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COVID-19, food relief, and social distancing: Evidence from the Bayan Bayanihan Program in the Philippines

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COVID-19, FOOD RELIEF, AND SOCIAL DISTANCING

EVIDENCE FROM THE BAYAN BAYANIHAN PROGRAM
IN THE PHILIPPINES

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ABSTRACT

At the onset of the coronavirus disease (COVID-19) lockdown in the Philippines in April 2020, the Asian Development Bank, in partnership with the Philippine government and the private sector, implemented the Bayan Bayanihan (BB) food relief program which served approximately 162,000 households in the National Capital Region and nearby provinces. This study evaluates the impact of in-kind transfers on social distancing by examining the effectiveness of the BB program in restricting mobility by enabling households to stay at home. We leverage plausibly random variations in the timing of the rollout of the program by employing recent developments in estimating staggered difference-in-differences strategies to more accurately identify the effect of the program. We find supportive evidence that the program could generally discourage mobility. Our findings suggest that in addition to mitigating food insecurity, food transfer programs can also generate multiple dividends by helping families stay home and reducing the spread of COVID-19.

Keywords: COVID-19, impact evaluation, mobile phone location data, food program, staggered DID

JEL codes: D04, I10, O12

This paper was prepared with the support the Asian Development Bank's (ADB) Technical Assistance (TA) 6926: Key Indicators for Asia and the Pacific 2021-2023 Subproject 3. It serves as a follow-up study to the concluded ADB TA 9356, which focused on the use of innovative data analytics, particularly machine learning algorithms, for population and poverty data disaggregation.

I. INTRODUCTION

A. Background of the Study

The coronavirus disease (COVID-19) pandemic forced countries to control the transmission of the virus through social distancing, lockdowns, and quarantines. These measures ushered in a new normal centered around remote work and limited mobility. Several studies reported the effectiveness of these measures in reducing physical mobility and slowing down COVID-19 transmission (e.g., Friedson et al., 2021; Haddawy et al., 2021; Fang et al., 2020; Jacobsen and Jacobsen, 2020; Moreland et al., 2020). However, the lockdown came with a trade-off between saving lives and protecting income (Besley and Stern, 2020), and the burden was more keenly felt in developing countries (Miguel and Mobarak, 2021). Other consequences include: deteriorating physical health (Kumar and Nayar, 2021; Ammar et al., 2020); induced feelings of fear, anxiety, and loneliness, and strained relationships (Tanaka and Okamoto, 2021); compromised food security (Matthews, 2021; Ibukun and Adebayo, 2020); and exacerbated pre-existing inequalities (Blundell et al., 2020).

Poor people, who were less likely to engage in remote work and thus had higher mobility and greater exposure to COVID-19, were more adversely affected. This was coupled with fewer coping resources and limited access to health services (Yechezkel et al., 2021; Blundell, et al., 2020; McNeely et al., 2020; Pullano et al., 2020). Government policy aimed to support these more vulnerable segments.

In March 2020, the Philippine government implemented a series of community quarantine measures across barangays (villages) which included mobility restrictions, curfews, transportation limits, and closure of non-essential businesses (Inter-Agency Task Force for the Management of Emerging Infectious Diseases [IATF], 2020a). From April to May 2020, the Asian Development Bank (ADB), the Philippine government, and private companies implemented the Bayan Bayanihan (BB) food relief program (ADB, 2021a). The program was an in-kind bridging assistance for households that had no access to food or suffered income losses, and those who could not afford to stay at home. It distributed food packages enough for 7 days to poor households in the National Capital Region (NCR) and nearby provinces. In-kind transfers are typically useful in targeting specific needs of vulnerable beneficiaries (as opposed to cash transfers) (Cunha et al., 2019). BB's aim was to target the most vulnerable areas, help keep people at home, and reduce COVID-19 transmission.

B. Objectives of the Study

This study evaluates the effectiveness of the BB program on mobility using novel data sources. We use barangay origin-destination mobile ping data (MPD) to measure physical (inward, outward, and within) mobility, and exploit the timing differences of food distribution to apply de Chaisemartin and D'Haultfoeulle's (2020) staggered difference-in-differences (DID) design and identify the treatment effect of BB on mobility. We test the correlation of mobility with the number of reported positive cases to gauge its ability to predict COVID-19 cases. We also estimate heterogeneous treatment effects stratified according to barangay-specific characteristics such as intensity of treatment, level of poverty, and presence of public markets.

C. Contributions of the Study

To our knowledge, this study is the first to expand COVID-19 literature by providing evidence on the impact of in-kind food programs in reducing mobility and COVID-19 transmission. We also contribute to the literature by using novel data sources like MPD as a proxy for mobility and ADB-generated small area poverty estimates from satellite imagery to analyze program effects on the village.

This study primarily contributes to the growing literature on governments' responses to COVID-19, particularly regarding the effectiveness of directly delivered food programs in reducing mobility and potentially limiting the transmission of COVID-19. This provides evidence on the usefulness of in-kind transfers in reducing the net social costs of social distancing and achieving socially optimal outcomes, particularly in developing countries, within the context of a crisis. Using MPD to proxy for mobility and correlating it with reported cases support the growing advocacy for the use of big, innovative data, e.g., geospatial information, mobility data, and satellite imagery, as convenient, cost effective, and highly informative means to collect data (in lieu of household surveys) that can be used to measure economic activity and standards of living as well as to design and implement humanitarian assistance in developing countries.

In development literature, in-kind transfers are used to nudge recipients to consume specific goods or impose greater selection for more vulnerable beneficiaries (as opposed to cash transfers which generally have lower administrative cost and allow for more freedom to choose) (Cunha, Giorgi, and Jayachandran, 2019). In the context of the COVID-19 pandemic, BB was a much-needed program implemented to target the most vulnerable sectors—those with lower socioeconomic status, those with innately higher mobility, those who cannot afford to stay at home, and therefore, those who are at higher risk of being exposed to the virus. Delivering necessities directly to households could keep people at home, decrease mobility, and hence, control COVID-19 transmission.

To preview our empirical results, we find that MPD strongly correlates with the daily reported cases in each barangay, reinforcing the link between mobility and transmission. Moreover, we implemented de Chaisemartin and D'Haultfoeuille's (2020) methodology to properly estimate a staggered DID setup, exploiting the timing of program rollout. We find that the BB program yields a decreasing effect on all inward-, outward-, and within-barangay mobility overall when it persists beyond the expected 7-day duration of the treatment. This effect is more pronounced for barangays with higher treatment intensity (a larger proportion of eligible households that can receive aid) and lower poverty rates (possibly due to relatively richer communities being employed in occupations that are capable of remote work).

II. THE BAYAN BAYANIHAN PROGRAM

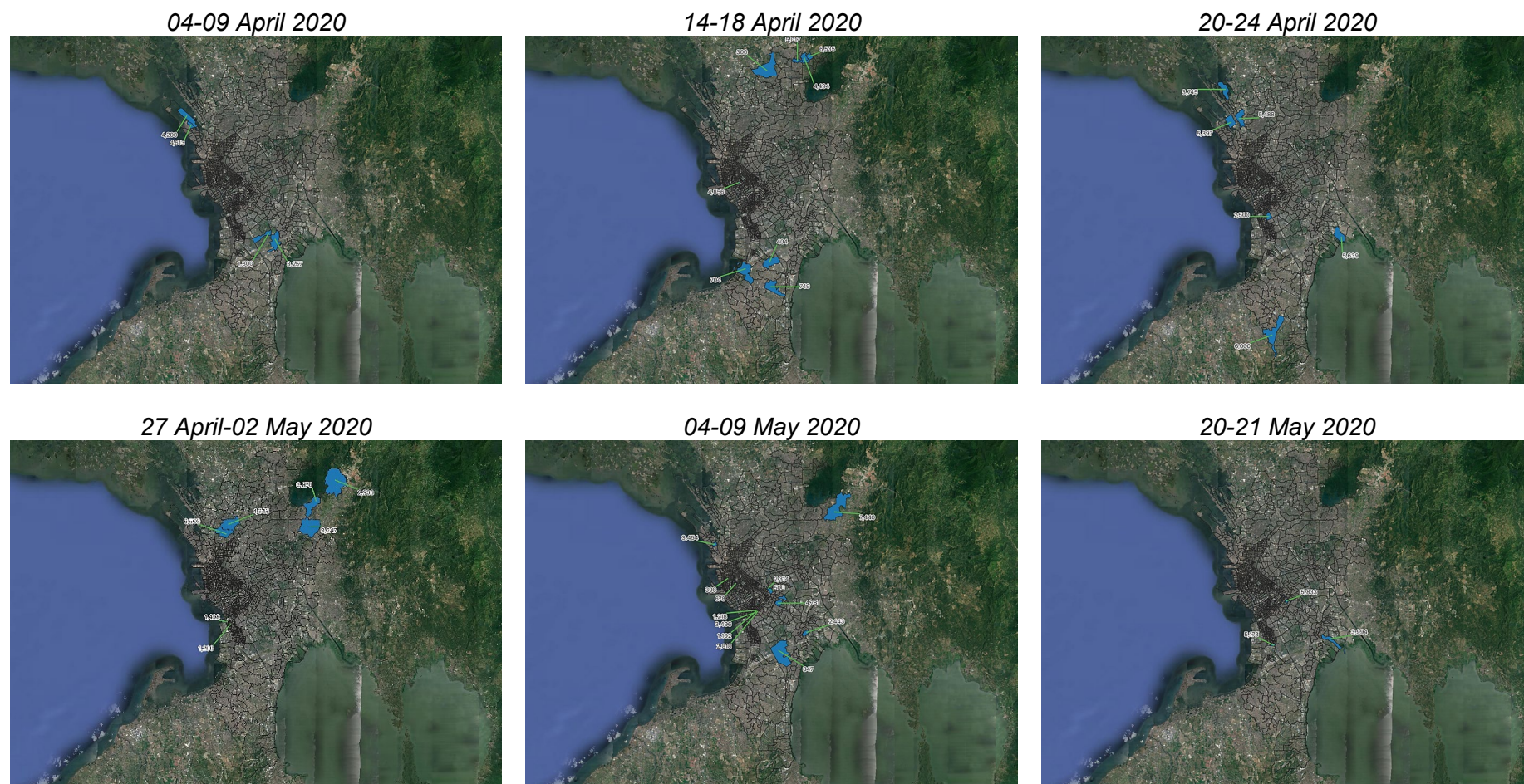
The Rapid Emergency Supplies Provision Project (Bayan Bayanihan) was a bridging assistance program designed to provide households with 7 days of food while waiting for longer-term, formal programs to be implemented (ADB, 2021a).¹ It aimed to encourage households to stay home during the quarantine. The program reached 162,000 households (approximately 810,000 individuals) in 44 barangays in NCR and contiguous barangays in Region 4A (CALABARZON) (ADB, 2021a). This covered around 2.57% of barangays in NCR (a total of 1,710 barangays) and approximately 6% of the 2020 NCR population (around 13,484,462) (Philippine Statistics Authority [PSA], 2021a).

