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Spatial Heterogeneity of COVID-19 Impacts on Urban Household Incomes

Between- and Within-City Evidence from Two African Countries

Yele Maweki Batana
Shohei Nakamura
Anirudh Rajashekar
Mervy Ever Viboudoulou Vilpoux
Christina Wieser

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Abstract

This paper examines spatial heterogeneity in the impacts of the early days of the COVID-19 pandemic on urban household incomes in Ethiopia and Kinshasa, Democratic Republic of Congo. Combining new panel household surveys with spatial data, the fixed-effects regression analysis for Ethiopia finds that households in large and densely populated towns were more likely to lose their labor incomes in the early phase of the pandemic, and their recovery was slower than other households. Disadvantaged groups, such as female, low-skilled, self-employed, and poor, particularly suffered in those towns. In Kinshasa, labor income-mobility elasticities are higher among workers—particularly female and/or low-skilled workers—who live in areas that are located farther from the city core area or highly dense and precarious neighborhoods. The between- and within-city evidence from two Sub-Saharan African countries points to the spatial heterogeneity of COVID-19 impacts, implying the critical role of mobility and accessibility in urban agglomerations.

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Yele Maweki Batana, World Bank

Shohei Nakamura, World Bank[1]

Anirudh Rajashekar, World Bank

Mervy Ever Viboudoulou Vilpoux, World Bank

Christina Wieser, World Bank

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[1] Corresponding Author: snakamura2@worldbank.org.

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1. Introduction

The COVID-19 pandemic has brought devastating economic impacts to low- and middle-income countries. The containment measures implemented by the governments to prevent the spread of the virus, such as the orders of lockdowns, the closure of non-essential businesses, and social distancing, have resulted in employment and income loss among people with limited coping strategies. The number of global extreme poor—who live on less than US$1.9 per day in 2011 PPP terms—is projected to have increased for the first time during the last two decades (World Bank 2020a). A recent study of harmonized household phone surveys in 34 developing countries highlights the immediate impacts of the pandemic: 36 percent of respondents stopped working because of the pandemic and 64 percent of respondents reported income loss (Bundervoet, Davalos, and Garcia 2021). Moreover, COVID-19 exacerbated existing inequalities and those who were disadvantaged before the pandemic, such as women, youth, and low-skilled workers, are experiencing even greater challenges.

Moreover, the impacts of the COVID-19 pandemic on household incomes and welfare have been spatially uneven. It has been widely observed that the pandemic more severely affected urban households—many of whom are informal, self-employed, or casual workers—in many low- and medium-income countries (Bundervoet, Davalos, and Garcia 2021). However, there are other important and less analyzed spatial factors that contributed to heterogeneous COVID-19 impacts on urban households' employment and incomes. Households in cities and towns with a larger population size and higher population density may have suffered from larger income losses, because of higher contagion risks and the government's implementation of tighter restrictions on people's movement and business operations. In addition, the mobility shocks induced by the COVID-19 pandemic probably had larger effects on households in larger and denser cities, as their agglomeration economies are hinged on connectivity and accessibility. Within a large city, workers in poorly connected neighborhoods in the suburbs and peri-urban areas may have found it difficult to access jobs and operate their businesses.

This paper aims to analyze such spatial heterogeneity in the COVID-19 impacts on urban household incomes. We look at the early days of the pandemic in Ethiopia for the analysis of between-city heterogeneity. We turn to Kinshasa, Democratic Republic of the Congo (DRC) to exemplify within-city heterogeneity. Our analysis primarily relies on panel household phone surveys—high-frequency phone surveys (HFPS)—that have been collected in many low- and middle-income countries since the COVID-19 outbreak.[2] We focus on the first six rounds of the survey from April to October 2020 for Ethiopia and the first six rounds from June to December 2020 for Kinshasa. During these periods, urban households' incomes experienced a gradual recovery from the initial shocks. In our Ethiopia analysis, we estimate two-way fixed-effects regression models to examine the changes in the probability of households experiencing income reductions across time and locations. For Kinshasa, we estimate the elasticities of the probability of income reductions with respect to mobility changes—which are captured by the Facebook movement data—and examine how the elasticities vary by locations, such as the distance from the central business district (CBD) and neighborhood density.

It is important to highlight the challenges and limitations of our empirical strategy. First, the HFPS data have limitations. The data were collected only from those who provided phone numbers in the baseline face-to-face surveys, which had been collected in June–September 2019 in Ethiopia and December 2018 in Kinshasa. While this is potentially a concern in case of rural households, many of whom do not own mobile phones, it is less of a concern for urban households with much higher phone penetration rates.

[2] World Bank COVID-19 High Frequency Monitoring Dashboard https://www.worldbank.org/en/data/interactive/2020/11/11/covid-19-high-frequency-monitoring-dashboard

Another, and more important limitation in the HFPS data relates to self-reported loss of household income. Income losses are collected through a binary indicator on whether households' incomes recently declined or not, which is susceptible to measurement errors and makes it difficult to quantify the COVID-19 impacts on their incomes. In addition, the mobility trend in the Facebook data may not represent Kinshasa residents, as the data is collected from the smartphone app users, who are likely to be richer and younger than other urban populations.

With these limitations in mind, the results of our analyses highlight the spatial heterogeneity of COVID-19 impacts on urban households' incomes as well as the key role of mobility and accessibility in urban agglomerations. In Ethiopia, households in large and dense towns were more likely to lose their labor incomes in the early phase of the pandemic, and their recovery was slower than other households. Disadvantaged households in those large and dense towns are particularly affected, such as those with female heads, low-skilled heads, self-employed heads, and poor households. The city-level analysis for Kinshasa demonstrates that workers' income is more elastic to mobility shocks in suburbs and precarious and highly densely populated neighborhoods. Disadvantaged workers, such as female and low-skilled workers, in those areas were particularly affected. These findings highlight the need for policies and infrastructure in the medium and long terms to enhance mobility and connectivity and build functional urban agglomerations.

Our study is related to two strands of literature. First, we contribute to the rapidly growing literature of the impacts of COVID-19 on individual/household labor and economic outcomes. Various studies analyze economic and welfare impacts at the household level, such as Adams-Prassl et al. (2020); Baek et al. (2020); Chetty et al. (2020); and Crossley, Fisher, and Low (2021) for developed countries and Bundervoet, Davalos, and Garcia (2021); Egger et al. (2021); and Khamis et al. (2021) for developing countries. While a few studies examine COVID-19 impacts on employment and incomes at the subnational levels (for example, Beyer, Jain, and Sinha 2020), a study on within-city variations of COVID-19 impacts is still rare. For instance, by combining a variety of private and public data sources, Chetty et al. (2020) analyze COVID-19 impacts on consumer spending, employment, and various other indicators at a geographically granular level (that is, zip code level) in the United States.[3] Our study adds to this literature on subnational and within-city analysis of COVID-19 impacts on employment and income.

Second, our work contributes to the literature on job accessibility in urban labor markets. Poor connectivity between firms and workers—as well as among themselves—is a major friction in urban labor markets, constraining productivity gains from agglomeration economies. Urban workers are more productive when job opportunities are physically more accessible, through, among others, lower job search costs and improved matching with firms (Combes and Gobillon 2015; Duranton and Puga 2004). Unfortunately, in many African countries, urban workers endure poor job accessibility in crowded, disconnected, and costly cities, where land use is fragmented and workers' mobility is constrained by the lack of affordable and reliable transportation (Lall, Henderson, and Venables 2017). To exacerbate low-skilled workers' situation, limited mobility and accessibility disproportionally affect them. Previous studies have found the effect of workers' residential areas within a city or metropolitan area on their labor outcomes (Chetty, Hendren, and Katz 2016; Gobillon, Magnac, and Selod 2011). Among the mechanisms of such location effects on employment is the limited physical accessibility to jobs, which could exacerbate labor outcomes of already disadvantaged workers, such as African Americans in the context of

[3] Several other studies also analyze at a similar geographic level but tend to focus on COVID-19 cases rather than employment outcomes—for example, Glaeser, Gorback, and Redding (2020) examine the effects of mobility for the spread of COVID-19 at a zip code level in New York City and a few other cities in the United States.

the United States (see a review of the literature on spatial mismatch hypothesis by Gobillon and Selod [2014]).[4] We contribute to these strands of literature by showing a link between job accessibility and employment outcomes cities in Sub-Saharan Africa.

This paper is structured as follows: Section 2 describes the contexts in urban Ethiopia and Kinshasa. Note that the background about the spatial structures of Ethiopia and Kinshasa are provided in Appendix B. Section 3 explains our empirical approach, such as the conceptual framework, data, and econometric models. Section 4 presents the results and section 5 concludes.

2. Context

Ethiopia

Ethiopia's first COVID-19 case was observed in mid-March 2020. The number of confirmed COVID-19 cases reached over 159,072 by the end of February 2021, with nearly 2,365 recorded deaths. While the number of cases in Ethiopia peaked in August, the fact that the positive rate for the tests conducted remains at over 5 percent suggests that infections are likely to be underreported (Panel A in Figure 1).

The Government of Ethiopia has put in place a range of measures to mitigate the economic impact of the COVID-19 pandemic, while aiming at containing transmission. Right after the first few cases of COVID-19 were detected, the government implemented a state of emergency—which remained in effect until September 2020—and adopted a comprehensive COVID-19 National Emergency Response Plan to ensure that efforts to fight the crisis are comprehensive and well-coordinated. Specifically, Ethiopia implemented surveillance at borders, conducted contact tracing, established designated quarantine facilities, ensured the supply of drugs and protective equipment, and embarked on several communication efforts to raise awareness on how to deal with the virus. To mitigate impacts on people and firms, authorities announced several economic measures, including additional expenditure on healthcare, provision of emergency food to the vulnerable, tax and social security payment deferrals, and liquidity injections and extension of forbearance measures in the financial sector.

The restrictions imposed by the government on people's movement and business operations in the early stage of the pandemic resulted in a sharp decline in mobility levels. As shown in Panel A of Figure 1, the Facebook movement data indicate that the mobility level plummeted in April 2020 to 50 percent of the baseline level—which is February 2020. This reduction in mobility was caused by both people's voluntary responses and government restrictions on public gatherings and transport services between regions.[5] Unlike other countries, there was no enforcement for the closure of nonessential businesses, including restaurants, and within-region transport services.

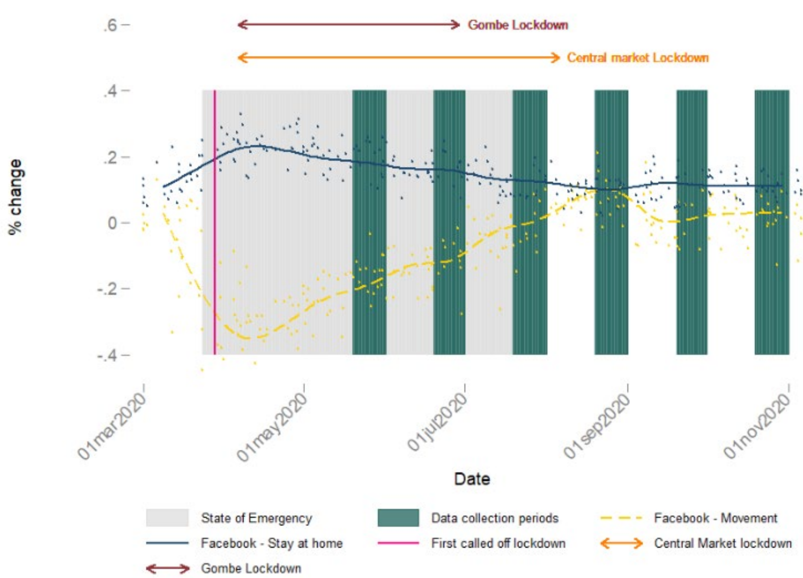
[4] Andersson et al. (2018), for example, find that better job accessibility reduced the duration of joblessness among low-income workers—especially blacks, women, and older workers—after a massive layoff in the United States. In the context of cities in developing countries, Franklin (2018) finds that a transport subsidy to young workers resulted in their successful job search in Addis Ababa, Ethiopia. Indeed, many workers face a limited level of job accessibility in Sub-Saharan African cities, as shown by Nakamura and Avner (2021) for Nairobi, Kenya.

[5] Ethiopia is a country with a federal system, consisting of 10 regions and 2 chartered cities.

Figure 1. COVID-19 situation and mobility trends in Ethiopia and Kinshasa

(A) Ethiopia (Nationwide)

(B) Kinshasa



Source: Authors' work based on Facebook mobility data; Johns Hopkins University Center for Systems Science and Engineering (CSSE) COVID-19 data last updated on March 1, 2021.

The COVID-19 pandemic has affected economic activity in Ethiopia with significant adverse effects on employment, particularly at the onset of the pandemic. The HFPS data show that employment rates plunged in the early days of the pandemic, with 8 percent of respondents losing their jobs at the beginning of the outbreak. Urban areas were particularly severely affected with 20 percent of urban respondents losing their jobs by April 2020, 64 percent of whom attributed their job loss to COVID-19. Those households with self-employed people or casual laborers—those who were already particularly vulnerable to poverty before the pandemic—were severely affected. The share of respondents who lost their job was highest in the hospitality, construction, and wholesale and retail trade (Panel A in Figure A1 in Appendix), sectors that either require close human contact or are highly covariate with the business cycle. This reduced employment severely affected household incomes, particularly in urban areas. More than 60 percent of urban households' incomes were either reduced or had completely disappeared in the early weeks of the pandemic, according to the first round of the HFPS. Yet, employment rates rebounded in the second half of 2020 reaching pre-COVID levels in rural areas while remaining slightly lower than before the pandemic in urban areas (Panel B in Figure A1 in the Appendix). This also ensured that incomes recovered; yet, in October, income losses continued for 27 percent of urban households.

