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FOOD ASSISTANCE AND MOBILITY DURING COVID-19 LOCKDOWNS

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Abstract

This paper examines the effects of emergency food assistance on human mobility patterns between March and August of 2020. We study a large public-private initiative in Colombia, created to deliver food aid to one million households at risk of falling into poverty and previously not included in other assistance programs. The impact is estimated using the quasi-exogenous roll out of the food distribution within municipalities. The high-frequency data set links detailed daily deliveries with georeferenced food recipients' location and mobility indicators measuring out-of-home events. This information is then aggregated at the urban tract level. The specification includes a rich set of fixed effects using sector, time and department-week trends. The main findings indicate that receiving food assistance delivered to the home reduced out-of-home mobility by 1.6 percent during a two-week window. The estimated coefficient after that window is imprecise, suggesting a short-term effect. The program reduced out-of-home activities by reducing visits to grocery stores. Delivering food assistance proved to be an effective intervention to reduce population movement, thus helping households in distress comply with national lockdown orders.

Keywords: food assistance, COVID-19, lockdown, human mobility
JEL codes: H12,I18,I38,O15

Mobility data used in this paper were provided by the United Nations Development Program (UNDP) and GRANDATA, under the umbrella of UNDP's call for papers "Exploring impact and response to the COVID-19 pandemic in Latin America and the Caribbean using mobility data", to promote policy-oriented research on the COVID-19 pandemic effects in LAC. Findings, interpretations, and conclusions are from the authors and do not necessarily represent UNDP's views.

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ASISTENCIA ALIMENTARIA Y MOVILIDAD DURANTE LA CUARENTENA POR COVID-19[1]

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Resumen

Este documento examina los efectos de la entrega de asistencia alimentaria de emergencia en los patrones de movilidad geográfica entre marzo y agosto de 2020. En específico, se enfoca en estudiar una iniciativa público-privada financiada por donaciones que repartió asistencia alimentaria a un millón de hogares vulnerables que no estaban incluidos en ningún programa de atención a la pobreza antes de 2020. Para estimar el impacto, se utiliza la variación exógena generada por el sistema de distribución de la ayuda alimentaria dentro de los municipios. Los datos incluyen información diaria de las entregas con la ubicación georreferenciada de los hogares beneficiarios y los datos diarios de indicadores de movilidad midiendo movimientos por fuera del hogar. Esta información se agrega al nivel de sector urbano. La especificación incluye un amplio conjunto de efectos fijos tales como sector urbano, día y tendencias por departamento. Los principales resultados indican que recibir un paquete de ayuda alimentaria entregado físicamente en el hogar reduce los movimientos por fuera del hogar en 1.6 puntos porcentuales en una ventana de dos semanas post-entrega. El programa reduce la movilidad por fuera del hogar principalmente al reducir el número de visitas realizadas a los supermercados y tiendas. En suma, la entrega de ayuda alimentaria resulto ser efectiva para reducir salidas del hogar, de esta forma ayudando a los hogares vulnerables a cumplir las medidas nacionales de aislamiento impuestas para reducir la expansión del coronavirus.

Palabras clave: asistencia alimentaria, COVID-19, cierres, movilidad humana
Clasificación JEL: H12,I18,I38,O15

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1. Introduction

The COVID-19 pandemic created a health threat and a subsequent economic crisis due to disruptions to social interactions aimed at curbing the virus's expansion. Given the limited intensive care capacity in their health systems, imposing lockdowns became one of the most common non-pharmaceutical interventions in many middle-income countries (Walker et al., 2020). However, mobility restrictions policies have a high cost for vulnerable households. Early evidence showed that compliance with lockdown directives is lower for low-income families (Wright et al., 2020; Bennett, 2021). Supporting households requires a series of emergency social protection programs to alleviate economic hardship and boost compliance with social distancing policies.

This paper presents novel evidence on the effect of food aid distribution on mobility behavior for the population under lockdown measures. The evidence brings a new perspective to the role of in-kind transfers within the policy portfolio for social safety nets. During a limited window, providing food assistance in a timely manner could have been effective for at-risk households that were not previously registered for any cash transfer program and do not have bank accounts to receive emergency cash maintenance. We hypothesize that food assistance could have been a more effective form of support during the early stages of the COVID-19 pandemic because it directly helps individuals to stay at home.

The emergency caused by the COVID-19 pandemic differs from natural disasters and other economic emergencies because it requires people to stay at home to mitigate virus propagation. Households at risk tend to have higher mobility because of informality rates, lower capacity to work from home, and because income frequency does not allow them to buy food for longer periods. In fact, visits to grocery stores represented the most important reason for leaving the home during lockdown, surpassed only by workplace visits. In-kind transfers directly induce changes to out-of-home events by reducing visits to stores and concentration in physical markets.

This paper presents estimates of the impact of food assistance on human mobility indicators in Colombia. Soon after the national quarantine was imposed in late March, the public- private initiative *Ayudar Nos Hace Bien* (ANHB) began delivering food aid packages to households in vulnerable conditions. The goal was to provide one million food support packages to families not previously included in any social assistance program covering all municipalities in Colombia.

The food aid campaign's distribution strategy made it possible to study its impact on aggregated geographic units. The food aid operation in the field produced a quasi-exogeneous variation in neighborhood exposure to the program. The typical municipality was divided into clusters to facilitate the deliveries. Distributors were required to get signatures and proof of delivery, introducing spatial variation across cities. Local distribution factors explain the variation in deliveries. Daily variation is also observed in the deliveries over the four-months program duration due to scheduling logistics. The staggered rollout across the country is helpful in estimating the program's effects.

We construct a rich data set that combines aggregated geocoded deliveries with a smartphone- based index of daily changes in out-of-home events. The high-frequency data set aggregates this information for urban tracts, defined as census geographic units located inside municipalities. The main specifications rely on a rich set of fixed effects using tracts, time and department-week trends and measures for the evolution of COVID-19 severity at the municipal level. The study aims to control unobserved factors that remain constant within urban tracts.

We assume that the remaining time-variant unobserved effects that change across units are not correlated with the program deliveries. The sample consists of urban tracts with a share of at least 60 percent of eligible households over the total number of families residing in the tract. Therefore, the estimations use the variation of deliveries among neighborhoods with households at the same socioeconomic level. Specifications with matching weights were also estimated to further improve the comparison of early, late and never-treated urban tracts according to pre-pandemic demographic characteristics.

We find a negative, statistically significant and robust effect of cumulative food assistance on out-of-home events with respect to the baseline. Food assistance reduced out-of-home events by 1.6 percent during a two-week delivery window. The estimated coefficients are robust to controls of daily COVID-19 severity lockdown restrictions and inverse probability weighting specifications. The effect is concentrated over the short term, driven by the cumulative deliveries in the previous two weeks. The estimated coefficients after two weeks of delivery are imprecise. The magnitude of the effect is important as the food assistance program was not designed to reduce mobility, but rather to help families cope with economic hardship. The primary mechanism likely explaining this result is a reduction in visits to grocery stores. Low-income families visit grocery stores more frequently because their irregular income does not allow them to buy enough food for extended periods. By reducing grocery-related movement, the program helped families comply with lockdown measures.

This paper contributes to the literature on the impact of social protection programs and safety nets during the COVID-19 emergency. In Latin America, traditional conditional cash transfer programs were scaled up during the pandemic, mostly by increasing the number of payments to current beneficiaries (Lustig et al., 2020). Even if these programs are not designed for emergency alleviation, the infrastructure they provide has been critical to delivering fast help to poor households. Additional payment under a non-contributory program in Bolivia improved food security conditions during the pandemic crisis (Bottan et al., 2020). However, individuals in the informal sector who were above the poverty line before the COVID crisis were not eligible for these programs. There are not enough programs that provide cover age for income shocks to these vulnerable families in the region. Many countries created temporary transfer programs to assist at-risk households (Busso et al., 2020).

In Colombia, the imposition of mobility restrictions for four months disproportionately affected vulnerable households in the informal sector. The two main programs from the Colombian government are the unconditional cash transfer known as *Ingreso Solidario* and the value added tax refunds to low-income residents (Alvarez et al., 2020). Early evidence suggests that unconditional cash transfer programs helped increase social distancing in developing countries (Banerjee et al., 2020). Cash transfers through the CARES Act reduced human mobility in the United States (Wright et al., 2020). Both cash and in-kind transfers could affect population movement patterns during the coronavirus pandemic. Compared to the literature on the effects of cash transfers on mobility during the COVID-19 emergency, little is known about the impact of in-kind transfers.

