Targeted Cash Transfers and Financial Well-Being: Findings from the In Her Hands and St. Louis GI Pilots

Authors: Roll, Stephen; Hamilton, Leah; Zheng, Haotian; Zhang, Guangli; Davis, Shadonna; Brugger, Laura; Quick, Aaron; Smith, Simone; Elliott, Desha; & Dobill, Alex

Abstract

This study examines the impact of guaranteed income (GI) on financial well-being through two U.S. pilot programs targeting historically marginalized communities. Using longitudinal survey data from the In Her Hands (IHH) pilot in Georgia and administrative credit records from the St. Louis Guaranteed Basic Income (GBI) pilot, we examine how GI influences recipients' credit health, debt, savings behavior, and reliance on high-cost financial services. In the IHH pilot, 654 low-income Black women across urban, suburban, and rural communities were randomly assigned to receive 24 monthly GI payments. Results indicate significant reductions in the use of alternative financial services, as well as an increased likelihood of having an emergency fund and higher overall savings. Debt balances remained largely unchanged. In the St. Louis GBI pilot, which provided $500 monthly payments to low-income families with school-aged children, participants experienced statistically significant improvements in credit scores and delinquency rates compared to a matched comparison group. A temporary legal pause in payments during the study period led to a reversal in these improvements, offering rare insight into the destabilizing effects of benefits withdrawal. Together, these findings suggest that GI can promote short-term financial stability and reduce reliance on predatory financial services, particularly among Black women and low-income families. However, the fragility of these gains underlines the importance of consistency and policy design in GI implementation. This study contributes to a growing body of literature on how unconditional cash transfers may advance economic justice in racially marginalized communities.

Economic inequality in the United States is deeply rooted in a history of racial capitalism and systemic exclusion, with Black families disproportionately affected by barriers to wealth accumulation, stable employment, and access to fair financial services. From slavery to redlining to discriminatory welfare policy, Black households have been denied opportunities for economic mobility and subjected to extractive financial practices that perpetuate intergenerational poverty (Baradaran, 2017; Roberts, 1997). These structural inequities continue to shape racial disparities in income, credit access, and asset ownership today (Friedline et al., 2024; Hasan et al., 2022).

In recent years, Guaranteed Income (GI) has emerged as a promising intervention to promote financial stability and racial equity. Unlike traditional means-tested programs, GI offers unconditional, regular cash payments that recipients can use as they see fit. This approach is grounded in recognizing that economic insecurity is not a product of individual failure but of systemic disinvestment and policy design that fail to meet the needs of marginalized communities (Widerquist, 2013). Early pilot programs—including the Stockton Economic Empowerment Demonstration (SEED), Magnolia Mother's Trust, and Baby's First Years—have provided growing evidence that GI can reduce income volatility, improve financial resilience, and enhance psychological well-being (Onifade et al., 2023; Shah & Gennetian, 2023; West & Castro, 2023).

Despite these promising findings, there is a lack of robust evidence regarding how GI impacts specific indicators of financial well-being, such as debt, credit health, savings, and reliance on alternative financial services. Furthermore, few studies have examined how GI may function as a tool for advancing racial equity, particularly when implemented in historically disinvested communities. This paper addresses these gaps by drawing on findings from two GI programs: In Her Hands (IHH) in Georgia, which provides monthly payments to Black women across urban, suburban, and rural communities; and the St. Louis Guaranteed Basic Income (GBI) pilot, which supports families with school-aged children in a city with a long history of racialized financial exclusion. Both programs aim to mitigate economic harm and promote long-term financial stability through unconditional cash support.

By analyzing longitudinal survey data from IHH and administrative credit records from the St. Louis GBI pilot, we investigate how guaranteed income influences credit scores, debt levels, savings behavior, and use of high-cost financial services. Additionally, the St. Louis program presents a unique opportunity to examine the effects of an unexpected pause in GI payments caused by a legal challenge, offering rare insights into the consequences of income instability among low-income households. Together, these analyses contribute to a growing body of research on how unconditional cash transfers can serve as a tool not just for poverty alleviation but for structural redress and economic justice.

Background

Black families in the United States have historically faced systemic economic precarity due to a legacy of racialized capitalism, exclusion from wealth-building opportunities, and economic

extraction through discriminatory financial practices. These structural barriers, rooted in slavery and post-emancipation economic exclusion, continue to shape disparities in income, employment, and asset accumulation (Baradaran, 2017). Today, the consequences of these historical patterns are visible in multiple forms. For example, despite significant progress in educational attainment and workforce participation, Black women continue to encounter workplace discrimination that limits their economic mobility (Williams & Wilson, 2019). Furthermore, the intersection of race and gender discrimination creates compounded barriers, restricting access to high-paying jobs and career advancement opportunities (Crenshaw, 1991). Earning significantly less than their white and male counterparts, Black women must work substantially longer to achieve the same financial outcomes, limiting their ability to accumulate savings, invest in assets, and achieve long-term financial stability (Williams & Wilson, 2019). This persistent gap reinforces the cycle of economic precarity.

Compounding these labor market inequities, Black families have also been systematically targeted by predatory financial practices. Economic extraction through high-interest loans and discriminatory lending policies has persisted from post-emancipation sharecropping arrangements to contemporary payday lending (Friedline et al., 2024). Research consistently demonstrates that payday lenders and other high-cost financial services are disproportionately located in Black and low-income communities. These lenders exploit economic vulnerability by offering high-interest loans that often lead to cycles of unmanageable debt (Faber, 2019).

While welfare programs were ostensibly designed to provide relief from financial precarity, Black families have historically been excluded or stigmatized when seeking assistance. Central to this exclusion is the racialized myth of the "welfare queen"—a harmful stereotype that emerged during the late 20th century to portray Black women as deceitful and undeserving of public support. This narrative has been used to justify restrictive policies and punitive measures that disproportionately affect Black women (Roberts, 1997).

From the start, social programs like those in the New Deal deliberately excluded domestic and agricultural workers, roles predominantly held by Black women, leaving them without essential support (Katznelson, 2005). As public assistance expanded, structural barriers such as asset limits and stringent work requirements continued to restrict access (Hancock, 2004). Eligibility rules often require participants to maintain incomes below a strict threshold, meaning that even small increases in earnings or in-kind support can result in a loss of benefits (Hamilton, 2020). These policy designs, shaped by stigma and rooted in racialized stereotypes, have left many Black women economically marginalized and forced to rely on exploitative financial alternatives such as payday loans and high-cost credit (Gustafson, 2011).

In response to these entrenched economic disparities and systemic poverty, Guaranteed Income (GI), sometimes known as Guaranteed Basic Income (GBI), Universal Basic Income (UBI), or Basic Income (BI), has emerged as a policy tool to promote financial stability and racial equity.

Unlike traditional welfare programs, GI provides unconditional cash transfers, offering recipients greater flexibility in allocating resources and potentially enhancing their financial autonomy (Widerquist, 2013). The concept of basic income dates back to the 1500s, when Sir Thomas More advocated for supporting the vulnerable beyond the realms of the church and individual charity. The first structured proposal came from Spanish humanist Johannes Ludovicus Vives, who argued for governmental responsibility in ensuring the subsistence of its citizens, a principle that informed the English Poor Laws of the late 1500s (Basic Income Earth Network, 2018).

This discourse evolved throughout the 1700s, with figures such as Antoine Caritat and the Marquis de Condorcet, and continued into the 1800s with advocates like Thomas Paine and Charles Fourier, expanding the conversation around social welfare and the role of government in providing for its citizens (Basic Income Earth Network, 2018). The notion gained new attention during the Civil Rights and Welfare Rights movements of the 1960s, with advocates such as Martin Luther King Jr. and the conservative economist Milton Friedman. This era sparked several federally funded Negative Income Tax (NIT) experiments, designed to assess the impact of basic income on various socioeconomic outcomes. While Nixon's Family Assistance Plan, inspired by the NIT trials, was ultimately defeated, the political momentum was instrumental in shaping key social safety net policies, including the Earned Income Tax Credit and Supplemental Security Income (Hamilton, 2020).