In selecting the beneficiaries for the program, ADB identified barangays using the following criteria: the highest prevalence of poverty in 2015; whether markets are available within the barangay; and distance to the nearest market if no market was present in the barangay. The barangay poverty incidence was calculated by machine learning applied to satellite imagery (Martinez and Mehta, 21 December 2020)² whereas the market indicator was taken from PSA's 2015 Census of Population and Housing. Additional areas were included after referrals were made by field implementers during program rollout, but only after validation by the organizing committee. Distribution was staggered during March-April 2020 and the sequence by which the barangays received food packages was exogenous. Figure 1 shows the weekly rollout of the program, Appendix Table A1 provides a list of these barangays in the chronological order they received aid, and Appendix Figure A1 provides a full picture of barangays that were initially identified during targeting (hereafter named “eligible” barangays) in addition to the actual barangays that received treatment.

¹ The uniform food package was based on the specifications of the Department of Social Welfare and Development. This included 10 kgs of rice, around 35 assorted canned goods (e.g., sardines, tuna flakes, corned beef), 20 milk/coffee/cereal sachets, instant noodles, and milk powder – roughly constituting the average weekly household food intake of urban households in the Philippines.

² Martinez and Mehta (2020) used previously developed poverty maps generated by applying machine learning with satellite imagery. Poverty maps were produced by training a computer vision algorithm to identify features in daytime satellite images to predict economic activity at levels more granular than what conventional data sources can provide (ADB, 2021). This is based on previous initiatives that trained the algorithm to develop measures for economic development based on night light intensity. This is similar to methods that used machine learning on satellite imagery to predict poverty (for reference, see Jean et al., 2016), and Tingzon et al., 2019). These granular poverty maps were then aggregated to each barangay, and selection was done at this level.

Figure 1: Weekly geographical rollout of the Bayan Bayanihan Program



Indicative administrative boundary produced by PSA, NMRIA, and UNOCHA. Basemap taken from Google Earth.
Source: ADB. 2021. *Bayan Bayanihan: A food program for Filipino families*. <https://www.adb.org/what-we-do/bayan-bayanihan> (accessed on 13 November 2021).

III. METHODOLOGY

A. Data Description

This study combines three datasets: 1.) the MPD dataset provided by a telecommunications company partnered with ADB; 2.) a satellite-based poverty mapping dataset for identifying beneficiaries during the implementation of the BB program, produced by the Data Division (ERDD) of ADB's Economic Research and Development Impact Department (ERDI); and 3.) a 2015 CPH Form 5 of the PSA.

The main outcome observed in this study is physical human mobility derived from the MPD dataset. The MPD dataset is a barangay origin-destination dataset that reports unique mobile phone numbers that made a transaction from an origin barangay to a destination barangay within a given hour. The data used in this study covers transactions from 1 January to 30 September 2020. A transaction is a transfer of signal or “ping” based on cell tower triangulation,³ meaning a person moving from barangay A to barangay B would register a cell phone signal transferred from a cell tower in barangay A to a cell tower in barangay B. These pings are what would constitute two of the three main outcomes observed in this study: “outward mobility” (when aggregating pings based on origin barangays given the aggregated period) and “inward mobility” (when aggregating pings based on destination barangays given the aggregated period). A ping that occurs within the same barangay implies a transfer of signals across cell towers within the same barangay and would therefore constitute the third outcome of this study, “within mobility”. Pings are aggregated daily to produce barangay-day outward, inward, and within mobility.

Mobile pings have previously been used to pinpoint mobile users' locations. While caution must be exercised in using mobile data since non-random sampling may occur due to selection on the possession of mobile phones (Moslem et al, 2021; Moreland et al, 2020), mobile phone ownership has been increasing significantly, making this source of big data a reliable way of measuring human mobility and implementing contact tracing (Agbehadji et al., 2020). Nouvellet et al. (2021) showed that automated mobility data and COVID-19 transmission shared a strong correlation. Studies have used mobile ping data to represent mobility (Yechezkel et al., 2021; Pullano et al., 2020), while some made use of smartphone apps with global positioning system (GPS) or location-tracking capabilities such as Google and Apple (Haddawy et al., 2021; Fang et al., 2020; Jacobsen and Jacobsen, 2020). Using mobile ping data is advantageous because of the wider coverage of subscribers, which would give better representation for the populations of each barangay. Given the available MPD data, this study includes 2,162 barangays across 226 cities/municipalities, over 274 days starting 1 January 2020. This covers barangays in NCR and contiguous regions, and the data has been cleaned to include only regions and barangays within a 100km radius around the centroid of NCR.⁴ Due to the nature of sampling of the MPD dataset

³ Cell tower triangulation is a widely available technology used by operators and service providers to collect location data (originally to aid emergency response teams in search and rescue operations and forensics teams in tracking down people). An operator can recognize signals based on handset-specific cellular identification frequencies. A user's location is determined by the angular approach of a signal from a cellular phone to a tower, the time it takes for a signal to travel between towers, and the strength of the signal upon reaching a tower. Alternative ways mobile phone data can be used to track user location are through the satellite-based Global Positioning System, or the Wi-fi Positioning System. Haddad et al. (2014) provide an excellent guide to the use of location data from mobile phones.

⁴ The MPD data originally included pings from barangays within the NCR going to far-flung areas of the Philippines (more than 100kms worth) which are physically impossible to traverse within an hour (e.g., from Manila to Davao). Given that the data was originally on an hour level, anomalous observations were

(and confidentiality-related issues), only 31 out of 44 barangays covered by the BB program have mobility data.⁵

As mentioned previously, poverty maps were generated through machine learning to aid in identifying beneficiary barangays. This study draws from the barangay poverty dataset to account for selectivity prior to implementation. To further account for the selectivity, this study complements the analysis of mobile data with other barangay characteristics by also integrating the PSA's 2015 CPH Form 5. The CPH Form 5 is a dataset with records of barangay characteristics like the presence of various kinds of establishments, service facilities, and the specified distance of these points from the area (PSA, 2021b). Of note is the indicator for the presence of a marketplace and the distance to the nearest market that was used in selecting the barangay.

B. Identification Strategy

In identifying the impact of the BB program on mobility, this study exploits the variation created by the timing of the rollout of the BB program. Looking at the weekly rollout of BB throughout its implementation (Figure 1), we discern no clear spatial pattern visually. We complement this with a comparison of poverty levels and market presence indicators of barangays by week (Appendix Table A2) and similarly find no clear pattern in terms of timing (i.e., higher poverty incidence barangays were not necessarily served first). Hence, we argue that treatment timing is plausibly random. We use a staggered DID approach to exploit the variation in treatment timing, while disentangling the treatment effect from time-related trends, seasonality, and structural changes (Tanaka and Okamoto, 2021).

The main strategy in identifying the impact of the BB program, therefore, is a staggered DID approach based on the timing of the program's rollout. A staggered DID setup would allow the disentanglement of the short-term treatment effect (for up to 7 days given the intended coverage of the food packs) for each barangay beneficiary from time-related trends, seasonality, and structural changes (Tanaka and Okamoto, 2021). The strategy provides viable identification of the treatment effect as the length of the data we have allows for a reasonable pre-treatment period to establish parallel trends, and the comparison of before and after treatment across treated and untreated barangays.

C. Confounding Factors

Apart from location-driven or time-driven trends in mobility, we note three potential confounding factors that may provide competing explanations and common time trends, and factor them into our model: 1.) the IATF's community quarantine (CQ) restrictions, 2.) the Social Amelioration Program (SAP), and 3.) a potential "announcement" effect.⁶

excluded by limiting the sample to barangays within a distance from the centroid of the NCR, around 100 km, which can be traversed reasonably around in an hour. However, this would also lead to inward and outward mobility being symmetric given that outward movement from a barangay would only be inward movement in another within the capital, and would be unable to capture processes that determine longer/farther movement. In essence, outward and inward mobility may alternatively be interpretable as a "cross-border" movement relative to the "within-movement" captured by the within-mobility variable.

⁵ After conducting a comparison of barangay characteristics, we found no structural difference from beneficiary barangays with mobility data.

⁶ A companion study considers modifying the model specification to account for 'announcement effect,' provided data is available on the specific dates when a barangay first learned about the relief program and when households were informed about the food packs (Cabuy et al. 2025).

CQ restrictions imposed stay-at-home orders, mobility restrictions, curfews, and transport limitations (IATF, 2020a; IATF, 2020b), which affected mobility for the entire region. While not explicitly accounted for in the specification, CQ restrictions are addressed through the day variables that disentangle short-term time trends from the longer-term CQ restrictions which lasted for approximately 156 days.

The SAP was implemented by virtue of Bayanihan to Heal as One Act (R.A. 11469) to provide emergency subsidies amounting to \$99–\$159 per month from April to May 2020. This was meant to smooth the consumption of poor and low-income households. Multiple forms of the SAP⁷ were administered by local governments and the timing of the disbursement observed no uniformity or structure. ADB collected data on SAP disbursement dates from the social media accounts of city and municipal governments and these were included as controls in the staggered DID model as barangay-day level dummy variables assumed to have a 7-day duration.