Kinshasa, DRC

Since the confirmation of the first COVID-19 case on March 10, 2020, the Government of the DRC has implemented various measures to prevent the spread of the virus (Panel B in Figure 1). The government declared a state of health emergency on March 24, prohibiting gatherings and nonessential activities. For example, restaurants were allowed to open only for a limited duration during the day for takeaway orders. All state services adopted minimum service. Only essential personnel were required to ensure the continuity of state services. No office could accommodate more than five employees. This state of emergency lasted until July 22, 2020.

In Kinshasa, the governor announced the lockdown of the entire city on March 28, 2020 but cancelled the announcement on the same day due to a rapidly spreading panic among citizens. Instead, the city government locked down only the central business district (CBD) area of the city—Gombe—from April 6 to June 29, 2020. The central market of the city, located in the CBD area, was also closed until August 3. For the first month and a half of the lockdown, people's entry into the CBD area was restricted. Later the restriction was relaxed, allowing people with a pass to come to work. Grocery stores and restaurants were also allowed to open on specified times and days. Even during this period, no lockdown policy was imposed to the areas outside the CBD and markets remained open.

It is worth noting that, according to official data from the Multisectoral Committee for the Response to COVID-19, as of mid-January 2021, Kinshasa had nearly 17,000 confirmed cases, representing about 80 percent of all identified cases in the DRC. As with many countries, the DRC is not immune to the second wave of the pandemic and saw an increase in confirmed COVID-19 cases by 75 percent in less than two months between the end of November 2020 and mid-January 2021. In addition to the measures taken previously, including the postponement of the resumption of school and academic activities, the government imposed a curfew from 9 p.m. to 5 a.m.

The immediate impact of the COVID-19 pandemic on citizens of Kinshasa was indicated by the fact that more than half of household heads were not working at the time of the first round of HFPS interviews in June 2020, about half of whom listed COVID-related reasons (see Figure A2 in Appendix A). For example, a third of workers did not work due to the lockdown policy. Yet, COVID-related reasons for not working declined in later rounds.[6] Even if employed, workers reported that they were not able to work as usual. In the first round of the HFPS, 22 percent of employed workers could not travel to work or work from home as usual in the past two weeks. The rate of workers who could not work as usual declined in later rounds, reaching 6 percent in September and only 1 percent in November.

[6] In the first round of the HFPS, respondents were also asked about the government policies that affected their jobs or their household members' employment. Most frequently reported was the lockdown policy (31 percent), followed by stay-at-home order (11 percent), closure of essential activities and markets (9 percent each), and movement restrictions (4 percent).

3. Empirical approach

3-1. Conceptual framework

The pandemic brought serious health and economic impacts that reduced urban households' incomes, leading to welfare losses. As described in the previous section, the results from the HFPS indicate severe employment and income impacts in Ethiopia and Kinshasa. An important channel of these income losses is the reduction in urban residents' mobility. For instance, the government restricted public gatherings in Ethiopia and people entering the CBD area in Kinshasa. Reduced mobility constrained workers' labor performance because of the difficulty in commuting to their workplace. Moreover, it constrained business operations, job search, and work-related interactions. In low-income countries like Ethiopia and the DRC, few can work remotely.

Most importantly, labor impacts of the COVID-induced mobility shocks are expected to be spatially heterogenous. A key question to be addressed in this paper is how COVID-19 impacts on workers' labor outcomes vary depending on their locations—for example, which towns and where in the towns. For town characteristics, we focus on population and population density. Given the expected higher contagion risks, the government may have implemented tighter non-pharmaceutical interventions in larger and denser towns. Fearing about contagion risks, people may also tend to travel less in such towns. Moreover, mobility and accessibility are probably more important for workers in larger and/or more densely populated towns, as their labor income premium stems from agglomeration economies. Within a city, workers living far from job opportunities, such as those who live in suburbs and peri-urban areas, are likely to rely more on freedom of movement to access jobs. With their movement more severely affected, impacts on labor outcomes are likely to be larger.

3-2. Data

Our empirical analysis primarily relies on panel household phone surveys that have been regularly collected since the outbreak of the COVID-19 pandemic in Ethiopia and Kinshasa. In addition, we use Facebook movement data to construct an index to capture mobility trends.

Ethiopia and Kinshasa high-frequency phone surveys

In Ethiopia, the World Bank designed and conducted an HFPS of households to monitor the effects of COVID-19 on Ethiopia's economy and people and to inform interventions and policy responses (Wieser et al. 2020). The HFPS builds on the national longitudinal Ethiopia Socioeconomic Survey (ESS) that the Central Statistical Agency (CSA), Ethiopia's national statistical office, carried out in 2019 in collaboration with the World Bank. The HFPS drew a subsample of the ESS sample that was representative of households with access to a working phone. The HFPS is collected every month for 12 survey rounds, starting in April 2020. The 15-minute questionnaire covers topics such as knowledge of COVID and mitigation measures, access to educational activities during school closures, employment dynamics, household income and livelihood, income loss and coping strategies, and assistance received.

To monitor the impacts of COVID-19, the National Institute of Statistics (*Institut National de la Statistique*, INS), the national statistical office of the DRC, and the World Bank have collected HFPS data every month since June 2020 (INS 2020). The HFPS builds on the baseline Kinshasa Household Survey, which was collected from about 2,600 households in Kinshasa by the INS and the World Bank in December 2018. The Kinshasa HFPS drew a subsample of the Kinshasa Household Survey sample that was representative of households with recorded phone numbers. Respondents of the surveys were not necessarily the heads of households, though the data include various employment information about household heads.

We use the Ethiopia HFPS data for our nation-wide analysis of urban areas, while relying on the Kinshasa HFPS data for our city-level analysis. We focus on the first six rounds of the Ethiopia HFPS, spanning April through October 2020 (Table 1). We restrict the sample for our analysis to 1,704 (Ethiopia) and 880 respondents (Kinshasa) who were interviewed in all included HFPS rounds.[7, 8] Summary statistics of the samples are reported in Table A1 for Ethiopia and Table A2 for Kinshasa in Appendix A.

Table 1. Survey samples: Ethiopia and Kinshasa

	Survey rounds					
	1	2	3	4	5	6
Ethiopia						
Period	APR 22 to MAY 13	MAY 14 to JUN 3	JUN 4 to JUN 29	JUL 27 to AUG 21	AUG 24 to SEP 18	SEP 21 to OCT 14
Total respondents in urban areas	2,233	2,113	2,064	1,978	1,934	1,885
Interviewed in all rounds	1,704	1,704	1,704	1,704	1,704	1,704
(number of towns)	(103)	(103)	(103)	(103)	(103)	(103)
Kinshasa						
Period	JUN 16 to JUL 9	JUL 23 to AUG 11	AUG 25 to SEP 17	OCT 16 to NOV 9	NOV 7 to NOV 24	DEC 5 to DEC 26
Number of respondents	1,038	967	1,001	959	942	926
Interviewed in all rounds	880	880	880	880	880	880

In Ethiopia, the main outcome variables of our analysis are indicators about a decrease in labor and total incomes at the household level. The labor income variable indicates whether the household experienced a decrease in labor income since the month of the outbreak of COVID-19 (the first round) or during the last four weeks (the second and third rounds). The share of households with reduced labor income was 72.7 percent in the first round of the survey, declining to 57.5 percent in the second round and 44.5 percent in the sixth round (Table 2). The other household-level outcome variable of interest indicates a decrease in *total* household income, declining from 62.2 percent in the first round to 27.1 percent in the six rounds. As further discussed in Section 3.3, our econometric analysis controls for assistance and remittances received by households.

In Kinshasa, the labor outcome variable indicates whether the worker did not work or was not fully paid during the last seven days. The share of individuals who experienced the labor income shocks declined from 57.7 percent in the first round to 47.0 percent in the second round and 14.4 percent in the sixth round. Unlike the Ethiopia HFPS, this variable indicates the income status of the respondents, who are household heads, instead of their households. Unfortunately, a household-level indicator is not available in the survey. Thus, even if the variable indicates the household head's income reduction, the household's incomes may have remained at the same level because of increased income from other household members.

[7] Attrition is explained by the weariness of some households to be surveyed on a regular basis. To reduce this attrition, a telephone call credit is offered to each household that answered the questionnaire as an incentive. On the other hand, data collection teams sometimes reach households that could not be reached in the previous round, which explains why in some cases there is an addition in a round over the previous round.

[8] In addition, we exclude respondents who have changed their residential locations since the baseline surveys, as their current locations are not known in the HFPS data. The HFPS asks whether the respondent has changed residential locations, although it does not ask the exact location.

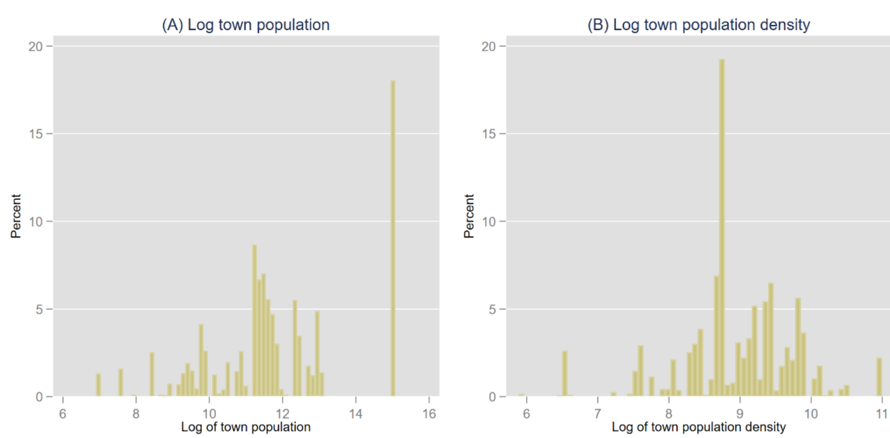
Table 2. Outcome variables in urban Ethiopia and Kinshasa (%)

		Survey rounds					
Country/City	Variable	1	2	3	4	5	6
Ethiopia	(a) Labor income decreased during the last 4 weeks	72.7	57.5	56.9	50.6	50.1	44.3
	(b) Total household income decreased during the last 4 weeks	62.2	49.1	46.7	38.7	34.8	27.1
	(c) Individual used to work pre-pandemic but did not work during the last 7 days	16.7	5.8	5.1	2.9	5.5	3.3
Kinshasa	(a) The worker did not work or labor income decreased during the last 7 days	57.7	47.0	31.3	29.6	27.4	14.4

Location variables

The key location variables to examine spatial heterogeneity in COVID-19 impacts in our Ethiopia analysis are town-level population and population density. We rely on the European Commission's Global Human Settlement-Settlement Model Grid (GHS-SMOD) 2015 dataset to identify urban areas across Ethiopia. We classified any grid cells defined as 'suburban or peri-urban', 'semi-dense urban clusters', 'dense urban clusters', and 'urban centers' as urban.[9] Any urban grid cells that were adjacent to each other were classified as a single urban entity (that is, town/city). We then overlaid the centroid geocoordinates of enumeration areas in the household survey onto the layer to identify to which town/city each household belongs. Population for each town was estimated by overlaying the GHS-POP 2015 data on each urban area. Our Ethiopia HFPS data cover 103 such towns. The town population is about 50,000 at the 25th percentile, 100,000 at the 50th percentile, and 350,000 at the 75th percentile, with the population of Addis Ababa being 3.5 million. The median population density is around 8,000 per km^2. Figure 2 shows the distribution of the log of town population (Panel A) and population density (Panel B) in the HFPS sample.

Figure 2. Distributions of town population and density in the HFPS sample, Urban Ethiopia



Sources: Authors' calculation using Ethiopia HFPS data and GHS-SMOD/POP data

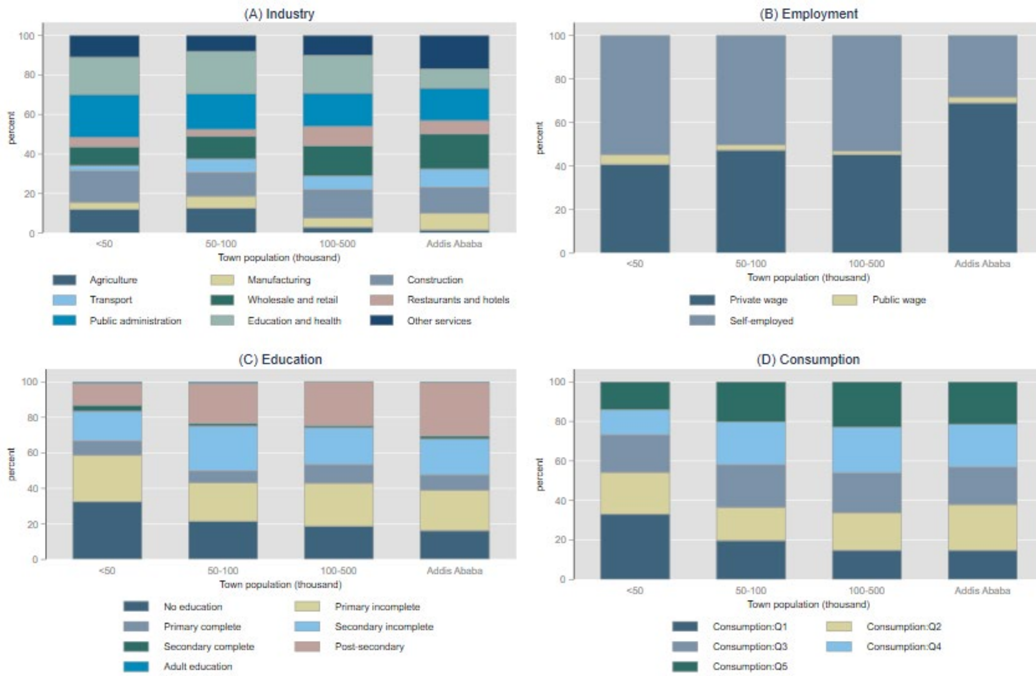
In Ethiopia, employment and worker characteristics vary by town population size (Figure 3). Larger towns, including Addis Ababa, have more workers in the service sector, whereas a large share of workers engage with agricultural jobs (Panel A).[10] Also, the share of private sector wage workers is higher in

[9] See Dijkstra et al. 2021 for more information on how urban grid cells are defined.