The late 20th century witnessed a resurgence in GI discourse, marked by various proposals, including social dividends and negative income taxes, which culminated in practical implementations, such as the Alaska Permanent Fund (Basic Income Earth Network, 2018). This growth continued into the 21st century, accelerating in response to the Great Recession of 2008 and the COVID-19 pandemic. The Stockton Economic Empowerment Demonstration (SEED), launched in 2017, served as a high-profile forerunner and model for the more than 150 pilot programs that have since emerged nationwide (Elliott et al., 2023). SEED offered $500 per month for 18 months to 131 randomly selected residents to assess its effects on income stability, emotional well-being, and future autonomy. The results indicated enhanced emotional health and increased full-time employment among participants (West & Castro, 2023).

While GI, UBI, GBI, and BI are often used interchangeably, there are distinct differences in their approaches and goals. UBI is a system in which every individual in society, regardless of their income, receives a basic income. The aim is to ensure a universal and equal distribution of wealth, thereby providing all citizens with a similar financial foundation. UBI is grounded in the principle of equality, ensuring that every person, irrespective of their circumstances, has access to basic financial support. In contrast, GI focuses on equity rather than equality. It acknowledges the social inequities that place certain groups at a disadvantage from the outset, particularly marginalized communities. It seeks to address these disparities by providing targeted support to those who are most in need. GI is often tailored to specific demographic groups, such as racial minorities or low-income communities, to ensure that those who have historically faced systemic disadvantages

receive the support needed to level the playing field. BI, on the other hand, refers more broadly to any periodic, unconditional cash payment provided to individuals, with no stipulations on how the money is spent. While UBI and GI are types of BI, the distinctions lie in their scope and objectives: UBI focuses on universal distribution, GI on targeted assistance for equity, and BI encompasses various unconditional cash payments designed to support individuals financially.

GI programs targeting low-income and marginalized communities have grown in recent years with increasing support from nonprofits and non-governmental organizations (NGOs) (Shah & Gennetian, 2023). For example, the Magnolia Mother's Trust, launched in 2018 to support Black mothers in Jackson, Mississippi, provided $1,000 monthly payments during the COVID-19 pandemic to 110 participants, alongside a comparison group of 40 non-recipients (Covert, 2021; Onifade et al., 2023). After one year, recipients reported greater financial security, improved family nutrition, increased access to healthcare, and reduced reliance on high-interest credit. Additional GI pilots explicitly seeking to advance racial equity include a randomized controlled trial in San Francisco and Oakland, which is evaluating the impact of GI on the financial well-being, mental health, and healthcare utilization of 300 low-income "Black emerging adults" over 24 months (Lippman et al., 2023). Similarly, Oakland Resilient Families provides $500 monthly to 600 low-income BIPOC families, including undocumented and homeless households, for at least 18 months (Schaaf & Tubbs, 2021).

GI initiatives have further garnered increased attention for their potential economic benefits, particularly in addressing poverty and enhancing financial well-being. Pilot data and economic modeling indicate that GI can effectively reduce poverty rates and positively impact recipient outcomes, thereby contributing to overall economic well-being (Marinescu, 2018; Nikiforos et al., 2017). For example, a study of the Barcelona municipal BI pilot found that the intervention significantly reduced the likelihood of individuals borrowing money from family or friends, decreased the probability of falling behind on rent or mortgage payments, and reduced material deprivation (Riutort et al., 2023). Similarly, West and Castro (2023) found that GI reduced income volatility and debt among SEED participants while enhancing participants' ability to cover emergency expenses and their overall financial outlook. A recent meta-analysis of poverty-related outcomes among BI initiatives in high-income countries found that BI was associated with improvements in self-reported financial well-being (Rizvi et al., 2024).

Study Overview and Research Questions

While early research suggests promising outcomes, existing literature on GBI has notable limitations. Many studies rely on small sample sizes and short pilot durations, making it difficult to assess long-term impacts. Further research is needed to investigate the effects of GBI on wealth accumulation, debt reduction, and intergenerational economic mobility. Expanding longitudinal studies, drawing on novel sources of administrative data, and incorporating diverse participant

experiences will be essential in building a comprehensive understanding of GBI's potential for economic transformation.

To that end, this paper examines the credit, debt, and savings impacts of GI programs by drawing on evidence from the IHH pilot in Georgia and the St. Louis GBI pilot. Building on early evidence of guaranteed income's potential to reduce economic hardship and address racial wealth disparities, the IHH pilot was developed through a participatory design process that actively engaged Black women in shaping the program's structure and goals (Brugger et al., 2024). This collaborative approach ensured that the intervention was grounded in the lived experiences of participants and responsive to the specific financial challenges they face. Jointly implemented by the Georgia Resilience and Opportunity Fund and GiveDirectly, the initiative drew on the principles of the "Black Women Best" framework, which posits that centering economic policy around the well-being of Black women—who have historically borne the brunt of systemic exclusion—can lead to a more equitable and thriving economy for all (Bozarth et al., 2020). The program's design emerged from community listening sessions held in Atlanta's Old Fourth Ward, a historically significant neighborhood and the birthplace of Dr. Martin Luther King Jr., where residents emphasized the need for unrestricted, unconditional cash assistance to support long-term financial stability. In the first phase of the program, which is the focus of this study, 654 women were randomly selected to receive an average monthly payment of $850 for a period of 24 months. To be eligible, applicants were required to live in one of three designated communities, identify as a woman, be aged 18 or older, and have a household income of less than 200% of the Federal Poverty Level.

Informed by similar motivations to advance racial and economic equity, the City of St. Louis launched its GBI pilot in 2023 to support families with children enrolled in local public and charter schools. St. Louis has a long and well-documented history of institutionalized racial discrimination—from redlining and racially restrictive covenants to wage disparities and exclusionary employment practices—that has contributed to persistent wealth gaps and financial exclusion among Black families (Hardy, 2017; Gramlich, 2005; Shelley v. Kraemer, 1948; Hasan et al., 2022). The GBI pilot was introduced as part of the city's broader Working Families legislative package and funded through the American Rescue Plan Act. Eligible participants—low-income residents with school-aged children—were selected through a lottery to receive $500 per month for a period of 18 months. Community leaders and policymakers framed the intervention not as a replacement for work but as a stabilizing income floor to help families recover from the economic shocks of the COVID-19 pandemic and address long-standing structural inequalities (City of St. Louis, 2024). The pilot's design reflects an intentional investment in Black families as a strategy for building economic resilience and advancing place-based equity.

The IHH and St. Louis GBI pilots took separate but complementary approaches to understanding the impact of GI payments on economic outcomes. In the IHH pilot (Study 1), we tracked differences in treatment and comparison group outcomes through a longitudinal survey that measured credit, debt, and savings indicators at one and two years post-baseline. In the St. Louis

GBI pilot, we drew on administrative credit records data to examine trends in monthly credit outcomes between payment recipients and a comparison group of St. Louis residents with similar credit profiles at baseline. By drawing on these pilots' respective data sources, our study aims to answer the following research questions:

1. What is the impact of GI payments on recipients' credit health, including credit scores, debt levels, and payment delinquencies?
2. What is the impact of GI payments on the use of alternative credit services, including payday loans, auto title loans, and pawn shop loans?
3. What is the impact of GI payments on recipients' savings behaviors and assets, including emergency savings and savings for their children's education?

In addition, we also leverage an unexpected temporary pause in the payments for the St. Louis GBI program–the result of a lawsuit against the city over the constitutionality of the program–to examine the effects of the unexpected withdrawal of payments on recipients' credit outcomes:

4. What is the effect of a temporary and unexpected pause in GI payments on recipients' credit health?

Study Design and Methods

Study 1 - In Her Hands

Design

Study 1 focuses on the In Her Hands guaranteed income program. This program, launched in 2022, provided two years of guaranteed monthly payments to women in three majority-Black Georgia neighborhoods: one urban, one suburban, and one rural. To be eligible for the payments, individuals had to identify as a woman, be at least 18 years old, and have a household income at or below 200% of the Federal Poverty Level. In total, there were 2,370 eligible program applicants. 654 of these applicants were randomly assigned to receive the payments, while the 1,716 women who were not selected comprised the comparison group. Women selected for the program were further randomized into two treatment groups: The first treatment group (n=329) received $850 per month for 24 months, while the second treatment group (n=325) received $4,300 for the first month and $700 for the remaining 23 months; each group received $20,400 in total over 24 months.

Data and Sample

Study 1 draws on two sources of data. The first is administrative program application data. As part of their application to participate in the IHH program, individuals reported their household income for the month preceding the application, their education level, marital status, employment status,

and the number of adults and children in their household. The second data source comes from a longitudinal survey administered to the treatment and comparison groups 12 months and 24 months after the program began. This survey was administered to all participants who consented to research contact, and survey respondents were compensated $20 for the 12-month survey and $40 for the 24-month survey.

