Household Response to a Guaranteed Income Policy: Evidence from a Randomized Experiment in Compton, California
Pre-Analysis Plan*

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Abstract

Government-provided income support and variants of cash transfer programs are prominent in new thinking about safety nets. In the US, for example, proposals include expansions of the Earned Income Tax Credit, implementing a negative income tax (NIT) and demonstrations and pilots of income support and cash transfer programs. In this project, we will study the impact of an ongoing guaranteed income program to low-income families in the City of Compton, CA using a randomized controlled trial. Launched in February 2021, in collaboration with the Fund for Guaranteed Income (F4GI), the Compton Community Development Corporation is delivering an unconditional guaranteed income to 698 low-income households for a period of 24 months, with an additional 1,402 households serving as the control group. Among the treatment group, the timing of transfers has been randomized such that half of recipient households receive transfers twice each month, while the other half receive transfers once per quarter. We will survey participants on two occasions, 4–6 months apart, using a comprehensive questionnaire that measures material, social, and psychological outcomes. We will also make use of administrative data whenever linkages are possible on housing and neighborhood characteristics, health care usage, child education, credit score, and criminal activity.

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1 Design of the Cash Transfer Program

Among eligible households (see eligibility criteria below), 2,100 were randomly chosen for study participation. Of these, 1,402 were randomly allocated to the control group, and 698 to the treatment group. Recipient households receive transfers of on average $6,400 per year. Transfers vary with the number of dependents, from $3,600 per year if the household includes no dependents, to $7,200 per year if the household has two or more dependents. Given that the average gross income of our sample is close to $25,000, the larger transfers correspond to approximately 25% of recipients' income. Among treated households, half of the recipients (349) receive a transfer twice each month, while the other half (349) receive transfers once per quarter. These transfers will continue for a total of 24 months. Once enrolled, the transfers are delivered to recipients unconditionally.

2 Disbursement of Cash Transfers

Disbursement of cash transfers is managed by the Compton Community Development Corporation (CCDC) and the Fund for Guaranteed Income (F4GI). Participants were given full information regarding the magnitude of the transfers, when they will receive those transfers, and the date on which the transfers will end. Transfers are being made through an online cash transfer platform provided by the Compton Pledge that provides recipients a range of payment methods including direct deposit, PayPal, and prepaid debit cards.

3 Sample Selection, Stratification and Enrollment

3.1 Eligibility and Stratification

Households were eligible if they were located in the City of Compton, California, had at least one household member aged 23 to 57, and were below 220% of the 2020 federal poverty threshold. Individuals receiving Social Security Income (SSI) and disability benefits (SSDI) were excluded from the study because cash transfers may affect these benefits. There were no other requirements for program eligibility. Undocumented households and formerly incarcerated populations were not excluded. The sample was stratified by sex. See Table 1 for enrollment by date.

3.2 Recruitment and Enrollment

To recruit individuals into the study, we obtained the contact information of potential study participants from the Compton 2018 and 2020 voter list, the Compton Public Housing list, community organization lists, and a random digit dialing sample. Using email, SMS messaging, voice calls, and mailers, we invited the individuals from these lists to participate in a well-being study for the City of Compton. To participate, people were asked to fill out a short survey which asked for

their name, age, sex, whether or not they had a disability, SSI/SSDI status, email address, mailing address, phone number, number of household members, number of minors in the household, and household income. Based on the responses to this initial screening survey, we determined whether respondents met the eligibility criteria for the study (cf. Section 3.1).

Our sample of 2,100 eligible households was created through 4 rounds of recruitment conducted on 4 separate dates (February 5th, February 19th, March 15th and March 25th, 2021):

Date	Total Surveys Filled	Total Eligible
February 5, 2021	889	538
February 19, 2021	446	317
March 15, 2021	1,681	1,015
March 25, 2021	299	230
Total	**3,315**	**2,100**

Table 1: Enrollment Assignment by Date

3.3 Assignment to Treatment Groups

We allocated 66.76% of our sample to the control group and 33.24% to the treatment group. The shares differ somewhat across the four rounds of recruitment due to requirements by the CCDC to expedite the launch of cash transfers; see Section 4.1. Table 2 presents the total number of treated participants in each recruitment round.