This paper also contributes to the understanding of emergency in-kind food transfers. Often perceived as a paternalistic intervention (Currie & Gahvari, 2008; Cunha, 2014), food support programs have higher impacts on caloric intake than cash transfers, but are not a cost-effective alternative (Skoufias, Unar & Gonzalez de Cossio, 2013; Hidrobo et al., 2014). In humanitarian and conflict settings, food assistance may have a higher impact on food security and nutrition (Tranchant et al., 2019). This paper provides evidence for the COVID-19 emergency with the rationale of increasing compliance with public health measures.

Finally, this project contributes to understanding the interventions that affect human movement during the COVID-19 pandemic. Restrictions such as city-wide quarantines (Fang, Wang & Yang, 2020), shelter-in-place orders, school and restaurant closures, and others are effective at reducing social interactions and COVID-19 rate contagion (Gupta et al., 2020; Alexander & Karger, 2020). Many of these papers find that households decreased their mobility and consumption even before lockdown measures were imposed. Factors such as media coverage and political views could affect social response to mobility restrictions (Allcott et al., 2020; Simonov et al., 2020). Recent evidence confirms that in Chile, lockdown policies reduced human mobility indicators (Aromi et al., 2020; Bennett, 2021). This paper adds to the understanding of the effect of social protection programs on mobility patterns in Latin America.

The paper is organized as follows: section 2 presents a description of the food assistance program and its targeting and operation in the field. Section 3 describes the data sources' empirical framework and limitations, while section 4 presents the main findings, heterogeneous effects and analysis of the mechanisms. Section 5 discusses the results and policy implications.

2. Background

Like many countries in Latin America, Colombia imposed drastic stay-at-home mandates, even when the COVID-19 contagion was not yet widespread. The early lockdown was intended to reduce the pressure on weak health care systems. On 25 March 2020, the government declared a national quarantine, limiting movement only to essential activities. From there, Colombia maintained one of the most prolonged mobility restrictions in the world, with measures continuing until 31 August 2020. However, compliance with the stay-at-home mandates started to decline after two weeks (Cardenas & Martinez-Beltran, 2020). Many restrictions were lifted in stages. On 4 May 2020, the government declared the first stage of reopening (*apertura parcial*), allowing wholesale, retail and non-essential manufacturing to reopen. On 1 June 2020, the government permitted additional sectors to reopen. The first pandemic peak with more than 650,000 cases and 21,000 deaths, when the country had already exhausted measures to contain the virus and compliance with social distancing measures was declining. The lockdown measures were successful in relieving pressure on the health care system.

2.1. Food Assistance Delivery Initiative

The ANHB initiative was a fundraising campaign led by the office of the First Lady. During the first weeks of the emergency and national lockdown, the campaign collected funds from a private organization and multiple small donations from anonymous individuals, amounting to more than US$22 million. The initiative distributed more than one million emergency food and hygiene kits across all municipalities in the country.

The initiative coordinated the effort by public offices, private suppliers and logistics operators in a centralized cloud-native platform developed and maintained by Analytic Lab Works. With the data collected in real-time, analysts designed optimal operation routes that were flexible to the field's logistics. The initiative distributed door-to-door deliveries through 1,172 distributors in 1,101 municipalities in a short period of time. Collecting data on deliveries in real-

time in difficult-to-access areas was a significant milestone in these initiatives. All interested stakeholders were able to monitor the operation through live dashboards, improving transparency and traceability. This detailed data collection enables the study of the short-term effects of in-kind transfers in the pandemic context.

The food aid package consisted of a box containing essential non-perishable food items identified as part of the regular consumption basket of Colombian families. The food kit is valued at COP187,000 (US$52), which represents 70 percent of the income per capita poverty line and 60 percent of average monthly food spending for a family of four. Thus, the food aid represented a sizeable share of household consumption.[1]

The target population was households at risk of poverty that were not included in any safety net program before the onset of the coronavirus crisis. The criteria for program eligibility are 1) households who are currently not beneficiaries of any social protection program and 2) those living in housing classified in category 1 of the *estrato*, Colombia's system for billing utilities. Using the estrato, utility companies charge differential fees to subsidize the price for low-income households. The estrato is sometimes used to target some social assistance since the vast majority of housing in the country is classified according to these categories. The estrato is correlated with socioeconomic status, but due to frequent misclassification of housing and lack of updates, it is imperfect. This category was used as an emergency criteria for the food initiative program, due to the lack of information on vulnerable households.

To identify eligible households, the National Planning Department (DNP) created the so-called master database, matching administrative records from several programs such as the cash transfer program *Familias en Acción*, the non-contributory program *Colombia Mayor*, and other programs that help victims of civil conflicts. The DNP matched those records to the National Census for Targeting Social Programs (SISBEN). The most recent census interviewed potential beneficiaries of social assistance programs in 2019. The DNP constructed the master database for the emergency cash transfer program *Ingreso Solidario*, which targets people who were not poor before March but were most vulnerable to poverty during the economic crisis. The ANHB program benefited from this identification effort to select most of its beneficiaries. In addition, local mayors and department governors were asked use the platform to submit potential beneficiaries to be considered for the program.

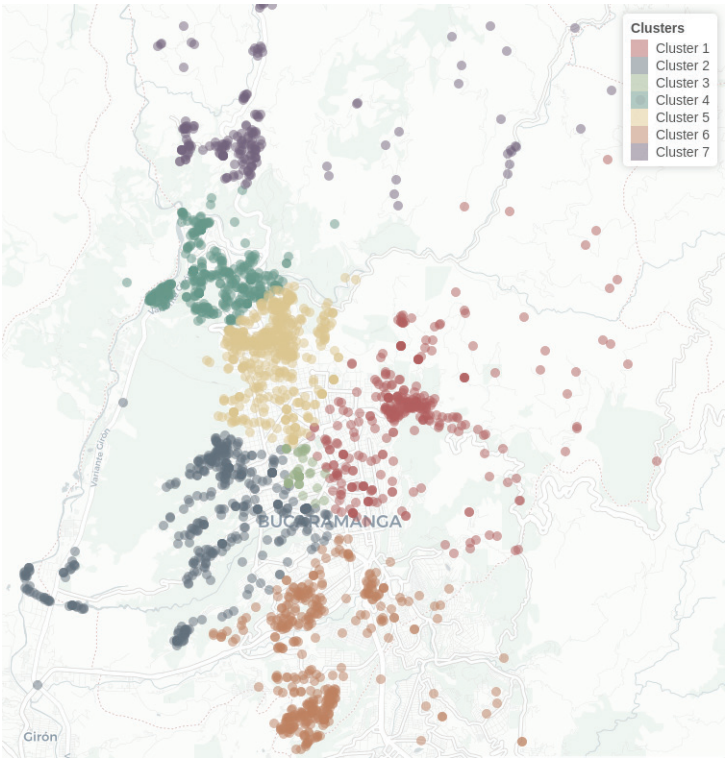
2.2. Exogeneity of the Rollout of Food Assistance Initiative

The evolution of food aid distribution across time and space is a critical feature of this study. First, there is exogenous cross-sectional variation coming from the operation of the program. The analysts designed optimal delivery routes, which were assigned to decentralized local distributors. In many cases, analysts created clusters of households according to geographic location. Then analysts posted the cluster to a specific local distributor. Figure 1 illustrates how the cluster operated in Bucaramanga, a medium-sized city in Colombia, for the week of 12 May 2020. Local distributors had to deliver the food packages to seven clusters during that

[1] Calculations based on the 2018 Survey of Spending and Budget, National Administrative Department of Statistics of Colombia (DANE).

week. The final delivery occurred on separate days that week because of the time required to find specific households on the list. Variation in the day of delivery can be explained by additional logistical factors that are to be expected in delivery operations. The cluster design and operation create variation in treatment reception within municipalities.