We examine study outcomes using two survey samples. The first sample includes anyone who completed the 24-month survey administered at the end of the program. This enables analysis of treatment and comparison group outcomes following the full disbursement of GI payments. A total of 452 participants completed the survey: 272 from the combined treatment group (within-group response rate, 41.5%) and 180 from the comparison group (within-group response rate, 9.9%). The analytical sample for this study consisted of individuals who completed the survey and responded to any outcome indicators. The second sample utilizes the survey's panel design to track outcomes at 12 and 24 months post-baseline, and includes only those who responded to both 12- and 24-month survey waves (n = 174 treatment; n = 89 comparison).

Measures

Outcome Measures. To capture household financial behaviors and resources, Study 1 examines three types of outcome variables—Alternative Financial Services (AFS), debt, and savings—each representing different aspects of short-term coping strategies and long-term financial stability. Specifically, participants were asked how many times in the past six months they or someone in their household used any of the following alternative financial services: (a) auto title loan, (b) payday loan, (c) pawn shop, (d) selling plasma, and (e) overdrafting a bank account. Response options were "Never," "1 time," "2 times," or "3 or more times." For analysis, each item was recoded into a binary variable (0 = never, 1 = at least once).

Beyond AFS usage, participants provided information on their household's outstanding balances across multiple debt categories: credit card, educational loan, auto loan, medical debt, and other bank loans. Because these debt amounts exhibited a right-skewed distribution, each variable was winsorized at the 95th percentile to minimize the influence of extreme values. In addition, a composite measure of total debt was created by summing all individual debt categories, which was also winsorized at the 95th percentile.

Finally, participants reported whether they had an emergency fund (0 = no, 1 = yes), their current general savings amount, and whether they were actively saving for a child's education (0 = no, 1 = yes). If respondents indicated they were saving for a child's education, they were also asked to report the amount saved for that purpose. All monetary values (general savings and child education savings) were winsorized at the 95th percentile to minimize the influence of outliers and provide a more representative view of typical savings levels.

Covariates. Multiple demographic variables obtained from administrative data were included as covariates in the analyses: number of adults per household (recoded as one, two, or three or more), number of children (recoded as none, one child, two, or three or more), age, and household income (reported in dollars descriptively and logged to address skewness in formal modeling). Additionally, the site each program applicant lived in at the time of their application—classified as urban, suburban, or rural—was included to capture geographic context.

Analytic Approach

We began by conducting univariate analyses of program application data to summarize characteristics of study participants and assess balance between the treatment and comparison groups. Next, we performed bivariate analyses to examine differences between the aggregate treatment group and the comparison group at the end of the study period. We also examine the extent to which there were any outcome differences between the two treatment conditions (lump sum + $700/month vs. $850/month).

To examine changes in outcomes over time and leverage the nested structure of repeated observations within comparison participants between Years 1 and 2, we employed a growth curve modeling approach (Raudenbush & Bryk, 2002; Singer & Willett, 2003) with a multilevel modeling framework. At level 1 (within-person), we modeled each individual's repeated measures (Y_{it}) as a function of time, allowing for person-specific intercepts (π_{0i}). For instance, in the level 1 model, total debt was predicted by wave to capture how each individual's debt changed across Years 1 and 2. Because different individuals may start at different baseline levels, we allow each person to have a unique (random) intercept.

At level 2 (between-person), these person-specific intercepts are further modeled as a function of time-invariant individual-level characteristics–such as the treatment indicator ($Treatment_i$, coded 0 or 1) and other covariates. In other words, level 2 explains why individuals differ in their average outcome (i.e., the intercept).

In addition, the growth models allow within-person rates of change to be predicted by the treatment status, which is achieved by specifying a cross-level interaction between treatment and wave. By specifying the slope in this manner, we can directly test whether participants in the treatment group exhibit different rates of change over time compared to those in the comparison group. That is, the cross-level interaction indicates whether treatment effects on the outcome vary across waves. The growth curve models were specified as follows:

$$\text{Level 1 (within-person): } Y_{it} = \pi_{0i} + \pi_{1i} \times Wave_{it} + \varepsilon_{it}$$

$$\text{Level 2 (between-person): } \pi_{0i} = \beta_{00} + \beta_{01} \times Treatment_i + \beta_{0k} X_i + b_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11} \times Treatment_i$$

where β_{01} captures the average difference in intercept at Year 1 between the treatment and comparison groups (i.e., Year 1 treatment effect), β_{10} represents the average difference between

Years 1 and 2, and β_{11} is the time-specific treatment effect parameter, reflecting the deviation in the treatment effect between Years 1 and 2. X_i stands for the covariates vector. ε_{it} is the level 1 residual term, assumed to be normally distributed with mean 0 and variance σ^2 , and b_{0i} is the random effects of intercepts at level 2, assumed to be normally distributed with mean 0 and variance τ_0^2.

Finally, all models were estimated in R version 4.4.2 using the $lme4$ package (Bates et al., 2025). This package provides flexible maximum likelihood estimation for hierarchical linear and generalized linear models, enabling the specification of both random intercepts and random slopes while accounting for the nested data structure.

Study 2 - St. Louis Guaranteed Basic Income

Design

Study 2 examines the St. Louis Guaranteed Basic Income program, which was administered by the City of St. Louis using funds from the American Rescue Plan Act of 2021. This program, launched in late 2023, provided 18 months of guaranteed monthly payments to low-income parents with children in St. Louis schools. To be eligible for the payments, individuals had to have at least one child in a St. Louis school (including public and charter schools), be at least 18 years old, and have a household income at or below 170% of the Federal Poverty Level. 540 individuals were randomly selected to receive payments of $500 per month, totaling $9,000. In June 2024, two St. Louis residents filed a lawsuit challenging the city's GBI program, arguing it violated the Missouri Constitution and the city charter by providing public funds to private individuals without services rendered. Subsequently, on July 18, 2024, a St. Louis Circuit Judge issued a temporary restraining order, halting the program's monthly payments until the case is resolved (Krull, 2024). Two months into the payment freeze, a local non-profit contributed $1 million to resume the GBI payments, ensuring that the 540 participating families received the full amounts promised under the program (Wimbley, 2024).

Due to funding limitations, no control or comparison group was recruited for this study. However, as we describe below, we utilize administrative credit records from Equifax to track monthly credit outcomes over the course of the program for the treatment group compared to a comparison group of St. Louis residents with similar credit profiles.

Data and Sample

Our primary data source is an anonymized panel dataset provided by Equifax Inc. (EQX), which tracks individuals' credit attributes on a monthly basis. This dataset offers comprehensive information on credit histories, including borrower geographic locations (at the ZIP code level), age, account balances, account utilization, payment behavior, delinquencies, and credit scores. Our study sample comprises a treatment group of St. Louis Guaranteed Basic Income recipients and a comparison group of non-recipients drawn from Equifax's credit records database. To locate

treated individuals in the credit records, a third-party company administering the program shared identifying information (name, birthdate, and recent address) for all individuals who consented to the research during the program application phase (n = 336) with EQX. In total, EQX was able to locate credit records for 193 payment recipients, 179 of whom had non-missing data.[1]

To construct the comparison group for this study, we begin with a random 10 percent sample of all individuals with credit records in the U.S. From this broader sample, we identify 50,000 randomly selected residents who lived in the St. Louis Metropolitan area during the study period to serve as our comparison group.

The St. Louis Guaranteed Basic Income program began in December 2023. We track outcomes for both treatment and comparison groups from November 2022 through October 2024, the most recent month for which credit data are available. This timeframe enables us to evaluate pre-treatment outcome trends between the two groups, while also monitoring the degree to which these outcomes diverge over the study period.

Measures

Outcome Measures. We draw on three categories of credit outcomes for this study. Our primary measure is an individual's credit score. An individual's credit score is a measure of their credit risk, i.e., their likelihood of defaulting on a loan. Credit scores are summative measures that factor in payment history (e.g., whether or not an individual became delinquent on defaulted on their debt), the number and types of loans held by an individual, debt levels and credit utilization ratios (e.g., the percent of an individual's credit limit being utilized), recent applications for credit, and the average age of their credit accounts (i.e., the length of time they have held their credit accounts open). In this study, we utilize the VantageScore 4.0 credit score, which ranges from 300 to 850, with higher scores indicating better credit health (or lower credit risk).

