Pre-Analysis Plan for

*Can Emergency Financial Assistance Prevent Financial Distress? Randomized Evidence from Funeral Assistance in Chicago*[*]

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# Contents



[*]This pre-analysis plan was finalized after study enrollment and randomization was completed but before any outcome data was received or analyzed. Only survey data collected at baseline has been analyzed and is summarized in the Appendix. Our main outcomes are sourced from Experian credit bureau records, which are shared with LEO on a quarterly basis with about a 12-15 month lag. At study launch, we registered a description of the study design, planned analyses, and outcomes on the AEA RCT Registry: https://doi.org/10.1257/rct.11031-1.2.

# I Overview

This is a pre-analysis plan for the randomized evaluation of emergency financial assistance covering burial and funeral expenses for low-income families living in the Chicago metro area. We begin with background and motivation for the study in Section II. Section III describes the research questions, study population, eligibility criteria, and enrollment and randomization processes. Section IV describes our planned data sources, and Section V defines primary and secondary outcomes. In Section VI, we present and discuss our power calculations, and conclude with a discussion of our empirical strategy in Section VII.

# II Background

One in three adults report they could not pay a $400 emergency expense with cash (Board of Governors of the Federal Reserve System, 2022). Despite this, emergency expenses are common. For example, 16 percent of adults experienced a financial disruption or hardship from a natural disaster or severe weather event in the prior year. One common financial disruption occurs when a close family member or friend dies, as the cost of a funeral and burial services are substantial. In 2021, the nationwide median rate for a funeral with viewing and burial was $7,848.[1] These expenses are hard to avoid for cultural and religious reasons, as nearly all deaths in the U.S. result in cremation or burial.[2] About 1 in 50 households experience a death each year.[3] Notably, low-income and Black households are disproportionately affected by these emergency expenses (Umberson et al., 2017; Sorlie et al., 1995).

Emergency cash assistance programs may provide support to low-income households in situations where urgent expenditures arise. The stimulus checks that were issued as part of the federal COVID-19 pandemic relief program have been shown to help at-risk households pay down debt and build a financial buffer for emergency expenditures (Coibion et al., 2020). Catholic Charities of the Archdiocese of Chicago (CCAC)'s burial assistance program is designed to allow for similar relief by providing financial support for low-income households who are facing the financial burden of a relative's funeral or burial. This financial assistance is meant to provide a buffer to prevent excessive borrowing, default, or bankruptcy. It is distinct from other interventions that relieve existing debt instead of preventing imminent debt, and may therefore differ in its impacts (e.g., Di Maggio et al., 2019; Dobbie et al., 2017; Dobbie and Song, 2020; Ganong and Noel, 2020; Dobbie and Song, 2015; Kluender et al., 2024). Further, the type of intervention we study here differs in particular from relieving medical debt, which has a low recovery rate compared to other types of debt (Kluender et al., 2024).

Despite the frequency of unavoidable emergency expenses for low-income households, there is little evidence on how low-income households weather negative financial shocks and the extent to which large emergency expenses could generate a debt-induced poverty trap.

[1]The median rate for a funeral with viewing and cremation was $6,970(NFDA, 2021).

[2]Annual deaths from the CDC and the 2021 NFDA Cremation & Burial Report.

[3]We estimate this statistic by combining two facts: There is an average of about 833 deaths per 100,000 annually, and an average household size of 2.7. Crude annual death rate per 100,000 from CDC Wonder for the years 1999-2019.

Mello (2021) finds that an unanticipated traffic ticket, with an average cost of \$195, leads to a 13% increase in the number of collections and a 3% increase in total collection balances. He shows that these fines also increase employment instability for low-income individuals, in part due to related driving sanctions. Other research has focused on significant life events, such as hospital admissions or job loss, finding that these events lead to increased risk of bankruptcy, poor credit outcomes, and long-term reductions in consumption (Dobkin et al., 2018; Stephens Jr, 2001; Keys, 2018). Low-income households, minority households, and households with lower levels of educational attainment are most at risk when facing an urgent expenditure due to limited liquidity and greater reliance on borrowing.

The burial assistance program we study operates in the greater Chicago area. 97% of participating households are Black or Hispanic and median household income is around \$17,000. Households that are randomized into the treatment group will receive up to \$8,000 towards burial and funeral expenses while those randomized into the control group will receive \$1,000. The cost of services is, on average, \$6,700, meaning that treatment-control differences in out-of-pocket burial and funeral expenses is about one-third of median annual household income. Importantly, all financial support was provided "in kind": CCAC directly paid for burial and funeral services and no support was provided without an invoice.