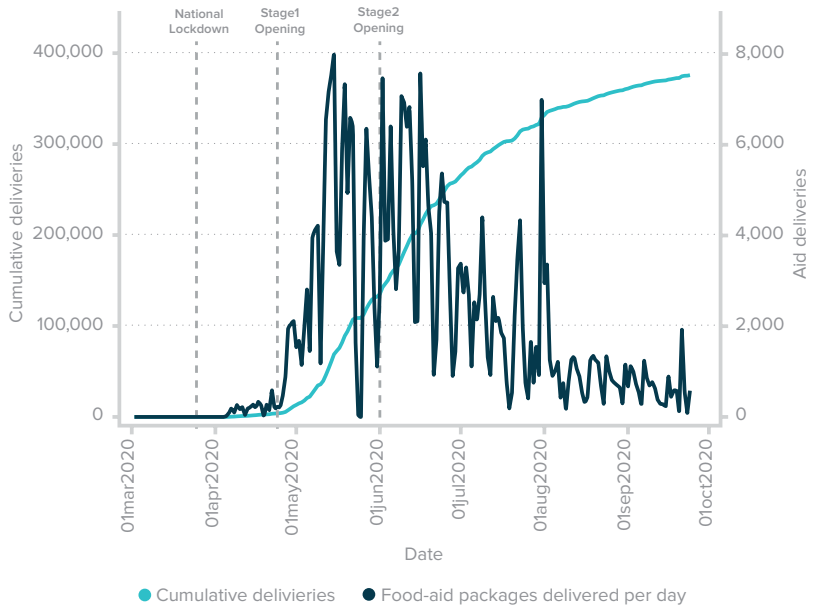
Figure 1. Food packages distribution: Delivery clusters



Notes: Figure shows the clusters of beneficiaries in Bucaramanga, a medium-size city in Colombia. Each point represents a geocoded household location for potential program beneficiaries. Different colors denote different clusters. Each cluster is assigned to a different local distributor. Delivery routes and clusters correspond to the week of May 12, 2020.
Source: Food aid deliveries data from ANHB and Analytic Lab.

The programs also exhibit time variation of food deliveries across the four months of analysis. Figure 2 presents the daily deliveries from 4 April 2020 to 31 August 2020. The figure also presents the cumulative deliveries by day. The program had reached about 40 percent of its goal before the government lifted major restrictions on 1 June 2020. Over months, the distribution schedule created variation in the timing for treating cities and neighborhoods within municipalities. Thus, the eligible neighborhoods could receive the delivery early or late in the pandemic depending on the program's operation.

Figure 2. Staggered roll out of food assistance deliveries initiative



Notes: The figure shows the number of daily food packages delivered in the right vertical axis. The left axis measures the cumulative deliveries.
Source: Food assistance data from ANHB and Analytic Lab. Observations from April 4, 2020 to August 31, 2020.

3. Data and Empirical Framework

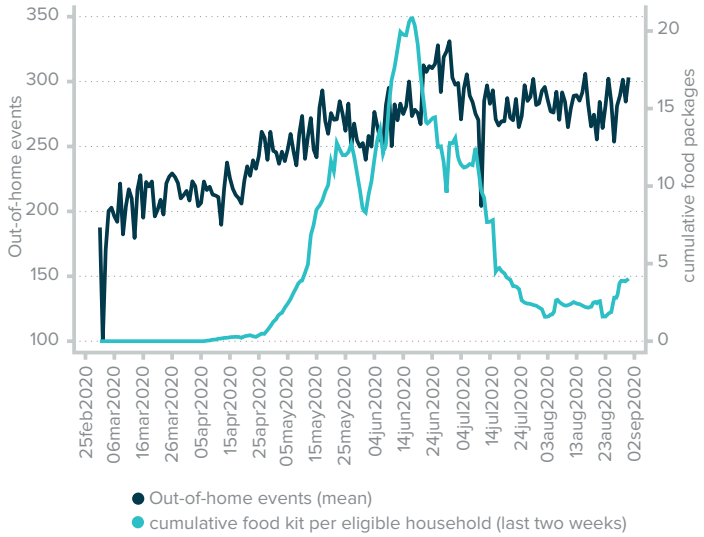
This study combines daily data on human mobility with georeferenced information on food aid deliveries in Colombia from March to August of 2020. For the food assistance initiative, the data set contains the geocoded location of households that received the food package. The geocoded data includes 376,504 families who received food aid packages at home between April 4 and 31 August 2020. Figure 2 presents the trend in food assistance distribution over the period of analysis. About 40 percent of the total distribution occurred before the second stage of reopening. This means the aid arrived when households were most severely restricted in their movements outside of their homes. The deliveries are aggregated at the level of urban tracts, the smallest geographic unit for which demographic information from the 2018 Colombian census in this analysis. Urban tracts are geographic areas created for the census and they cover urban and suburban areas. For the analysis, eligible urban tracts are defined as areas where at least 60 percent of housing units are classified as category 1 of the *estrato* according to the census.

Mobility indicators are provided by Grandata and UNDP-LAC at the urban tract level.[2] The mobility information comes from a country sample of around 1 to 2 percent of smartphone phone users tracking their location via GPS. In this index, the most common location is the home. All other events are measured with respect to a radius from the home location. The

[2] UNDP AND GRANDATA https://www.latinamerica.undp.org/content/rblac/en/home/coronavirus/data- covid-region.html

original variable is the percent change of out-of-home events with respect to the baseline (2 March 2020). For this study, the outcome is constructed as an index from 0-100, where 100 is the number of events in the baseline day. Thus, a value of 75 can be directly correlated to a 25 percent decrease in out-of-home events with respect to the baseline. Figure 3 shows mobility trends only for the eligible urban tracts. Human mobility had started to decline even before the national lockdown was declared on 25 March 2020. At its peak, out-of-home events declined up to 50 percent with respect to the baseline.

Figure 3. Change in mobility and food assistance delivery for eligible tracts



Notes: This figure focuses on the eligible urban tracts. This figure shows the change in the out-of-home events index from a baseline on March 2, 2020. The figure also shows the number of daily food packages delivered by the program.
Source: Mobility index from Grandata and UNDP-LAC. Food assistance deliveries from ANHB and Analytic Lab. Observations from March 1, 2020 to August 31, 2020.

The use of smartphone origin data to measure human activity could create sample selection because of differences in ownership, usage and access to mobile internet. Mobile phone usage is high in Colombia, with 78 percent of individuals reporting ownership of smartphones.[3] According to the 2019 National Quality of Life Survey, 61.6 percent of residents have internet access and 47.2 percent have mobile internet access in the urban areas that were studied. However, there are significant socioeconomic and urban-rural gaps in internet access. Studies in education during the pandemic provide evidence of existing large gaps, with an average of 22 percent of students in poor households having internet access, compared to a 93 percent of students in wealthier households (Rieble-Aubourg & Viteri, 2020). Socioeconomic gaps in internet access are a concern for this analysis. The possible selection was addressed by including only a sample of eligible urban tracts with very similar shares of households in the same socioeconomic stratum.

We construct panel data of package deliveries aggregated by urban census tract using

[3] Report of Technology of information, 2018 National Quality of Life Survey (ECV), DANE. https://www.dane.gov.co/files/investigaciones/boletines/tic/boltichogaresdepartamental2018.pdf

the individual georeferenced household location of program beneficiaries. The panel data includes demographic variables for the urban tracts from the 2018 Colombian population census. Demographic variables are population, density and housing units classified by socioeconomic categories. The *estrato* classifies housing into six categories for pricing and subsidy of home utilities and approximates socioeconomic status in Colombia. The food aid initiative targeted the deliveries to category 1 households with no other public social programs. These variables correspond to information available prior to the onset of COVID-19. Due to the high frequency and geographic aggregation level, the demographic information remains fixed for the sample period.

In addition, we collected data on daily new COVID-19 cases and the weekly index for pandemic severity at the municipality level.[4] The Health Ministry designed an index to measure the pandemic severity starting on 8 July 2020. The index weights four components: COVID-19 cases per thousand people, the test positivity rate, COVID cases and death growth rate from the previous week. When a municipality exhibits no COVID cases, it is classified as non-affected. The index has four categories: non-affected, low, medium and high severity. The index was updated and published every week. Several policies rely on this index, including mobility restrictions at the national level. The Colombian government imposed a series of social distancing rules, including shelter-in-place orders and lockdowns. Municipalities classified as non-affected and low-severity were permitted to forgo the national restrictions.[5] This produced a variation across municipalities that this study used to approximate mobility restrictions in the sample period. Local governments also imposed their own social distancing policies, but this variation is not part of this study.

Table 1 presents the descriptive statistics for the period between March and August of 2020. The sample of 2,816 geographic units includes only eligible tracts. Eligible tracts are defined as those where at least 60% of total housing units are in *estrato* category 1. The average eligible census tract has 3,334 residents and 1,077 housing units. The average share of category 1 housing is 87 percent. An average of 160 households per tract meet the requirements to participate in the program: being a household classified in category 1 and not previously receiving any social assistance. On average, 42 food packages were delivered to the tract, with 4.43 food packages delivered over the last two weeks tract-day. About 24 percent of tracts were treated on a given day. The eligible tracts had, on average, higher mobility than during the baseline period. The out-of-home events index average is 262.13; this implies an average 162 percent change in the recorded GPS events for the sample period. Finally, we include information on the pandemic severity at the municipality level (a higher level than tract). On average, 16.95 percent of eligible tracts are in municipalities classified as highly-affected on the pandemic severity index. Based on the pandemic severity, a city under restriction dummy per day was calculated. On average, 78.14 percent of tracts are mandated to comply with national lockdown policies.