The second category of outcomes we investigate is direct measures of credit distress. While credit scores, to some degree, measure credit distress, in that falling behind on credit payments leads to lower credit scores, they also take into account other factors that are not necessarily related to credit distress, such as account age or the number of accounts opened recently. In addition, credit scores are, to an extent, a lagging indicator of an individual's current credit health, as credit scores

[1] There are several reasons why individuals may not be identifiable in credit records. The first is that their information is not sufficient to produce a unique match in the credit records database. For example, if an individual's name, recent address, and birthdate do not appear in the database, EQX will be unable to identify that individual's credit profile. Another reason is that, to appear in a credit records database, an individual must have a credit history. If someone has never taken out a loan through a mainstream financial institution (i.e., not an alternative credit provider such as a payday lender), they will likely not appear in the credit records and be "credit invisible". In our data, we cannot identify whether someone is missing because they have credit records but were unable to be matched, or if they are missing because they do not have a credit history. However, we would anticipate credit invisibility to be a major contributor to missingness. One estimate of credit invisibility rates found that 11 percent of the general population is credit invisible, and that low-income individuals are nearly 10 times as likely to be credit invisible (Brevoort, Grimm, & Kambara, 2015).

can factor in up to seven years of payment history. For example, if an individual were delinquent on a credit card payment in 2022, that delinquency would still be reflected in their credit score in 2025, although the effect diminishes over time. Given that guaranteed income programs are typically time-limited (often ranging from one to three years), credit scores may not be as sensitive to changes in financial behavior as contemporary measures of financial distress. In this study, we measure financial distress in two ways: (1) the number of 30-day (minor) payment delinquencies and (2) the number of 60-day (severe) payment delinquencies.

The final category of outcomes we investigate concerns debt levels. Here, we examine four measures of indebtedness: (1) the amount of revolving debt (e.g., credit card debt), excluding debt from home equity lines of credit; (2) the amount of installment debt; (3) the amount of student debt; and (4) the utilization ratio of revolving credit, which is the percent of an individual's revolving credit currently owed by the individual, and can function as a measure of liquidity access.

Analytic Approach

We estimate a two-way fixed effects (difference-in-difference) model to identify whether individuals' credit outcomes changed in response to cash transfers with the following specification:

$$y_{it} = \alpha + \sum_{e=-13}^{11} \beta_e V_{it}[E_{it} = e] + \gamma_i + \epsilon_{it}$$

where y is a set of outcomes that measure an individual i's credit score, credit distress, and indebtedness at calendar year-month t. D_{it} is an indicator that is equal to 1 if individual i received the guaranteed income and t is after December 2023, the post-treatment period for the GI recipients. We include calendar year-month fixed effects (τ) to account for time-specific shocks common to all individuals, and treatment status fixed effects (γ) to control for time-invariant group characteristics. In a more restrictive specification, we substitute treatment status fixed effects with individual fixed effects; results remain qualitatively similar. The coefficient of interest β thus captures the effect of the guaranteed income on credit outcomes for the treated group. Standard errors are clustered at the individual level.

To assess the validity of the parallel trends assumption – that is, the assumption that in the absence of cash transfers, the potential credit outcome for treated and comparison groups should follow parallel trends – we estimate an event study model (Sun and Abraham, 2021) with the following specification:

$$y_{it} = \alpha + \sum_{e=-13}^{11} \beta_e V_{it}[E_{it} = e] + \gamma_i + \epsilon_{it}$$

Here, $V_{it}[E_{it} = e]$ is a dummy variable equal to 1 if the calendar year and month are e months from the event date (i.e., December 2023). This allows us to estimate a separate coefficient for each lead or lag month. We omit November 2023 (e=−1) as the reference period so that all

estimated coefficients are relative to the treatment and comparison group's outcome difference from this period.

Results

Study 1 Findings

Descriptive Results

Table 1 summarizes the baseline characteristics of the In Her Hands analytic sample (N = 520) by treatment and comparison groups. Households most typically had one adult (65.4%), with similar proportions across comparison (73.0%) and treatment (71.7%) groups. Notably, treatment households were more likely to reside in urban areas (35.2% vs. 24.1%, $p < 0.05$) and less likely to reside in suburban areas (41.2% vs. 52.2%, $p < 0.05$). Rural residency was comparable (23.6% treatment vs. 23.7% comparison). While household income was descriptively lower in the treatment group ($13,856 vs. $14,615 comparison), this difference was not statistically significant. Age distributions were similar across groups, with a mean age of approximately 39–40 years, and no significant differences in the number of children per household.

As shown in Table 2, treatment participants reported lower use of high-cost financial services relative to the comparison group. For instance, pawn shop use was significantly reduced in the treatment group (21.2% vs. 35.1%, $p < 0.01$), with fewer instances of repeated use (e.g., 4.5% vs. 10.1% reported three or more uses, $p < 0.01$). Similarly, plasma selling was less prevalent among treated households (13.7% vs. 28.1%, $p < 0.001$), and overdrafts were reported by 42.4% of treatment participants versus 59.9% of comparison participants ($p < 0.01$). Auto title and payday loan use did not differ significantly between groups. Debt balances showed variability, with treatment households holding higher auto loan balances ($6,023 vs. $4,856) and medical debt ($5,755 vs. $4,634), although these differences were not statistically significant. Credit card and educational loan balances were comparable across groups.

Table 3 shows differences in emergency fund and savings outcomes. Treatment participants were more likely to report having an emergency fund (25.9% vs. 11.5% comparison, $p < 0.001$), with durations skewed toward shorter-term reserves (e.g., 10.5% vs. 6.9% reported maintaining funds for less than one month, $p < 0.01$). General savings were significantly higher in the treatment group ($477 vs. $134 comparison, $p < 0.001$), and saving for a child's education was more common (33.5% vs. 23.4%, $p < 0.05$), though the amounts saved for education did not differ significantly ($746 vs. $506).

Growth Models

In Tables 4 through 6, we present the results of longitudinal growth models that examine the change in study outcomes for both the treatment and comparison groups over time. Table 4 shows sustained treatment effects in reducing reliance on high-cost services. Relative to the comparison,

treatment participants had lower probabilities of using payday loans (−0.14, $p < 0.05$), pawn shops (−0.12, $p < 0.05$), plasma selling (−0.13, $p < 0.01$), and overdrafts (−0.17, $p < 0.05$) at Wave 2. These effects persisted at Wave 4, with no significant interactions between treatment and wave, indicating stable reductions over time, as shown in the lower panel of Table 4. Table 5 showed limited treatment effects on debt balances. While auto loan balances were directionally lower in the treatment group (-$4,857), this difference was not statistically significant. Credit card balances showed no significant differences between treatment and comparison groups.

Table 6 indicates delayed treatment effects on setting aside an emergency fund, general savings, and savings for children's education. Treatment participation increased the likelihood of setting aside an emergency fund by Wave 4 ($\beta = 0.22$, $p < 0.05$), and treated households accumulated $376 more in general savings than comparison households ($p < 0.001$), represented by a significant treatment-by-wave interaction ($\beta = 302.54$, $p < 0.001$); and $616 more in savings for children's education, represented by a significant treatment-by-wave interaction ($\beta = 606.33$, $p < 0.05$).

Study 2 Findings

Figure 1 presents event study plots for three categories of credit outcomes in the St. Louis GBI program, estimated using the methodology proposed in Sun and Abraham (2021). Panel A illustrates the event study for credit scores. The pre-treatment period shows no significant deviations between the treatment and comparison groups, providing visual support for the parallel trends assumption. Following the initiation of treatment in December 2023, credit scores for the treated group increased steadily relative to the comparison group, with the effect stabilizing at approximately 10 points ($p < 0.05$) by the end of the observation period. Panel B displays the event study for credit distress indicators, specifically the number of 30-day and 60-day payment delinquencies. The pre-treatment trends appear parallel, suggesting the identifying assumptions hold. Both delinquency measures exhibit a noticeable decline for the treated group in July or August 2024. Finally, Panel C presents the event study results for indebtedness measures. We do not observe statistically or economically significant changes in any of the indebtedness outcomes over the study period.