[10] In addition to household fixed effects and the economic sector variable, we carry out a robustness check for our regression analysis by excluding agricultural workers from the sample. As presented in Section 4, key parameter estimates in our regression analysis remain unchanged.

larger towns, particularly in Addis Ababa (Panel B).[11] In terms of worker characteristics, larger towns accommodate better educated and/or wealthier workers (Panels C and D). As explained in the next section, in our econometric analysis, the household fixed effects capture the differences in these time-invariant employment and worker characteristics. In some specifications, the fixed effects are interacted with survey round fixed effects to further remove their trends.

Figure 3. Employment and worker characteristics by location, Ethiopia



Source: Authors' calculations using Ethiopia Socioeconomic Survey (ESS) 2019

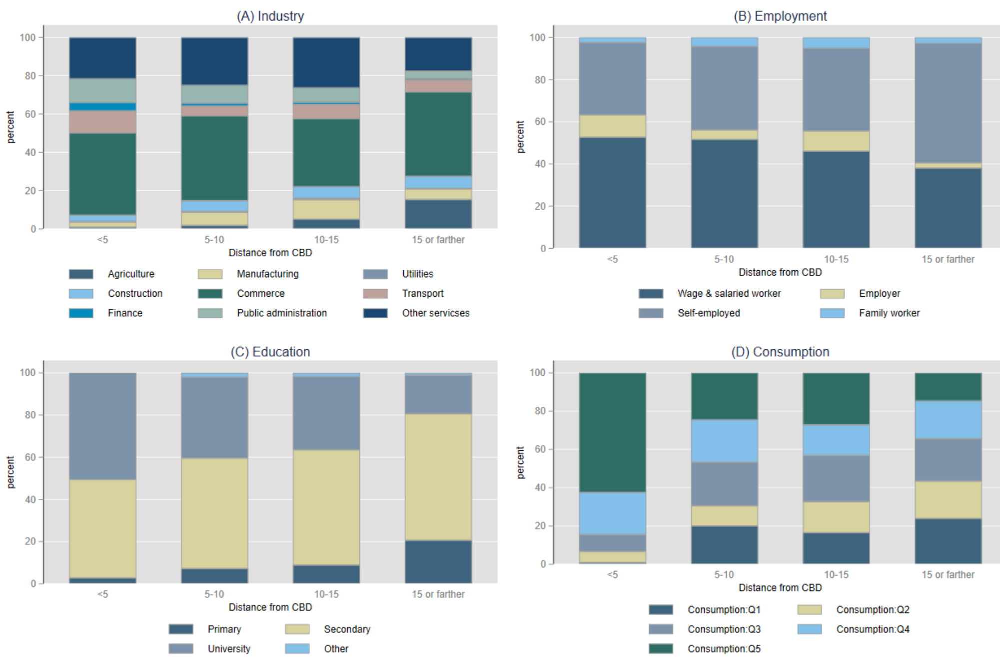
In Kinshasa, we measure each workers' accessibility based on the distance from the CBD. In our sample, 3 percent of households live within 5 km from the CBD, 24 percent between 5 and 10 km, 37 percent between 10 and 15 km, and 37 percent beyond 15 km from the CBD (Figure A5 in Appendix A). Both employment and population characteristics are closely related to their residential locations in Kinshasa. Figure 4 shows how the industries of primary jobs, employment types, education levels, and consumption levels vary by the distance from the CBD. Workers who live in neighborhoods closer to the CBD tend to work in the sectors of finance, commerce, and public administration, while a higher share of workers in outer areas engage in agriculture (Panel A). Corresponding to this pattern, the share of self-employment workers is higher in areas farther from the CBD (Panel B). The education level of workers is also clearly correlated with the distance from the CBD, as the share of workers with tertiary education is higher near the CBD (Panel C). Finally, wealthier people, in terms of consumption expenditures, tend to live near the CBD (Panel D).

Our Kinshasa analysis also utilizes another locational variable which indicates neighborhood characteristics, such as the precariousness and the building density of the neighborhoods (see Panel A in Figure B3 in Appendix B for a map). In the baseline Kinshasa survey, precarious areas are defined based

[11] Kamei and Nakamura (2020) find a strong correlation between town population size and wage jobs, as opposed to self-employment jobs, in Ethiopia.

on their characteristics of dwellings and geographic and environmental features.[12] Building density is classified based on the number of buildings per hectare: low (less than 10), medium (10 to 20), and high (more than 20). The survey methodology and results are described in a series of World Bank reports (World Bank 2020b, 2020c, 2020d). Our analysis focuses only on urban households. Overall, non-precarious neighborhoods tend to be located closer to the CBD, whereas low-density neighborhoods spread in the outer areas (see Figure A5 in Appendix A).

Figure 4. Employment and worker characteristics by locations, Kinshasa



Source: Authors' calculations using Kinshasa HBS 2018

Mobility trends

We draw on Facebook movement data to capture mobility trends since the outbreak of COVID-19 in Kinshasa. The index indicates the percentage change of movement between administrative boundaries relative to the baseline level—which is the mobility level in the four weeks in February. The index is calculated using data from Facebook Disease Prevention Maps' Movement between Administrative Regions function to illustrate aggregate patterns of movement.[13] The data are recorded from the users of the smartphone app with enabled location history three times per day within an eight-hour interval, starting from 0 a.m., 8 a.m. and 4 p.m. Each data set contains the number of Facebook users moving between combinations of geographic polygons (grids approximately 600 m by 600 m in size) during the recording period and the baseline period.

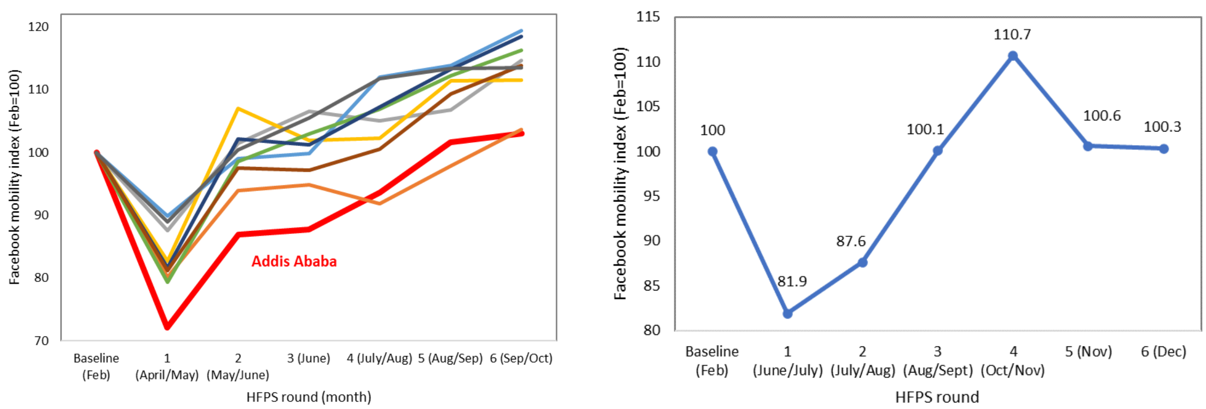
[12] Precarious neighborhood is defined as a neighborhood whose dwellings are built by the occupants on land acquired in undeveloped areas, on farmland and market gardens, or on uneven ground (exposure to erosion and flooding). Buildings are anarchic and the use of recycled materials (cardboard, plastics, and sheet metal) is common. Most often, they are located in parts of the city abandoned by the more affluent categories: on steep slopes or near industrial areas, which makes them all the more dangerous and where misery is concentrated. Collective facilities (water, electricity, sanitation, and transport) are reduced and availability is low.
[13] Facebook movement data have been used in several analyses, such as Maas et al. (2019) for disaster response and Bonaccorsi et al. (2020) for the analysis of COVID-19 impacts in Italy.

As with other big data, a concern about the Facebook movement data is the selection of the data sources. The users of the Facebook smartphone app are unlikely to represent the urban population, particularly in low-income countries like Ethiopia and the DRC. Those users are likely wealthier, younger, and more mobile. Google mobility data, another commonly used mobile phone data, probably have less selective data sources than Facebook movement data, as they only require the location history in their Android mobile phones to remain active.[14] While Google mobility data are unfortunately not available in Ethiopia or the DRC, we find similar mobility trends based on Facebook and Google mobility data in 21 African countries where both types of data are available.[15] While the observed correlation does not ensure the representativeness of the Facebook data, it is at least assuring that the Facebook mobility trends do not deviate from the Google ones.

Mobility in urban Ethiopia and Kinshasa plummeted in March 2020, shortly after the COVID-19 outbreak, but has since recovered (Figure 1). Figure 5 shows mobility trends in each of the HFPS rounds in Ethiopia and Kinshasa.[16] In Ethiopia, out of 79 zones, Facebook data include observations of at least 6 days in 20 zones and at least 40 days in 14 zones (see map in Figure A3).[17] Panel A shows a sharp decline in the mobility level and its slow recovery in Addis Ababa.[18] Kinshasa also shows a sharp decline in the mobility level at the first HFPS round (Panel B).

Figure 5. Mobility trends and HFPS rounds in Ethiopia and Kinshasa

(A) Ethiopia (zones) **(B) Kinshasa**



Source: Authors' calculations using Facebook movement data

[14] Google mobility data are used in various research in the COVID-19 context (Maloney and Taskin 2020; Marcén and Morales 2021; Nouvellet et al. 2021).
[15] The result available upon request.
[16] The index indicates the mobility level relative to February 2020 instead of the same month in the previous years. Thus, it does not account for seasonality.
[17] Zones are the second-level administrative division in Ethiopia.
[18] As presented in Section 4, removing Addis Ababa from the sample does not substantially change the results of our regression analyses.

3-3. Econometric models

Between-city analysis: Ethiopia

Given the household fixed effects, how has the trajectory of COVID-19 income shock varied by location in urban Ethiopia? To answer the question, we estimate the following two-way fixed-effects (FE) model using the baseline Ethiopia Socioeconomic Survey (ESS) data and the six rounds of Ethiopia's HFPS:

$$y_{ijt} = \alpha + \beta_1 \mathrm{Round}_t + \beta_2 \left(\mathrm{Round}_t \times \mathrm{Pop}_j\right) + \beta_3 X_{it} + \delta_i + \varepsilon_{ij} \quad (1)$$

where y_{ijt} is a dummy variable indicating whether the household i in town j experienced an income reduction at round t since the previous survey round t-1; Round_t is a dummy indicator for the survey round; Pop_j indicates a location characteristic for town j, such as the log of town population; δ_i is household FE. Since Pop_j is a time-invariant variable, it is interacted with the round dummies. β_2 is the parameter of interest, indicating how the probability of households' income reduction varies by the location characteristics. In addition, we control for remittances and private and public assistance received by households, which are time-variant variables in X_{it}.

To examine whether the estimated heterogeneity by town population above further differs by town population density, we add another interaction term to Equation (2) as follows.

$$y_{ijt} = \alpha + \beta_1 \mathrm{Round}_t + \beta_2 \left(\mathrm{Round}_t \times \mathrm{Pop}_j\right) + \beta_3 \left(\mathrm{Round}_t \times \mathrm{Den}_j\right) + \\ \beta_4 \left(\mathrm{Round}_t \times \mathrm{Pop}_j \times \mathrm{Den}_j\right) + \beta_5 X_{it} + \delta_i + \varepsilon_{ij} \quad (2)$$

where Den_j indicates the log of town population density. In this way, we can distinguish, for example, towns with a large population size and high population density from large towns with low population density.

Similarly, we explore another heterogeneity by household characteristics, such as sex, education, self-employment, and consumption levels, by replacing Den_j in Equation (2) with each of these indicators.

Within-city analysis: Kinshasa

To explore within-city impacts, we aim to estimate income elasticities to the exogenous mobility changes and more primarily the heterogeneity of the estimated elasticities by household location characteristics. With the Facebook mobility index, MOB_{jt}, the model is expressed as follows:

$$y_{ijt} = \alpha + \beta_1 \mathrm{MOB}_{jt} + \beta_2 \left(\mathrm{MOB}_{jt} \times \mathrm{LOC}_j\right) + \beta_3 X_{it} + \delta_i + \varepsilon_{ijt} \quad (3)$$

We use two types of location variables LOC_j: the log of distance from the CBD and neighborhood characteristics in terms of precariousness and density.

In all our estimations, standard errors are clustered at the town level for Ethiopia and at the enumeration area level for Kinshasa.

4. Results

4-1. Within-country impacts: Urban Ethiopia

We first estimate the FE model in Equation (1) and report the estimation results in Table 3. In addition, Figure 6 visually summarizes the results, showing the predicted probability of households experiencing income reduction over the six survey rounds by town population size.

Column 1 in Table 3 reports the result for the probability of households losing labor incomes. The interaction terms between the survey rounds and the log of town population are statistically different from zero in the second and sixth rounds (0.020 and 0.016, respectively), indicating that households in large towns faced a higher chance of reduced labor incomes between the first and second round (i.e., latter half of May 2020) and between the fifth and sixth round (August/September 2020). By contrast, we do not observe such spatial heterogeneity for household total incomes in column 3. Panels A and B in Figure 6 show the trajectories of the predicted probability of labor and total incomes for towns with different population sizes.