During the rollout of the BB program, no standard procedures were imposed on barangays, and some exercised their discretion in its execution. Anecdotal evidence of an “announcement effect” was gathered through consultations with officials of some beneficiary barangays. Some local governments posted about the program on Facebook, whereas some distributed leaflets and tickets in advance. Households then needed to queue to receive the package on the day of the distribution. Expectedly, this might have encouraged households to stay indoors and decreased mobility days prior to implementation, and then spiked up mobility during the day of the distribution. We adjusted the specification of our empirical strategy to include this announcement effect by extending the treatment duration to include the 3 days before distribution, rather than setting the treatment on the day of the distribution.

We also accounted for possible selection bias from the mechanism in identifying beneficiaries. First, we took the subsample of all barangays in the eligibility list from which the organizing committee selected the final beneficiaries (Appendix Figure A1). The second strategy employed propensity score matching (PSM) to produce a subsample of exact matches⁸ based on the likelihood of being treated, conditional poverty incidence, and market presence. Kernel density and p-scores are presented in Appendix Figure A2. These two strategies yield tighter counterfactuals compared to the full sample which, by including barangays that are structurally different from beneficiaries and have virtually no chance of being selected for treatment, may potentially overestimate treatment effects.

We conducted a covariate balance test between beneficiaries and non-beneficiaries across all samples (Table 1). Compared to all barangays in the sample, beneficiaries have a statistically higher poverty incidence, access to markets, highways, hospitals, health centers, and population sizes; none have access to seaports. The finding about higher poverty incidence may be expected. These barangays are also closer to the region’s center (where most business is conducted) and therefore have better access to facilities. When filtering non-beneficiaries according to the two subsampling strategies, a different picture is seen. For the eligible-only

⁷ SAP included both cash and in-kind assistance (Reyes et al., 2020): a.) distribution of food and personal hygiene items, and unconditional cash assistance to affected formal sector workers, senior citizens, persons with disability, pregnant, single parents, overseas Filipinos in distress, indigenous peoples, homeless, and informal economy workers; b.) microloans, loan concessions, and livelihood assistance for microenterprises for small farmers and fishermen; c.) temporary work programs; and d.) an expanded conditional cash transfer program of the DSWD.

⁸ The matching is done using 1:1 nearest neighbour matches without replacement.

subsample, poverty incidence is slightly higher for beneficiaries, and access to markets is lower—which reflects the objective of BB to provide aid to the most vulnerable areas. As may be expected, the chosen covariates are balanced between beneficiaries and non-beneficiaries in the PSM1:1 subsample.

Table 1 presents the covariate balance tests for the characteristics enumerated earlier. This is performed across the various proposed samples, including a sample with all barangays in the dataset. First, compared to all barangays in NCR and contiguous regions, beneficiaries have a statistically higher incidence and proportion of poor people, access to markets, highways, hospitals, health centers, and population sizes, and are statistically closer to the NCR centroid. None have seaport access. Second, when comparing the eligible subsample, the above is generally true for beneficiary barangays except that they have lower access to markets. This suggests that the policy was implemented in the most vulnerable areas, where it mattered the most. The only balanced characteristic under this subsample is the access to hospitals. Under the 1:1 matching via PSM, all characteristics are statistically similar between the treatment and control groups. In evaluating the effect of the BB program on human mobility, we need to include these covariates to isolate the effects these characteristics may have on people’s mobility during the pandemic, but a more parsimonious specification may be utilized when using the PSM 1:1 subsample.

Table 1: Means and T-tests of Covariates for Bayan Bayanihan Beneficiaries and Non-beneficiaries, Across Subsampling Specifications

		All		Eligible (ERDD)		PSM (basic)	
		BB	Non-BB	BB	Non-BB	BB	Non-BB
Number of Poor People*	Mean	1,853	441	1,853	1,691	1853	2,181
	p-value		0.000		0.000	0.6128	
Proportion of Poor People	Mean	0.040	0.034	0.040	0.031	0.040	0.036
	p-value		0.000		0.000	0.2771	
Access to Market Indicator	Mean	0.600	0.413	0.600	0.837	0.600	0.767
	p-value		0.000		0.000	0.1708	
Access to National Highway	Mean	1.000	0.945	1.000	0.953	1.000	0.9667
	p-value		0.000		0.000	0.3215	
Access to Hospital	Mean	0.420	0.173	0.420	0.419	0.400	0.267
	p-value		0.000	0.8935		0.2811	
Access to Health Center	Mean	0.936	0.788	0.936	0.884	0.933	0.767
	p-value		0.000		0.000	0.0727	
Access to Seaport	Mean	0.000	0.027	0.000	0.047	0.000	0.000
	p-value		0.000		0.000		.

Continued on the next page

		All		Eligible (ERDD)		PSM (basic)	
		BB	Non-BB	BB	Non-BB	BB	Non-BB
Population Size*	Mean	44,602	14,372	44,602	51,292	44,598	57,182
	p-value	0.000		0.000		0.356	
Distance to NCR Centroid	Mean	11.50	32.49	11.51	11.14	11.27	10.798
	p-value	0.000		0.000		0.740	
No. of Observations**		31	2110	31	43	30	30

BB=Bayan Bayanihan beneficiaries, non-BB=non-beneficiaries

Note: *Number of poor people and population size is for 2015, estimated by machine learning. Reported p-values for t-ratios test against $H_1: diff \neq 0$.

** Number of observations for all barangays is lower than previously proposed because of barangays that were excluded from the mobile ping dataset.

Source: Authors' calculations.

D. Empirical Strategy

Figure 1 underscores the importance of employing a formal event study design within a staggered DID framework. This approach, which uses the pre-treatment period as a reference, places all observations within a more comparable timeframe. Specifically, we estimate the homogenous treatment effect using the different approaches to staggered DID frameworks developed by Sun and Abraham (2021) (hereafter, SA), Borusyak, Jaravel, and Spiess (2024) (hereafter, BJS), and (de Chaisemartin and Haultfoeuille, 2020) (hereafter, dCDH) in addition to the two-way fixed effects model (hereafter TWFE), which involves the issue of the so-called "forbidden comparison" problem involving negative weights.⁹

These methods address potential complications arising from TWFE given the variation in timing, intensity, and on-off nature of treatment (given that food aid is expected to last 7 days but may last longer depending on how the household manages the food supply). The SA, BJS, and dCDH frameworks, respectively, are fully saturated TWFE, imputation method, and rolling method.

As mentioned earlier, during the rollout, no standard procedures were imposed on barangays, allowing them to exercise discretion in their implementation. Through our consultations with officials from beneficiary barangays, we found that some local government units (LGUs) posted about the program on Facebook, while others distributed leaflets and tickets a few days in advance. We take this as a ground for what may be considered an "announcement effect". Then, on distribution day, households were required to queue while maintaining proper social distancing. This advance notice might have encouraged households to stay indoors and reduced mobility in the days leading up to the distribution. Due to the very close proximity of these two related events, and without precise knowledge of when announcements were made per barangay, disentangling the announcement effect from the effect of the actual distribution and treatment would prove difficult for the event study design. Hence, we estimate the impact of these two events together and the reference time for the subsequent event studies is set at $t = -4$.

⁹ Note that the imputation method by Gardner et al. (2022) is basically identical to BJS if we adopt the bootstrap standard errors.

We estimate the following equation using an event study specification:

$$Y_{bd} = \sum_{j=-10, j \neq -4, -\infty}^{14} \beta_j 1[E_b + j = d] + \beta X_{bd} + \gamma_b + \tau_d + u_{bd} \quad (1)$$

Where:

Y_{bd} = {inward, outward, within} mobility for barangay b on day d

This is specified in levels, log, per capita, and log of per capita mobility terms

E_b = Is the event day when the barangay b is given food aid and $1[E_b + j = d]$ represents an indicator function of the j days relative to the treatment

X_{bd} = Is an indicator that takes 1 when the barangay d received a disbursement of SAP

γ_b = vector of barangay fixed or random effects to account for location-/local government unit-specific factors

τ_d = Day-specific fixed effects for short-term time trends and other day-specific competing explanations

u_{bd} = Idiosyncratic well-behaved error term

For the BJS estimator, the specification is as follows:

$$Y_{bd} = \sum_{j \geq -3}^{14} \beta_j 1[E_b + j = d] + \beta X_{bd} + \gamma_b + \tau_d + u_{bd} \quad (2)$$

Where the period between $j = -10$ to -4 is estimated as the pre-trend.

In evaluating the impact of the BB program on mobility, we first test the correlation of mobility (measured through MPD) with COVID-19 cases. This step gauges how much the chosen representation of mobility can be linked to COVID-19 transmission. We then present parallel trends, followed by the main results. We explore several possible heterogeneous effects. First, we test the heterogeneity according to treatment intensity (proportion of eligible households recorded to have been given food packs) classified as above or below the median treatment intensity of 27.4%, the upper 75% of the treatment intensity distribution (56.4%), and the lower 25% (19.6%). Second, we look at heterogeneity by presence of a market within the barangay. Third, we look for heterogeneity across barangays above and below the median poverty incidence (3.2%). Lastly, to explore possible coverage effects, we look at four pairwise combinations of above/below median treatment intensity and above/below median poverty incidence. We also extend the analysis to heterogeneous treatment effects using a specification of treated-only barangays and a barangay measure of the percentage of eligible households that benefited from the program.

IV. RESULTS AND DISCUSSION

A. Correlating Mobile Ping Data with COVID-19 Cases

First, we determine the link between human mobility and COVID-19 transmission by establishing the correlation between mobile ping data and the reported confirmed cases of COVID-19. In doing so, we look at the condensed correlation matrix between our daily measures of mobility and the daily reported confirmed cases (Appendix Table A3) and perform simple regressions of the contemporaneous confirmed cases, and 3-day and 7-day lead confirmed cases (Table 2).¹⁰

Table 2: Correlating Mobile Ping Data with Confirmed Cases, Municipalities

	Dependent Variable	Confirmed Cases (Contemporaneous)	Confirmed Cases (3-day lead)	Confirmed Cases (7-day lead)
Inward Mobility	Coeff. Std. Err. R ²	9.65e-06*** (1.17e-07) 0.309	4.73e-06*** (1.36e-07) 0.074	5.06e-06*** (1.35e-07) 0.085
Outward Mobility	Coeff. Std. Err. R ²	9.65e-06*** (1.17e-07) 0.309	4.73e-06*** (1.35e-07) 0.074	5.06e-06*** (1.35e-07) 0.085
Within Mobility	Coeff. Std. Err. R ²	1.34e-05*** (1.67e-07) 0.299	6.58e-06*** (1.92e-07) 0.072	7.01e-06*** (1.91e-07) 0.082

Note: Each set of coefficients, standard errors, and R² represents a different regression.