The credit score and credit distress outcomes highlighted in Figure 1 also present suggestive evidence of the impact of the unexpected GI payment delay that occurred during the St. Louis GBI program period. As mentioned above, the City of St. Louis faced a lawsuit over the constitutionality of the program in its first year. This led to the payments being frozen by a judge, although they resumed approximately two months later after a private philanthropy stepped in to cover the program's costs. The first payment delays occurred about nine months into the program, and the event studies show that individuals' measures of credit distress also reversed their downward trends around this time.

Table 7 displays the difference-in-differences (DiD) results with treatment status fixed effects. The GBI program resulted in a statistically significant increase in credit scores of 5.4 points ($p < 0.05$)

among treated individuals, representing a 0.93% improvement relative to the pre-treatment mean of 578.6 in the treatment group. Furthermore, indicators of credit distress exhibited meaningful reductions: the number of 30-day (minor) and 60-day (severe) payment delinquencies declined by 0.171 and 0.131, respectively (both $p < 0.05$), amounting to an approximate 30% reduction in credit distress. Consistent with the event study results, the DID analysis finds no statistically significant effects on any of the four measures of indebtedness. These results are robust to an alternative specification that uses individual, rather than treatment, fixed effects (see Table A1 in the Appendix).

Discussion

This study contributes to the growing evidence base on guaranteed income by examining its impact on financial well-being through two pilot programs intentionally designed to address racial and economic inequality. Drawing on longitudinal survey data from the In Her Hands pilot in Georgia and administrative credit data from the St. Louis Guaranteed Basic Income pilot, we find that GI can contribute meaningfully to financial stability, particularly among women and low-income families in predominantly Black communities—populations historically excluded from traditional wealth-building mechanisms.

In the IHH pilot, receipt of GI was associated with significant reductions in reliance on high-cost financial services, such as payday loans, pawn shops, plasma sales, and bank overdrafts. Participants were also 14 percentage points more likely to report having an emergency fund and had accumulated an average of $376 more in general savings relative to the comparison group. While debt balances remained relatively unchanged, these findings suggest that unconditional cash transfers primarily support short-term financial stability and coping capacity rather than immediate debt reduction. In the St. Louis pilot, early administrative data provide a unique opportunity to track the credit behavior of participants and to assess the effects of a temporary payment disruption. GI payments were associated with significant improvements in credit scores (+5.4 points) and roughly 30% reductions in both minor (30-day) and severe (60-day) payment delinquencies. These effects were especially pronounced during the first nine months of the program. However, the gains in credit distress began to reverse following a temporary pause in payments due to a legal challenge. This disruption offered insight into the fragility of financial improvements under conditions of income volatility. While we do not yet have data for the final months of the St. Louis program, it is possible that participants' financial outcomes resumed their positive trajectory once payments restarted.

Taken together, the findings indicate that guaranteed income programs can serve as a stabilizing force for families navigating persistent income volatility and systemic financial exclusion. While the gains observed are modest relative to the scale of structural disadvantage these households face, the results suggest that even relatively small, unconditional payments can support participants' ability to meet urgent needs, plan for the future, and avoid financially harmful alternatives.

As GI programs continue to proliferate, future research should examine not only standalone cash transfer initiatives but also GI-like policies currently under debate, including expansions to the Child Tax Credit, Earned Income Tax Credit, and state-level refundable credits. Understanding how these policies interact with the broader social safety net and how design features such as payment amount, duration, and delivery method affect outcomes is essential for informing equitable policy development. Additionally, tracking recipients' financial well-being over longer time horizons will be critical to assessing the sustained impact of recurring cash supports. The findings from In Her Hands and the St. Louis GBI pilot point to the promise of these approaches not only in reducing economic hardship but also in counteracting the legacies of systemic exclusion and promoting more equitable financial outcomes for historically marginalized communities.

Acknowledgement

Funding

The authors gratefully acknowledge funding support from the Robert Wood Johnson Foundation, GiveDirectly, the Georgia Resilience and Opportunity Fund (GRO), and the City of Saint Louis.

Conflict of Interest

The authors declare no conflicts of interest.

References

Baradaran, M. (2017). *The color of money: Black banks and the racial wealth gap*. Harvard University Press.

Basic Income Earth Network. (2018). *History of basic income.* BIEN. http://basicincome.org/basic-income/history/

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2025). *Lme4: Linear Mixed-Effects Models using 'Eigen' and S4* (pp. 1.1–36) [Computer software]. Comprehensive R Archive Network. **https://CRAN.R-project.org/package=lme4**

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: W. H. Freeman.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology,* 52, 1–26. https://doi.org/10.1146/annurev.psych.52.1.1

Bhutta, N., Chang, A. C., Dettling, L. J., & Hsu, J. (2020). *Disparities in Wealth by Race and Ethnicity in the 2019 Survey of Consumer Finances*. Board of Governers of the Federal Reserve. https://www.federalreserve.gov/econres/notes/feds-notes/disparities-in-wealth-by-race-and-ethnicity-in-the-2019-survey-of-consumer-finances-20200928.html

Bozarth, K., Western, G., & Jones, J. (2020). *Black Women Best: The Framework We Need for an Equitable Economy*. Roosevelt Institute. https://rooseveltinstitute.org/publications/black-women-best-the-framework-we-need-for-an-equitable-economy/

Brevoort, K. P., Grimm, P., & Kambara, M. (2015). *Data Point: Credit Invisibles. Washington, D.C.*: Consumer Financial Protection Bureau.

Brugger, L., Davis, S., Elliott, D., Hamilton, L., Quick, A., Roll, S., Rollins, L., Smith, S., & Zewde, N. (2024). *In Her Hands: First Year Research Summary*. Family Economic Policy Lab. https://appwell.appstate.edu/sites/default/files/ihh_year_1_report_2.23.24.pdf

Castro Baker, A., Samra, S., & Taylor, S. (2021). *The impact of guaranteed income on financial well-being: Evidence from Stockton's SEED program*. Center for Guaranteed Income Research.

City of St. Louis. (2024). *STL Guaranteed Basic Income Pilot Program* [22]. Stlouis-Mo.Gov. https://www.stlouis-mo.gov/government/departments/mayor/initiatives/gbi.cfm

Covert, B. (2021). *Cash Strapped: What national democrats can learn from basic income experiment from Mississippi mothers. Signs & Wonders.* The New Republic.

Crenshaw, K. (1991). Mapping the margins: Intersectionality, identity politics, and violence against women of color. *Stanford Law Review*, 43(6), 1241-1299. https://doi.org/10.2307/1229039

Elliott, D., Hamilton, L., & Smith, S. (2023). Current and Recent Basic Income and Guaranteed Income Pilots in the United States. In M. Torry (Ed.), *The Palgrave International Handbook of Basic Income* (pp. 463–491). Springer International Publishing. https://doi.org/10.1007/978-3-031-41001-7_23

Faber, J. W. (2019). Segregation and the geography of creditworthiness: Racial disparities in credit scores in the United States. *Housing Policy Debate*, 29(6), 857-890. https://doi.org/10.1093/sf/soy129

Friedline, T., Morrow, S., Atkinson, D., Gracey, A., Johnson, J., Muntaqim, A., Taylor, E., & Wolfe, A. (2024). "There Is No Winning": The Racialized Violence of Debt on Health and How Women Resist. *Du Bois Review: Social Science Research on Race*, *21*(2), 341–367. https://doi.org/10.1017/S1742058X23000164

Gramlich, E. (2005). *Building assets, building credit: Creating wealth in low-income Communities* (N. P. Retsinas & E. S. Belsky, Eds.). Brookings Institution Press.

Gustafson, K. (2011). *Cheating welfare: Public assistance and the criminalization of poverty*. NYU Press.

Hamilton, L. (2022). *HudsonUP Basic Income Pilot: Year Two Report HudsonUP Basic Income Pilot: Year Two Report.* Jain Family Institute. https://jainfamilyinstitute.org/wp-content/uploads/pdf/hudsonup-year-two-report_leah-hamilton-jfi.pdf?_gl=1

Hamilton, L., Yorgun, M., & Wright, A. (2022). "People nowadays will take everything they can get": American perceptions of basic income usage. *Journal of Policy Practice and Research, 3*(2), 77-95. https://doi.org/10.1007/s42972-021-00035-0

Hamilton, L. (2020). *Welfare Doesn't Work: The Promises of Basic Income for a Failed American Safety Net*. Springer Nature.

Hancock, A. M. (2004). *The politics of disgust: The public identity of the welfare queen*. NYU Press.