We then estimate the model in Equation (2) to look at both town population and population density. Columns 2 and 4 in in Table 3 summarize the results for labor incomes and total incomes, respectively. Similar to column 1, the interaction terms between the first and sixth-round indicators, the log of town population and the log of town population density are significant in column 2 (0.032 and 0.025), pointing to higher impacts on labor incomes among households who live in large and densely populated towns. As shown in Panel (C) in Figure 6, households in large and densely populated towns indeed struggled, as indicated by their higher probability of income loss and the slow recovery. As for household total incomes, we see a clear interaction only in the first survey round (column 4).

As a robustness check, we estimate the models above using subsamples and different specifications. First, we estimate the specifications in columns 2 and 4 in Table 3 by using only the subsample of households that do not live in Addis Ababa. This is to test the possibility that our findings are driven by households in Addis Ababa, by far the largest city in Ethiopia and unique in many aspects. Second, we estimate the same set of FE regression models by excluding households whose main jobs are in agriculture, as those households may have been less affected by the pandemic. Finally, we add to the model in Equation (2) additional controls for household characteristics, such as age, sex, education, marital status, household size, consumption quintiles, and the industry of their primary jobs. We control for their trends by interacting those time-invariant variables with round FE. As shown in Table A3 in Appendix A, our findings are robust against all these variations.

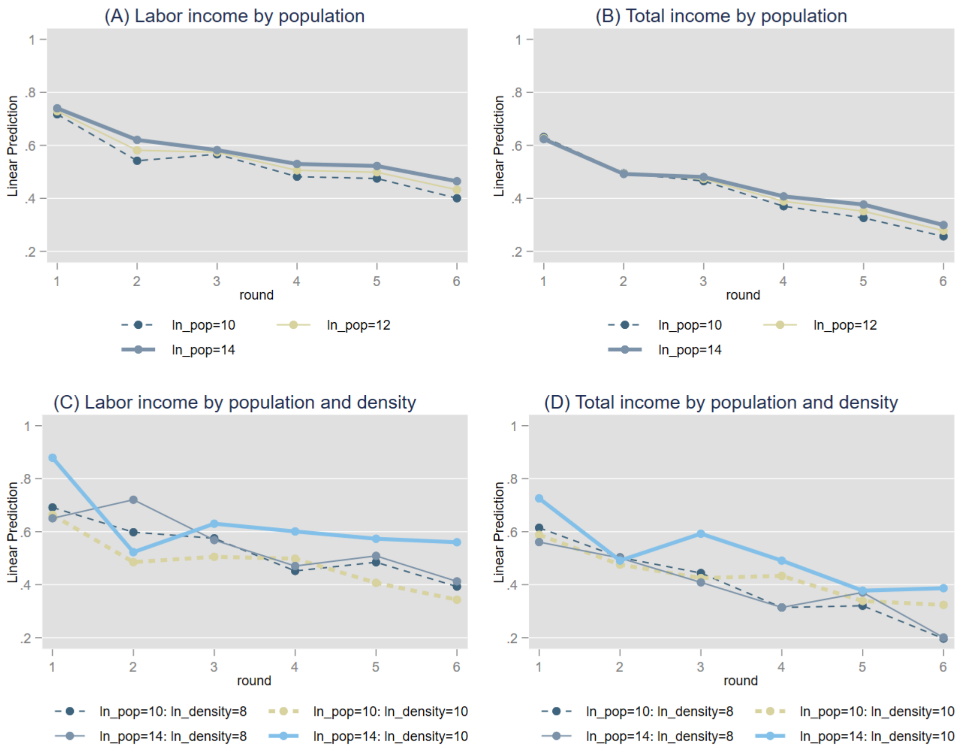
We also find that disadvantaged group of households in large towns particularly struggled. Figure 7 summarizes the estimated results of the labor-income model in Equation (2) with the density variable replaced with other household characteristics (see Figure A4 in Appendix A for the results for total incomes). The pace of recovery among female-headed households has been slow in terms of labor incomes—particularly in large towns—in Panel (A), though the difference with male-headed households is not significant in the case of total incomes (Panel B). Low-skilled households have experienced higher probability of income loss throughout the six rounds and the pace of recovery has been a bit slower in large towns (Panels C and D). Self-employed households experienced severer income loss in earlier rounds, but they recovered fast in terms of the probability of further reducing labor incomes both in small and large towns (Panel E). Finally, poor households experienced severer income shocks in the early rounds, but those who live in small towns recovered fast (Panels G and H). By contrast, poor households in larger towns still had a higher probability of income loss even in round six.

Table 3. Estimation results of two-way FE models: Urban Ethiopia

	Labor income		Total income	
	(1)	(2)	(3)	(4)
Round 1	0.664***	3.477***	0.654***	2.771***
	(0.127)	(0.998)	(0.139)	(0.967)
Round 2	0.349***	-0.103	0.504***	0.797
	(0.111)	(1.086)	(0.159)	(1.534)
Round 3	0.530***	2.190	0.430**	2.635
	(0.114)	(1.412)	(0.192)	(2.292)
Round 4	0.366***	1.066	0.280*	0.410
	(0.124)	(1.060)	(0.149)	(1.470)
Round 5	0.360***	2.161*	0.203	0.017
	(0.121)	(1.285)	(0.143)	(1.246)
Round 6	0.244**	2.521***	0.153	0.271
	(0.108)	(0.938)	(0.104)	(0.910)
Round 1 × ln(Population)	0.006	-0.267**	-0.002	-0.205**
	(0.010)	(0.103)	(0.011)	(0.098)
Round 2 × ln(Population)	0.020**	0.116	-0.001	-0.018
	(0.008)	(0.107)	(0.012)	(0.161)
Round 3 × ln(Population)	0.004	-0.133	0.004	-0.211
	(0.008)	(0.142)	(0.015)	(0.206)
Round 4 × ln(Population)	0.012	-0.080	0.009	-0.057
	(0.009)	(0.109)	(0.012)	(0.141)
Round 5 × ln(Population)	0.012	-0.136	0.013	0.023
	(0.009)	(0.127)	(0.012)	(0.119)
Round 6 × ln(Population)	0.016*	-0.193**	0.011	-0.058
	(0.008)	(0.096)	(0.008)	(0.094)
Round 1 × ln(Density)		-0.335***		-0.252**
		(0.123)		(0.118)
Round 2 × ln(Density)		0.050		-0.036
		(0.133)		(0.189)
Round 3 × ln(Density)		-0.199		-0.263
		(0.169)		(0.269)
Round 4 × ln(Density)		-0.082		-0.012
		(0.132)		(0.177)
Round 5 × ln(Density)		-0.217		0.023
		(0.152)		(0.146)
Round 6 × ln(Density)		-0.272**		-0.010
		(0.114)		(0.110)
Round 1 × ln(Population) × ln(Density)		0.032**		0.024**
		(0.012)		(0.011)
Round 2 × ln(Population) × ln(Density)		-0.011		0.002
		(0.012)		(0.019)
Round 3 × ln(Population) × ln(Density)		0.016		0.025
		(0.016)		(0.024)
Round 4 × ln(Population) × ln(Density)		-0.11		0.007
		(0.013)		(0.016)
Round 5 × ln(Population) × ln(Density)		0.018		-0.001
		(0.014)		(0.013)
Round 6 × ln(Population) × ln(Density)		0.025**		0.007
		(0.011)		(0.011)
Assistance received	0.019	-0.014	-0.041	-0.043
	(0.040)	(0.027)	(0.042)	(0.043)
Remittances received	0.010	0.053	-0.152***	-0.148***
	(0.054)	(0.079)	(0.049)	(0.050)
Household FE	Yes	Yes	Yes	Yes
Obs.	10982	10982	11668	11668

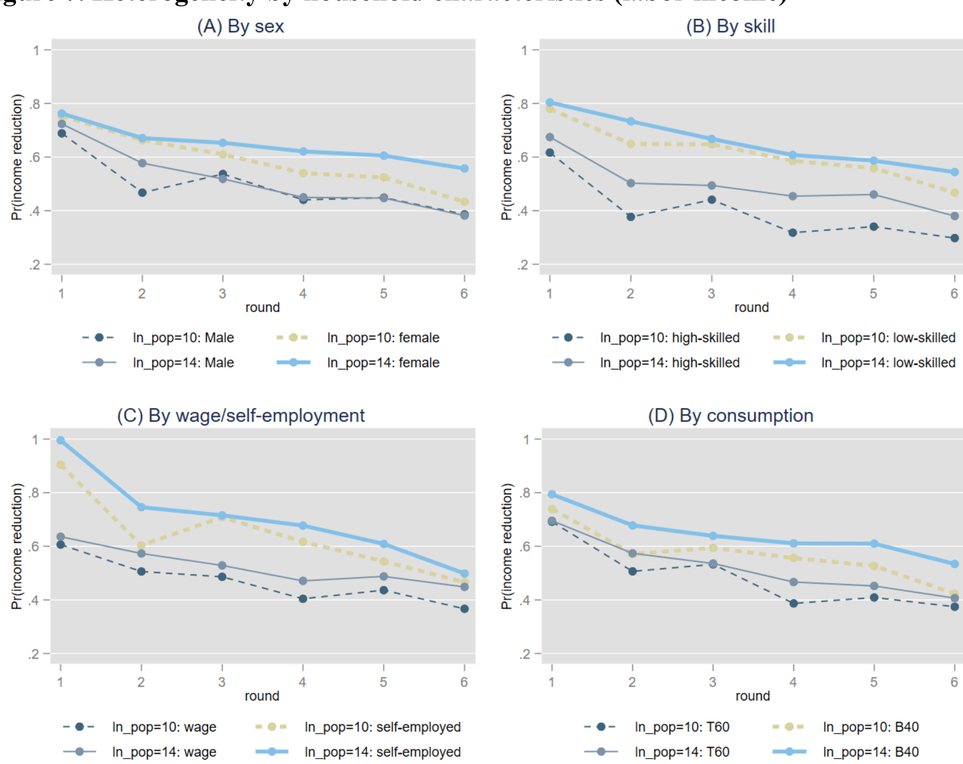
Note: Cluster-robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variables are dummy indicators about whether the household reduced their labor incomes (columns 1 and 2) or total incomes (columns 3 and 4) since the last survey round.

Figure 6. Predicted probability of income reduction



Sources: Authors' calculation using Ethiopia HFPS data, Ethiopia ESS data, and GHS-SMOD/POP data

Figure 7. Heterogeneity by household characteristics (labor income)



Sources: Authors' calculation using Ethiopia HFPS data, Ethiopia ESS data, and GHS-SMOD/POP data

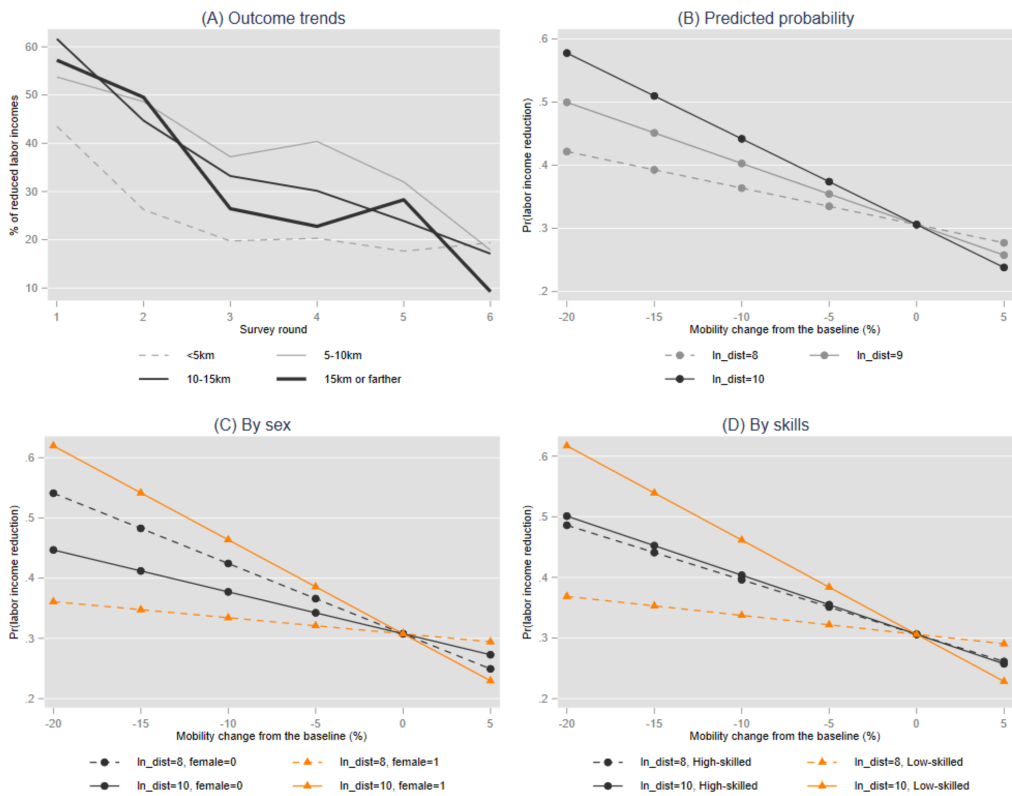
4-2. Within-city impacts: Kinshasa and Addis Ababa

Kinshasa

For Kinshasa, we examine how the link between mobility changes and the chance of experiencing labor shocks differs depending on workers' residential locations—measured by the distance from the CBD.

Before presenting the results of our regression analyses, we first look at the trends of our outcome variable over the survey rounds by the distance from the CBD (Panel A in Figure 8). At the descriptive level, the probability of households experiencing an income reduction declined over the survey periods, regardless of the distance from the CBD. Compared to other households, those who lived within 5 km from the CBD shows a lower probability between the first and fifth rounds.

Figure 8. Trend of income shock by location



Sources: Authors' calculation using Kinshasa HFPS data.

We report the estimation results of the fixed-effects models with the Facebook mobility index (Equation 4) in Table 4. Columns 1 and 2 include survey-round fixed effects and their interactions with individual and household characteristics, while columns 3 and 4 instead interact the mobility index with controls.