[4] *Metodología de Clasificación de municipios de Colombia de acuerdo a su afectación por COVID-19* https://sig.sispro.gov.co/afectacionCovid/

[5] Decretos 636,689,749,815,847,878,990,1076 de 2020, Presidencia de la Republica Colombia.

Table 1. Descriptive for urban census tracts

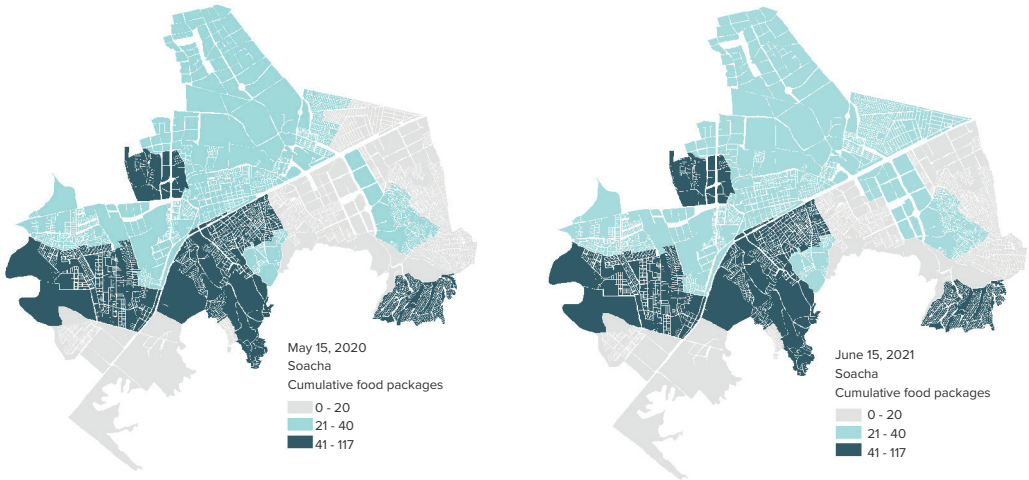
	Eligible tracts			
	mean	sd	min	max
Urban Census tracts				
population density hab/km2	7,948.12	9,094.42	0	91,337.03
population total	3,334.51	4,773.86	0	37,937
housing units	1,077.53	1,519.57	0	13,482
housing units with electricity	904.75	1,304.87	0	11,333
housing classified category 1	767.94	1,101.54	0	10,297
share housing classified category 1	0.87	0.12	0.22	1
Food assistance program				
number households eligible	160.30	264.27	0	3,111
total food packages delivered	42.22	112.78	0	2,796
daily deliveries	0.28	3.73	0	373
last two weeks cumulative deliveries	4.43	27.55	0	1,579
total cumulative deliveries	23.72	81.89	0	2,796
proportion with last two weeks deliveries	0.16	0.37	0	1
proportion with any daily delivery	0.03	0.17	0	1
Out of home events (baseline=100)				
daily out of home events	262.13	57.21	0.37	45,200
change in out of home events (%)	78.54	8.86	-0.996	451
Covid restrictions and severity				
municipality under restriction (%)	78.14	41.32	0	100
high severity covid municipality (%)	16.95	37.52	0	100

Notes: N = 2,816. Eligible tracts. Urban census tracts are a geographic unit within municipalities created for census proposes.
Sources: Demographic data Population Census 2018, National Bureau of Statistics DANE. Food aid deliveries statistics starting from April 2020 are reported from from "Programa Ayudar nos hace bien". Out-of-home events statistics, March 1 to August 31 2020, at the level of tract from by GranData-UNDP. Covid severity index is calculated at the municipality level by Health Ministry. Based on severity, we calculate a potential mobility restriction index by day.

The empirical strategy relies on the quasi-exogeneous variation in food assistance deliveries across urban tracts within municipalities per day. First, Figure 5 illustrates the within-city variation in the outcome and measured as the change in out-of-home activities, as presented in. This figure illustrates the change in the movement index for urban tracts within the city of Soacha, part of the Bogota, D.C. metropolitan area. Figure 4 illustrates an example of the evolution of food deliveries across urban tracts. The observed variation in deliveries within cities is mainly

determined by the logistics factors of the local program operation. Local distributors need to pinpoint the household assigned to them, sometimes without proper address information. The only time-varying factor that could affect the deliveries is local lockdowns and COVID case evolution, and these factors are controlled for in the following analysis.

Figure 4. Food aid deliveries in Soacha, Cundinamarca



Notes: Figures depict the variation in food assistance for urban tracts within the municipality of Soacha, Cundinamarca.
Sources: Food assistance deliveries from ANHB and Analytic Lab.

3.1. Empirical Strategy

This study on the effect on human mobility indicators uses a difference in differences framework, taking advantage of the staggered rollout of the food aid distribution and the high frequency of geocoded deliveries and mobility indicators. We estimate the equation is:

$$Y_{ct} = \beta_1 foodaccum_{ct} + \alpha_c(X_{mt}) + \lambda_c + \gamma_t + \Gamma_t + \delta_c(s \times \omega_t) + \varepsilon_{ct}$$

Here, Y represents the index of out-of-home events, observed in tract c day t. The treatment variable $food\ acum_{ct}$ indicates the cumulative food aid packages per eligible household delivered within the tract. The coefficient β_1 is the estimated effect of the cumulative food aid distribution. $alpha_c$ indicates tract fixed effects which control for time-invariant characteristics within the tract. γ_t represents day fixed effects. The specification also includes day-of-the-week fixed effects Γ_t to control for seasonality patterns in mobility within a week. Furthermore, $\delta_c(sX\omega_t)$ state-week fixed effects aim to control for time-varying trends in human mobility that differs by department. In addition, X_{mt} aim to control for specific policy interventions changing during this period and implemented at the level of department or municipality creating trends not fully captured in the state-time fixed effects. In particular, these policy interventions are restrictions to mobility. Standard errors are calculated cluster by urban tract, but the results are also robust when using a three-way clustering approach by county, day and department × fixed effects.

The sample only includes eligible tracts, thus restricting the analysis to neighborhoods with similar household characteristics. The tracts in the sample have a similar share of households classified in the lowest socioeconomic status based on the estrato. Moreover, the variation in the intensity of the treatment creates a group of neighborhoods that received a high exposure in terms of higher shares of cumulative packages per capita vs other neighborhoods with lower exposure in terms of lower shares of cumulative packages per capita. Then, we are comparing neighborhoods with similar socioeconomic characteristics, but that happened to receive more or less packages by exogenous logistic motivations.

The identifying assumption is that changes in mobility in tracts with low exposure to the program will be a good potential comparison to the changes in mobility we should have observed for the tracts who received larger shares of packages per capita, if they were to receive the same cumulative delivery rates of the food packages.

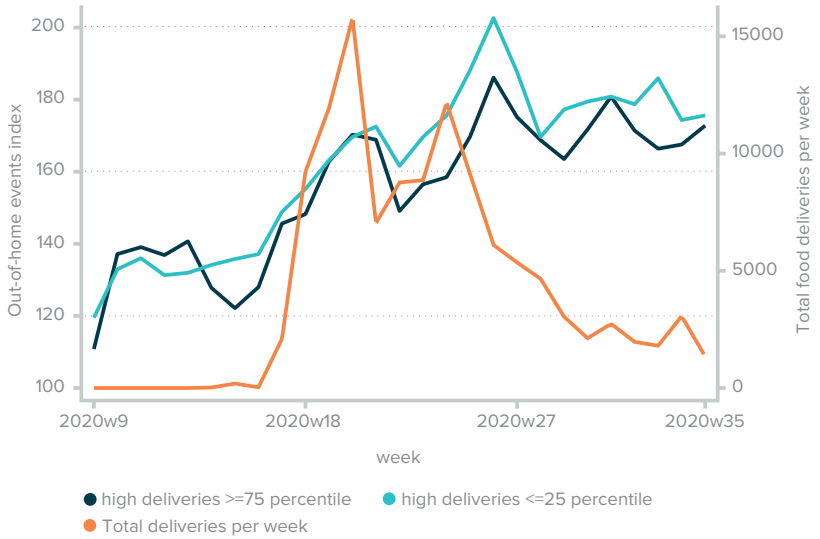
In addition, this assumption implies that the tracts would have observed the same mobility patterns in absence of the treatment not only before the program was implemented but, in the time after. For instance, there should not be any covid related reason around the time of the program delivery that motivated additional health policy measures with a pattern differing by eligible neighborhoods. An example of this concern is the distinct policies implemented within cities like Bogota. Bogota implemented different mobility restrictions by locality and even by UPZ according to the evolution of covid cases. While we do not have the data to check the precise timing between ANHB and possible intra-city variation in policies or covid evolution affecting mobility, here we assume the logistic reasons creating variation in delivery do not exactly match the abrupt change in lockdown measures by neighborhood. Also, these intra city measures were only implemented in large cities like Bogota and Medellin, while our eligible tracts are mostly concentrated in medium sized cities.