Date	Total Treatment	Quarterly	Bi-monthly	Control	Total respondents
February 5, 2021	296	152	144	242	538
February 19, 2021	167	82	85	150	317
March 15, 2021	196	97	99	819	1,015
March 25, 2021	39	20	19	191	230
Total	**698**	**351**	**347**	**1,402**	**2,100**

Table 2: Treatment Assignment by Date

4 Econometric Specifications

4.1 Enrollment Balance

To assess enrollment balance, we use the standard approach of regressing the outcome variables of interest as measured at baseline on the treatment indicators. To guarantee the comparability of the enrollments, we assign weights in each round so we have the same target proportion of treated and control households after weighting. The weights are therefore as follows:

$$\text{Weight Control}_t = \frac{\text{Target Share Control}_t}{\text{Actual Share Control}_t} \tag{1}$$

for the control group, and

$$\text{Weight Treated}_t = \frac{\text{Target Share Treated}_t}{\text{Actual Share Treated}_t} \tag{2}$$

for the treatment groups (bimonthly and quarterly), where t is the recruitment round. With these weights, we run regression (3) for the following variables measured at recruitment: household income; number of people in the household; number of minors in the household; an indicator for the respondent being Hispanic; an indicator for the respondent being Black or African American; age; and sex:

$$y_i = \beta_0 + \beta_1 T_i + \varepsilon_i \tag{3}$$

Where i is the individual and T_i is a treatment dummy. Weights are assigned following (1) and (2).

Finally, we test for joint significance across all outcomes of interest using seemingly unrelated regression (SUR).

4.2 Attrition

We will use three approaches to assess the severity of attrition. First, we test whether attrition is correlated with treatment by regressing an indicator variable for whether a participant attrited on the treatment indicators. Second, we test whether attriters differ from non-attriters by asking whether attrition status can be predicted from baseline outcomes and stratification variables. Finally, we test whether baseline characteristics of attriters in the treatment group are different from those of attriters in the control group by restricting the sample to attriters and regressing on baseline outcomes on treatment assignment. If we find worrying levels of attrition, we will conduct robustness checks in which we use matching and bounding techniques to obtain corrected or bounded estimates.

4.3 Estimating Equations

The main equation to assess treatment effects of transfers across both frequency treatments arms is:

$$y_{iE_t} = \beta_0 + \beta_1 T_i + \gamma' X_i + \delta E_2 + \varepsilon_i \tag{4}$$

The equation to analyze the treatment effects of the frequency randomization is:

$$y_{iE_t} = \beta_0 + \beta_1 T_i^{\text{High Frequency}} + \beta_2 T_i^{\text{Low Frequency}} + \gamma' X_i + \delta E_2 + \varepsilon_i \tag{5}$$

Here y_{iE_t} is an outcome of individual or household i measured at endline E_t, where t takes value 1 or 2 depending on the survey round. E_2 is a dummy variable for the second survey round. $T_i^{\text{High Frequency}}$ and $T_i^{\text{Low Frequency}}$are treatment indicators for high-frequency and low-frequency transfers, respectively; and X_i is a vector of controls, including household income, number of

people in the household, number of minors in the household, an indicator for the respondent being Hispanic, an indicator for the respondent being black or African American, age, and sex. We do not include a baseline term in the equations above because we do not have baseline data on all outcomes, but we will include a baseline term for the outcomes which we do observe at baseline. The error term is ε_i . Because the trial is not clustered, neither are the standard errors (except in cases where there is more than one respondent per household, in which case we cluster at the household level; if multiple respondents per household differ in treatment status, the household will be considered partially treated). The coefficient β_1 in (4) captures the average effect of treatment across the high- and low-frequency treatment groups, and β_1 and β_2 in (5) capture the separate effects of high- and low-frequency transfers.

4.4 Heterogenous Treatment Effects

We test for heterogeneous treatment effects along three dimensions:

1. Race/ethnicity (Black, Hispanic, White)
2. Income at baseline (median split)
3. A dummy for the receipt of the American Rescue Plan/Child Tax Credit, conditional on whether the household has children
4. Sex (indicator for female respondent/recipient)

The econometric specification for heterogeneous treatment effects is as follows:

$$y_{iE_t} = \beta_0 + \beta_1 T_i + \beta_2 T_i \times H_i + \beta_3 H_i + \gamma' X_i + \delta E_2 + \varepsilon_i \tag{6}$$

Here, H_i is an indicator variable for the dimension of heterogeneity. Note that this specification averages across the high- and low-frequency treatment groups. Analogous regressions will be run for the cross-randomization.

4.5 Multiple Comparisons

To adjust for multiple comparisons during analysis, we define an index or focal variable for each of several outcome families. We then apply the false discovery rate across these summary variables (Anderson, 2008). The correction will be applied across outcomes, but not across the high- and low-frequency treatment arms. We will not adjust for multiple inference within outcome families.

5 Outcome Variables

Primary outcomes are marked with an asterisk (*), and secondary outcomes are marked with an obelus (†). The remainder of the outcomes listed are exploratory analysis.