For cultural and religious reasons, households often carry through with the funeral service and burial even if they cannot afford to do so. Without financial support, households are more likely to deplete their savings, pay on credit, or rely on payday loans. While descriptive studies elucidate the hardships associated with emergency expenses among low-income households (e.g. Desmond (2016); Morduch and Schneider (2017), more evidence is needed on how financial shocks may ripple into downstream borrowing, debt, housing insecurity, reduced earnings, or even job loss. Using administrative data sources, the control group will provide the lens to study such ripple effects. We will be able to see how a substantial financial shock – amounting to 20-40% of annual household income – affects important quality-of-life outcomes, such as credit market measures, employment, earnings, eviction filings, use of homelessness services, and housing stability.

The treatment group, on the other hand, provides information on the potential of emergency financial assistance (EFA) to mitigate related economic hardship. While there are over thirty local experiments studying guaranteed basic income (GBI) for low-income households (Stanford Basic Income Lab, 2024), less attention has been paid to emergency financial assistance for low-income households. Two studies have shown that one-time financial assistance to households at risk of imminent homelessness for use toward rent, security deposits, or utility bills, reduced the likelihood of entering a homeless shelter by 76 percent or more (Evans et al., 2016; Phillips and Sullivan, 2022). The burial assistance program we will study here is similarly geared toward families facing an immediate financial hardship that, if left unaddressed, could force households into debt and become further entrenched in poverty.

More broadly, this program provides an example of an EFA program that, if implemented widely, could insure low-income households against prolonged financial hardship. Since past income and the timing of these events are difficult to manipulate, EFA programs may also be less likely to distort labor market participation relative to GBI. Further, by targeting assistance to households when they realize a very bad state, the marginal value of assistance may be higher than typical transfers. Burial and funeral support could fit into a broader suite of emergencies that could qualify low-income families for financial assistance that protects them against realizing extreme economic hardships that are difficult to recover from.

# III Study Design

## A Research Questions

1. Primary: What is the impact of receiving large burial and funeral assistance (up to $8,000) compared to low burial and funeral assistance ($1,000) on financial distress (delinquency, debt, and payday borrowing)?

2. Secondary:

    - What is the impact of receiving large burial and funeral assistance (up to $8,000) compared to low burial and funeral assistance ($1,000) on credit access, housing stability, and labor market outcomes (earnings and employment)?
    - What is the impact of both experiencing a familial death and receiving burial and funeral assistance up to $8,000 on the aforementioned outcomes (comparing treatment group to similar families outside of the RCT)?
    - What is the impact of both experiencing a familial death and receiving burial and funeral assistance up to $1,000 on the aforementioned outcomes (comparing treatment group to similar families outside of the RCT)?

## B Enrollment Process & Eligibility Criteria

For the evaluation, CCAC agreed to cover the full cost of burial and funeral services (up to $8,000) for households randomized into the treatment group. The control group received $1,000 towards burial and funeral services, similar to CCAC's previous support limits and the level of support provided by local government programs. Importantly, all financial support was directly to the burial and funeral service providers; no support was provided without an invoice.

Individuals seeking financial assistance with a funeral or burial called into the CCAC hotline and were directed to the funeral and burial assistance team. The client was then told about the burial assistance program and the research study. Interested clients were asked to provide finalized invoices for funeral and burial, documentation verifying household income, a consent form required for participation in the program, and a voluntary consent form for participation in the study. With this paperwork complete, the intake staff completed a short Qualtrics survey over the phone, regardless of study consent. This survey consisted of two sections: eligibility and intake.

There were two separate components to the eligibility screen: eligibility for the program and eligibility for the study.

Program Eligibility

Callers were eligible for the burial assistance program if they met the following criteria:

- Had income at 40% Area Median Income (AMI) or below[4]
- The deceased was not themself or the spouse of an honorably discharged veteran (honorably discharged veterans were referred to the Veterans Funeral Assistance program)
- The total cost on their invoice was below $12,000

CCAC then confirmed callers' income by asking them to provide proof of income (for example, pay stub, benefit letters, letters from employer, etc.), or, if they did not have proof of income, asking them to complete a self-attestation form. CCAC ensured that they had a copy of a caller's invoice and that the invoice was within the program's eligibility range before they began intake with the caller. In addition to these forms, callers completed a CCAC program consent form and a consent form for participation in the research study.