In column 1, the coefficient estimate for the interaction between the mobility index and the distance variable is −0.283 (95% CI [−0.606, 0.041]), suggesting that the recovering mobility levels are more strongly associated with a lower chance of labor income shock among workers in suburban and peri-urban areas. The result remains robust when including the interaction between the mobility index and individual and household characteristics (−0.385 column 2). Very similar coefficient estimates are also obtained in columns 3 and 4. Based on the result in column 4, the coefficient estimate for MOB is –0.58 and –1.16 in areas 3 km and 13 km from the CBD, respectively. This means that a 10 percent increase in the mobility level in Kinshasa reduces the chance of workers experiencing income decrease by 5.8 percent and 11.6 percent, respectively. Panel A in Figure 8 visually illustrates the result.

As a robustness check, we estimate the same set of specifications by restricting the sample only from the first to the fourth rounds, the period in which the mobility level continuously grew (Panel B in Figure 5). Restricting the sample for the first four rounds does not substantially change the results (columns 5 to 8 in Table 4).

We then analyze the additional heterogeneity of the income-mobility elasticities by worker characteristics, such as sex, skills, self-employment, and poverty status. The estimation results of the fixed-effects models with additional interactions with those characteristics are summarized in Table 5. We find that the labor incomes of female and/or low-skilled workers in neighborhoods that are located farther from the CBD are more elastic to mobility changes. As shown in Panel C (female workers) and Panel D (low-skilled workers) in Figure 8, the probability of their experiencing income reductions changes to a greater degree corresponding to the mobility changes.

Another analysis of Kinshasa involves the neighborhood characteristics based on their precariousness and building density. Table A4 in Appendix A summarizes the estimation results of regressions that interact the mobility index with the indicator about neighborhood characteristics. The positive coefficient estimates for the neighborhood characteristics dummies—with the precarious and high-density neighborhoods as the reference category—imply that labor incomes are more elastic to mobility changes in precarious and high-density neighborhoods. The results are, however, not clear enough to distinguish density across precarious neighborhoods due to wide standard errors in the estimates (see Figure A6 in Appendix).

Table 4. Regression results with distance from CBD: Kinshasa

	Whether the household head did not work or decrease labor income during the last 7 days							
	Rounds 1 to 6				Rounds 1 to 4			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MOB			1.527	4.908**			1.398	4.677*
			(1.530)	(2.453)			(1.533)	(2.392)
MOB × ln(Distance from CBD)	-0.283*	-0.385*	-0.281*	-0.387*	-0.251	-0.388*	-0.247\	-0.387*
	(0.164)	(0.206)	(0.163)	(0.207)	(0.163)	(0.203)	(0.163)	(0.204)
Assistance received (private)		-0.014		-0.010		-0.013		-0.029
		(0.027)		(0.027)		(0.034)		(0.038)
Assistance received (government)		0.053		0.083		0.023		0.064
		(0.079)		(0.067)		(0.090)		(0.077)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	No	No	Yes	Yes	No	No
Round × Ind/HH characteristics	No	Yes	No	No	No	Yes	No	No
MOB × Ind/HH characteristics	No	No	No	Yes	No	No	No	Yes
Obs.	5235	5016	5235	5016	3614	3466	3614	3466

Note: Cluster-robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. MOB indicates the Facebook mobility index with the mobility level in February 2020 as the baseline. Individual and household characteristics include age, sex, education, household size, dependency ratio, self-employment, industries, internet access, and consumption quintiles.

Table 5. Heterogeneity by worker characteristics: Kinshasa

	Whether the household head did not work or decrease labor income during the last 7 days							
	Rounds 1 to 6				Rounds 1 to 4			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MOB	-1.953	0.789	3.777*	5.166**	-2.193	1.260	4.142*	4.968*
	(2.743)	(2.965)	(2.119)	(2.560)	(2.819)	(2.742)	(2.164)	(2.601)
MOB × ln(Distance from CBD)	0.236	-0.038	-0.377**	-0.554**	0.262	-0.070	-0.423**	-0.550**
	(0.268)	(0.292)	(0.185)	(0.251)	(0.278)	(0.275)	(0.191)	(0.258)
MOB × Female	7.960**				8.533***			
	(3.094)				(3.245)			
MOB × ln(Distance from CBD) × Female	-0.882***				-0.922***			
	(0.322)				(0.338)			
MOB × Low-skilled		5.252*				4.599		
		(2.914)				(2.874)		
MOB × ln(Distance from CBD) × Low-skilled		-0.583*				-0.529*		
		(0.315)				(0.311)		
MOB × Self-employed			1.682				0.263	
			(2.916)				(2.804)	
MOB × ln(Distance from CBD) × Self-employed			-0.136				0.014	
			(0.309)				(0.296)	
MOB × Poor				-4.856				-5.000
				(3.916)				(3.940)
MOB × ln(Distance from CBD) × Poor				0.536				0.552
				(0.408)				(0.411)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	No	No	No	No	No	No	No	No
Round × Ind/HH characteristics	No	No	No	No	No	No	No	No
MOB × Ind/HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5139	5016	5016	5016	3552	3466	3466	3466

Note: Cluster-robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. MOB indicates the Facebook mobility index with the mobility level in February 2020 as the baseline. Individual and household characteristics include age, sex, education, household size, dependency ratio, self-employment, industries, internet access, and consumption quintiles.

5. Discussion and conclusions

This paper examines spatial heterogeneity of the impacts of the early days of the COVID-19 pandemic on urban households' incomes in Ethiopia and Kinshasa. Drawing on new panel household surveys, the fixed-effects regression analysis for Ethiopia finds that households in large and densely populated towns were exposed to higher risk of labor income reductions at the beginning of the pandemic and their recovery was slower than other households. Disadvantaged groups, such as female, low-skilled, self-employed, and poor workers, particularly suffered in large and densely populated towns. In the case of Kinshasa, we find that labor incomes are more elastic to the changes in mobility among workers—particularly female and low-skilled workers—who live in areas that are located farther from the city core area and/or highly dense and precarious neighborhoods.

Our analyses do not allow to distinguish specific paths in the COVID-19 impacts on urban households' incomes. The disadvantaged groups may have been particularly vulnerable to mobility shocks, as they need to travel around for their jobs in self-employment, with no option to work remotely. Their employment may also be unstable due to the lack of written contracts and informality. In large and densely populated towns, people are less likely to travel during the pandemic in view of the high contagion risk. The disadvantaged group of workers who live far from their workplace must have been hit hard by mobility restrictions, further reducing their incomes. In the short term, it is important to provide direct support to those households in the form of, for example, cash transfers. In the medium term, it might be effective to build their resilience against shocks by improving their accessibility to jobs. This could be achieved by reducing the distance between jobs and residential locations through, among others, land use management, transport development, and/or the provision of transport subsidies to workers.

We conclude by mentioning limitations of this study. First, relying on the Facebook mobility data has drawbacks. The data may not represent the mobility trend of urban workers and households, as it only captures the movement of Facebook users who keep the smartphone app and location information on—they are probably younger and wealthier. Moreover, the Facebook mobility data track the mobility trend only at a geographically aggregated level. Thus, we cannot differentiate within-city locations or individual characteristics. Second, the HFPS data do not capture the initial shock period between mid-March and May in Kinshasa. People who were relatively resilient against the COVID-19 shock might have already recovered by the first round of the HFPS. If the share of those workers is correlated with town population or density, our estimation would be biased. Third, the HFPS data record employment conditions of only one respondent, typically the household head. As a result, we cannot analyze other workers within the household. This limits, for example, the possibility of differentiating the estimated impacts for youth and female workers. Finally, the HFPS data do not record the exact amount of labor income of individuals and households, let alone their consumption levels. As a result, we cannot quantify the welfare impacts of the COVID-19 pandemic in our research design.

References

Adams-Prassl, A., T. Boneva, M. Gollin, and C. Rauh. 2020. "Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys." *Journal of Public Economics* 189.

Andersson, F., J. C. Haltiwanger, M J. Kutzbach, H. O. Pollakowski, and D. H. Weinberg. 2018. "Job Displacement and the Duration of Joblessness: The Role of Spatial Mismatch." *The Review of Economics and Statistics* 100 (2): 203–218.

Baek, C., P. B. McCrory, T. Messer, and P. Mui. 2020. "Unemployment Effects of Stay-at-Home Orders: Evidence from High Frequency Claims Data." Review of Economics and Statistics.

Beyer, R. C. M., T. Jain, and S. Sinha. 2020. "Lights Out? COVID-19 Containment Policies and Economic Activity." World Bank Policy Research Working Paper No. 9485.

Bonaccorsi, G., F. Pierri, M. Cinelli, A. Flori, A. Galeazzi, F. Porcelli, A. L. Schmidt, C. M. Valensise, A. Scala, W. Quattrociocchi, and F. Pammolli. 2020. "Economic and Social Consequences of Human Mobility Restrictions under COVID-19." *PNAS* 117 (27): 15530–15535.

Bundervoet, T., M. E. Davalos, and N. Garcia. 2021. "The Short-Term Impacts of COVID-19 on Households in Developing Countries: An Overview Based on a Harmonized Data Set of High-Frequency Surveys." World Bank Policy Research Working Paper 9582.

Chetty, R., J. N. Friedman, N. Hendren, M. Spencer, and the Opportunity Insights Team. 2020. *The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data.* https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf.

Combes, P. P., and L. Gobillon. 2015. "The Empirics of Agglomeration Economies." In *Handbook of Regional and Urban Economics* (Vol. 5, pp. 247–348*)*, edited by G. Duranton, J. V. Henderson, and W. C. Strange. North-Holland, Amsterdam.

Crossley, T., P. Fisher, and H. Low. 2021. "The Heterogeneous and Regressive Consequences of COVID-19: Evidence from High Quality Panel Data." *Journal of Public Economics* 193.

Dijkstra, L., A. J. Florezyk, S. Freire, T. Kemper, M. Melchiorri, M. Pesaresi, and M. Shiavina. 2021. "Applying the Degree of Urbanisation to the Globe: A New Harmonized Definition Reveals a Different Picture of Global Urbanization." *Journal of Urban Economics*.

Duranton, G., and D. Puga. 2004. "Micro-foundations of Urban Agglomeration Economies." In *Handbook of Regional and Urban Economics* (Vol. 4, pp. 2063–2117), edited by J. V. Henderson and J. F. Thisse. North-Holland, Amsterdam.

Egger, D., E. Miguel, S. S. Warren, A. Shenoy, E. Collins, D. Karlan, D. Parkerson, et al. 2021. "Falling Living Standards during the COVID-19 Crisis: Quantitative Evidence from Nine Developing Countries." *Science Advances* 7: 1–12.

Franklin, S. 2018. "Location, Search Costs and Youth Unemployment: Experimental Evidence from Transport Subsidies." *The Economic Journal* 128 (614): 2353–79.

Gibson, J., S. Olivia, G. Boe-Gibson, and C. Li. 2021. "Which Night Lights Data Should We Use in Economics, and Where?" *Journal of Development Economics* 146.

Glaeser, E. L., C. Gorback, and S. J. Redding. 2020. "How Much Does COVID-19 Increase with Mobility? Evidence from New York and Four Other U.S. Cities." *Journal of Urban Economics*.

Gobillon, L., T. Magnac, and H. Selod. 2011. "The Effect of Location on Finding a Job in the Paris Region." *Journal of Applied Economics* 26 (7): 1079–1112.

Gobillon, L., and H. Selod. 2014. "Spatial Mismatch, Poverty, and Vulnerable Population." In *Handbook of Regional Science* (pp. 93–107), edited by M. M. Fischer and P. Nijkamp. Springer: Heidelberg.

Institut National de la Statistique (INS). 2020. *Conditions de vie des ménages à Kinshasa Mesure de l'impact de la COVID-19.*

Kamei, A., and S. Nakamura. 2020. "Urban Agglomerations and Employment Transitions in Ethiopia." World Bank Policy Research Working Paper 9184.

Khamis, M., D. Prinz, D. Newhouse, A. Palacios-Lopez, U. Pape, and M. Weber. 2021. "The Early Labor Market Impacts of COVID-19 in Developing Countries: Evidence from High-Frequency Phone Surveys." World Bank Jobs Working Paper No. 58.

Lall, S. V., J. V. Henderson, and A. J. Venables. 2017. *Africa's Cities: Opening Doors to the World.* Washington, DC: World Bank.

Maas, P., A. Gros, L. McGorman, S. Iyer, W. Park, and C. Nayak. 2019. "Facebook Disaster Maps: Aggregate Insights for Crisis Response and Recovery." Proceedings of the 16th ISCRAM Conference Valencia (Spain) May 19-22.

Maloney, W., and T. Taskin. 2020. "Determinants of Social Distancing and Economic Activity during COVID-19: A Global View." World Bank Policy Research Working Paper 9242.

Marcén, M., and M. Morales. 2021. "The Intensity of COVID-19 Non-Pharmaceutical Interventions and Labor Market Outcomes in the Public Sector." *Journal of Regional Science.*

Masaki, T., S. Nakamura, and D. Newhouse. 2020. "How Is the COVID-19 Crisis Affecting Nitrogen Dioxide Emissions in Sub-Saharan Africa?" World Bank Poverty and Equity Notes 21.

Nakamura, S., and P. Avner. 2021. "Spatial Distributions of Job Accessibility, Housing Rents, and Poverty: The Case of Nairobi." *Journal of Housing Economics* 51.

Nouvellet, P., S. Bhatia, A. Cori, K. E. C. Ainslie, M. Baguelin, S. Bhatt, A. Boonyasiri, et al. 2021. "Reduction in Mobility and COVID-19 Transmission." *Nature Communications* 12 (1090): 1–9.