The study takes advantage of the operation of the program. The primary reason for the timing across municipalities are logistics, road infrastructure and supplies availability. Within municipalities, a tract received earlier deliveries if it had a higher concentration of beneficiaries.

To further understand the variation in the treatment, we plot the trends for the eligible tracts, but now dividing them in two groups: low deliveries and high deliveries. Low deliveries group concentrates the tracts that totaled less than 25 percentiles of deliveries. High deliveries concentrate the tracts that are classified as above the 75th percentile of deliveries. Figure 5 shows the trends in mobility for low and high deliveries groups. These figure shows clearly how the mobility trends start to decline for the high deliveries group after the biggest week of food distribution.

Our empirical strategy relies on strong version of common trend assumption in human mobility for different groups of food package exposure. This common trend assumption difficult to test statistically because of the case of continuous treatment (Callaway, Goodman-Bacon, Sant'Anna 2021). On the one hand, classical no pre-trend test is plausible since we expect those eligible tracts with very similar demographic and socioeconomic characteristic exhibit similar mobility patterns during the pandemic in absence of the food assistance program. More exactly, the mobility pattern for these eligible tracts exhibits the same time-varying influencing factors during the pandemic probably associated with the fact that low-income households' members worked in occupations that were required for in-person services. In figure 5, we plot the average by week for two groups tracts the high deliveries and the low deliveries acting as comparison group. Before the program started delivering, those tracts had roughly the same mobility patterns.

Figure 5. Change in mobility and food assistance delivery by treatment intensity



Notes: This figure focuses on the eligible urban tracts. This figure shows the change in the out-of-home events index from a baseline on March 2, 2020 for two groups: High intensity deliveries and low intensity deliveries. The figure also shows the total of daily food packages delivered by the program.
Sources: Mobility index from Grandata and UNDP-LAC. Food assistance deliveries from ANHB and Analytic Lab. Observations from March 1, 2020 to August 31, 2020.

Urban tract fixed effects control any variation in human mobility correlated with specific local characteristics that remain fixed over the sample period. Time fixed effects control time-varying factors that are constant across urban tracts, like national economic conditions that changed during the four months. Furthermore, state-week fixed effects aim to control for time-varying trends at the regional level. Overall, we use a rich set of fixed effects are used at a high frequency.

On the other hand, to get an unbiased estimate of the average treatment effect from a continuously valued treatment we further need that there is no systematic forward-looking sorting in the delivery exposure (no-selection on the gains) (Callaway ,Goodman-Bacon, Sant'Anna 2021). In this case, this assumption translated in that high-deliveries tract did not receive a larger intensity as a response to daily shocks to covid pandemic correlated with human mobility patterns. In table A1, we regress total deliveries against covid cases and mobility restrictions per municipality-day. The coefficients on covid cases per 100 thousand inhabitants is small but statistically significant. We rely in within tract variations inside municipalities, that removes possible causes varying at a daily frequency, but probably not all correlation between dosage of food assistance and covid evolution is eliminated. There are not many sources of information available at the level of tract-day. While additional characteristics at the tract-day level could not be collected, we assume that there are no significant remaining factors caused by unobserved daily variant characteristics correlated both with distribution timing and mobility patterns.

In addition, the estimates in this paper are sensitive to heterogeneous responses from 1) group of tracts treated in different timing (earlier in April vs late May) and within the same week group of tracts treated with different intensities (high-deliveries vs low deliveries). In particular, receiving the food packages in early April could have a higher effect in this context because the severity of the lockdown measures that were relaxed later in May. For the estimate to recover an average causal response, we need to assume that there

is homogeneous response across groups and intensity. In this case, this is equivalent to assume that families had the same response to the food packages during our time of study, that could be plausible since we focus on a short period of time.

Moreover, we implement an estimator using inverse probability weighting in the spirit of doubly robust estimators where the parallel trend assumption holds conditional on covariates. We estimate inverse probability weighting (IPW) models with the goal of better approximating valid counterfactuals between early, late and never receivers of the deliveries. The probability of treatment is modelled using observable demographic characteristics such as population density and population size. Next, we use the estimated probability as a weight in the IPW specification. The coefficients of this model are observed in Table A.2 and the common support is presented in Figure A.1. We also include Demographic characteristics like age structure are also included to control differences in smartphone usage, as these could affect the mobility patterns in the data. Since only the demographic covariates before the sample period are available, they are used in the matching strategy to address these concerns.

Besides limitations for the exogeneity of the program and the estimation of continous treatment, the analysis only uncovers patterns from mobile phone users. While mobile phone usage is high in Colombia—78 percent of individuals report owning smartphones—smartphone ownership could be more varied at different income levels and age groups. This could create sample selection within a tract and across tracts (Couture et al, 2021). Within tract, there are blocks with higher income (geographics units called manzanas in Colombia) that could be more represented in the sample than others. Second across tracts, there could be underrepresentation of certain group of tracts with lower smartphone ownership and internet connectivity in our sample. Still, fixed effects by tract and the use of a sample of comparable tracts, including household characteristics highly associated with smartphone ownership, will address most of the sample composition bias that remains invariant over the period of analysis.

Finally, the cash transfer program *Ingreso Solidario*, which targets a similar population to the food assistance initiative, had a higher population coverage and number of payments. However, the programs were deployed with different geographic patterns The ANHB program covered all municipalities in Colombia, while *Ingreso Solidario* only covered 176 municipalities during the sample period. The cash transfer payments have a different frequency, with all payments made on a specific day. With municipality and state-by-week fixed effects, possible regional and national policies affecting all units simultaneously are controlled for. However, the eligibility criteria to receive both cash and food assistance were fairly similar. Recent papers find that cash transfers programs targeted to the same vulnerable population induced higher human mobility during the same period (Londono & Querubin, 2022) Since the eligibility conditions for receiving the cash transfers and the food assistance were very similar, our estimates are probably underestimating the magnitude of the effect of food assistance program. While any transfer could help beneficiaries comply with mobility restrictions, this study does not directly address the interactions of cash and food transfers.

4. Results

4.1. Main results

Table 2 presents the estimated coefficients for the specifications in equation (1) using OLS regression with a rich set of high-frequency fixed effects. In column 1, the additional food package per capita delivered in the previous two weeks reduces the number of out-of-home

activities by 4.25 points. The food deliveries decreased the short-term mobility by 1.65 percent with respect to the pre-pandemic baseline. Our preferred treatment indicator measures the food assistance delivered per eligible household over the previous two weeks. Since the package contains items valued at two weeks of household consumption, the food package is expected to affect mobility behavior for at least as long as groceries are delivered. The outcome variable measures the change in out-of-home events calculated with respect to the baseline. We construct a 0-100 scale index, where 100 represents the events in the baseline. The first three columns report estimated coefficients using OLS fixed effects regressions. The last three columns report the estimated coefficient using IPW and fixed effects.

