The mobility data has inherent ownership bias, which means that we might not have data for the poorest populations, or it is not representative for the entire community. Furthermore, these data are highly aggregated temporally and spatially (daily flow, and up to the 2.4 km resolution to match the RWI dataset). We are also aware that the RWI data contains a prediction error, meaning that there are uncertainties with the provided values, which have not been incorporated in our analysis. Additionally, even though the RWI dataset is much more granular than previous approaches it is likely still too coarse to detect the finer variations inside cities.

Secondly, another limitation is related to how we calculate the EA i.e., it is a proportional sum of accessed RWI values from a starting cell, and therefore, it might not account for all the nuances of human mobility related to accessing economic opportunities (Section 5.3). Furthermore, we only used the number of trips to describe mobility patterns, and thus have not considered the actual underlying road networks nor the distances in kilometers or hours between two locations. Adding these data could provide further insights into how people travel. Future studies could use Google Maps to define the actual driving distances or time between two points and add this information to the analysis. This could potentially reveal greater insights into how different wealth groups travel (who travels the furthest, most minutes, etc., to reach a certain cell with a given RWI value) and how this changed due to lockdown policies. Similarly, we have not specifically looked at movement related to earning income. This could be further explored in the future by comparing weekdays and weekend mobility flows, and by focusing only on the conventional home to work and back commuting times e.g., 7-9 and 16-18 hours. Finally, we limited ourselves to pre-lockdown and lockdown period in 2020, future work could also look into defining an end-lockdown or a 'new-normal' period and tie it together with mass vaccinations and the implementation of the vaccination certificate.

Despite the limitations of this study, we believe that it has provided valuable insights into the relationship between changes in mobility patterns during COVID-19 lockdowns and its impact on the economic opportunities of different socio-economic communities and has inspired many new avenues for future research. While further studies still need to be performed, to refine current findings and to explore whether they could one day be applied universally, our study shows potential in uncovering the impacts of COVID-19 mobility restrictions on the different communities in distinct urban environments. Taken together, our results cast additional insights on the connection between the changes in mobility patterns due to lockdowns and access to the economy in specific cities. Given that the pandemic is still very much around us, we anticipate many more studies on this topic in the coming months and years. Understanding the impact of lockdown measures on the different urban populations is the first step in the direction of developing public policy measures to reduce income inequalities, enable the regaining of livelihoods during the recovery period, and ultimately support the creation of inclusive, resilient, and sustainable cities in line with the UN SDGs.

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