Roberts, M. 2021. "Tracking Economic Activity in Response to the COVID-19 Crisis Using Nighttime Lights: The Case of Morocco." World Bank Policy Research Working Paper No. 9538.

Schmidt, E., Dorosh, P., Jemal, M.K., and Smart, J. 2018. "Ethiopia's Spatial and Structural Transformation: Public Policy and Drivers of Change." IFPRI/EDRI Strategy Support Program Working Paper 119.

Wieser, C., A. A. Ambel, T. Bundervoet, and A. Haile. 2020. *Monitoring COVID-19 Impacts on Households in Ethiopia: Results from a High-Frequency Phone Survey of Households.* World Bank.

World Bank. 2020a. *Poverty and Shared Prosperity 2020: Reversals of Fortune.* Washington, DC: World Bank.

World Bank. 2020b *Monetary Poverty and Shared Prosperity in Kinshasa*. Washington, DC: World Bank.

World Bank. 2020c. *Profiling Living Conditions of DRC Urban Population: Access to Housing and Services in Kinshasa Province.* Washington, DC: World Bank.

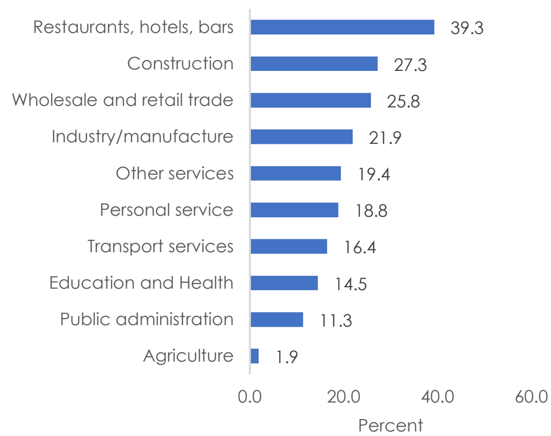
World Bank. 2020d. *Overview of the Labor Market: Demographic and Spatial Disparities in Outcomes within the Kinshasa Urban Landscape.* Washington, DC: World Bank.

World Bank. 2020e. *Ethiopia Poverty Assessment: Harnessing Continued Growth for Accelerated Poverty Reduction.* Washington, DC: World Bank.

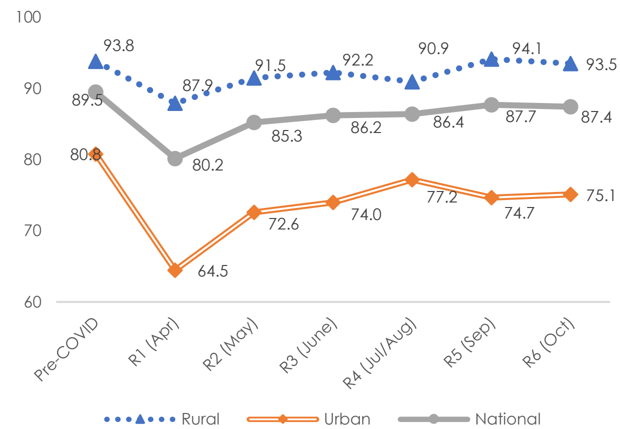
Appendix A: Additional figures and tables

Figure A1. Employment impacts in urban Ethiopia

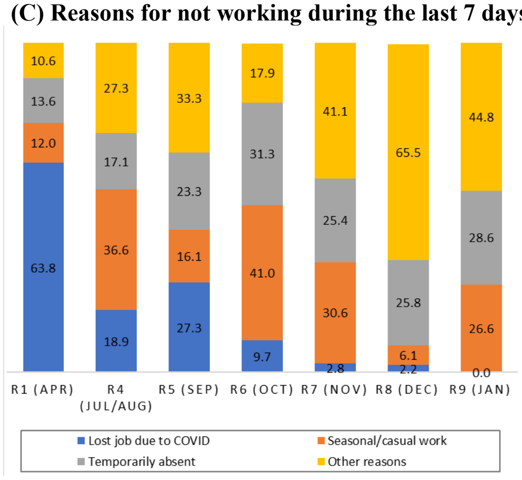
(A) Share of respondents who lost their job, by sector



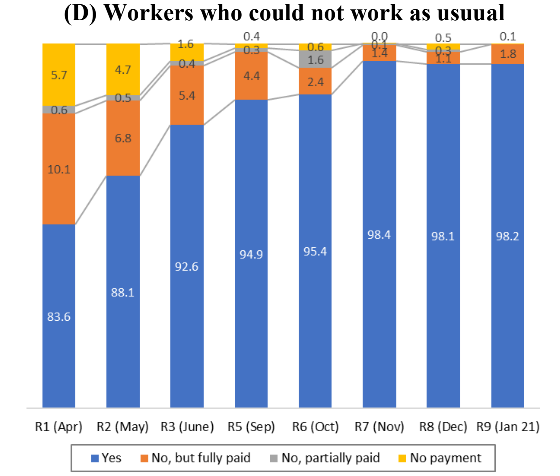
(B) Share of respondents that are employed



(C) Reasons for not working during the last 7 days



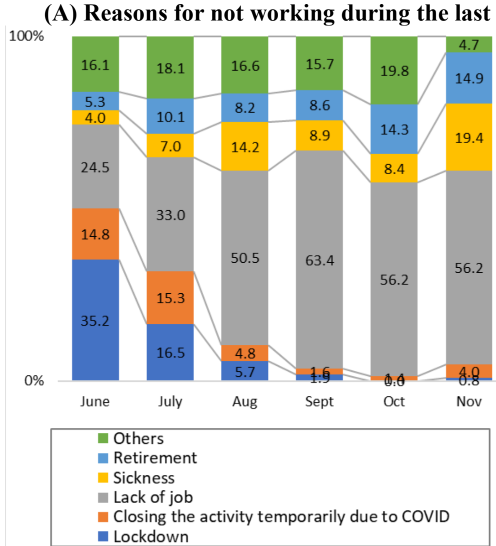
(D) Workers who could not work as usuual



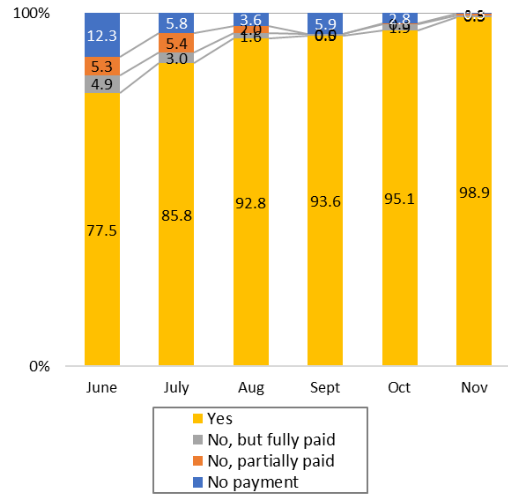
Source: Authors' calculations using Ethiopia HFPS data.

Figure A2. Working conditions since the COVID-19 outbreak in Kinshasa

(A) Reasons for not working during the last 7 days

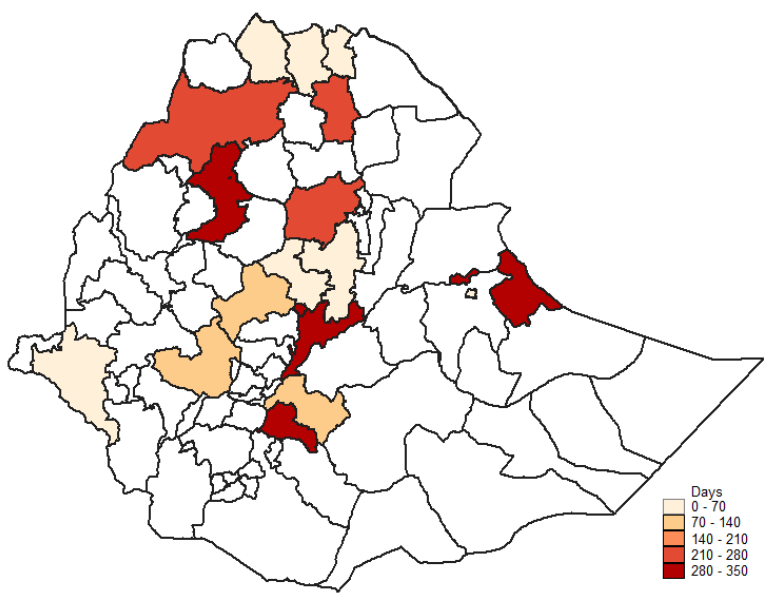


(B) Workers who could not work as usual



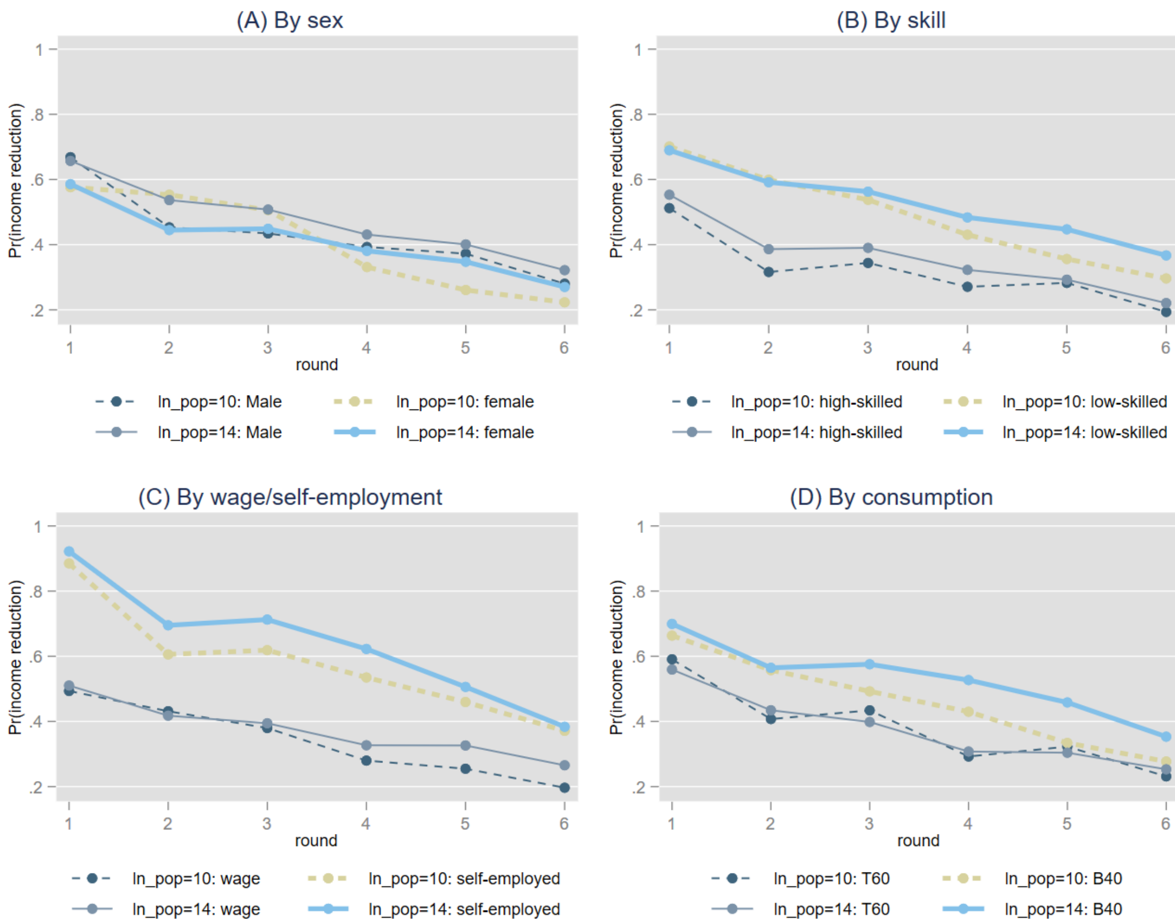
Source: Authors' calculations using Kinshasa HFPS June–November 2020.
Note: Numbers based on the matched sample between HBS and HFPS data.

Figure A3. Facebook movement data in Ethiopia



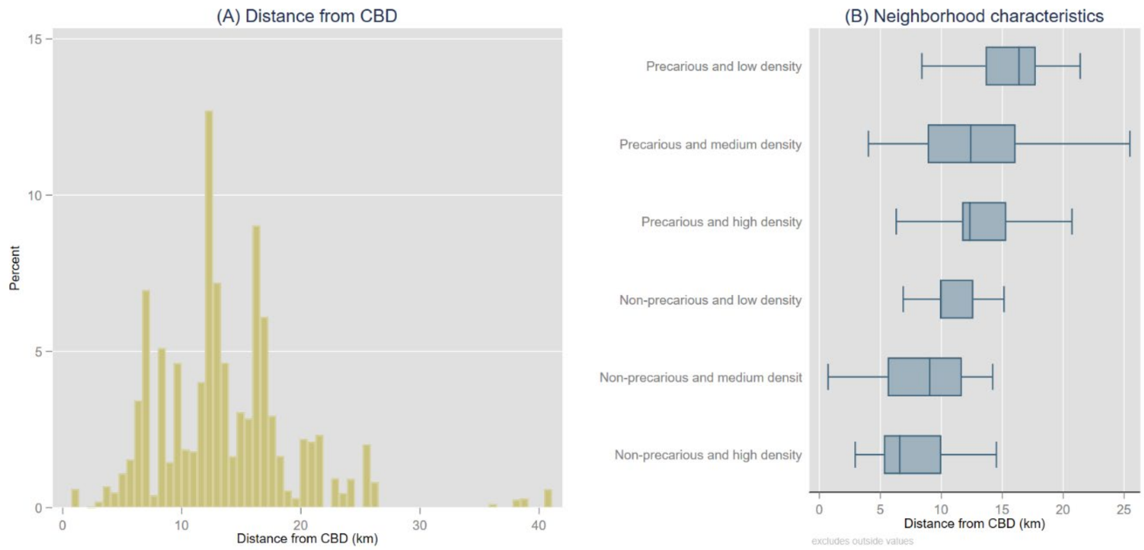
Source: Facebook movement data

Figure A4. Heterogeneity by household characteristics (total incomes)



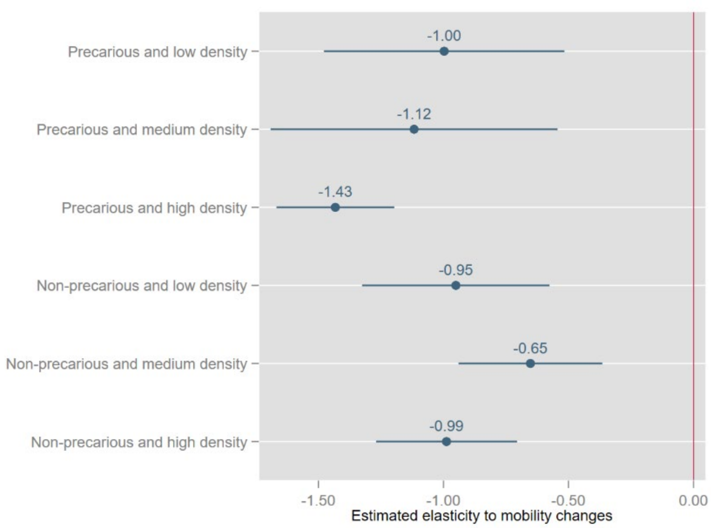
Sources: Authors' calculation using Ethiopia HFPS data, Ethiopia LSMS data, and GHS-SMOD/POP data

Figure A5. Location characteristics in Kinshasa



Sources: Authors' calculation using Kinshasa HFPS data.