*, **, *** denote significance at the 10%, 5%, and 1%, respectively.

Source: Authors' calculations.

We take the daily reported confirmed cases from the COVID-19 Tracker Data Drop of the Department of Health (DoH) (2021). These confirmed cases are aggregated daily by city/municipality, starting from 6 March 2020. Barangay disaggregation only started in September 2020, limiting the correlational analysis to cities/municipalities, and preventing this study from looking at reported confirmed COVID-19 cases as an alternative outcome. In both the correlation matrix (Appendix Table A3) and simple regressions (Table 2), we find that all measures of mobility are positively (and statistically significantly) correlated with contemporaneous reported cases, with within-mobility having the strongest correlation. The strength of the correlation and the degree of explanatory power of mobility captured by R² taper as we introduce lag times, and this is seen for all types of mobility. Like the findings of Nouvellet et al. (2021), Yechezkel et al. (2021), and Pullano et al. (2020), these results reinforce that MPD as a representation for mobility can be linked strongly to COVID-19 transmission.

¹⁰ Using leading indicators of a certain duration as dependent variables would be equivalent to lagging independent variables by the same duration. The rationale behind including this is that it takes 2-7 days for testing to return results. Hence, we cannot limit the correlation exercise to just contemporaneous cases because the effects of mobility on the confirmed cases may only be felt after a few days when they have been confirmed to be positive.

B. Parallel Trend

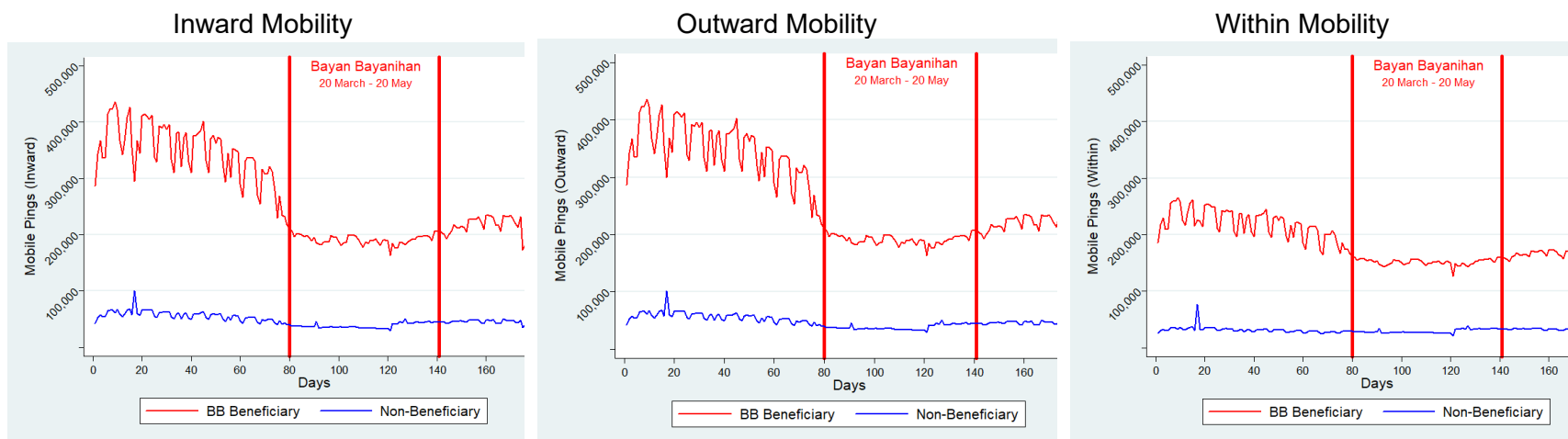
We determine whether a parallel trend assumption is supported by examining the trend of mobility for beneficiaries and non-beneficiaries across three subsamples before and after the treatment periods: (a) all barangays, (b) eligible-only barangays, and (c) PSM 1:1 matched barangays (Figure 2, (a), (b), and (c), respectively). The first observation we make is that across all subsamples, both beneficiaries and non-beneficiaries observe the same daily fluctuations in mobility, but beneficiaries have structurally higher mobility, suggesting that poverty level and mobility are closely correlated especially in normal times. The parallel movement can be observed much closer for the PSM 1:1 matching subsample and is closest for the eligible-only subsample. This may be suggestive that the best comparison can be made using the two subsampling techniques. In the discussion, we present only the results for the eligible-only subsamples for brevity.

Prior to the implementation of the BB program, mobility had been going down drastically. This is likely reflective of both the imposition of movement restrictions and panic induced by media reports on the risks of contracting COVID-19. Upon entering the period when BB was implemented, a slight downward trend may be seen for both beneficiaries and non-beneficiaries at the beginning. An uptrend is then noticeable towards the end of the implementation of BB, and this persists even after implementation. This potentially reflects the relaxation of restrictions from enhanced community quarantine to general community quarantine, which allowed some business and some forms of public transport to operate.

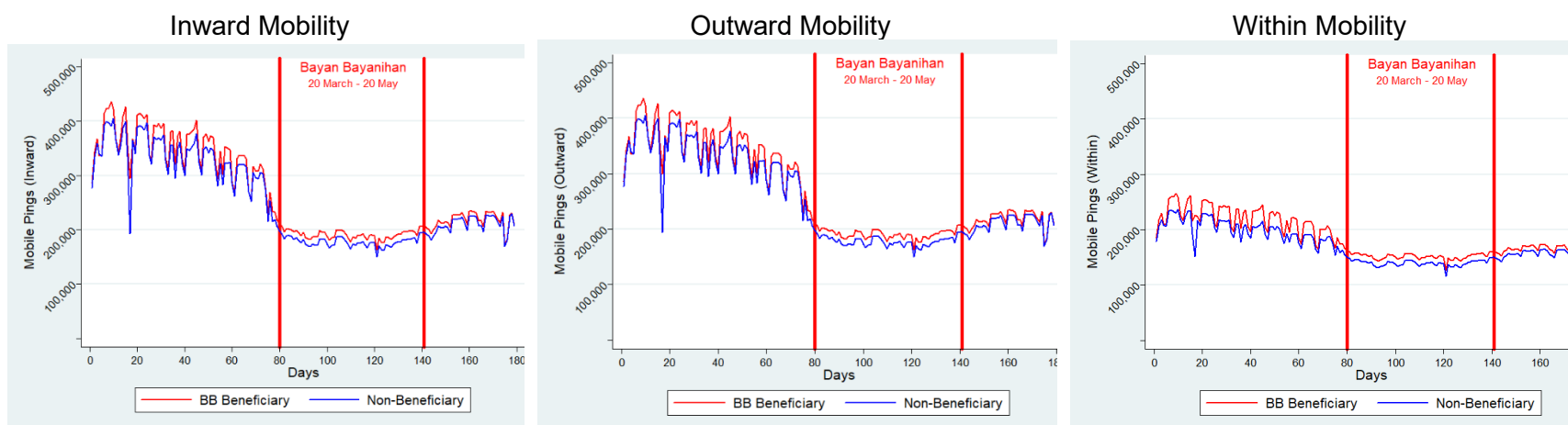
The limitation when looking at mobility on average is that the BB program's rollout varies per barangay and is expected to cover only 7 days' worth of necessities. Very likely, this will not be reflected across all treatment barangays during the implementation period. With only about one to four barangays being treated per day, the average across all barangays should not exhibit much change even when a few barangays' treatment overlaps for a few days within the same week.

Figure 2: Inward (left), Outward (middle), and Within Mobility (right) of Bayan Bayanihan Beneficiaries and Non-beneficiaries, for (a) All Barangays, (b) Eligible-only Barangays, and (c) PSM 1:1 Matched Barangays

(a) All Barangays

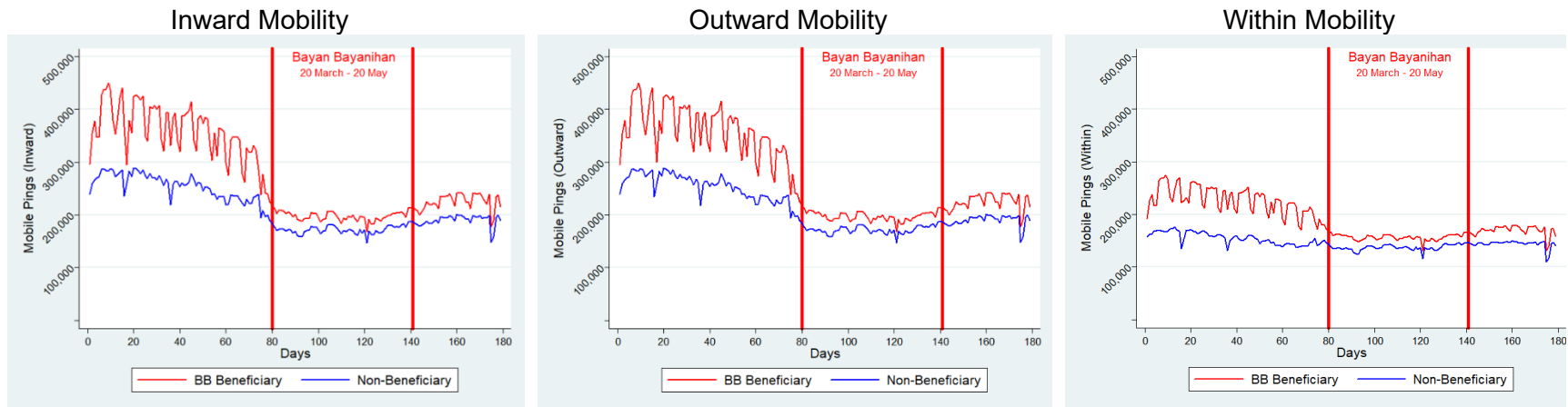


(b) Eligible-only Barangays



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(c) PSM 1:1 Matched Barangays



