Exploring the Mobility Data

• Income
• Background

The COVID-19 pandemic has disproportionately affected low-income populations. Using granular mobility data for five Mexican cities, we explore the relationship between local income, education, and the behavior associated with COVID-19 risk: staying home, going to work, and going to other places. While low-income people are disproportionately likely to contract COVID-19 and die from associated illnesses in Mexico, we find very mixed evidence that people living in low-income urban census blocks are engaging in observably riskier behaviors. In general, people in low-income locations spend more time at home and less time going other places. During the COVID-19 pandemic, people in low income and less educated places appear to shift their movement behaviors less in response to Mexico's national lockdown. However, we find enormous variance within cities and in some cases people in low income places change their behavior more. This finding contradicts, to some extent, similar research from the United States focused on larger geographic (county-level) units. At global cities become more common, it is crucial to understand how income inequality and subnational diversity impacts citizens’ lives and behaviors to better predict where vulnerabilities will emerge.

Background

Income Dynamics of Coronavirus in Mexico

- The disparities of COVID-19 patients in Mexico vary considerably depending on income, and related quality of health care coverage (Diaz-Cayeros 2020). While the Mexican government has not released individual income data to match to COVID-19 cases or fatalities, we are able to learn a lot about the composition of cases based on which municipality they are located in.
- Many scholars attribute COVID-19 outcomes in sub-populations to be driven by risky behaviors of individuals. More specifically, a significant body of research has argued that low income people, due to income uncertainty, liquidity constraints, or associated low levels of education, are more likely to engage in risky behaviors and lack self control (Jalan and Ravallion 2001; Banerjee and Mullainathan 2008; Tanaka, Camerer and Nguyen 2016; Dupas and Robinson 2015).

Empirical Expectations

- We expect individuals in rich census blocks to change their behavior more in response to the pandemic. Those in rich areas are expected to shift more to staying at home, and shift away from going to places other than work or home. 10 2
- We expect people in more educated census to be more likely to change their behavior in response to the pandemic, staying at home more and going other places less. Across all variables, we anticipate different relationships in the variables by city.
- We expect these differences across cities reflect different economic structures, perception of virus risk, and relationship to the national government.

Explaining the Mobility Data

- Our analysis relies on the identifiable and privacy enhanced data collected from individual personal electronic devices (PED) that opted in to share location data anonymously for research purposes.
- The location analytics company Cuebiq inc., provided us access to Mexico’s pseudonomization and privacy-enhanced PED location data between January 1 and June 30, 2020. All data is collected with informed consent from anonymous users who opted-in to share their data for research purposes through a GDPR compliant framework.

- Data is collected in both online and offline mode, so if the connection is lost with the proximate cellular towers, locations would still be recorded and published later.
- Individual devices are pseudonymized based on their International Mobile Equipment Identity (IMEI) and their locations can be plotted for one day indicating patterns over the city; such as Figure 1, showing simulated movement for an individual.

Methods

Data and Workflow

The data consisted of 43.5 GB of raw PED data. Using PostgreSQL, the following analyses were executed:

- Each of the five experimental cities were spatially tooned with their respective shapefiles, allowing for each PED data point to be identified on a specific day and hour in a census tract.
- Each unique ID’s PED data was counted and grouped by each census tract, allowing for analysis of each ID’s frequency in a census tract.
- The ID’s home area was determined as the census tract with the highest number of hits and the work area as the second highest number of hits. All other census tracts were considered as “other”.
- All data points for each ID were tagged and grouped as “homeowner”, “workplace”, or “other” and ordered by date and census tract.

- Figure 2 shows the workflow described above.

Variables

- Independent variables are as follows: relative income, relative levels of education, healthcare access, internet access. All independent variables were collected from the 2010 urban census of the Instituto Nacional de Estadística y Geografía (INEGI).
- Dependent variable is as follows: the level and change in the share of time people are spending at home, at work, or outside of home or work.

Figure 2: Workflow Chart, Capturing Home, Work, Other

Note: In the analytic workflow, each ID’s home area, work area, and other areas were determined through a series of custom SQL queries that counted and ranked the frequency of each ID in different census tracts.

Methods (con’t)

Regression Model

- We use a simple regression model to show correlations between our socioeconomic predictors and our movement dependent variables (home (% total), work (% total), and other (% total)) where (index) denotes the city
- M measures the share of PED hits, by location, by individuals with a home in that census block.
- \( r \) represents the time before and after the national lockdown on March 23rd.
- E measures income (household residence per month).
- F measures education (percent without completed primary education).
- M is city and date fixed effects, respectively.
- \( \epsilon \) is a vector of controls for observable characteristics (including work, education, medical care access, internet access, and average pre-lockdown level of movement).

Conclusions

Our work examines variation in individual risk behavior of people at different levels of income during the COVID-19 pandemic across cities in Mexico. We use a variety of methods to examine changes in behavior across these cities after the common national lockdown in Mexico on March 23, 2020. We find, overall, that lower income people spend more time at home and less time in non-work places outside the home that do affluent people. This is the case before and during the pandemic. Overall, therefore, we might expect lower income people would have lower COVID-19 risk based on their individual movement. Our results thus push against relaxed work in the United States that focuses exclusively on changes in movement, rather than levels, to implicate low income people for putting themselves more at risk of COVID-19 exposure. Of course the pandemic in Mexico, as in the United States, is affecting poor people in greater numbers, despite these differences.

The percentage of time spent away from home, but not at work, is the clearest indicator of “voluntary” COVID-19 risk. Overall and during the pandemic, people spend less time in “other” places. In Mexican low-income census blocks, the reduced percentage of time they spent in other places was less than those in affluent areas. People in low education census blocks did not reduce their movement to other places as much as those in higher education blocks.