The goal of the $12,000 upper bound was to prevent very large bills, and if a caller had a bill above this threshold, CCAC worked with the caller to determine if there was anything that could be done to reduce the bill. Placing this limit on the size of invoices that were eligible for the program also served as a second way of ensuring that the program targeted those most in need, in addition to the income requirement. $12,000 was chosen as the cutoff as it was approximately equal to the largest historical requests.[5]

Clients who were eligible for the program completed the intake portion of the Qualtrics form with a CCAC staff member by phone. This form collected baseline demographic information on callers, their household, and the deceased, including their race, gender, age, and income. Once complete, the anonymous study IDs of consented (and eligible) households were automatically sent to a Google spreadsheet that randomized them into the Treatment or Control groups.[6]

Study Eligibility

Callers were be eligible for the study if they met the following criteria:

- Were eligible for the burial assistance program
- Consented to participate in the research study
- Had an invoice of $3,000 or more

The requirement that invoices had to be $3,000 or more for the client to be eligible for the study served two purposes. First, it ensured that the program was targeted towards those who were experiencing a more significant financial shock (and thus had higher need). Second,

[4]Implementing this income threshold allowed us to target the program to those who were most in need. In particular, we chose the cutoff of 40% AMI because past program experience has shown that 30% AMI cutoffs make it difficult to recruit enough people into programming, while 50% AMI cutoffs screen out very few people. We chose 40% AMI as a midpoint between these two, and at the beginning of the study, we closely monitored intake data to determine if this threshold needed to be adjusted.

[5]During the study period, only two individuals reported invoices greater than $12,000. These individuals reported invoices of $12,253 and $13,631.

[6]Specifically, the spreadsheet randomized households by matching the caller with a pre-randomized list to determine treatment or control status. This list was only visible to the research team and not the intake staff so as to avoid any bias in assignments.

the cutoff increased statistical power by ensuring that there was a substantial difference between the financial assistance provided to treatment and control groups.

Those who did not consent to the study, including those who were ineligible for the study, automatically received $750 of assistance, while those who consented and were eligible were randomized to receive either $1,000 (control group) or the amount of their invoice up to $8,000 (treatment group). $750 was chosen as the minimum payment because it was large enough to provide substantive benefit to those who did not consent but also small enough that the majority of limited resources were directed towards those in the study.

To prevent coercion, we set the difference between the payments of the control group and non-consenting group at $250. Importantly, all enrollment and consenting materials did not mention the potential of the higher treatment group payment. Instead, it informed potential participants that they might receive an additional "$250 or more" if they participated in the study. This design allowed us to test a high "dosage" of financial support that eliminates debt for the overwhelming majority of the treatment group. All study processes were vetted and approved by the Institutional Review Board at the University of Notre Dame.

## C Background on Funeral and Burial Expenses

To set study payment amounts, LEO contacted 41 funeral homes in Chicago that had worked with previous CCAC clients and analyzed a random sample of 25 historical bills submitted to CCAC for reimbursement with redacted personal information. Bill amounts ranged from $4,375 - $11,344 and often involved a funeral and cremation or burial. About one-third of historical invoices did not include cemetery expenses, so even if a participant is randomized to the treatment group, they may still face some additional expenses.[7]

## D Randomization Procedure

To maximize power given a limited amount of funds, we initially randomized a 1:2 ratio of Treatment to Control households. However, in October 2023 we switched to a 1:1 ratio in order to deplete all allocated funds by the end of the calendar year[8]. We stratified the total invoice amount so that burial and funeral expenses were balanced across treatment and control groups. In particular, we drew on the distribution of expenses gleaned from our random sample of 25 historical bills to predict equally sized expense bins. The resulting bins were: $3,000-5,000; $5,000-6,500; $6,500-8,000; ≥$8,000. Bin-specific randomized lists were generated using Stata and were integrated into the intake workflow using Google Sheets. Importantly, treatment assignment was automatically assigned upon completion of the intake survey and was not visible to intake staff ex ante.[9]

Tables A.4 and A.3 in the Appendix show mean baseline characteristics for the treatment and control groups. Callers tend to be married, middle-aged, female, Black or Hispanic, and have a high school education. The deceased tend to be men of color. We find observable characteristics across treatment and control groups are balanced: an F-test that compares the joint distribution of payer characteristics across the two groups yields a p-value of 0.569.