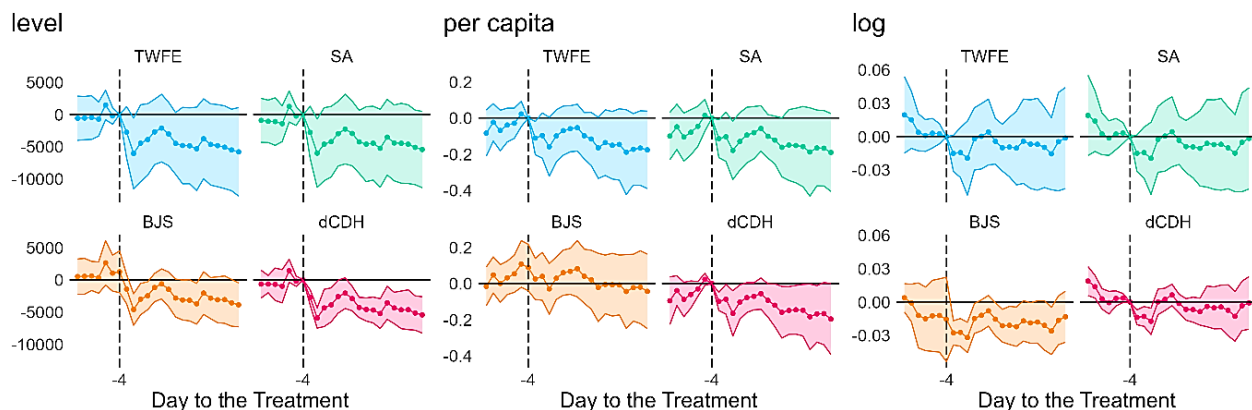
Source: Mobile ping dataset.

C. Impact of the BB Program on Mobility

Figure 3 presents the event study graphs depicting the impact of the BB program on various forms of inward mobility data derived from MPD, including levels, per capita, and logarithmic mobility measures, using the TWFE, SA, BJS, and dCDH methods. Although we analyze all mobility metrics, we focus on inward mobility for brevity, as the qualitative findings are comparable for outward and within mobility.

The main findings are summarized as follows. First, as a conventional diagnostic approach, the pre-trends test examines whether the treatment appears to affect the outcome before its actual rollout. In Figure 4, the confidence intervals of the pre-treatment coefficients are essentially on the zero line across all cases, indicating no significant differences between the treatment and control barangays prior to the BB program. Since no pre-trends are detected, we may conclude that the parallel trends assumption is satisfied.

Figure 3. Event Study Full Sample: Inward Mobility



BJS = Borusyak, Jaravel, and Spiess (2024); dCDH = de Chaisemartin and Haultfoeulle (2020); SA = Sun and Abraham (2021); TWFE = two-way fixed effects model.

Notes: This figure presents the estimates of the impact on inward mobility over 14 days. Reference period is -4 for TWFE, SA, and dCDH, $j \leq -4$ is used for the first stage of BJS. Standard errors are clustered by barangay for TWFE, BJS, and dCDH, and obtained for SA using bootstrap. Error regions represent 95% confidence interval.

Source: Authors' calculations.

Second, we observe an initial dip in the estimated treatment effects, followed by a downward trend in the dynamic treatment effects, suggesting that the BB program significantly reduced mobility at the beginning, likely due to announcement effects, and successfully encouraged families to stay at home. A less subtle, flat downward trend, particularly for the level and per capita specifications, may indicate that mobility growth slowed after the program. However, the precise statistical significance of these estimated treatment effects is somewhat mixed, potentially due to the program's limited rollout. Interviews with barangay officials revealed that only a fraction of households were covered relative to the total population. For instance, while 2,300 packs were distributed, the barangay housed approximately 90,000 families.

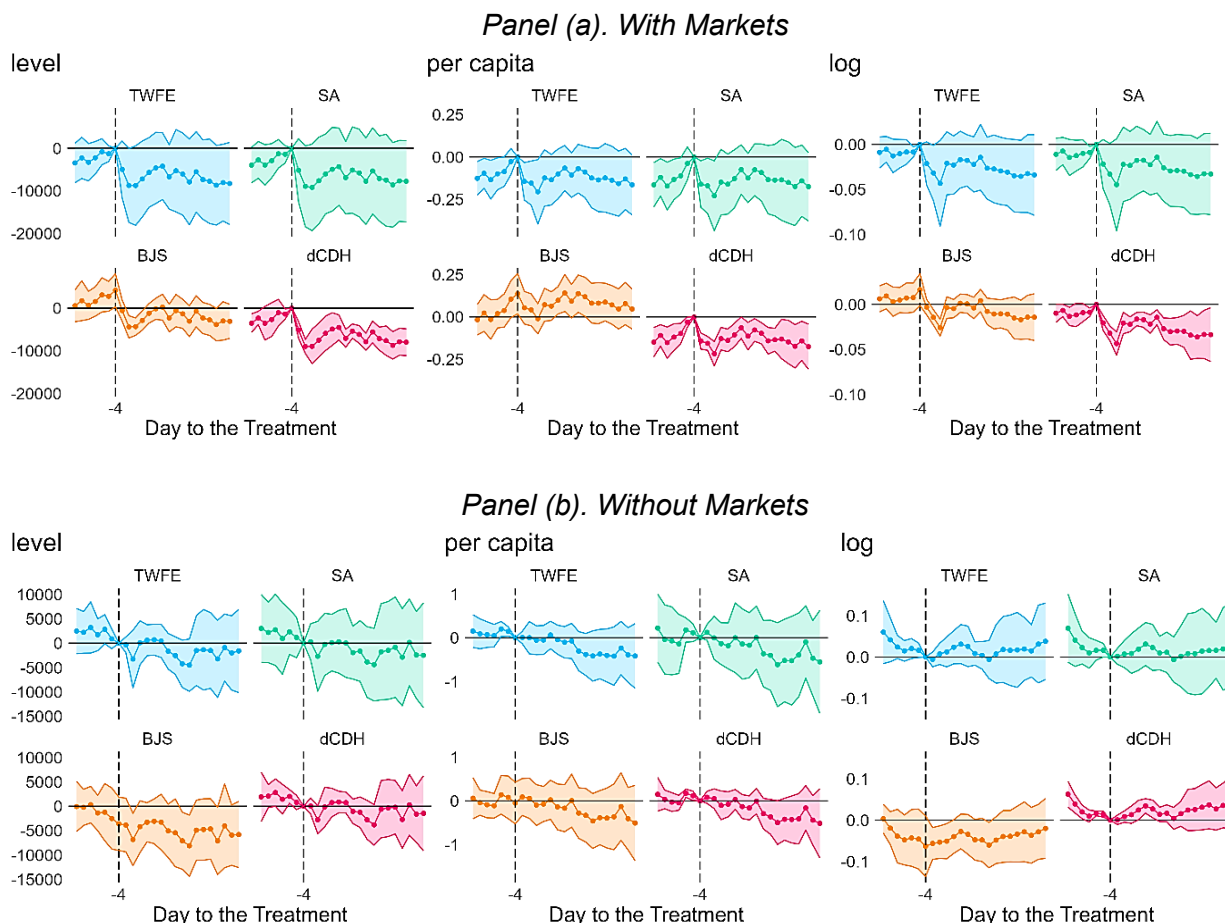
D. Heterogeneity

We also explore possible heterogeneous effects according to the market presence, poverty incidence, and treatment intensity (defined as the proportion of eligible families that received treatment). For brevity, we only present the linear specifications for outward mobility.

Regarding the heterogeneities based on market availability within barangays, Figure 4 presents the event study charts for barangays with and without markets, (Panels a and b, respectively). The initial impacts of the BB program appear more pronounced in barangays with market access compared to those without. These differences may be attributed to varying behaviors driven by different levels of market access. In barangays with markets, families are less likely to store buffer food supplies at home, as the transaction costs of shopping are relatively low. In contrast, in barangays without markets, the higher transaction costs of food shopping lead households to accumulate more food stock at home, and therefore the treatment effect is less apparent. Given these behavioral differences, it is expected that the presence of markets is associated with a larger impact of the BB program on mobility.

We also observe comparable downward trends in the estimated treatment effects for both barangays with and without markets. These similar trends could be attributed to the fundamental nature of the BB program as a direct food transfer scheme, which allowed families to stay home by reducing their need to go out and purchase groceries.

Figure 4: Event Study for Inward Mobility, with and without Markets



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BJS = Borusyak, Jaravel, and Spiess (2024); dCDH = de Chaisemartin and Haultfoeuille (2020); SA = Sun and Abraham (2021); TWFE = two-way fixed effects model.

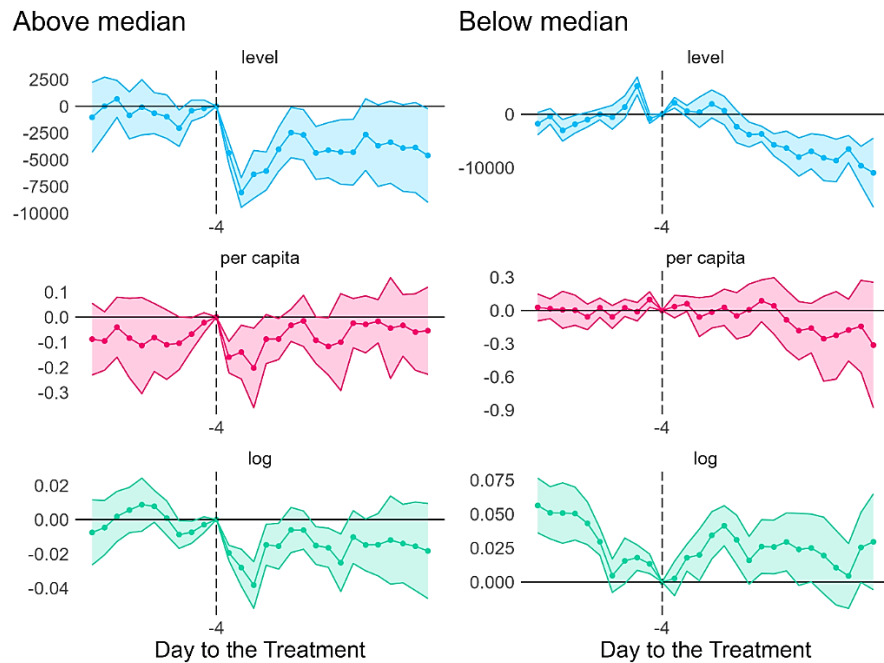
Notes: This figure presents the estimates of the impact on inward mobility over 14 days. Reference period is -4 for TWFE, SA, and dCDH, $j \leq -4$ is used for the first stage of BJS. Standard errors are clustered by barangay for TWFE, BJS, and dCDH, and obtained for SA using bootstrap. Error regions represent 95% confidence interval.