Hasan, T., Lucas McKay, K., & Smith-Ramani, J. (2022). *Disparities in debt: Why debt is a driver in the racial wealth gap*. Aspen Institute. https://www.aspeninstitute.org/wp-content/uploads/2022/02/FINAL-ASP-FSW_Disparities-in-Debt_020722-3.pdf

Johnson, E., Villadsen, A., Parra Mujica, F., Webster, H., Thorold, R., Morrison, J., Cooke, J., Mathers, A., Reed, H., Lansley, S., Chen, T., Kypridemos, C., Oflaherty, M., Nettle, D., Cookson, R., Pickett, K., & Johnson, M. (2022). Challenging the mental health crisis NOVEMBER 2022. https://www.thersa.org/globalassets/_foundation/new-site-blocks-and-images/reports/2022/10/rsa-ubi-full-report-final.pdf

Katznelson, I. (2005). *When affirmative action was white: An untold history of racial inequality in twentieth-century America*. W. W. Norton & Company.

Kovski, N., Pilkauskas, N. V., Michelmore, K., & Shaefer, H. L. (2023). Unconditional cash transfers and mental health symptoms among parents with low incomes: Evidence from

the 2021 child tax credit. SSM - population health, 22, 101420. https://doi.org/10.1016/j.ssmph.2023.101420

Krull, R. (2024, July 19). Judge Halts St. Louis' Guaranteed Basic Income Pilot Program. *St. Louis Magazine*. https://www.stlmag.com/news/judge-halts-st-louis%E2%80%99-guaranteed-basic-income-pilot-program/

Lippman, S. A., Libby, M. K., Nakphong, M. K., Arons, A., Balanoff, M., Mocello, A. R., Arnold, E. A., Shade, S. B., Qurashi, F., Downing, A., Moore, A., Dow, W. H., & Lightfoot, M. A. (2023). A guaranteed income intervention to improve the health and financial well-being of low-income black emerging adults: study protocol for the Black Economic Equity Movement randomized controlled crossover trial. *Frontiers in Public Health, 11,* 1271194. https://doi.org/10.3389/fpubh.2023.1271194

Loopstra, R., & Tarasuk V. (2013). Severity of household food insecurity is sensitive to change in household income and employment status among low-income families. *J Nutr.* 143(8):1316-23. doi: 10.3945/jn.113.175414.

Marinescu, I. (2018). *No Strings Attached: The Behavioral Effects of U.S. Unconditional Cash Transfer Programs* (Working Paper 24337). National Bureau of Economic Research. https://doi.org/10.3386/w24337

Moore, A., Christyl, M., Ebba, W., Karim, N., Rowe-Harriott, S., & Campos, S. (2023b). *Magnolia Mother's Trust Alumni Study Report.* https://springboardto.org/wp-content/uploads/2023/04/MMT-Alumni-Study-Report.Final_.pdf

Nikiforos, M., Steinbaum, M., & Zezza, G. (2017). *Modeling the Macroeconomic Effects of a Universal Basic Income*. Roosevelt Institute. http://rooseveltinstitute.org/modeling-macroeconomic-effects-ubi/

Onifade, E., Shishane, K., Elonge, F., & Glover, L. (2023). Guaranteed income: Experiences of African American mothers in the Magnolia Mother's Trust Project. *Journal of Community Practice, 31(*1), 1–16. https://doi.org/10.1080/10705422.2023.2190327

Power, E. , Abercrombie, D. , Fafard St-Germain, A.-A. , & Vanderkooy, P. (2016). *Prevalence, severity and impact of household food insecurity: A serious public health issue*. Dietitians of Canada. https://www.dietitians.ca/DietitiansOfCanada/media/Documents/Resources/HFI-Background-DC-FINAL.pdf?ext=.pdf

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods*. SAGE. **https://books.google.com?id=uyCV0CNGDLQC**

Riutort, S., Laín, B., & Julià, A. (2023). Basic Income at Municipal Level: Insights from the Barcelona B-MINCOME Pilot. *Basic Income Studies*, *18*(1), 1–30. https://doi.org/10.1515/bis-2021-0047

Rizvi, A., Kearns, M., Dignam, M., Coates, A., Sharp, M. K., Magwood, O., Labelle, P. R., Elmestekawy, N., Rossiter, S., Al-Zubaidi, A. A. A., Dewidar, O., Idzerda, L., Aguilera, J. M. P., Seal, H., Little, J., Martín, A. M. A., Petkovic, J., Jull, J., Gergyek, L., … Kristjansson, E. (2024). Effects of guaranteed basic income interventions on poverty-

related outcomes in high-income countries: A systematic review and meta-analysis. *Campbell Systematic Reviews*, *20*(2), e1414. https://doi.org/10.1002/cl2.1414

Roberts, D. (1997). *Killing the Black body: Race, reproduction, and the meaning of liberty*. Vintage.

Rose, R. (1985). The State's Contribution to the Welfare Mix. United Kingdom: Centre for the Study of Public Policy, University of Strathclyde.

Schaaf, L., Tubbs, M. (2021, March 23). Mayor Schaaf announces guaranteed income pilot, Oakland resilient families. [Press Release]. Retrieved from https://www.oaklandca.gov/news/mayor-schaaf-announces-guaranteed-income-pilot-oakland-resilient-families#:~:text=The%20project%20will%20support%20600,said%20Oakland%20Mayor%20Libby%20Schaaf.

Seamster, L., & Charron-Chénier, R. (2017). *Predatory inclusion and education debt: Rethinking the racial wealth gap*. Social Currents, 4(3), 199-207. https://doi.org/10.1177/2329496516686620

SEED. (2022). SEED Data Dashboard. Tennessee.edu. https://seed.sworps.tennessee.edu/findings.html

Shah, H., Gennetian, L. (2023). *Unconditional cash transfers for families with children in the U.S.: A scoping review*. NBER Working Paper Series, National Bureau of Economic Research. Available at https://www.nber.org/system/files/working_papers/w30965/w30965.pdf

Singer, J. D., & Willett, J. B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. Oxford University Press, USA. **https://books.google.com?id=PpnA1M8VwR8C**

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175-199. https://doi.org/10.1016

West, S., & Castro, A. (2023). Impact of Guaranteed Income on Health, Finances, and Agency: Findings from the Stockton Randomized Controlled Trial. *J Urban Health 100*, 227–244. https://doi.org/10.1007/s11524-023-00723-0

Widerquist, K. (2013). *Independence, propertylessness, and basic income: A theory of freedom as the power to say no*. Palgrave Macmillan.

Williams, J., & Wilson, V. (2019). *Black workers endure persistent racial disparities in employment outcomes* (Labor Day 2019 How Well Is the American Economy Working for Working People?). Economic Policy Institute. https://www.epi.org/publication/labor-day-2019-racial-disparities-in-employment/

Wimbley, L. (2024, October 22). *McDonnell Foundation helps fund St. Louis' basic income program through December.* St. Louis Public Radio. https://www.stlpr.org/government-politics-issues/2024-10-22/mcdonnell-foundation-funds-st-louis-basic-income-program

Tables and Figures

Table 1. Baseline Summary Statistics, In Her Hands (N = 505, Administrative Data)

	Aggregate Sample	comparison (n = 238)	Treatment (n=267)	Treatment by Conditions	
				$700 (n = 138)	*$850 (n = 129)*
	%/Mean (S.D.)				
Number of Adults: One	68.5	73.9*	72.9*	71.7**	60.8*
Number of Adults: Two	22.4	19.6*	21.1*	20.8**	25.6*
Number of Adults: Three or more	9.2	6.5*	6.0*	7.5**	13.6*
Number of Children: None	26.4	28.3	25.6	27.1	25.6
Number of Children: One	25.7	25.4	28.6	30.6	23.9
Number of Children: Two	23.3	18.8	25.6	21.9	25
Number of Children: Three or more	24.6	27.5	20.3	20.4	25.6

Age	38.7 (12.0)	39.4 (11.9)	38.9 (12.9)	39.5 (13.3)	38.0 (11.2)
Household Income (in dollar)	$12,905.1 ($11771.2)	$13,762.6 ($12,100.2)	$11,386.6 ($10,580.5)	$13,856.5 ($10,584.6)	$13,380.0 ($12,309.1)
Site: Urban	27.2	32.6*	33.6*	35.2**	18.3*
Site: Suburban	37.4	37*	34.3*	41.2**	40*
Site: Rural	35.4	30.4*	32.1*	23.6**	41.7*

* p < .05, ** p < .01, *** p < .001. Two tailed tests: χ^2 test for correlation between treatment conditions and categorical variables. T test for mean differences among treatment conditions.