[7] See the Appendix for further details on these exercises.

[8] A donor provided $2 million for this research to be spent by the end of 2023, of which $1.8 million was used directly for burial assistance payments.

[9] Only the research staff had access to the randomized lists.

# IV Data

We anticipate using five data sources for this research. Our main outcomes will come from Experian's quarterly credit bureau records and, if available, Clarity Services. The second source is survey data gathered for both study groups in the baseline survey. The third source is court data from eviction proceedings in Cook County. The fourth includes information on homelessness and housing insecurity sourced from Cook County HMIS records. Fifth, we would like to explore employment and earnings information available in Illinois Unemployment Insurance data or IRS tax records. Below we provide information on each potential data source.

## A Financial Health

Quarterly credit bureau data will comprise our main outcomes, allowing us to study impacts on the financial health of participants. We plan to purchase panel data from Experian that will provide quarterly information on how a given participant's financial health evolves over the year prior to receiving financial assistance and throughout the post-assistance period. These data provide comprehensive consumer credit and borrowing information gleaned from public records, collection agencies, and trade lines (such as credit card balances, auto loans, and mortgages). Quarterly pulls of these data will allow for panel measures of credit balances, credit scores, unpaid bills, delinquencies, and bankruptcy. We plan to purchase additional financial health data from Clarity Services. Clarity has data on over 70% of subprime users in the United States and includes information on payday credit outcomes (Miller and Soo, 2020).

## B Baseline Survey

Prior to randomization, all potential participants complete a baseline survey. This survey contains detailed demographic questions about the deceased, the caller, and their household. For the caller, we collect information on race, age, SSI receipt, address, marital status, educational attainment, household composition, household income, and personal identifiers, such as date of birth and SSN/ITIN, for data linkage purposes. CCAC also collects information on the total cost of burial and funeral services submitted for reimbursement.

## C Homeless Management Information System Records

As described in Collinson et al. (2022) and Evans et al. (2016), the Cook County HMIS database is managed by All Chicago and includes individual-level information on stays in emergency shelters as well as other interactions with homelessness prevention services. The database is managed by All Chicago, is linked to Census identifiers, and can be studied within the Census RDC.

## D Eviction Court Records

We plan to request court records on eviction cases in the Forcible Entry and Detainer Section of the Circuit Court of Cook County. Cook County contains the entirety of the City of Chicago and eviction cases filed in the city represent about three-quarters of the county's case volume (Collinson et al., 2022). Using data from 2022 through 2025, we aim to characterize the likelihood of a landlord filing an eviction case against a study participant in the one-year lead-up and two-year aftermath of financial assistance.

## E Labor Market Information

We hope to link our study sample to employment and earnings from Illinois Unemployment Insurance (UI) records. UI records are stored in the Longitudinal Employer-Household Dynamics (LEHD) Employer History File, a restricted Census Bureau data set.[10] As in Collinson et al. (2022), we will measure employment as a flag for having any positive earnings in any of the fifty states or the District of Columbia. Quarterly earnings data are available in the LEHD for Illinois, the District of Columbia, and several other states that grant access to researchers.

# V Outcomes

## A Primary Outcomes

We are primarily interested in understanding how emergency financial assistance may protect low-income households from experiencing financial distress and the downstream consequences of that financial distress. Our main outcome will therefore aggregate rich consumer credit data into a singular measure of financial distress. Our main index will be comprised of two separate indices – a delinquency index and a payday borrowing index. These indices are adapted from Miller and Soo (2021) and Collinson et al. (2022). Together, they provide a holistic measure of financial distress. The exact variables that enter these indices may also change as we learn more about data availability and quality.

Following Kling et al. (2007), each component of the index will be standardized based on the control mean and standard deviation in the year prior to receipt of financial assistance. Each component will then be summed, assigning directions to components such that they appropriately point in the direction of financial distress, and then we will re-standardize the aggregated index using the control group mean and standard deviation in the year prior to receipt of financial assistance. All other standardized indices described in B will be constructed in a similar manner.

Delinquency Index

- Amount held 30 days past due or more on all open accounts (e.g., overdue credit bill)
- Amount held 90 days past due or more on all open accounts
- Amount in tax liens or overdue taxes
- Amount ordered to be paid by a court judgment (e.g., unpaid rent cases or child support)
- Debt past due held by third-party collection agencies

[10] See Vilhuber et al. (2018), for more details.