Source: Authors' calculations.

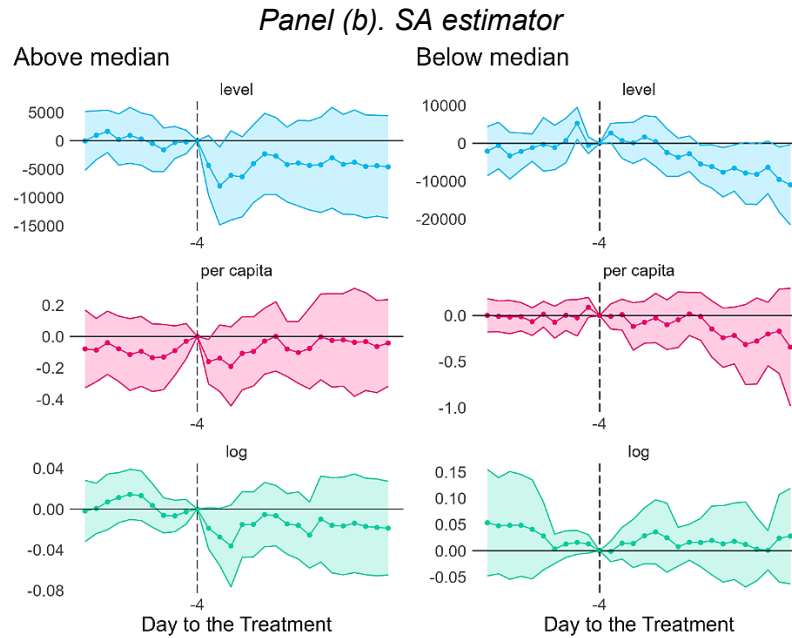
Next, we examine heterogeneity by poverty incidence, comparing barangays with above and below median poverty levels. According to Figure 5, the impact of the BB program is clearly more pronounced in poorer barangays than in wealthier ones. Theoretically, poorer households are less likely to maintain sufficient food stock at home due to constraints such as income shortages and limited access to credit. As a result, these households are more likely to engage in activities requiring physical presence and higher mobility to earn income and smoothen consumption. It is natural to observe that the BB program is more effective in high-poverty barangays with higher mobility. Food transfers allow poorer households to stay indoors more easily. In contrast, relatively wealthier families, who already have sufficient food stock at home, are less impacted by direct food transfers.

Figure 5: Event Study for Inward Mobility, by Poverty Incidence, using dCDH and SA Estimators

Panel (a). dCDH estimator



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dCDH = de Chaisemartine and Haultfoeuille (2020); SA = Sun and Abraham (2021).

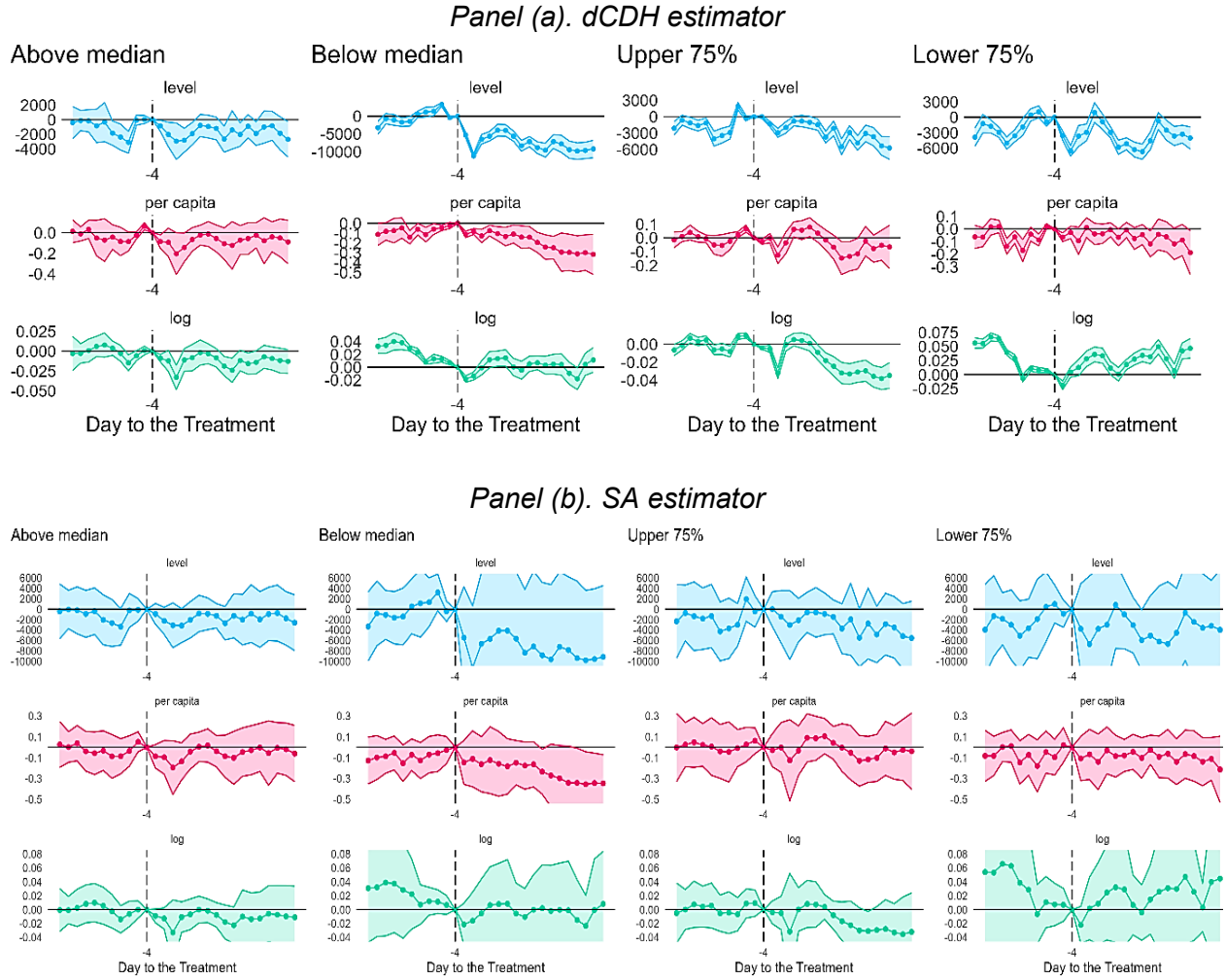
Notes: This figure presents the estimates of the impact on inward mobility over 14 days. Reference period is -4 for SA and dCDH estimators. Standard errors are clustered by barangay for dCDH, and obtained for SA using bootstrap. Error regions represent 95% confidence interval.

Source: Authors' calculations.

Lastly, Figure 6 presents the findings according to treatment intensity, defined as the proportion of eligible households that received the food pack. The impact is not as straightforward. It may be seen that the magnitude of impacts – the size of mobility decreases – is larger for barangays that had below median to bottom 25% of treatment intensity. There is evidence that this impact is short-lived – there are times when mobility increases during distribution, and even some time after that. However, the logarithmic specification for below median and bottom 25% treatment intensity reveals trends that revolve around zero, or even positive. Theoretically, this makes sense – it may be said that the program was generally successful in reducing mobility. However, not many households were given food packs in these barangays, so people started going out sooner and impacts were not as long-lasting.

The magnitude of impacts is much tamer for above median and upper 25% barangays – however, they display a more persistent downward trend. This is expected since barangays that received higher treatment intensity were also those with higher poverty incidence. This links up with the earlier heterogeneity found for poorer barangays. Poorer barangays that have higher mobility (due to the reliance on work that demand physical presence) typically have a higher eligible population who received treatment as well. The treatment effect is expected to be longer-lasting for these barangays than in barangays with lower poverty incidence which, in turn, also have lower treatment intensity. This suggests that the targeted nature of the treatment was successful in discouraging mobility.

Figure 6. Event Study for Inward Mobility, by Treatment Intensity, using dCDH and SA Estimators



dCDH = de Chaisemartin and Haultfoeulle (2020); SA = Sun and Abraham (2021).

Notes: This figure presents the estimates of the impact on inward mobility over 14 days. Reference period is -4 for SA and dCDH estimators. Standard errors are clustered by barangay for dCDH, and obtained for SA using bootstrap. Error regions represent 95% confidence interval.

Source: Authors' calculations.