Income and Employment

Focal variable: Labor supply in hours*

Index: sum of total income from 6.*

1. Participation in the labor market (formal, informal and self-employment jobs; dummy variable)
2. Participation in unpaid work (care and housework; dummy variable)†
3. Satisfaction with employment situation (five-point Likert scale)
4. Whether or not respondent has been looking for work (dummy variable)
5. Whether or not respondent would like to be working more than current situation (dummy variable)
6. Income
   (a) Income earned in the labor market Income from rent payments, dividends or interest
   (b) Income from other household members
   (c) Unemployment insurance benefits
   (d) Social Security (OASDI) or Supplemental Security Income (SSI)
   (e) CalWorks benefits
   (f) CalFresh/SNAP/WIC benefits
   (g) Income from any other sources (excluding transfers from relatives)

Expenditure and Consumption

Index: Total per capita expenditure.*

1. Alcohol and tobacco consumption elicited using a list experiment†
2. Consumption expenditure
   (a) Food and drinks at home
   (b) Food and drinks outside the home
   (c) Alcohol†
   (d) Cigarettes and tobacco†
   (e) Lottery tickets
   (f) Apparel
   (g) Home expenditure

i. Mortgage payment
ii. Rent
iii. Utilities
iv. Internet and phone bills

(h) Health expenditure
(i) Child and elder care expenditure
(j) Education expenditure
(k) Vehicle expenditure
(l) Transportation expenditure

Physical and Psychological Well-being

Indices: Standardized PCA index of 2.–6.*

1. Self-assessment of physical health (1–5)
2. Depression frequency (1–5)
3. Stress frequency (1–5)
4. Self-assessment of life satisfaction (1–10)
5. Self-assessment of happiness (1–4)
6. Kessler 6 questionnaire

Financial precarity

Index: Standardized index of 1.–6.*

1. Whether or not the household can cope with a $400 emergency bill (binary variable where 0 = "household must go into debt to handle the expense or cannot handle the expense" and 1 = "the household can pay for the expense with current resources")
2. Whether or not household could pay all bills in past 30 days (dummy variable)
3. Whether or not household could put money aside for future in past 30 days (dummy variable)
4. Whether or not household could pay down debt in past 30 days (dummy variable)
5. Whether or not household had to ever forgo medical care over the last six months because of expense (dummy variable)
6. Whether or not respondent has health insurance (dummy variable)

Food insecurity

Index: Standardized index of 1.–2.*

1. Whether or not anyone in household had to eat less than they felt they should in past 30 days (dummy variable)
2. Whether or not household had to eat a lower quality diet because of cost in past 30 days (dummy variable)

Time use

1. Time spent on unpaid child or eldercare (daily hours over the past 7 days)
2. Time spent asleep (daily hours over the past 7 days)

Assets and Debts

Index: Total sum of movable assets and savings minus total debts*

1. Value of liquid assets held by household members
2. Total dollar amount held in retirement accounts by household members
3. Value of business owned by household members
4. Total dollar amount owed on mortgages and all other loans by household members
5. Value of home if owned
6. Total dollar amount of loans from relatives
7. Total dollar amount of loans to relatives
8. Total dollar amount of gifts from relatives
9. Total dollar amount of gifts to relatives
10. Total dollar amount of student loans owed by household members
11. Total dollar amount owed on credit cards by household members
12. Total dollar amount of medical debt owed by household members
13. Total dollar amount of any other debt (vehicle loans, legal bills, etc.) owed by household members
14. Net change in total value of durable goods since January 2021 across the following categories[1]:

[1] We will obtain the value of these items from existing sources.

(a) Washing machine
(b) Clothes dryer
(c) Dishwasher
(d) Microwave oven
(e) Vacuum cleaner
(f) Home entertainment system with television and audio
(g) Gaming console
(h) Gym equipment
(i) Air conditioner
(j) Valuable jewelry or watches
(k) Musical instruments
(l) Power tools
(m) Other real estate in the U.S. or another country
(n) Computer or tablet
(o) Mobile phone
(p) Car or truck
(q) Motorcycle
(r) Bicycle
(s) Weapons

COVID-19

1. Whether or not any household member has had COVID-19
2. Whether or not any household member has died of COVID-19

Intimate Partner Relationships

Index: Standardized index of 1.–3.[†]

1. Intimate partner violence (IPV) elicited using a list experiment (dummy variable)
2. Whether or not respondent was physically abused by partner (dummy variable)
3. Whether or not respondent was forced into physical intimacy by partner (dummy variable)

Housing

Index: Standardized index of 1.–4.[†]

1. Housing security (binary variable)
2. Housing security (Likert scale)
3. Number of months behind on rent
4. Ability to pay rent/mortgage (dummy variable)
5. Likelihood of eviction (Four-point Likert scale)
6. Number of months behind on rent/mortgage
7. Crowding: Number of household members divided by the number of bedrooms in house

Political engagement

1. Whether or not respondent voted in 2021 mayoral election (dummy variable)
2. Trust in government officials (four-point Likert scale)

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