

The Effect of Emergency Financial Assistance on Employment and Earnings

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Abstract

We examine the labor supply effects of short-term income transfers for families experiencing a housing crisis. We link callers to an emergency assistance homelessness prevention hotline to their federal tax records and measure their employment & earnings in years surrounding their calls. Our methodology exploits quasi-random variation in the availability of assistance to compare similar families receiving and not receiving funds. Looking up to four years post-assistance, we find evidence, especially for the lowest earners, of earnings and employment gains, and overall we find no evidence that assistance lowers earnings or employment. Our results indicate that any income effect of temporary transfers for those in crisis is minimal and that these transfers may convey labor market benefits for the poorest of the poor.

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1. Introduction

A primary goal of social safety net programs is to help households maintain economic well-being when faced with a transitory shock ([Gruber, 1997, 2000](#)). Research has shown that such shocks, particularly for the poor, can create a downward spiral of economic challenges. For example, a temporary loss of income may result in an inability to pay rent and ultimately eviction, which, in turn, leads to increased likelihood of homelessness and reduced earnings ([Collinson, Humphries, Mader, Reed, Tannenbaum, and Van Dijk, 2024](#)). To prevent this type of chain reaction, most US communities have programs that make emergency financial assistance available to low-income families facing housing instability. This type of aid expanded dramatically during the COVID-19 pandemic, with Congress allocating more than \$70 billion to state and local governments for emergency housing assistance ([CARES Act, 2020](#); [Consolidated Appropriations Act, 2020](#); [American Rescue Plan Act, 2021](#)).

However, there is little direct evidence on whether such assistance can preserve or improve earnings and employment for those experiencing a housing crisis. On the one hand, an income transfer that targets those in crisis may improve a recipient’s economic stability, leading to better job search or job matching outcomes and increased employment or earnings ([Desmond, 2016](#); [Collinson et al., 2024](#)). Moreover, policymakers often claim that housing assistance stabilizes recipients’ lives in a way that better positions them to work. For example, the executive director of the US Interagency Council on Homelessness states, “[H]ousing is indeed the foundation for getting and keeping a job, addressing mental health and substance use, and reconnecting with family, friends, and community” ([Olivet, 2023](#)). A growing body of research indicates that temporary income transfers targeted towards those facing a housing crisis can have important nonpecuniary benefits for recipients, including reduced homelessness ([Evans, Sullivan, and Wallskog, 2016](#); [Phillips and Sullivan, 2023](#)) and arrests for violent crimes ([Palmer, Phillips, and Sullivan, 2019](#)).

On the other hand, behavioral responses to short-term income transfers might lessen the incentive to work. A simple labor supply model predicts that a pure non-labor income trans-

fer such as emergency financial assistance would reduce labor supply if leisure is a normal good. A large literature has shown evidence of a negative income effect in a variety of contexts, including the Negative Income Tax experiments (Robins, 1985; Price and Song, 2018) and cash transfers that result from lotteries (Imbens, Rubin, and Sacerdote, 2001; Cesarini, Lindqvist, Notowidigdo, and Östling, 2017; Golosov, Graber, Mogstad, and Novgorodsky, 2024). As we discuss below, work on housing-based transfers for the disadvantaged has found both negative and positive effects on employment and earnings, although it is unclear if these results would extend to a temporary emergency assistance context.

We examine whether short-term income transfers for housing affect labor supply using a quasi-experimental setting where, conditional on a set of observable characteristics, the availability of funding is exogenous. In particular, we examine the effect of emergency financial assistance coordinated by the Homelessness Prevention Call Center (HPCC) in Chicago, Illinois, which connects individuals and families in need with agencies that provide one-time assistance with rent (about \$900-1,000) or utilities.

Availability of funding varies over time and across agencies, and is at any moment unobservable to both the callers and the staff who receive calls. Each funding agency has clear eligibility rules; the HPCC systematically triages callers according to these rules so that the resulting referrals are a function of characteristics observed by the call center (and by us) and unpredictable variation in the availability of funds. As in prior studies (Evans et al., 2016; Palmer et al., 2019; Downes, Phillips, and Sullivan, 2022), we exploit these rules to compare, among callers deemed potentially eligible for funds, those referred to assistance versus those who are not. Callers who are successfully referred differ from other callers on a number of observable characteristics, but after controlling for the fund-specific rules we find that those referred to assistance have similar predicted wages (based on all ex-ante observables) and similar pre-trends in economic outcomes compared to those not referred. We then link callers to federal administrative tax data on earnings and other outcomes to determine whether those who call when funding is available have different subsequent earnings

and employment rates compared to those who call when funding is unavailable. Our linking allows us to follow callers for many years both before and after they call.

We have several findings. First, our results do not support the hypothesis that families in crisis reduce their labor supply in response to temporary income transfers. For the full sample of eligible callers, our results suggest that, if anything, temporary assistance leads to greater earnings over time, although the estimated effect varies somewhat across specifications. Generally, we can reject that earnings over the following four years fall by more than 3 percent of their pre-transfer average.