E. Extended Analysis: Directly Checking for Treatment Intensity

As an extended analysis that potentially complements the previous exercise on heterogeneity according to the combination of poverty rates and treatment intensity, we estimate a heterogeneous treatment effect specification. We explore the impact of different treatment timing and depth within the treatment group, i.e., beneficiaries of the BB program, by modifying Equation (1). We estimate Equation (3):

$$Y_{bcd} = \beta_0 + \beta_1 T_BBB_d + \beta_2 \ln(T\%_BBB_b) + SAP_{b,d} + CQ_d + \pi X + \gamma_c + \mu_m + \omega_d + u_{bcd} \quad (3)$$

Where:

$\ln(T\%_{BBB_b})$	= Natural log of the proportion of households in barangay b that received aid from the BB program
X_b	= Barangay level characteristics: {number of poor people in 2015 estimated using machine learning, percentage of poor people relative to 2015 population size, 2015 population size, and distance to the NCR centroid (in kms); and binary indicators for access to {markets (defined as any place or building where trading activities are carried out at least once a week (PSA, 2021b)), national highways, hospitals, health centers, and seaports}, = 1[barangay has access to facility]
γ_c	= vector of city/municipality fixed effects to account for location-/LGU-specific factors
μ_m	= Month-specific effects
ω_d	= Day-of-week effects

Standard errors are also clustered by barangay. Note that $T\%_{BBB_b}$ is introduced in natural logarithm because its value ranges from 0 to 1, and if interpreted in a linear manner would mean a change from 0 to 1 (none to full). Introducing a natural log transformation would allow for the incremental change in the percentage of households, giving a more reasonable interpretation of results.¹¹ Also note the addition of barangay characteristics and city/municipality fixed effects. To allow for variation of treatment depth, we replace barangay fixed effects with city/municipality fixed effects and add the barangay characteristics for additional controls. It may be noted that T_{BBB_d} follows the same rollout of the BB program and assumes a 7-day duration of the food pack. Equation is estimated using OLS and only results for inward mobility are presented for brevity.

Table 3 reports the estimates of our treatment depth specification. It may be seen that the estimated of treatment timing are statistically insignificant whereas the coefficients of the treatment depth variable are consistently negative and significant across different outcome variables and specifications. This suggests that the BB program helped decrease mobility levels consistently: treated barangays with a larger proportion of households receiving the food pack have lower mobility on average. Mobility is reduced by 2.3% on average (relative to the average mobility of treated barangays) for every 10% increase in the proportion of households receiving the food pack. This means that doubling the number of households receiving food packs could potentially lower mobility by 23% for the duration of the program. This suggests that what potentially influences barangay mobility more is the extent of coverage of households receiving aid within each barangay, rather than the timing or expected duration of food packs.

¹¹ Note that the treatment variable BBB_b is expectedly dropped because we are restricting to treated barangays exclusively. $T_{BBB_{bd}}$ no longer varies by barangay, and now only varies by day, hence T_{BBB_d} .

Table 3: Treatment Depth Effects, Treated-only Sample

<i>Panel A. Dependent Variable: Inward Mobility</i>		
Variable	Basic	Full
T_BBB_d	14,012 (12,422)	22,602 (17,131)
$\ln(T\%_BBB_b)$	-63,855* (35,326)	-180,022** (79,545)
Ave. Mobility	-23,478 (124,143)	656,333* (340,604)
Obs.	8,466	8,193
R ²	0.399	0.580

Notes: Standard errors clustered at barangay level in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1%, respectively. ^ For the timing-only specification, “Basic” includes barangay fixed effects in addition to the DID variables. “Full” includes variables in “Basic” plus vector of dummies for IATF resolutions, 7-day SAP disbursement, vector of month dummies and vector of day-of-week dummies. ^^ For the treatment depth specification, “Basic” includes vector of dummies for IATF resolutions, 7-day SAP disbursement dates, vector of city/municipality fixed effects, vector of month dummies and vector of day-of-week dummies. “Full” includes variables in “Basic” plus 2015 barangay characteristics: number of poor estimated by machine learning, percentage of poor households, access to markets, national highways, hospitals, health centers, seaports, population size, and distance to NCR centroid.

Source: Authors’ calculations.

V. CONCLUSION

A. Summary

The COVID-19 pandemic adversely affected the lives of many, and while lockdowns, mobility limitations, and community quarantine restrictions were effective in limiting the transmission of the virus, more vulnerable demographics such as those from a lower socioeconomic standing were disparately penalized. People with lower-paying jobs could not work from home; lacked savings to finance their daily needs and access medical treatment and healthcare; and were more susceptible to comorbidities and the COVID-19 virus itself. This rationalized the BB program, a food in-kind program which had great potential in helping the most vulnerable households stay home by delivering critical food supplies to residences to alleviate hunger. Through partnership with local and national governments, the BB program targeted the poorest barangays and those without readily accessible markets and reached a good number of households.

This study estimated the impact of the BB program on MPD data as a proxy for physical mobility by exploiting the timing of the rollout and employing the recent developments in staggered DID. MPD data is often used as a measure for mobility, and we showed that it is strongly correlated with COVID-19 cases – implying that our measure of mobility translates to disease transmission. We found that the BB program has been able to discourage mobility during the pandemic, and this impact is more pronounced for barangays with higher poverty incidence and greater treatment intensity. However, the treatment effect appeared to be larger for barangays with markets given behavioral differences where households are less likely to keep a stock of food at home if markets are readily accessible. Barangays without markets displayed a downward trend but only in some specifications – this may be indicative that households are more likely to keep a stock of food at home, and so treatment effects may not be as apparent. Lastly, directly testing the effect of targeting more eligible households (higher treatment intensity), we find that higher treatment intensity may play a larger role in reducing mobility than actual treatment timing.

This study primarily contributes to relevant literature in two ways. First, this study contributes to the debate of cash vs. in-kind transfers, particularly in the context of a crisis where behavior (mobility) needs to be influenced. This knowledge should be informative should succeeding outbreaks occur and similar movement restrictions need to be put in place once again. Secondly, this study contributes to the growing advocacy of using big data, particularly mobile data, to measure key economic activities. Traditional ways of gathering data (i.e., surveys) still enable the collection of more accurate and comprehensive information, but it is also becoming increasingly difficult to do. Big data such as those collected by telecommunications providers or satellite imagery can fill the gap for the immediate need for data. They also tend to be more efficient and potentially less costly to collect.

B. Policy Implications

In the context of the pandemic, appropriate policy responses need to strike a balance between the desired extent of disease transmission control and the economic, health, social, and psychological consequences of highly restrictive responses (i.e., lockdowns) (Besley and Stern, 2020). Furthermore, pre-existing inequalities impinge on people's resilience to the pandemic, and in turn, the pandemic exacerbates these inequalities, making people increasingly vulnerable (Blundell et al., 2020). In general, flexible responses to the pandemic are needed, and these can range from stronger cross-sector collaborations (Jablonski et al., 2021), reinforcing local adaptable supply chains (Thilmany et al., 2021), to directly filling in for gaps in services and social protection that should be directed towards groups that are disparately more vulnerable.

Overall, we can paint the results of the program in a positive light. BB was successful in developing a model for policy response that fostered partnership with the public sector. It fulfilled its objective of limiting mobility during the lockdown and bridged the gap that was created when formal social protection took time to be deployed and to take effect, given the unprecedented impact and magnitude of the affected vulnerable segments of the population. The program was able to complement national and local governments' immediate efforts to provide for the basic needs of poor Filipinos, especially those living in relatively remote areas or away from retail facilities or markets. Lastly, it serves as an example for the adoption of novel applications of big data and technology to aid targeting, and as a viable substitute to traditional data sources such as household surveys.

We separate the implications we draw for policy and impact evaluation. In terms of policy, the design of the program from conceptualization, targeting, to implementation, was enforced as primarily intended. It sought to target the most vulnerable segments of the population since these segments cannot afford to stay home and secure their food supply, and are in occupations that cannot successfully implement a remote work setup. The targeting innovated by using machine learning applied to satellite imagery to identify the poorest barangays. Based on the chosen measure—MPD, which was shown to be strongly correlated to COVID-19 transmission—the program ultimately led to a decrease in physical mobility for targeted barangays. The only limitation is that the extent of the rollout was fairly limited for an effect to be statistically detectable.

On the other hand, these design choices pose a great challenge for impact evaluation studies to provide an accurate estimate of the true impact of the program. The highly selective nature of the targeting and the use of on-the-ground discretion led to non-random sampling and treatment, thus greatly limiting the generalizability of results. In a way, these issues were circumvented through the inclusion of relevant controls, application of reasonable subsampling via eligibility criteria and matching techniques and use of flexible empirical specifications. However, while these methods represent the “best we can do” given constraints relating to data and program design, they do not

fully address endogeneity issues. Given these considerations, we caution that our results should be interpreted as suggestive, while still evaluative and informative at best.

C. Limitations and Avenues for Future Research

In preparing this study, a limitation is the use of MPD itself. While MPD data via triangulation can be easily collected for a wider proportion of the population (and since more people are owning mobile phones, this could potentially render concerns about representativeness as moot), its accuracy in terms of geographic location needs to be verified and validated with the grid system implemented by telecommunications providers. A potential problem in the MPD is that the raw data is already aggregated in barangays with no means of disaggregating down to user levels. The degree of measurement error both in what is being picked up as mobile ping, and whether cell towers in contiguous regions may be picking up pings from users in other regions (misattribution) is another potential problem. A potential avenue is the use of location data (particularly GPS) as it provides better, and more precise pinpointing of people's locations, hence increasing both the depth and variety of the analysis that may be performed. The use and the sharing of big data such as MPD need to be normalized and standardized. The process through which this information is collected needs to be made more apparent (while keeping anonymity) to encourage the use and improvement of the methodology. A potential avenue for future research is investigating the possibility of spatial dependence or spillover effects of the BB program – whether neighboring non-beneficiaries benefited from the program as well or were likely to adopt something similar after observing the policy being implemented. While non-random treatment remains an issue from an impact evaluation standpoint, we conjecture that this issue should take the backseat when designing policy, especially when more pressing concerns need to be addressed, such as more precise targeting and getting the aid to where it is needed, in light of circumstances that disparately expose segments of the population to heightened vulnerability. What is needed are further methodologies that allow for more reliable evaluation of treatments that are non-random by nature.