Table 2. Effect of food assistance delivery on human mobility

	Outcome: Total out-of-home events					
	OLS			Inverse Probability Weighting		
	(1)	(2)	(3)	(4)	(5)	(6)
Food assistance pc. cumulative last two weeks	-4.25***	-4.22***	-4.21***	-4.31***	-5.06***	-5.06***
	(0.736)	(0.660)	(0.727)	(0.800)	(1.39)	(1.5)
municipality under restriction		-1.32			-2.05	
		(8.13)			(8.44)	
Food aid × municipality under restriction		-0.679			-0.433	
		(4.98)			(5.07)	
High covid severity index			-15.4			-9.63
			(14.1)			(13)
Food aid × High covid severity index			-1.91			-0.718
			(15.9)			(15.5)
mean control	256.57	257.49	258.74	258.74	255.91	256.49
R2	0.46	0.46	0.46	0.46	0.47	0.47
N units	2,816	2,816	2,816	2,816	2,816	2,816
N days	184	184	184	184	184	184
Fixed effects:						
Urban tract	Yes	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Department × week	Yes	Yes	Yes	Yes	Yes	Yes
Week of year	Yes	Yes	Yes	Yes	Yes	Yes
Day of week fixed	Yes	Yes	Yes	Yes	Yes	Yes

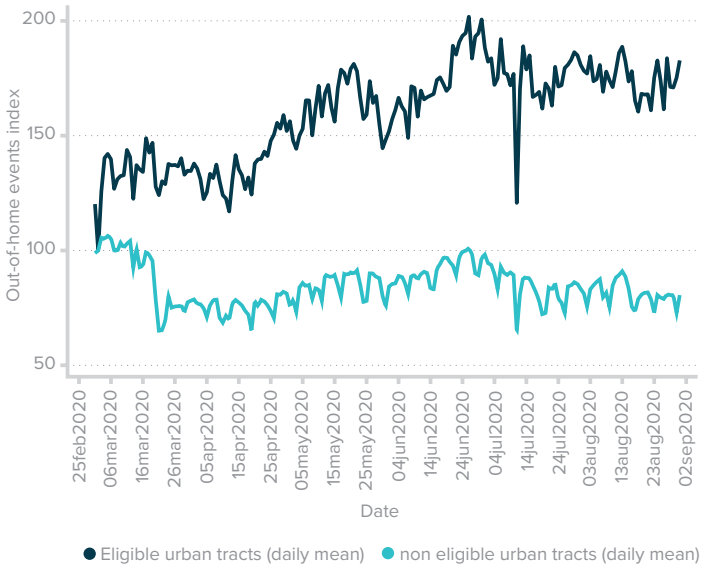
Notes: N= 476,345. Sample includes only eligible tracts. Outcome is daily out-of-home events as an index from 0 to 100, where 100 is the baseline on March 2. Treatment variable measures the program rollout as the cumulative number of food packages delivered per eligible household over the last two weeks in the urban tract. Municipality under restrictions is a dummy variable indicating that the municipality is mandated to comply with national lockdown policies. . Cols 1-3 estimated with fixed effects OLS regressions using panel of tract-day observations from March 1 to August 31, 2020. Cols 4-6 use Inverse probability weighting with the pscore estimated on urban tract eligibility criteria and pre- pandemic covariates (Model in Table A.2. Urban tract is a geographic unit for statistical proposes created by the National Department for Statistics of Colombia (DANE). Standard errors reported in parentheses are clustered by urban census tract. Observations from March 1, 2020 to August 31, 2020.
Sources: Demographic data Population Census 2018, National Bureau of Statistics DANE. The COVID severity index is calculated at the municipality level by the Health Ministry using information on COVID cases, test positivity rate and deaths growth by week. Mobility index from Grandata and UNDP-LAC. Food assistance deliveries from ANHB and Analytic Lab.

This coefficient is robust in the IPW specifications in column 4. Columns 2 and 3 include controls and interactions with daily mobility restrictions and daily COVID severity index at

the municipality level. The coefficient is robust to these controls. In column 2, the estimated effect is -4.22 points, and the estimated impact in column 3 is -4.21 points. Finally, in columns 5 and 6, the specification is estimated using IPW weights, controls for COVID severity and mobility restrictions. The estimated coefficient in these columns is 5.06 points, slightly higher than in previous columns. The estimated effect remains statistically significant when using three-way clustered errors by tract-day and state-week fixed effects.

The magnitude of the effect of approximately 1.6 percent is compared with a mean of 256 events. On average, the eligible tracts exhibit higher mobility than non-eligible tracts during the four months. The average of 256 events represents an increase with respect to the baseline of 100 events. Figure 6 illustrates the mobility patterns for eligible and non-eligible tracts, using the out-of-home event index. The eligible tracts are low-income neighborhoods, where the families have more significant difficulties complying with lockdown orders. The workers probably work in essential sectors and have jobs that cannot be done at home. This pattern is consistent with previous papers that document the gap in mobility linked to socioeconomic status and poverty during the first months of the pandemic (Wright et al., 2020; Bargain and Aminjonov, 2020). In this sense, food assistance is probably inducing those households to reduce out-of-home activities and thus helps them comply with COVID mitigation measures. The magnitude of the effect is important considering that the program was not intended to increase compliance with stay-at-home orders but rather mitigate the economic hardship caused by the pandemic.

Figure 6. Change in out-of-home events by eligibility of urban tracts



Notes: Eligible tracts defined as >60 percent share of households are eligible to the program. Change in total out-of-home events index from a baseline on March 2, 2020.
Source: Mobility index from Grandata and UNDP-LAC.

Table 3 examines different measures of food deliveries to the tract. We calculate daily, the last two weeks and cumulative daily deliveries. All variables are deliveries per eligible household. Overall we observe a negative effect of the food aid deliveries on the change in human mobility across all specifications. The estimated coefficient for daily deliveries in column 1 is higher than the previous two weeks but is imprecisely estimated. The coefficient in column 3 for total cumulative food deliveries ($\beta 1 = -3.56$) is lower than the previous two

weeks deliveries ($\beta 1 = -4.25$) but is not statistically significant. Column 4 subtracts today's delivery from the last two weeks of cumulative food deliveries. Because of the implied human activity caused by the delivery, we expect that the same day of delivery affects mobility patterns. The estimated coefficient ($\beta 1 = -4.48$) is still statistically significant and higher, as expected. Overall, the deliveries have a higher impact in the short term (two weeks after delivery). Still, the effect is likely fading away after the two-week window. The food package was valued as two weeks of household consumption, thus explaining the short-term effect on mobility patterns.

Table 3. Effect of food assistance delivery on human mobility: roll-out measures

	Outcome: daily out-home-events			
	daily delivery	last two weeks cumulative	total daily cumulative	last two weeks minus today
	(1)	(2)	(3)	(4)
Food per capita cumulative deliveries	-10,8 (13.6)	-4.25*** (0.73)	-3,56 (4.36)	-4.48** (0.83)
R2	0.487	0.488	0.488	0.489
N units	2,813	2,813	2,813	2,311
N days	184	184	184	184
Fixed effects:				
Urban tract	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes
Department × week	Yes	Yes	Yes	Yes
Day of week fixed effect	Yes	Yes	Yes	Yes
Week of year fixed effect	Yes	Yes	Yes	Yes

Notes: N=476,345. SSample includes only eligible tracts. Outcome is daily out-of- home events as an index from 0 to 100, where 100 is the baseline on March 2. The preferred treatment variable, in column 2, measures the program roll out as the cumu- lative number of food packages delivered per eligible household over the previous two weeks. Column 1 uses the deliveries per household eligible registered in the tract in one day as the treatment variable. Column 3 uses the total cumulative deliveries from March 1 to August 31, 2020. Cols 1-4 estimated with fixed effects OLS regressions using panel of unit-day observations from March 1 to August 31, 2020. Urban tract is a geographic unit for statistical purposes created by the National Department for Statistics of Colombia (DANE). Standard errors reported in parentheses are clustered by urban census tract.
Sources: Mobility index from Grandata and UNDP-LAC. Food assistance deliveries from ANHB and Analytic Lab. Observations from March 1, 2020 to August 31, 2020.

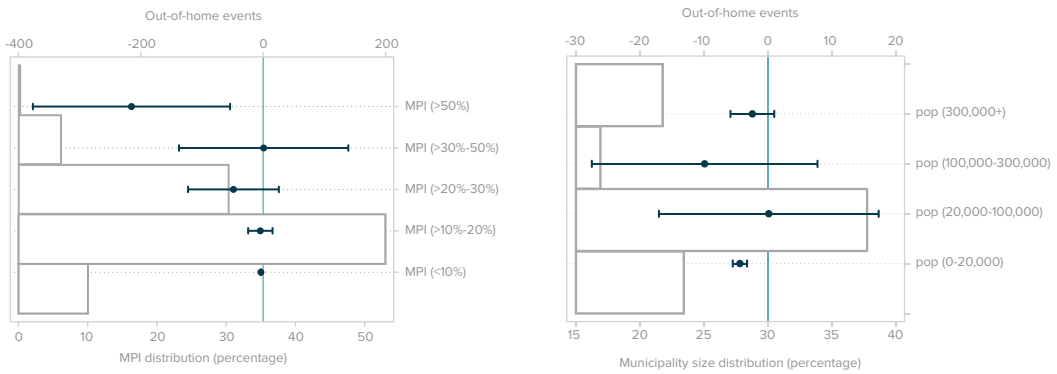
4.2. Heterogeneous effects

It would be ideal to explore whether food assistance has a differential impact depending on the pre-pandemic conditions of the urban tract, specifically the degree of informality in the labor market. The potential beneficiaries' households were not poor before the pandemic. They were not included in any social protection program (cash transfers and non-contributory pensions). These households probably had decent jobs in the informal sector before the pandemic, many of which require in-person labor. The income from these informal jobs was probably high enough to overcome poverty conditions but not steady. The households at risk do not have social protection against a big shock. The COVID pandemic indeed moved many of these households into poverty.