Figure A6. Estimated elasticity by neighborhood characteristics, Kinshasa



Sources: Authors' calculation using Kinshasa HFPS data.

Table A1. Summary statistics (the first round of HFPS): Urban Ethiopia

	Households interviewed in all the six rounds				
	Obs.	Mean	S.D.	Min	Max
Household labor income decreased during the last 4 weeks	1587	0.727	0.445	0.000	1.000
Household total income decreased during the last 4 weeks	1702	0.622	0.485	0.000	1.000
Individual used to work pre-pandemic but did not work during the last 7 days	1703	0.167	0.373	0.000	1.000
ln(population)	1671	11.81	1.953	6.908	15.07
ln(population density)	1671	8.970	0.808	5.886	10.99
Age	1688	37.23	13.88	14.00	97.00
Female	1688	0.418	0.493	0.000	1.000
Marital status: Single	1688	0.198	0.399	0.000	1.000
Marital status: Married (monogamous)	1688	0.573	0.495	0.000	1.000
Marital status: Married (polygamous)	1688	0.012	0.108	0.000	1.000
Marital status: Divorced	1688	0.104	0.305	0.000	1.000
Marital status: Separated	1688	0.031	0.174	0.000	1.000
Marital status: Widowed	1688	0.081	0.273	0.000	1.000
Marital status: Co-habiting	1688	0.001	0.029	0.000	1.000
Household size: 1	1704	0.122	0.328	0.000	1.000
Household size: 2	1704	0.177	0.382	0.000	1.000
Household size: 3	1704	0.218	0.413	0.000	1.000
Household size: 4	1704	0.174	0.379	0.000	1.000
Household size: 5	1704	0.134	0.340	0.000	1.000
Household size: 6 or more	1704	0.175	0.380	0.000	1.000
Education: No education	1686	0.251	0.434	0.000	1.000
Education: Primary incomplete	1686	0.221	0.415	0.000	1.000
Education: Primary complete	1686	0.078	0.268	0.000	1.000
Education: Secondary incomplete	1686	0.146	0.353	0.000	1.000
Education: Secondary completed	1686	0.032	0.177	0.000	1.000
Education: Higher education	1686	0.263	0.440	0.000	1.000
Education: Adult education	1686	0.009	0.096	0.000	1.000
Consumption quintile: 1	1703	0.307	0.461	0.000	1.000
Consumption quintile: 2	1703	0.214	0.410	0.000	1.000
Consumption quintile: 3	1703	0.196	0.397	0.000	1.000
Consumption quintile: 4	1703	0.149	0.356	0.000	1.000
Consumption quintile: 5	1703	0.134	0.341	0.000	1.000
Self-employed	1704	0.315	0.465	0.000	1.000
Industry: Agriculture	1704	0.146	0.353	0.000	1.000
Industry: Manufacturing	1704	0.078	0.268	0.000	1.000
Industry: Wholesale and retail	1704	0.184	0.388	0.000	1.000
Industry: Transport	1704	0.044	0.204	0.000	1.000
Industry: Restaurants and hotels	1704	0.056	0.231	0.000	1.000
Industry: Public administration	1704	0.166	0.372	0.000	1.000
Industry: Personal services	1704	0.084	0.278	0.000	1.000
Industry: Construction	1704	0.089	0.285	0.000	1.000
Industry: Education and health	1704	0.039	0.194	0.000	1.000
Industry: Others	1704	0.114	0.318	0.000	1.000
Assistance received	1704	0.021	0.144	0.000	1.000
Remittance received	1704	0.006	0.079	0.000	1.000
Region: Tigray	1703	0.082	0.275	0.000	1.000
Region: Afar	1703	0.011	0.106	0.000	1.000
Region: Amhara	1703	0.224	0.417	0.000	1.000
Region: Oromia	1703	0.327	0.469	0.000	1.000
Region: Somali	1703	0.030	0.169	0.000	1.000
Region: Benishangul Gumuz	1703	0.010	0.100	0.000	1.000
Region: SNNP	1703	0.140	0.347	0.000	1.000
Region: Gambela	1703	0.006	0.079	0.000	1.000
Region: Harar	1703	0.006	0.075	0.000	1.000
Region: Addis Ababa	1703	0.154	0.361	0.000	1.000
Region: Dire Dawa	1703	0.010	0.101	0.000	1.000

Note: Time-variant variables are household income, mobility, nightlights, assistance, and remittances. All the other variables are time invariant.

Table A2. Summary statistics (the first round of HFPS): Kinshasa

	Obs.	Mean	S.D.	Min	Max
Labor income shock (experienced shock during the last 7 days)	857	0.576	0.494	0.000	1.000
Facebook mobility index (MOB)	880	-0.181	0.000	-0.181	-0.181
ln(Distance from CBD)	880	9.434	0.466	6.574	10.623
Precarious and low density	880	0.291	0.455	0.000	1.000
Precarious and medium density	880	0.191	0.393	0.000	1.000
Precarious and high density	880	0.326	0.469	0.000	1.000
Non-precarious and low density	880	0.078	0.269	0.000	1.000
Non-precarious and medium density	880	0.067	0.250	0.000	1.000
Non-precarious and high density	880	0.047	0.211	0.000	1.000
Age	880	48.65	12.64	20.00	88.00
Male	880	0.804	0.397	0.000	1.000
Education: Elementary or less	858	0.118	0.323	0.000	1.000
Education: Secondary	858	0.557	0.497	0.000	1.000
Education: Tertiary	858	0.312	0.464	0.000	1.000
Education: Others	858	0.012	0.109	0.000	1.000
Household size: 1	880	0.023	0.149	0.000	1.000
Household size: 2	880	0.054	0.227	0.000	1.000
Household size: 3	880	0.057	0.233	0.000	1.000
Household size: 4	880	0.123	0.328	0.000	1.000
Household size: 5	880	0.202	0.401	0.000	1.000
Household size: 6 or more	880	0.541	0.499	0.000	1.000
Dependency ratio	864	0.532	0.811	-0.500	5.000
Consumption quintile 1	880	0.106	0.308	0.000	1.000
Consumption quintile 2	880	0.137	0.344	0.000	1.000
Consumption quintile 3	880	0.211	0.408	0.000	1.000
Consumption quintile 4	880	0.243	0.429	0.000	1.000
Consumption quintile 5	880	0.303	0.460	0.000	1.000
Internet access	874	0.610	0.488	0.000	1.000
Assistance (private)	853	0.151	0.358	0.000	1.000
Assistance (government)	853	0.166	0.372	0.000	1.000
Industry: Agriculture	880	0.038	0.192	0.000	1.000
Industry: Industry and infrastructure	880	0.033	0.180	0.000	1.000
Industry: Transport	880	0.092	0.289	0.000	1.000
Industry: Construction	880	0.082	0.275	0.000	1.000
Industry: Finance and technology	880	0.047	0.212	0.000	1.000
Industry: Education	880	0.038	0.192	0.000	1.000
Industry: Public administration	880	0.110	0.313	0.000	1.000
Industry: Other services	880	0.304	0.460	0.000	1.000
Industry: Others	880	0.254	0.436	0.000	1.000

Note: Respondents in rounds 1 to 6. Time-variant variables are labor shock, mobility, and assistance. All the other variables are time invariant.

Table A3. Robustness check: Urban Ethiopia

	Labor incomes			Total incomes		
	Without AA	Without Agriculture	With HH controls	Without AA	Without Agriculture	With HH controls
	(1)	(2)	(3)	(4)	(5)	(6)
Round 1	3.870***	3.525***	3.314***	3.254***	2.810***	2.363***
	(0.950)	(0.966)	(0.926)	(0.933)	(0.994)	(0.866)
Round 2	0.330	-0.133	-0.209	1.291	0.765	0.191
	(1.141)	(1.075)	(1.086)	(1.420)	(1.557)	(1.224)
Round 3	2.384*	2.125	2.233	3.113	2.620	2.216
	(1.412)	(1.435)	(1.573)	(2.249)	(2.308)	(2.344)
Round 4	1.177	0.889	1.020	0.826	0.277	-0.758
	(1.102)	(1.085)	(1.217)	(1.418)	(1.486)	(1.619)
Round 5	2.537**	2.106	1.415	0.696	0.070	-1.280
	(1.251)	(1.293)	(1.345)	(1.205)	(1.244)	(1.460)
Round 6	2.443**	2.556***	2.612***	0.458	0.298	-0.702
	(0.957)	(0.939)	(0.957)	(0.913)	(0.898)	(0.967)
Round 1 × ln(Population)	-0.283***	-0.277***	-0.273***	-0.229**	-0.213**	-0.186**
	(0.097)	(0.100)	(0.101)	(0.091)	(0.101)	(0.092)
Round 2 × ln(Population)	0.095	0.119	0.091	-0.044	-0.015	0.035
	(0.113)	(0.106)	(0.110)	(0.147)	(0.163)	(0.133)
Round 3 × ln(Population)	-0.143	-0.130	-0.160	-0.235	-0.211	-0.159
	(0.142)	(0.144)	(0.150)	(0.203)	(0.207)	(0.212)
Round 4 × ln(Population)	-0.084	-0.060	-0.095	-0.077	-0.044	0.079
	(0.110)	(0.112)	(0.122)	(0.137)	(0.143)	(0.155)
Round 5 × ln(Population)	-0.156	-0.134	-0.084	-0.009	0.014	0.165
	(0.124)	(0.127)	(0.129)	(0.116)	(0.118)	(0.138)
Round 6 × ln(Population)	-0.188*	-0.198**	-0.210**	-0.068	-0.064	0.082
	(0.096)	(0.096)	(0.099)	(0.091)	(0.092)	(0.099)
Round 1 × ln(Density)	-0.417***	-0.340***	-0.326***	-0.344***	-0.257**	-0.238**
	(0.120)	(0.120)	(0.115)	(0.116)	(0.121)	(0.110)
Round 2 × ln(Density)	-0.036	0.057	0.072	-0.126	-0.029	0.028
	(0.142)	(0.132)	(0.131)	(0.180)	(0.192)	(0.150)
Round 3 × ln(Density)	-0.237	-0.191	-0.194	-0.355	-0.259	-0.203
	(0.171)	(0.172)	(0.185)	(0.264)	(0.271)	(0.274)
Round 4 × ln(Density)	-0.108	-0.058	-0.075	-0.095	0.006	0.127
	(0.143)	(0.136)	(0.148)	(0.173)	(0.179)	(0.192)
Round 5 × ln(Density)	-0.292*	-0.210	-0.127	-0.116	0.015	0.181
	(0.148)	(0.153)	(0.158)	(0.141)	(0.146)	(0.173)
Round 6 × ln(Density)	-0.257**	-0.276**	-0.257**	-0.046	-0.013	0.128
	(0.120)	(0.114)	(0.118)	(0.117)	(0.109)	(0.118)
Round 1 × ln(Population) × ln(Density)	0.037***	0.033***	0.032**	0.030***	0.025**	0.022*
	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)
Round 2 × ln(Population) × ln(Density)	-0.005	-0.011	-0.010	0.008	0.002	-0.004
	(0.013)	(0.012)	(0.012)	(0.017)	(0.019)	(0.015)
Round 3 × ln(Population) × ln(Density)	0.019	0.016	0.017	0.032	0.025	0.019
	(0.016)	(0.017)	(0.017)	(0.023)	(0.024)	(0.024)
Round 4 × ln(Population) × ln(Density)	0.012	0.008	0.011	0.013	0.005	-0.008
	(0.013)	(0.013)	(0.014)	(0.016)	(0.016)	(0.018)
Round 5 × ln(Population) × ln(Density)	0.023	0.017	0.010	0.008	-0.000	-0.018
	(0.014)	(0.014)	(0.015)	(0.013)	(0.013)	(0.016)
Round 6 × ln(Population) × ln(Density)	0.024**	0.025**	0.025**	0.010	0.008	-0.008
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Assistance received	0.011	0.014	0.013	-0.033	-0.044	-0.027
	(0.050)	(0.041)	(0.038)	(0.051)	(0.043)	(0.039)
Remittances received	0.001	0.002	0.013	-0.147**	-0.149***	-0.132**
	(0.063)	(0.055)	(0.048)	(0.058)	(0.050)	(0.051)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Round × HH characteristics	No	No	Yes	No	No	Yes
Obs.	8096	10755	10882	8717	11424	11668

Note: Cluster-robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variables are dummy indicators about whether the household reduced their labor incomes (columns 1 and 2) or total incomes (columns 3 and 4) since the last survey round.