APPENDIX TABLES AND FIGURES

Table A1. List of Barangay and City Beneficiaries Under the Bayan Bayanihan Program

Date of distribution	Barangay and city	Beneficiaries
31-Mar-20	Pasay City, Caloocan City, Quezon City, Manila City	2,000 households
04-Apr-20	Barangay Hulong Duhat, Malabon City	4,613 households
06-Apr-20	Barangay Pinagsama, Taguig City	3,257 households
08-Apr-20	Barangay Dampalit, Malabon City	4,200 households
09-Apr-20	Fort Bonifacio, Taguig City	1,300 households
12-Apr-20	Sitio Taniman, Barangay Batasan Hills, Quezon City	3,766 households
14-Apr-20	Barangay Valley 8, Paranaque City	749 households
	Barangay San Dionisio, Paranaque City	704 households
	Barangay 187, Caloocan City	5,017 households
15-Apr-20	Barangay Manggahan 2, Paranaque City	404 households
	Barangay Manggahan 1, Paranaque City	267 households
	Barangay 186, Caloocan City	4,494 households
16-Apr-20	Barangay 185, Caloocan City	6,535 households
	Barangay 171, Caloocan City	300 households
18-Apr-20	Barangay 310 Sta Cruz, Manila City	4,856 households
	Barangay Tanza 2, Navotas City	4,793 households
20-Apr-20	Barangay Palanan, Makati City	2,500 households
	Barangay Napindan, Taguig City	5,639 households
22-Apr-20	Barangay Panghulo, Malabon	5,397 households
23-Apr-20	Barangay Almanza Dos Las Pinas City	6,000 households
24-Apr-20	Barangay Malinta, Valenzuela City	5,488 households
	Barangay Coloong, Valenzuela City	3,745 households
25-Apr-20	Barangay Malinta, Valenzuela City (additional)	3,204 households
27-Apr-20	Barangay San Jose, Rodriguez, Rizal	2,300 households
	Barangay Marulas, Valenzuela City	6,500 households
28-Apr-20	Sitio Kalayaan, Batasan Hills, Quezon City	9,247 households
30-Apr-20	Barangay Gen. T. De Leon, Valenzuela City	4,348 households
01-May-20	Barangay 22, Zone 2, Pasay City	1,200 households
	Barangay 1, Zone 1, Pasay City	1,498 households
02-May-20	Payatas (Lupang Pangako), Quezon City	6,876 households
04-May-20	Barangay Bagong Silangan, Quezon City	7,440 households
05-May-20	Barangay Addition Hills, Mandaluyong City	4,781 households
06-May-20	Barangay Perfecto, San Juan City	2,314 households
	Sitio Isla, Barangay Batis, San Juan City	500 households
	Barangay 90, Tondo, Manila City	398 households
	Barangay 261, Tondo, Manila City	678 households
07-May-20	Barangay 775, San Andres, Manila City	3,496 households

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Date of distribution	Barangay and city	Beneficiaries
	Barangay 773, San Andres, Manila City	1,218 households
	Barangay 772, San Andres, Manila City	1,102 households
	Barangay 770, San Andres, Manila City	2,818 households
08-May-20	Barangay Sta. Ana, Pateros City	2,443 households
09-May-20	Barangay Western Bicutan, Taguig City	847 households
	Barangay San Agustin, Malabon City	3,454 households
	Barangay Gen. T. De Leon, Valenzuela City (Additional)	1,749 households
15-May-20	Barangay Paglingon, Taguig City	3,994 households
19-May-20	Barangay 184, Pasay City	5,173 households
20-May-20	Barangay Poblacion, Mandaluyong City	5,833 households

Source: ADB. 2021. *Bayan Bayanihan: A food program for Filipino families*. <https://www.adb.org/what-we-do/bayan-bayanihan> (accessed on 13 November 2021).

Table A2: Means and T-tests of Covariates for Bayan Bayanihan Beneficiaries Across Weekly Groupings

Panel A. Means by weekly grouping						
	1	2	3	4	5	6
Number of poor people*	869	2,788	1,143	3,295	1,608	351
Proportion of poor people	0.042	0.048	0.046	0.045	0.025	0.024
Access to market indicator	0.750	0.750	0.600	0.500	0.667	0.000

Panel B. Means and t-tests by biweekly grouping							
		Biweekly 1 and 2		Biweekly 1 and 3		Biweekly 2 and 3	
		1	2	1	3	2	3
Number of poor people*	Mean	2,148	2,100	2,148	1,294	2,100	1,294
	p-value	0.3836		0.000		0.000	
Proportion of poor people	Mean	0.0459	0.0457	0.0459	0.0245	0.0457	0.0245
	p-value	0.4891		0.000		0.000	
Access to market indicator	Mean	0.750	0.556	0.750	0.500	0.556	0.500
	p-value	0.000		0.000		0.002	
No. of Observations		3,280	2,457	3,280	2,185	2,457	2,185

Note: *Number of poor people for 2015, estimated by machine learning. Reported p-values for t-ratios test against $H_1: diff \neq 0$.

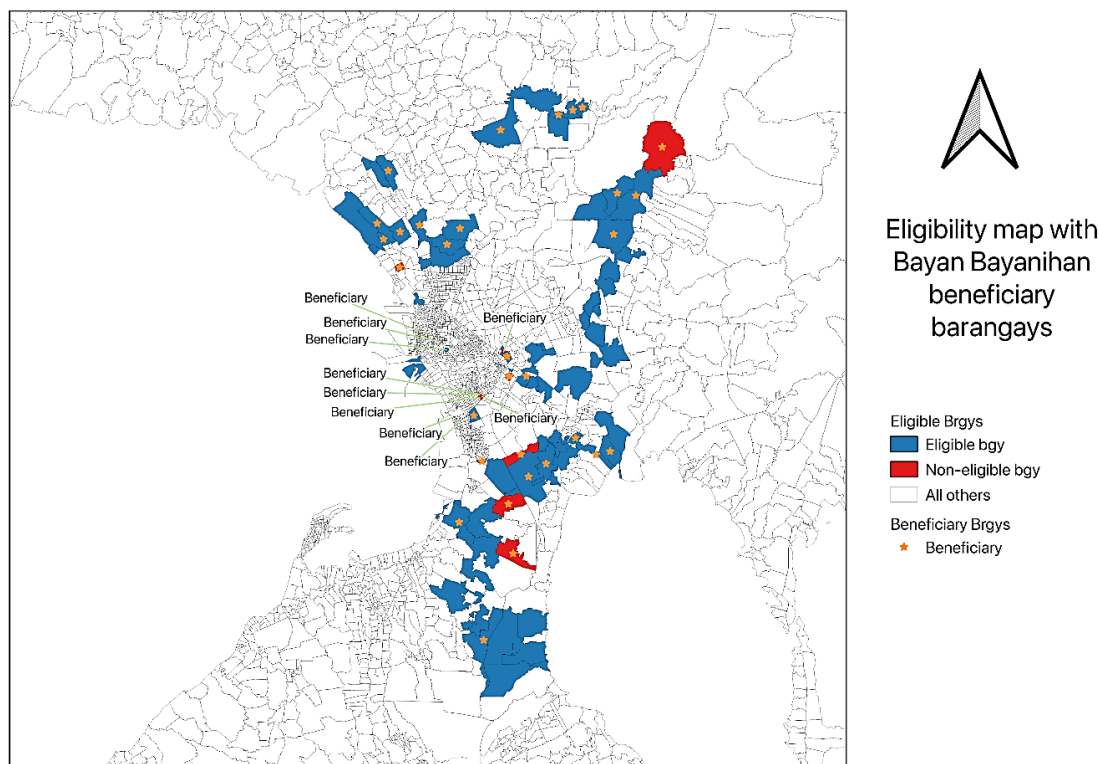
Source: Authors' calculations.

Table A3: Summarized Correlation Matrix for Confirmed Cases and the Measures of Mobility

	Inward Mobility	Outward Mobility	Within Mobility
Confirmed	0.556	0.5559	0.5469
Confirmed (Lead 7 days)	0.2912	0.2912	0.2858
Confirmed (Lead 3 days)	0.2727	0.2727	0.2685

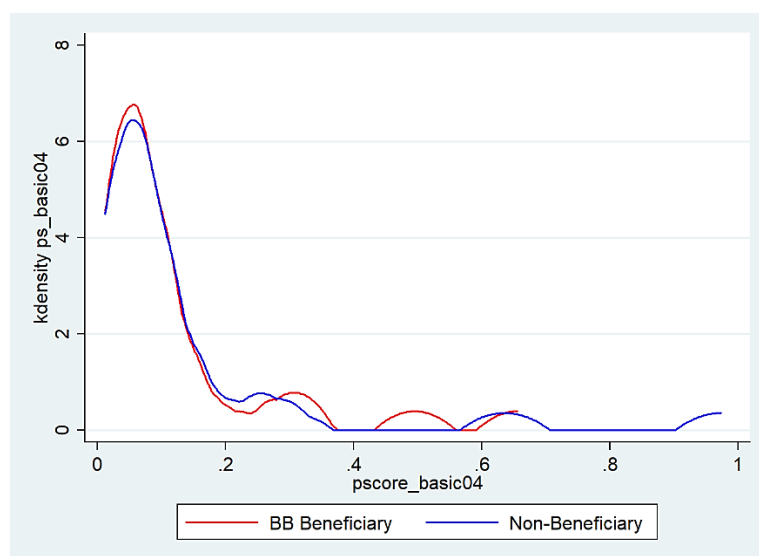
Source: Authors' calculations.

Figure A1. Eligible Barangays Identified by the ADB's Data Division plus Bayan Bayanihan Beneficiary Barangays



Source: ADB. 2021. *Bayan Bayanihan: A food program for Filipino families*. <https://www.adb.org/what-we-do/bayan-bayanihan> (accessed on 13 November 2021).

Figure A2: Kernel Density Graphs of Propensity Scores of Treated and Untreated Barangays Given the Extent of Poverty and Access to Markets



Propensity scores of treated and untreated barangays based on extent of poverty and access to a market.
 Source: Authors' calculations.

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COVID-19, Food Relief, and Social Distancing

Evidence from the Bayan Bayanihan Program in the Philippines

This paper evaluates the impact of in-kind transfers on social distancing by examining the effectiveness of the Bayan Bayanihan Program in restricting mobility by enabling households to stay at home. It uses random variations in the timing of the rollout of the program by employing recent developments in estimating staggered difference-in-differences strategies to more accurately identify the effect of the program. It finds supportive evidence that the program could generally discourage mobility. Findings suggest that in addition to mitigating food insecurity, food transfer programs can also generate multiple dividends by helping families stay home and reducing the spread of COVID-19.

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