- Credit utilization (e.g., % of credit card limit used across all credit cards)

We would like to collect information on payday loans from Clarity, as used in Miller and Soo (2021) and Collinson et al. (2022). Clarity maintains the largest database of subprime borrowers, containing over 62 million unique consumers and covering about 70% of payday loans. It is unclear whether these data will become available for this research. If they are, we will construct an index using some or all of the following variables (depending on data availability and quality).

Payday Borrowing Index

- Amount borrowed across all payday loans
- Amount borrowed across payday loans taken out online
- Payday amounts borrowed in person at physical storefronts
- Any payday loan inquiry
- Number of payday loan inquiries
- Any payday loan
- Number of payday loans

Historical credit bureau data and baseline survey information will allow us to evaluate the comparability of treatment and control samples that survive the match to credit bureau data. We also plan to probe the source of collections prior to randomization so as to understand factors that contributed to participants' financial hardship. For example, we can explore how collections are distributed across Experian's six categories: student loans, non-medical, medical, financial institutions (banking, financial, or credit union), retail, and utilities.

## B Secondary Outcomes

In addition to financial distress, we will explore three other outcome domains: credit access, housing stability, and labor market experience. To reduce the concern of multiple hypothesis testing, we will combine all of our four outcome indices – financial distress index, credit access index, housing instability index, and labor market index – into a central standardized index, applying equal weight to each index. To understand what drives aggregate effects, we will also report effects for each index and its sub-components. All of the below measures will be captured over the two years after the caller receives financial assistance. Data sources are denoted in brackets.

Credit Access Index

- Credit score estimated using VantageScore[11]

[11] A consumer's credit score uses their payment history, delinquencies, number of accounts, and credit applications to provide a numeric assessment of their "likelihood to be over 90 days delinquent on loans" (Miller and Soo, 2021).

- Indicator for any positive balance on an auto loan or lease, a proxy for durable good consumption (Dobkin et al., 2018; Collinson et al., 2022)
- Has a source of revolving credit, a proxy for having access to credit (−) (Collinson et al., 2022)
- Total amount of credit available on all accounts (Miller and Soo, 2021)
- Total credit limit across all active credit cards (Miller and Soo, 2021)

Housing Instability Index

- Any eviction filing [Eviction Court Records]
- Was ever evicted [Eviction Court Records]
- Any interaction with other homelessness prevention services [HMIS]
- Any stay in emergency shelter [HMIS]
- Number of interactions with homelessness services (or fraction of days spent in shelters if data are available) [HMIS]

Labor Market Index

- Quarterly earnings as captured in UI records[12]
- Indicator for having any positive earnings
- Indicators for having earnings above various thresholds (i.e. $15,000; $30,000; $50,000)

# VI Power Calculations

We enrolled 576 households in the study over the past year. 226 households (39%) were randomized into treatment and received assistance equal to the total cost of burial or funeral expenses (or up to $8,000). 350 households (61%)[13] were randomized into the control group and received $1,000 towards burial and funeral expenses. An additional 218 households were either ineligible due to a low invoice amount or did not consent to the research and received $750 towards burial and funeral expenses. Given the above sample size and conventional power assumptions, the minimal detectable effect size on a standardized index of credit

[12]As described in Collinson et al. (2022), UI records "only cover formal employment and exclude individuals not covered by UI benefits, such as the self-employed."

[13]Our partner received 1.8 million dollars to spend towards these services from March to December 2023. To improve power, we initially randomized one-third to treatment and two-thirds to control. When it became clear that the funds would not be depleted by the year's end, we switched to a 50-50 randomization scheme in October 2023. As a result, 39% of the sample was randomized into Treatment.

market outcomes is 0.21 standard deviations.[14] The minimum detectable effect size on a binary outcome with a base rate of 20%, such as having any bad credit market outcome, using HMIS services, or being unemployed, is at least 8.5 percentage points. Given these values, we are powered to detect a 8.5 percentage point decrease in negative credit market outcomes.

While it is difficult to predict the financial ramifications of the death of a relative, detectable effect sizes are considerably smaller than effects observed following a hospital admission or job loss (Dobkin et al., 2018; Stephens Jr, 2001; Keys, 2018) and within the range of effects found by Mello (2021) following a traffic ticket with an average cost of $195, a fee that is roughly 30 times smaller than treatment-control differences in our study.