Note. Missing values are not included in computing descriptive statistics.

Table 2. In Her Hands Credit and Debt Outcomes by Treatment Status (N = 452, Year 2 Survey Data)

	Aggregate Sample	**comparison (n = 180)**	**Treatment (n = 272)**	**Treatment by Conditions**	
				$700	*$850*
Variables	*%/Mean (S.D.)*				
Panel A: High-Cost Financial Services					
Used Auto Title Loan: Yes	13.2	12.5	13.7	13.4	13.9
Used Auto Title Loan: Never	86.8	87.5	86.3	86.6	86.1
Used Auto Title Loan: 1 time	7.8	9.5	6.6	5.9	7.4
Used Auto Title Loan: 2 times	4.4	2.4	5.8	5	6.6
Used Auto Title Loan: 3+ times	1	0.6	1.2	2.5	0
Used Payday Loan: Yes	23.8	27.8	21	22.5	19.5
Used Payday Loan: Never	76.2	72.2	79	77.5	80.5
Used Payday Loan: 1 time	10.7	13.6	8.6	8.3	8.9
Used Payday Loan: 2 times	7.8	7.1	8.2	10	6.5
Used Payday Loan: 3+ times	5.3	7.1	4.1	4.2	4.1
Used Pawn Shop: Yes	26.3	35.1	21.2**	18.3	22
Used Pawn Shop: Never	73.7	64.9	79.8**	81.7	78
Used Pawn Shop: 1 time	11.2	15.5	8.2**	8.3	8.1
Used Pawn Shop: 2 times	8.3	9.5	7.4**	5.8	8.9

Used Pawn Shop: 3+ times	6.8	10.1	4.5**	4.2	4.9
Sold Plasma: Yes	19.6	28.1	13.7***	11.6	15.8
Sold Plasma: Never	80.4	71.9	86.3**	88.4	84.2
Sold Plasma: 1 time	5.9	8.4	4.2**	4.1	4.2
Sold Plasma: 2 times	3.4	3	3.7**	3.3	4.2
Sold Plasma: 3+ times	10.3	16.8	5.8**	4.1	7.5
Overdrafted: Yes	49.6	59.9	42.4**	44.9	40
Overdrafted: Never	50.4	40.1	57.6**	55.1	60
Overdrafted: 1 time	14.3	15.6	13.5**	14.4	12.5
Overdrafted: 2 times	12.1	12	12.2**	11.9	12.5
Overdrafted: 3+ times	23.2	32.3	16.8**	18.6	15
Panel B: Debt[a]					
Credit Card Balance	$866.2 ($2,006.8)	$778.8 ($1,963.4)	$927.4 ($2,038.4)	$1,013.8 ($2,078.1)	$839.7 ($2,002.2)
Educational Loan	$16,340.7 ($26,600.9)	$16,540.8 ($23,285.5)	$16,197.1 ($25,550.4)	$15,649.5 ($25,442.8)	$16,713.8 ($25,744.0)
Auto Loan	$5,533.4 ($9,296.0)	$4,856.4 ($8,634.3)	$6,023.4 ($9,735.3)	$5,035.6 ($8,940.2)	$6,970.6 ($10,389.9)
Medical Debt	$5,286.0 ($2,0267.0)	$4,634.4 ($10,882.8)	$5,754.9 ($24,939.4)	$4,671.5 ($15,552.6)	$6,793.9 ($31,452.7)
Other Bank Loan	$1,012.1 ($2,566.7)	$1,203.6 ($2,704.2)	$877.1 ($2,461.9)	$899.2 ($2,604.4)	$855.9 ($2,327.4)

Total Debt	\$29,137.0 (\$35,448.4)	\$2,8861.1 (\$32,819.0)	\$29,328.9 (\$37,232.6)	\$27,763.9 (\$37,091.7)	\$30,820.6 (\$37,450.7)

* p < .05, ** p < .01, *** p < .001. Two tailed tests: χ^2 test for correlation between treatment conditions and outcomes in Panel A. T test for mean differences in Panel B.

Note. Missing values are not included in computing descriptive statistics.

[a] Amounts are winsorized at the 95-percentile distribution.

Table 3. In Her Hands Savings Outcomes by Treatment Condition (N = 452, Year 2 Survey)

	Aggregate Sample	comparison (n = 180)	Treatment (n = 272)	Treatment by Conditions	
				$700	*$850*
Variables	*%/Mean (S.D.)*				
Panel A: Emergency Fund Duration					
Set Aside Emergency Fund: Yes	19.7	11.5	25.9***	27	24.8
Duration: No Emergency Fund	80.3	88.5	74.1**	73	75.2
Duration: Less than One Month	9	6.9	10.5**	12.2	8.9
Duration: One to Three Months	6.2	2.3	9.2**	7	11.5
Duration: More than Three Months	4.5	2.3	6.1**	7.8	4.4
Panel B: Savings[a]					
Savings	$334.3 ($765.9)	$134.4 ($453.6)	$477.2*** ($900.9)	$435.6 ($860.5)	$518.7 ($941.3)
Saving for Child Education: Yes	29.2	23.4	33.5*	34	33.1
Savings for Child Education	$644.6 ($1,467.6)	$505.9 ($1,287.8)	$746.1 ($1,582.8)	$687.6 ($1,583.3)	$799.4 ($1,590.5)

* p < .05, ** p < .01, *** p < .001. Two tailed tests: χ^2 test for correlation between treatment conditions and outcomes in Panel A. T test for mean differences in Panel B.

Note. Missing values are not included in computing descriptive statistics.

[a] Amounts are winsorized at the 95-percentile distribution.

Table 4. In Her Hands High-Cost Credit Outcomes, Longitudinal OLS Models

	Auto Title Loan	**Payday Loan**	**Pawn Shop**	**Plasma Selling**	**Overdraft**
	Coef. (S.E.)	*Coef. (S.E.)*	*Coef. (S.E.)*	*Coef. (S.E.)*	*Coef. (S.E.)*
Condition: Treated	-0.07 (0.05)	-0.14* (0.05)	-0.12* (0.06)	-0.13** (0.05)	-0.17* (0.07)
Wave: 4	-0.04 (0.05)	0.03 (0.05)	-0.02 (0.05)	0.01 (0.04)	0.03 (0.06)
Condition: Treated × Wave: 4	**0.04 (0.06)**	**-0.03 (0.07)**	**-0.02 (0.06)**	**-0.02 (0.05)**	**-0.08 (0.08)**
Baseline Administrative Controls[a]	Yes	Yes	Yes	Yes	Yes
Wave 2 Treatment Effect	-.07 (.05)	-.14* (.05)	-.12* (.06)	-.13** (.05)	-.17* (.07)
Wave 4 Treatment Effect	-.03 (.05)	-0.17** (.05)	-.14* (.06)	-.15** (.05)	-.25*** (.07)
N	482	485	485	483	478

* p < .05, ** p < .01, *** p < .001. Two tailed tests.

[a] Baseline controls include: number of adults, number of children, study site, age, and logged household income.

Table 5. In Her Hands Debt Outcomes, Longitudinal OLS Models						
	Credit Card	**Educational Loan**	**Auto Loan**	**Medical Debt**	**Other Bank Loan**	**Total Debt**
	Coef. (S.E.)	*Coef. (S.E.)*	*Coef. (S.E.)*	*Coef. (S.E.)*	*Coef. (S.E.)*	*Coef. (S.E.)*
Condition: Treated	223.61 (260.70)	135.43 (1179.75)	-4874.67 (3279.15)	-980.09 (2228.33)	-309.46 (332.49)	-5910.91 (4695.53)
Wave: 4	36.16 (167.87)	86.55 (841.79)	2650.49 (2025.60)	201.4 (2298.37)	-127.04 (279.15)	4088.54 (3131.90)
Condition: Treated × Wave: 4	**76.84 (208.29)**	**-28.83 (1047.06)**	**2469.57 (2526.11)**	**3070.03 (2855.36)**	**200.81 (345.54)**	**4214.46 (3869.01)**
Baseline Administrative Controls[a]	Yes	Yes	Yes	Yes	Yes	Yes
Wave 2 Treatment Effect	$223.61 ($260.70)	$135.43 ($1,179.75)	-$4,874.671 ($3,279.16)	-$980.09 ($2,228.33)	-$309.46 ($332.49)	-$5,910.91 ($4,695.53)
Wave 4 Treatment Effect	$300.45 ($258.27)	$106.61 ($1,174.09)	-$2,405.11 ($3,253.19)	$2,089.94 ($2,203.90)	-$108.65 ($330.54)	-$1,696.45 ($4,670.50)
N	491	489	484	484	484	497

* p < .05, ** p < .01, *** p < .001. Two tailed tests.