Table A4. Regression results with labor income and neighborhood characteristics: Kinshasa

	Whether the household head did not work or decrease labor income during the last 7 days			
	(1)	(2)	(3)	(4)
MOB			-1.509***	1.093
			(0.208)	(0.861)
MOB × Precarious and low density	0.453	0.397	0.453	0.435
	(0.355)	(0.340)	(0.359)	(0.360)
MOB × Precarious and medium density	0.434	0.288	0.444	0.315
	(0.404)	(0.370)	(0.408)	(0.370)
MOB × Precarious and high density [reference]				
MOB × Non-precarious and low density	0.496*	0.477*	0.493*	0.482*
	(0.265)	(0.279)	(0.266)	(0.275)
MOB × Non-precarious and medium density	0.793***	0.752***	0.794***	0.780***
	(0.251)	(0.233)	(0.251)	(0.235)
MOB × Non-precarious and high density	0.683***	0.431**	0.680***	0.445**
	(0.256)	(0.212)	(0.256)	(0.211)
Assistance received (private)		-0.011		-0.007
		(0.027)		(0.027)
Assistance received (government)		0.062		0.092
		(0.074)		(0.062)
Individual FE	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	No	No
Round × Individual/HH characteristics	No	Yes	No	No
MOB × Individual/HH characteristics	No	No	No	Yes
Obs.	5239	5016	5239	5016

Note: Cluster-robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. MOB indicates the Facebook mobility index with the mobility level in February 2020 as the baseline. Individual and household characteristics include age, sex, education, household size, dependency ratio, self-employment, industries, internet access, and consumption quintiles.

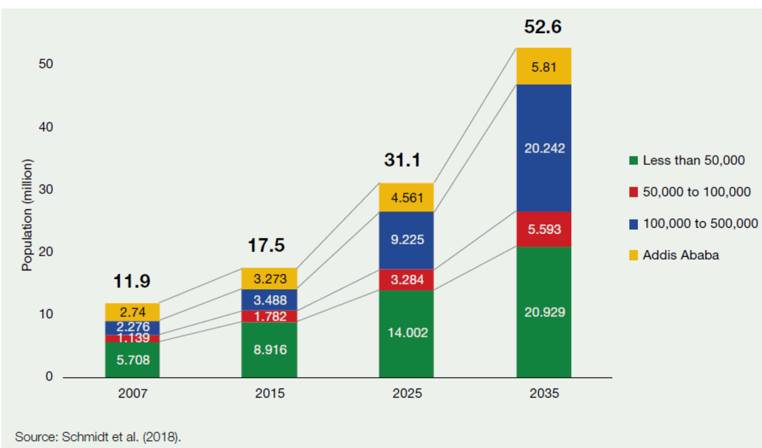
Appendix B: Spatial contexts of Ethiopia and Kinshasa

Spatial structure of urban Ethiopia

Ethiopia has a relatively fast-growing population and, though still among the lowest in Sub-Saharan Africa, a rapid growth in urban population. About 20 percent of the Ethiopians live in urban areas and the urban population has increased by 6.2 percent annually since 2011, adding nearly 1 million people to the urban population every year (World Bank 2020e). Schmidt et al. (2018) estimate that there are 45 cities of at least 50,000 population as of 2015 in Ethiopia and its urban population is projected to reach 42 million by 2032.

Going forward, urban population growth is projected to take place mainly in small towns and secondary cities with rural to urban migration expected to outpace natural population increase (World Bank 2020e). Between 2015 and 2025, around 5 million people are projected to be added in small towns with a population of less than 50,000 (Figure B1). Secondary towns with a population of greater than 100,000 (such as the regional capitals) will also grow at a similar scale, adding 5.7 million people between 2015 and 2025. In the meantime, the contribution of Addis Ababa to the overall urban population will decline—though it will remain by far the biggest city (Schmidt et al. 2018).

Figure B1. Urban population trends and projections, 2007–2035



Source: Schmidt et al. 2018

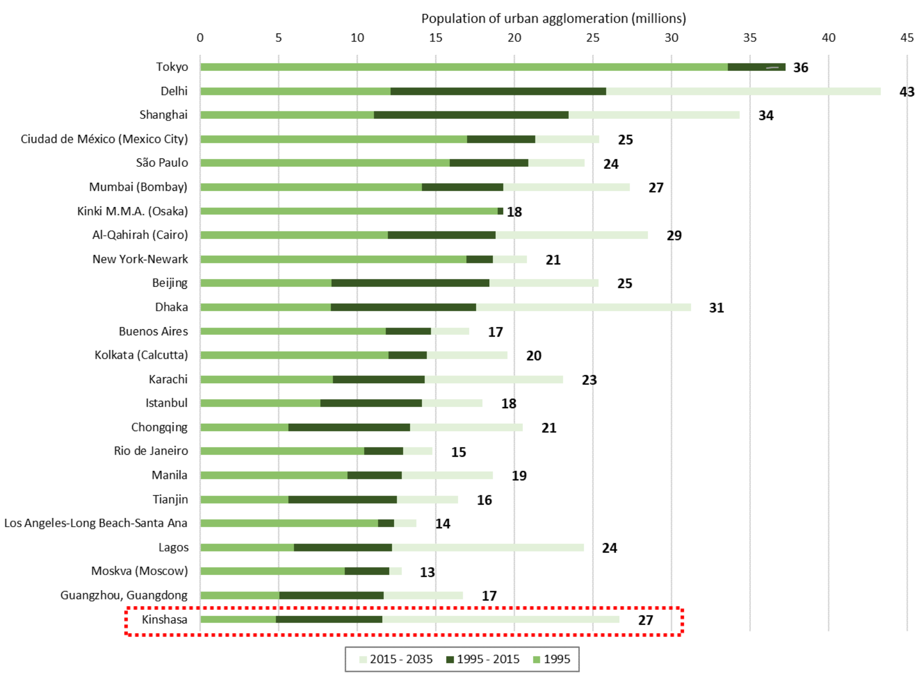
Spatial structure of Kinshasa

Kinshasa's already enormous population is projected to double in the next 20 years, according to the projection by the United Nations. Due to the lack of a recent census in the DRC, the last being in 1984, all population figures for Kinshasa—either Kinshasa Province or Kinshasa City—are projection based. According to the United Nations World Urbanization Prospects, the population size of the Kinshasa urban agglomeration is about 12 million as of 2015, ranked 24 in the world (Figure B2). By 2035, Kinshasa is projected to be the sixth-largest urban agglomeration with a population of 27 million, ranking just after Delhi, Tokyo, Shanghai, Dhaka, and Cairo. This anticipated addition of 15 million people to Kinshasa over the next two decades urges the government to act proactively.

Unplanned growth has made Kinshasa's land use fragmented and sprawling haphazardly. With the latest urban plan approved in 1967, another consequence of unplanned growth is the proliferation of precarious neighborhoods with low livability and walkability, suffering from poor services and various environmental and disaster risks (Panel A in Figure B3). Building density is high, particularly in and around the CBD while areas farther from the CBD are more sparsely populated with a lower density of buildings. The nature of neighborhoods also changes according to distance from the city core. More specifically, precarious neighborhoods have largely developed outside the city core and its immediate vicinity. According to one estimate, around 60 percent of Kinshasa residents live in such precarious neighborhoods. Not surprisingly, people living in precarious neighborhoods tend to be less educated and poorer—about 64 percent of Kinshasa's poor live in precarious areas (World Bank 2020b). Formal and well-paid jobs are concentrated in the CBD areas, while informal jobs spread across a few pockets of high-density neighborhoods (Panel B in Figure B3).

Workers' mobility is constrained by their income. In urban Kinshasa, low-income workers tend to commute by foot, while higher-income workers rely on motorized transport modes (Panel A in Figure B4).[19] For example, 60 percent of workers with a monthly income of less than US$100 per household walk to work, as opposed to less than 20 percent among workers with a monthly income of US$ 500 or more per household. Minibuses are increasingly used as workers' income level improves. Commuting by private car is an option only for the richest Kinshasans. As a result, commuting times tend to be longer among richer workers (Panel B), likely explained by traffic congestion, a common phenomenon in the city.

Figure B2. Population growth of major urban agglomerations in the world

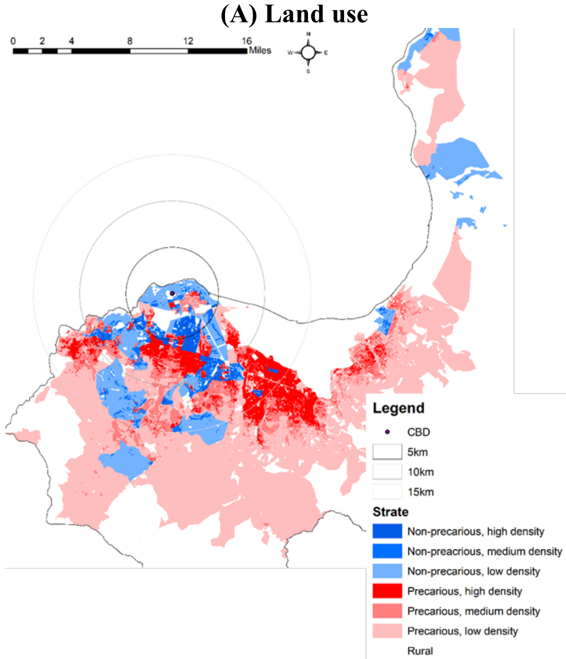


Source: United Nations World Urbanization Prospects, 2018 Revision.
Note: Cities are ordered by their populations as of 2015.

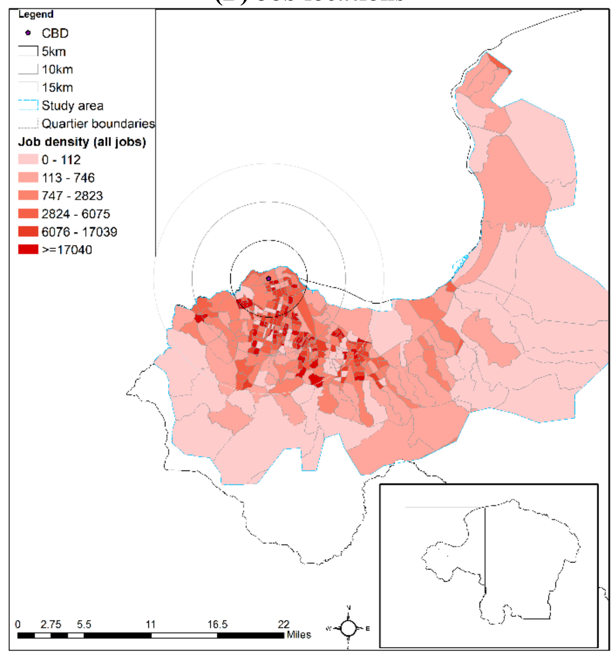
[19] The analysis is based on the 2017 Japan International Cooperation Agency (JICA) Commuter Survey. It was conducted in 2017 with the aims of informing the Urban Transport Master Plan toward 2030 and identifying priority projects. The study area of the survey mainly covers urban parts of Kinshasa Province and spans over 1,450 km^2 (out of the total area of Kinshasa covering 9,985 km2). For the survey, 8,000 households were sampled and randomly selected based on a satellite image of the study area. Surveyors were dispatched to visit the selected households and conduct face-to-face interviews with their representatives to answer the survey questionnaires. The questionnaire was designed to collect socioeconomic and commuting information of each household member.

Figure B3. Spatial structure of Kinshasa

(A) Land use



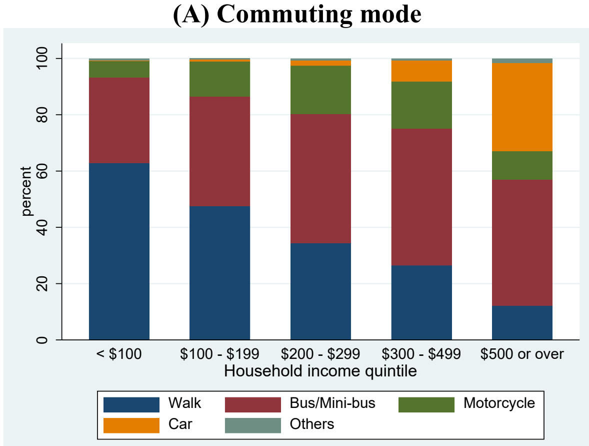
(B) Job locations



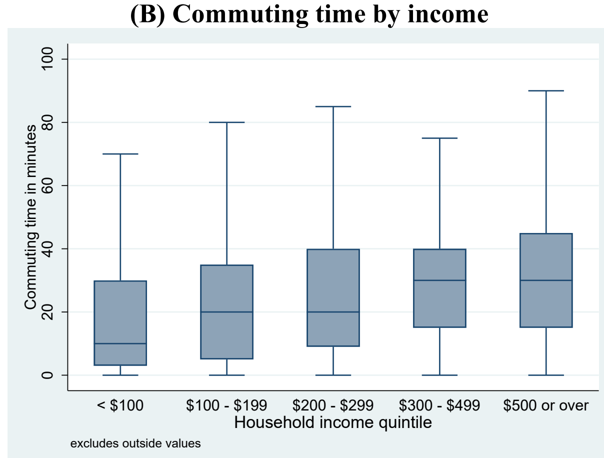
Source: World Bank 2020c, 2020d.

Figure B4. Commuting patterns in Kinshasa

(A) Commuting mode



(B) Commuting time by income



Source: Authors' calculation using JICA Commuter Survey