# VII Empirical Strategy

## A Impact of High versus Low Assistance with Common Financial Shock

### A.1 Intention to Treat

Our primary specification estimates the impact of being offered large financial assistance (treatment) versus being offered "small" financial assistance (control) on financial outcomes. The basic specification is

$$y_{it} = \beta Treatment_i + \gamma y_i^0 + \alpha_{s(i,t)} + \epsilon_{it} \tag{1}$$

where $y_i$ is an outcome for enrolled participant $i$, $Treatment_i$ indicates whether participant $i$ was randomly assigned to the "high assistance" treatment group, $y_i^0$ is the dependent variable measured at baseline, and $\alpha_{s(i)}$ are strata fixed effects.[15] Our randomization procedure stratified on bill amount bins, so $\alpha_{s(i)}$ contains these fixed effects. These strata may also include fixed effects for time of enrollment (e.g. at the week, two week, or monthly level) if substantial time trends are apparent in the outcome data. The coefficient of interest $\beta$ estimates the average difference in outcomes between treatment and control groups, controlling for baseline outcome levels. This is our preferred specification provided that treatment and control groups do not meaningfully differ (by chance) in observable baseline characteristics.

We will also estimate treatment effects conditional on control vector $X_i'$ to account for any sampling variation in the composition of treatment and control groups and improve precision:

$$y_{it} = \beta Treatment_i + X_i'\delta + \gamma y_i^0 + \alpha_{s(i,t)} + \epsilon_{it} \tag{2}$$

$X_i'$ includes household-level controls that will be selected from the following variables collected on enrollment documents and baseline survey: household composition (size, children count, adult count), demographics of household head (gender, race and ethnicity, age bins),

[14] We make the following assumptions: 80% statistical power, 5% statistical significance, and 20% of the outcome variance is explained by controls and a lagged dependent variable. All power calculations are conducted in Stata using the "power" command.

[15] We will likely define $y_i^0$ over the year prior to the date of death, although the exact time window will depend on data availability and coverage.

religious affiliation, household income bins, and burial and funeral service information. To improve precision, we will select these variables based on their joint explanatory power, although we will show robustness to including all possible control variables.

### A.2 Treatment on Treated

We anticipate take-up to be over 95% given that both treatment and control groups will receive at least \$1,000 and that potential participants must complete their paperwork to be eligible for randomization. If take-up is close to 100%, we will focus on the intention-to-treat estimates. If take-up is lower than expected, then we will estimate treatment-on-treated effects using a two-stage least squares approach that instruments for program take-up with an indicator for assignment to the treatment group. Program take-up will be defined as an indicator for receiving any amount from CCAC that is greater than the \$3,000 cutoff.

## B Impact of Financial Shock with Low or High Assistance versus No Financial Shock

To estimate the dynamic effect of these shocks on the control and treatment groups, we plan to explore two different identification strategies: a standard event-study design, and a matched event-study design.

Dynamic effects on the control group is of particular interest: even though these households received \$1,000 in financial assistance, they still faced an average total bill of about \$6,370. The evolution of outcomes for this group can therefore provide insight on the impact of familial death, itself, on financial distress and other outcomes.

### B.1 Standard Event Study

Using a simple event-study design, we will explore the dynamic effect of a familial death with low or high financial assistance. separately for each study group. We will separately estimate the following estimating equation for each study group:

$$y_{it} = \sum_{\tau \neq 0} \delta_\tau + \kappa_t + \epsilon_{it} \tag{3}$$

in this equation, $\tau = t - j$ (j representing the number of quarters since the event) serves as an index for the time of the event. $\kappa_t$ represents panel fixed effects. We also may add individual fixed effects – $\phi_i$ – to control for confounding omitted variables that vary at the individual level (Mello, 2021). The comparison period is set at the quarter prior to the death of the study participant's relative.

### B.2 Matched Event Study

If data linkage is feasible, we are also interested in exploring how financial distress outcomes vary for both study groups relative to individuals who display similar characteristics in the pre-period but do not experience a funeral or burial shock. The matched event-study design will match study participants to individuals who display similar credit histories and have similar observable characteristics in the years prior to a family member's death. The appropriate matching approach may involve propensity score matching or coarsened exact matching. Such an analysis would complement the event-study approach by shedding light on the counterfactual: how would these households have fared without the familial death. This may be particularly important to characterize pre-trends and could improve our understanding of the generalizability of our findings.