To approximate informality, we use the municipality population size. The regional pattern of informality reveals a gap between capital cities and intermediate and small cities. Cities with more than 300,000 inhabitants concentrate most of the formal sector in the country. Big cities also concentrate most of the industries that can be performed at home. We examine how the food program effects vary by municipality population size. The four categories are created based on the administrative classification of the country's 1100 municipalities. In addition, the study explores the heterogeneous effects by poverty levels using the multidimensional poverty index (MPI). The DANE published the MPI at the level of census block using census and administrative information. The MPI includes an informality component. While the components data was unavailable, the study benefits from the index being calculated at these granulated geographic units.

Figure 7 present the results of this analysis. The results suggest that the food aid deliveries had a higher effect on out-of-home mobility for small municipalities and intermediate cities (100,000-300,000). The coefficient t is slightly higher than in big cities (about four points more than cities with 300,000+ inhabitant) but is not precisely estimated. The results suggest a higher effect for urban sectors where 50 percent or more households were in poverty before the pandemic. Since urban tracts with similar households were compared, this result addresses marginal differences in poverty incidence. Overall, the food assistance programs seem to benefit more households that were more vulnerable before the pandemic.

Figure 7. Heterogeneous effects of food deliveries on mobility



Notes: Figures present the estimated marginal effects and underlying distribution of covariates. For reported coefficient, see Table A.3
Sources: Demographic data Population Census 2018, National Bureau of Statistics DANE. Multidimensional Poverty Index (MPI) calculated at the block census level by the National Bureau of Statistics DANE. Mobility index from Grandata and UNDP-LAC. Food assistance deliveries from ANHB and Analytic Lab.

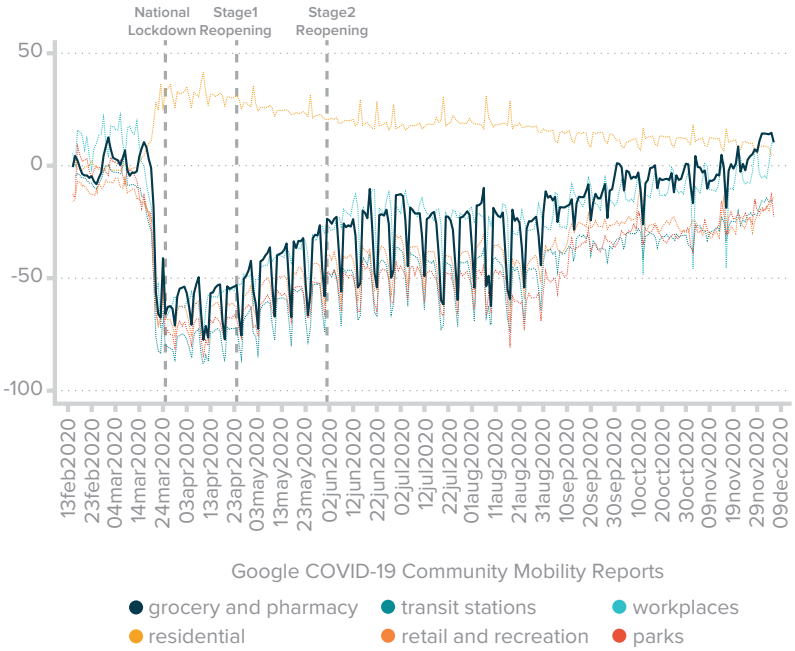
4.3. Mechanism: The grocery store effects

Next, mobility patterns by place were examined to understand the mechanism behind the effect of food assistance deliveries on human mobility. Shopping for groceries is one of the most common out-of-home activities even before the pandemic, as presented in Figure 8. Eligible households often buy groceries more frequently because their income source is not steady, with some living on a day-to-day basis. During lockdowns in Bogota, households report that getting groceries is one of the main reasons to leave the home during the pandemic.[6] Figure 8

[6] Encuesta de cultura ciudadana Bogota https://bogota.gov.co/monitoreo-al-aislamiento-bogota

illustrates that even during the pandemic, mobility to grocery stores and pharmacies remains one of the most important reasons to leave the home, only after mobility to workplaces.

Figure 8. Change in mobility trends by place category. Google Mobility Report



Notes The Google community reports variables published for Colombia at the municipal level were used to study whether the food deliveries have an effect on mobility by place. A municipality level database was constructed of the daily food deliveries and the Google mobility indicators to transit stations, groceries, workplaces, residential, retail and parks. The Google report started as a national report and later begun to present disaggregated information by political division units. The data only include 95 municipalities. We estimate a similar specification as in equation (1) but at the municipality level instead of the urban tract. Table 4 presents the results of this exercise.
Source: Mobility index from Google Mobility Report. Food assistance deliveries from ANHB and Analytic Lab.

The Google community reports variables published for Colombia at the municipal level were used to study whether the food deliveries have an effect on mobility by place. A municipality level database was constructed of the daily food deliveries and the Google mobility indicators to transit stations, groceries, workplaces, residential, retail and parks. The Google report started as a national report and later begun to present disaggregated information by political division units. The data only include 95 municipalities. We estimate A similar specification as in equation (1) but at the municipality level instead of the urban tract. Table 4 presents the results of this exercise.

In Table 4, column 2, cumulative food delivery per capita for the previous two weeks reduced visits to grocery stores by 2 percentage points and the coefficient is statistically significant at the 10 percent level. This effect represents a 5 percent decrease in mobility to grocery stores and pharmacies with respect to the mean. There is also a negative estimated coefficient to workplaces, but it is not statistically significant. We interpret these results as the program helping households staying at home for a short period by reducing mobility to grocery shops. The program probably does not affect working decisions. These households probably need to leave the home to work because they do not have social protections or savings to sustain spending over extended lockdowns.

Table 4. Food assistance delivery and mobility trends by place

	Transit	Groceries	Work places	Residential	Retail	Parks
	(1)	(2)	(3)	(4)	(5)	(6)
Food assistance pc cumulative deliveries	1.308	-2.014*	-0.648	0.098	0.033	0.509
	(1.662)	(1.141)	(0.767)	(0.279)	(0.959)	(0.693)
municipality under restriction	3.698	-0.188	-0.453	0.247	-0.260	0.003
	(4.144)	(1.359)	(0.918)	(0.256)	(1.065)	(1.248)
high covid severity index	-0.379	-1.513	-1.749**	0.393	-0.753	-1.14
	(3.104)	(1.579)	(0.788)	(0.261)	(1.018)	(1.169)
Constant	-57.85	-35.58	-35.77	20.09	-55.13	-50.13
	(3.292)	(1.1)	(0.760)	(0.214)	(0.864)	(0.960)
R2	0.886	0.812	0.924	0.938	0.917	0.886
Observations	6,733	13,704	13,635	11,107	12,796	13,624
Days	184	184	184	184	184	184
N	47	95	95	86	89	84
Fixed effects:						
Day	Yes	Yes	Yes	Yes	Yes	Yes
Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Department × week	Yes	Yes	Yes	Yes	Yes	Yes
Day of week fixed	Yes	Yes	Yes	Yes	Yes	Yes
Week of year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Outcomes are the mobility trends by municipality in Colombia, calculated in Google COVID-19 Community Mobility Reports. Sample varies depending on the availability of Google Mobility Data. We restricted the sample for municipalities with groceries mobility trends. The food delivery variable measures the program roll-out as the cumulative number of food packages delivered per eligible household over the last two weeks. Municipality under restrictions is a dummy variable indicating that the municipality is mandated to comply with national lockdown policies. Covid severity index is calculated at the municipality level by the Health Ministry using information on covid cases, test positivity rate and deaths growth by week. Cols 1-46 estimated with fixed effects OLS regressions using panel of unit-day observations from March 1 to August 31, 2020. Standard errors reported in parentheses are clustered by urban census tract.
Source: Mobility index from Google Mobility Report. Food assistance deliveries from ANHB and Analytic Lab.