[a] Baseline controls include: number of adults, number of children, study site, age, and logged household income.

Table 6. In Her Hands Savings Outcomes, Longitudinal OLS Models

			Savings for Child Education	
	Emergency Fund: Yes	**Savings**	**Saving: Yes**	**Amount of Savings**
	Coef. (S.E.)	*Coef. (S.E.)*	*Coef. (S.E.)*	*Coef. (S.E.)*
Condition: Treated	0.10 (0.06)	73.83 (80.09)	0.12 (0.08)	9.86 (249.26)
Wave: 4	-0.07 (0.05)	-38.74 (67.39)	-0.03 (0.07)	-398.94 (242.17)
Condition: Treated × Wave: 4	**0.12* (0.06)**	**302.54*** (84.41)**	**0.00 (0.08)**	**606.33* (293.01)**
Baseline Administrative Controls[a]	Yes	Yes	Yes	Yes
Wave 2 Treatment Effect	.10 (.06)	$73.83 ($80.09)	.12 (.08)	$9.86 ($249.26)
Wave 4 Treatment Effect	.22*** (.05)	$376.38*** ($80.21)	.12 (.08)	$616.19* ($245.43)
N	476	487	306[b]	306[b]

* p < .05, ** p < .01, *** p < .001. Two tailed tests.

[a] Baseline controls include: number of adults, number of children, study site, age, and logged household income.

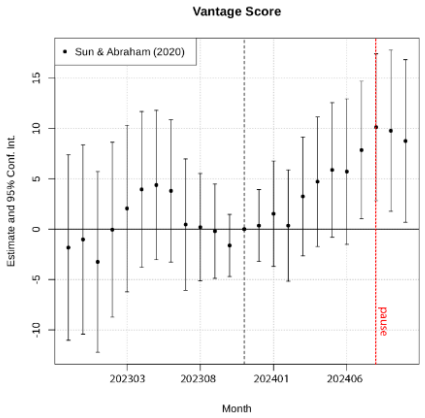
[b] The analytic sample for child education savings is restricted to those who have children. The reference level is Number of Children: One.

Table 7: Impact of St. Louis GBI Program on Credit Outcomes, Difference-in-Differences (Administrative Credit Data)							
	(1) Vantage Score	(2) Num. 30 DPD	(3) Num. 60 DPD	(4) Bal. Revolv.	(5) Bal. Install.	(6) Bal. StuLoan.	(7) Util. Revolv
Treatment x Post	**5.396***	**-0.171***	**-0.131***	**286.4**	**1,580.60**	**-120.3**	**-0.015**
	(2.716)	(0.068)	(0.057)	(223.1)	(1600.4)	(635)	(0.049)
Baseline Outcome Mean	578.6	0.577	0.452	1,691.60	19,288.10	10,517.90	0.286
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treatment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	965,584	965,584	965,584	965,584	965,584	965,584	965,584

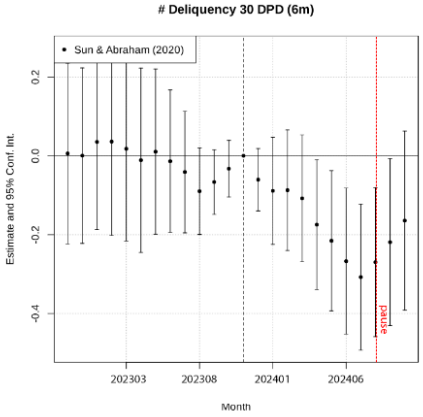
+p<0.1, * p < .05, ** p < .01, *** p < .001. Standard errors are clustered at the individual level.

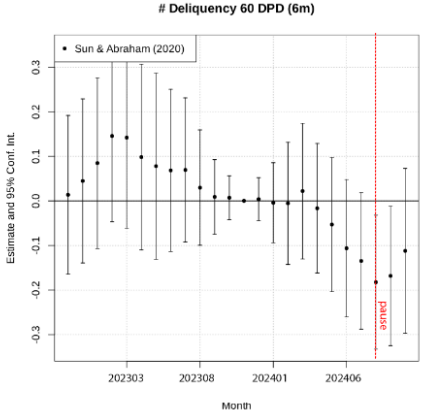
Figure 1. Sun-Abraham Event Study Results, St. Louis GBI Program (Administrative Credit Data)

Panel A: Credit Score

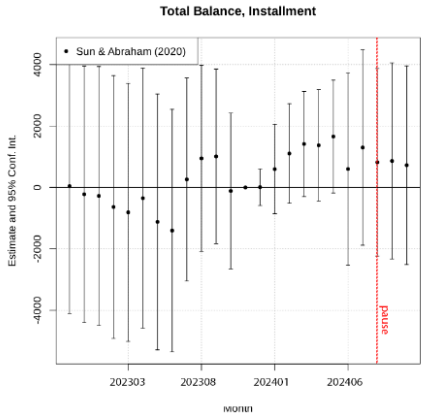


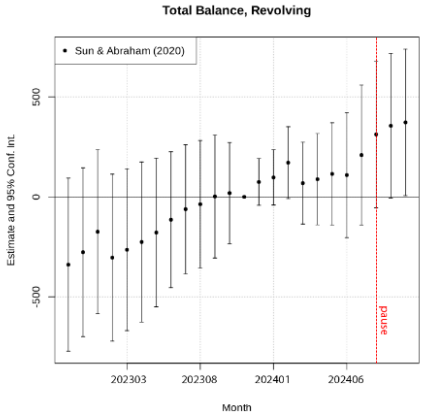
Panel B: Credit Distress

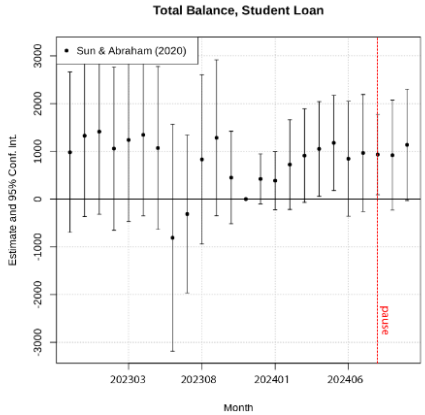


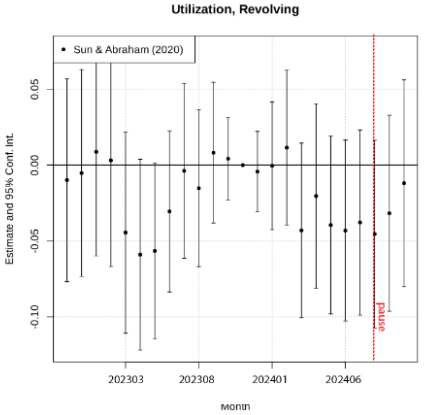


Panel C: Indebtedness









Note: Red line indicates temporary payment pause due to lawsuit

Appendix

Table A1: Impact of St. Louis GBI Program on Credit Outcomes, Difference-in-Differences (Administrative Credit Data, Individual Fixed Effects)

	(1) Vantage Score	(2) Num. 30 DPD	(3) Num. 60 DPD	(4) Bal. Revolv.	(5) Bal. Install.	(6) Bal. StuLoan.	(7) Util. Revolv
Treatment x Post	**4.805+**	**-0.168***	**-0.130***	**330.5**	**1,153.60**	**105.4**	**-0.009**
	(2.669)	(0.069)	(0.058)	(226.5)	(1619.1)	(633.4)	(0.023)
Baseline Outcome Mean	578.6	0.577	0.452	1,691.60	19,288.10	10,517.90	0.286
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	965,584	965,584	965,584	965,584	965,584	965,584	965,584

+ p<0.1, * p < .05, ** p < .01, *** p < .001. Standard errors are clustered at the individual level.