For individual $i$ in matched group $g$, this approach takes the following form:

$$y_{it} = \sum_{\tau \neq 0} \delta_\tau^T Treat_\tau + \sum_{\tau \neq 0} \delta_\tau^C Control_\tau + \mu_g + \kappa_t + \epsilon_{it} \qquad (4)$$

where the reference period is the quarter prior to a relative's death and the omitted group includes individuals matched to participant $i$ using credit histories and demographic information. As before, we will explore specifications that add individual fixed effects ($\phi_i$). We may also re-weight observations to reflect our matching procedure and plan to validate our findings by exploring various placebo tests, such as by exploring treatment effects over an earlier period without a death.

## C Heterogeneity of Treatment Effects

This study will estimate the impact of burial and funeral financial assistance within several subgroups. Our focus will be on examining differences in treatment outcomes based on the size of the financial burden and whether the payer was of a working age. Additionally, if data is available, we will split treatment outcomes by the nature of death and the financial standing of the person who died. These sub-group analyses are summarized below.

1. Size of the financial shock: We will look at the differences in financial distress (delinquency, debt, and payday borrowing), credit access, housing stability, and labor market outcomes (earnings and employment) among those with a small financial shock compared to those with a large financial shock.

2. Elderly versus working age adults: We are also interested in examining the differences in the aforementioned outcomes by whether or not the payer is of a working age.

3. Unexpected nature of death (if available): If data is available on the nature of death, we will look at the difference in treatment outcomes by whether or not a death was unexpected.

4. Financial standing of person who died (if available): Additionally, we will look at the differences in treatment outcomes by the financial standing of the person who died.

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# I Appendix

## A Background on Funeral and Burial Expenses

LEO contacted 41 funeral homes in Chicago that had worked with previous CCAC clients to estimate the average cost of a basic funeral and burial. Funeral homes indicated that the cheapest option for families would be direct cremation with no funeral or burial of cremated remains (see Option A in Table A.1). The most typical option, as indicated by the calls with funeral homes, was the basic funeral package plus cemetery burial (Option D). However, families could forgo a funeral and have only a burial, which required cremation (Option C).

Table A.1: Average Price of Basic Cremation, Funeral and Burial Services in Chicago Area

| | **Average Price** | **Option A** | **Option B** | **Option C** | **Option D** |
|---|---|---|---|---|---|
| Direct Cremation[c] | \$2,400 | X | X | X | |
| Basic Funeral Package[c] | \$6,800[a] | | X | | |
| Cemetery[c] | \$4,800[a] | | | X | X |
| Price Range | | \$0.7-5.3k | \$4-7k[b] | \$4-7.2k | \$7-11.6k |

(a) Only one quarter of the funeral homes indicated their funeral package was \$5,000 or less. Similarly for cemeteries, only one quarter of those called indicated it would be possible to bury someone for less than \$4,000. While direct burial is also an option, funeral homes told us it was extremely rare.

(b) Some of the services are common between columns (1) and (2), so the total price may be less than the sum.

(c) Direct cremation typically includes transport, refrigeration, crematorium, fee, medical examiner fee, death, certificate(s), and an urn. The basic funeral package typically includes transport, refrigeration, death certificate, washing, dressing, casket, one night visitation, hearse and hearse driver. It sometimes includes obituaries, pamphlets, videos, and prayer cards (does not include church cost and does not usually include flowers). Cemetery typically includes a lot, grave, opening, grave closing, cement vault, and tombstone.

In addition, LEO received a random sample of 25 historical bills submitted to CCAC for reimbursement with redacted personal information, which are summarized in Table A.2 below. Historically, bills submitted to CCAC for reimbursement ranged from \$4,375 - \$11,344. Options B, D.1, and D.2 were most common. Option D.2 involves individuals who do not receive help paying for cemetery costs, and thus likely have paid for these additional expenses out of pocket. Overall, bills received by CCAC in the past were about \$1,000 lower than the quoted prices in Table A.2 in part because they often included a “friends and family” discount provided by funeral homes to CCAC. Based on these data, we believe that \$8,000 is a reasonable cap on assistance provided by CCAC since it would allow CCAC to cover all or a significant portion of both funeral and burial expenses.