5. Conclusion

Social distancing is considered one of the most important factors to contain the transmission of the COVID-19 virus. The government of Colombia imposed strong lockdown directives as the leading non-pharmaceutical policy to reduce the spread of COVID-19. Compliance with these rules represents a high cost for households at risk of falling into poverty. Understanding how emergency aid worked during the first wave of the COVID pandemic is key for designing and implementing effective policies in subsequent COVID waves.

This document presents robust evidence that properly timed food assistance deliveries at home reduced human mobility for households under lockdown measures. After controlling for a rich set of fixed effects in high-frequency data, the cumulative food deliveries per eligible household decrease out-of-home events observed at the urban tract level by 1.6 percent. The result is short-lived because it is driven by the deliveries from the previous two weeks. The primary mechanism is likely reduced visits to grocery stores because this

program delivered the food packages to homes. Introducing emergency food assistance helped families in economic hardship comply with social distancing measures.

The estimations are valid under strong assumptions on common trends and homogeneous response across different groups of food delivery exposure. We argue those are plausible assumptions in a short time period of analysis where mobility patterns for eligible tracts are likely affected by the same time varying factors. The study only uncovers patterns from mobile phone users. Because access to mobile internet could vary by different income, we address this limitation by estimating all our main specifications with a sample of urban tracts with similar socioeconomic characteristics. The results are robust when using matching weights to improve the comparison of urban tracts of similar pre-pandemic characteristics. But assessing the representativeness of mobile phone information will be important for future research. Additional limitations are possible spillover effects. One might hypothesize that families could share their food packages with other relatives and friends. Spatial spillover effects across neighborhoods can also affect mobility patterns.

The findings highlight an unintended role of in-kind support during lockdown measures. For this COVID pandemic emergency, in-kind assistance delivered to the home encouraged families to remain there, ultimately providing a health benefit in addition to the crisis alleviation effect. The program was implemented as a one-time delivery to alleviate the economic distress of families that had no other social protection program coverage prior to the pandemic. The short-term effect in mobility reflects that the program's goal was not to reduce mobility for extended periods. However, the targeted families have more reasons to leave the house, such as the lower possibility of working from home and high informality rates. These households make more visits to stores to buy food for daily consumption. Targeted economic relief in the form of food aid has a direct incentive to reduce out-of-home mobility for these households, thus helping them to comply with lockdown measures.

During the pandemic, the food aid initiative proved that rapidly scalable solutions are available to meet food delivery goals. The critical point was to quickly identify potential beneficiaries using updated administrative data with complete location information. These impacts could be studied because of the availability of timely data on geocoded deliveries and high-frequency mobility information. Efforts to collect more data at a high frequency and geographic dimension are still relevant to evaluate policies and design new interventions in the context of COVID mitigation.

In addition, new policy solutions that help households comply with lockdowns become relevant to the effectiveness of measures to contain COVID. Programs like subsidizing food deliveries to homes instead of pure cash transfers could boost the social assistance effect on public health measures. The cash transfer program *Ingreso Solidario* was implemented during the same period as the food aid initiative. Receiving food deliveries could have a higher effect on reductions in mobility. The cash transfer program required a financial account, which many households do not have at the pandemic early stages. Many households need to visit physical locations to claim the benefit. Also, using the cash requires getting out of the house. These factors could increase the effectiveness of food aid relative to cash transfers. However, these hypotheses need to be proved empirically. The interaction of cash transfers with in-kind transfers is a question for future research.

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Appendix

Additional Tables and Figures

Table A.1. Food assistance deliveries and mobility restrictions

	Outcome: Per-capita Food assistance deliveries	
	last two weeks cumulative delivery	daily deliveries
	(1)	(2)
mobility restrictions	-0.019*	-0.000
	(0.011)	(0.000)
covid cases per 100,000 hab	-8.041×10^{-9}*	-6.53×10^{-10}**
	(4.134×10^{-9})	(3.125×10^{-10})
R2	0.059	0.023
N units	2,816	2,816
N days	184	184
Urban tract fixed effects	Yes	Yes
Day fixed effects	Yes	Yes
Municipality fixed effects	Yes	Yes
Department × week	Yes	Yes
Day of week fixed effects	Yes	Yes
Week of year fixed effects	Yes	Yes

Notes: N=476,345. Sample includes only eligible tracts. Outcome is number of food packages delivered per eligible household in the urban tract, measured as daily delivery and cumulative deliveries over the last two weeks. Municipality under restrictions is a dummy variable indicating that the municipality is mandated to comply with national lockdown policies. Daily COVID cases per 100,000 are reported at the municipality level. Columns 1-2 are estimated with fixed effects OLS regressions using panel of unit-day observations from March 1 to August 31, 2020. Urban tract is a geographic unit defined in the census by the National Department for Statistics of Colombia (DANE). Standard errors reported in parentheses are clustered by urban census tract.
Source: The COVID severity index is calculated at the municipality level by the Health Ministry using information on COVID cases, test positivity rate and deaths growth by week. Food assistance deliveries from ANHB and Analytic Lab.

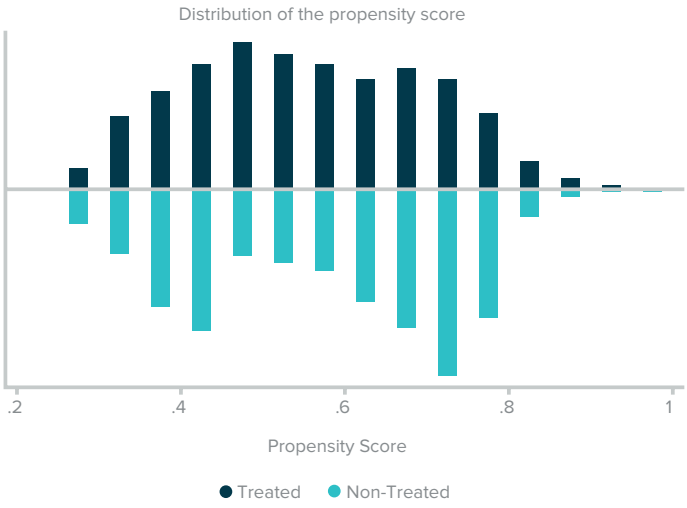
Table A.2. Probability receiving deliveries for eligible tracts

	(1) Ever treated	(2) total deliveries
population density	0.001*** (0.00)	0.001*** (0.00)
share eligible households	0.397*** (0.04)	0.423 (10.41)
Municipality population	base= state-capital cities	
Between 0-20.000	0.134*** (0.03)	31.850*** (4.78)
Between 20.000-100.000	0.094*** (0.03)	41.294*** (5.40)
More than 100.000	0.037 (0.03)	31.118*** (8.10)
Age Structure	share over tract population	
share age 0-19	-0.072 (0.05)	2.383 (7.49)
share age 20-40	0.248*** (0.08)	53.838*** (11.64)
share age 41-59	0.347*** (0.08)	54.597*** (14.22)
share age 60 plus	0.217* (0.11)	11.130 (13.99)
Constant	0.272*** (0.03)	2.061 (7.78)
Observations	2,816	2,816
R-squared	0.091	0.114

Notes: Ever treated= 1,887, not treated=929 from March 1 to August 31, 2020.

Sample includes only eligible tracts. Columns 1 and 2 present a OLS regression on demographic and eligibility covariates. The share of eligible households is calculated using the eligible households in the urban tract over the total eligible households in the municipality. Municipality size is grouped in four categories according to population size. This classification is used frequently by the central government for statistical proposes. Urban tract is a geographic unit defined in the census by the National Department for Statistics of Colombia (DANE). Standard errors reported in parentheses are robust.
Sources: Demographic data Population Census 2018, National Bureau of Statistics DANE. Multidimensional Poverty Index (MPI) calculated at the block census level by the National Bureau of Statistics DANE. Food assistance deliveries from ANHB and Analytic Lab.

Figure A.1. Common Support for the pscore



Notes: This figure shows the common support for the estimated pscore. The included covariates represent the eligibility criteria of the program (share of eligible population) and other covariates for the urban track (population density, municipality population). The model is presented in Table A2.
Sources: Demographic data Population Census 2018, National Bureau of Statistics DANE. Multidimensional Poverty Index (MPI) calculated at the block census level by the National Bureau of Statistics DANE. Food assistance deliveries from ANHB and Analytic Lab.