Table A.2: Average Price of Funeral and Burial Services

| | Fraction of Bills | Average Cost | Range |
|---|---|---|---|
| Option A: Cremation Only | 4% | $4,500 | $4,500 |
| Option B: Cremation and Basic Funeral | 36% | $5,162 | $4,375 - $6,333 |
| Option C: Cremation and Cemetery | 4% | $4,671 | $4,671 |
| Option D.1: Basic Funeral and Cemetery | 20% | $8,075 | $5,598 - $11,344 |
| Option D.2: Basic Funeral (No Cemetery Invoice) | 36% | $6,483 | $4,500 - $9,471 |
| **All Bills:** | **100%** | **$6,174** | **$4,375 - $11,344** |

# B Balance Tables

Table A.3: Deceased Balance Table

| | Control Mean | Treatment Mean | P-value |
|---|---|---|---|
| Female | 0.353 | 0.412 | 0.177 |
| *Race* | | | |
| White, non-hispanic | 0.028 | 0.031 | 0.730 |
| Black, non-hispanic | 0.849 | 0.845 | 0.717 |
| Hispanic | 0.123 | 0.119 | 0.964 |
| Other | 0.000 | 0.004 | 0.167 |
| *Other* | | | |
| Deceased is a veteran | 0.000 | 0.004 | 0.321 |
| Caller receives SSI or disability SSI | 0.275 | 0.310 | 0.464 |
| Victim of violence | 0.077 | 0.074 | 0.966 |
| Joint F-test | | | |
| F-statistic | | | 0.996 |
| P-value | | | 0.433 |

Notes: $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.10$.

Table A.4: Caller Balance Table

| | **Control Mean** | **Treatment Mean** | **P-value** |
|---|---|---|---|
| Age | 47.930 | 51.367 | 0.258 |
| Female | 0.866 | 0.841 | 0.390 |
| *Race* | | | |
| White, non-hispanic | 0.028 | 0.031 | 0.730 |
| Black, non-hispanic | 0.854 | 0.858 | 0.905 |
| Hispanic | 0.118 | 0.111 | 0.960 |
| *Educational Attainment* | | | |
| Less than high school | 0.115 | 0.133 | 0.614 |
| High school | 0.493 | 0.425 | 0.231 |
| Some college | 0.286 | 0.310 | 0.738 |
| Associate's degree | 0.034 | 0.062 | 0.116 |
| Bachelor's degree | 0.062 | 0.058 | 0.849 |
| More than bachelor's degree | 0.011 | 0.013 | 0.984 |
| *Marital Status* | | | |
| Divorced | 0.039 | 0.040 | 0.825 |
| Married | 0.154 | 0.133 | 0.387 |
| Separated | 0.053 | 0.044 | 0.891 |
| Single | 0.754 | 0.783 | 0.493 |
| *House Information* | | | |
| Number of people in household | 2.008 | 1.814 | 0.245 |
| 0-20% AMI | 0.651 | 0.617 | 0.451 |
| 20-30% AMI | 0.250 | 0.298 | 0.366 |
| 30-40% AMI | 0.099 | 0.085 | 0.894 |
| *Payment Information* | | | |
| Invoice amount (current dollars) | 6,369 | 6,474 | 0.701 |
| Apprx. percentage paid by credit card | 0.508 | 0.532 | 0.839 |
| Apprx. percentage paid by fundraising | 0.420 | 0.361 | 0.834 |
| Apprx. percentage paid by loans | 0.619 | 0.603 | 0.584 |
| Apprx. percentage paid by savings | 0.400 | 0.422 | 0.794 |
| Apprx. percentage paid by other source | 0.117 | 0.108 | 0.792 |
| Missing payment information | 0.479 | 0.381 | 0.992 |
| *Relationship to Deceased* | | | |
| Close family | 0.843 | 0.836 | 0.892 |
| Extended family | 0.151 | 0.142 | 0.668 |
| Unrelated | 0.006 | 0.022 | 0.064* |
| *Referred From* | | | |
| CCAC programming | 0.591 | 0.593 | 0.880 |
| Religious institution | 0.034 | 0.044 | 0.439 |
| Funeral home | 0.157 | 0.204 | 0.197 |
| Other/Missing | 0.218 | 0.159 | 0.155 |
| *Other* | | | |
| Caller is a veteran | 0.006 | 0.000 | 0.325 |
| Caller receives SSI or disability SSI | 0.202 | 0.155 | 0.319 |
| Joint F-test | | | |
| F-statistic | | | 0.942 |
| P-value | | | 0.569 |

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.