Second, any long-term positive effect on earnings is driven by callers with low baseline earnings. The poorest callers are of particular interest as they may be at greatest risk of a downward spiral of unemployment and housing instability, and financial assistance has larger treatment effects for them in prior studies of emergency shelter use, violent crime arrests, and healthcare use (Evans and Moore, 2011; Palmer et al., 2019; Downes et al., 2022). For this group, we can reject the hypothesis that temporary assistance discourages work. In fact for this group, we find that being referred to financial assistance increases annual earnings over the next four years by \$400-\$500. This is a reasonably large effect, representing nearly 10% of the control group mean or about 55% of the total long-term effect of eviction on earnings in Collinson et al. (2024). The estimated effects on employment are largely consistent with those for earnings—our results do not support a negative employment effect but there is some evidence of a positive employment effect for those with low baseline earnings.

Third, looking beyond labor supply, we find that one-time emergency assistance has little impact on non-labor income sources—the effects for adjusted gross income (AGI) are consistent with those for earnings. We also do not find evidence of economically significant changes in takeup of government programs such as unemployment insurance. Fourth, we also find little evidence that the impact of financial assistance on labor market outcomes differed across groups, other than the noticeable difference by baseline earnings. Our main specification provides some evidence that earnings gains may be largest for those who are

seeking assistance because they lost their job and for those without kids. However, these heterogeneous effects are less apparent with alternative specifications.

These results have several implications. First, any work disincentives created by housing assistance appear to depend on the intensity of assistance. While some long-term subsidies have shown signs of moderate work disincentives ([Jacob and Ludwig, 2012](#); [Gubits, Shinn, Wood, Brown, Dastrup, and Bell, 2018](#)), we can reject large work disincentives for temporary housing assistance.

Second, any improvements in employment resulting from stable housing appear over the long run, through the first 4 years post-treatment. This persistence is important because even modest income gains each year, if accrued, could dramatically bolster the overall estimated net present value of emergency assistance. Also, future work on the benefits of housing support should explore effects not just at the time of award, but in the years following, as the benefits we document would have been impossible to identify with only short-term outcome data.

Third, these results are much stronger for the lowest-income individuals. All people in the study face serious disadvantages—those calling the HPCC start out in worse economic situations than their neighbors, as we show below. But even among a particularly low-socioeconomic-status population, our results differ by baseline earnings.

Together, these results support the idea that housing instability matters for labor market outcomes. If exceptionally low-income individuals lack the ability to insure against housing shocks, then these shocks can lead to negative effects in other outcomes. Our estimates suggest that, for the poorest of poor, emergency housing assistance can help to prevent the type of downward spiral that can be associated with a negative shock.

2. Income Transfers and Labor Market Outcomes

Economists have long been interested in the labor supply effects of a wide variety of cash transfer programs including means-tested transfer programs such as Temporary Assistance to Needy Families ([Ziliak, 2015](#)), the Supplemental Nutrition Assistance Program ([Han, 2022](#); [Hoynes and Schanzenbach, 2015](#)), and Supplemental Security Income ([Duggan, Kearney, and Rennane, 2015](#); [Deshpande, 2016](#)). Because these programs provide an income guarantee for those who do not work and then apply a benefit reduction rate for those with earnings that exceed some (typically low) threshold, they disincentivize work through negative income and substitution effects. Other redistribution programs, such as the Earned Income Tax Credit ([Nichols and Rothstein, 2015](#); [Whitmore Schanzenbach and Strain, 2021](#)), share the feature of having a negative income effect, but because they provide a wage subsidy the substitution effect is positive over certain ranges of pre-tax earnings.

Emergency financial assistance differs from these programs in important ways. Unlike the means-tested transfer programs mentioned above, financial assistance is very short-term and eligibility for assistance or the size of the benefit typically does not depend on employment status or earnings level. For this reason, financial assistance can be viewed as a pure income transfer, implying no substitution effect but potentially a negative income effect. A recent literature has examined pure income transfers such as casino profits distributed to tribal members ([Akee, Copeland, Keeler, Angold, and Costello, 2010](#)), or the distribution of Alaska Permanent Fund dividends to state residents ([Jones and Marinescu, 2022](#)). In addition, many recent policies have been implemented, or are under consideration, that provide pure income transfers to low-income households including the expanded Child Tax Credit that was available in 2021 and that many have proposed making permanent, as well as scores of local guaranteed income programs.¹ The possible work disincentives have been central to debates over expanding these transfers ([Corinth et al., 2021](#); [Hoynes and Rothstein, 2019](#)).

¹The American Rescue Plan Act of 2021, which was signed into law in March 2021, expanded the Child Tax Credit and made it fully refundable, eliminating the work incentives of the original Child Tax Credit ([Corinth, Meyer, Stadnicki, and Wu, 2021](#); [Enriquez, Jones, and Tedeschi, 2023](#)).

Our context differs from these studies because we focus on transfers that are less permanent and target a uniquely vulnerable population: those facing a housing crisis.

Understanding the labor supply effects of transfers has also been the focus of studies of programs that aim to promote housing stability, such as housing subsidies. [Jacob and Ludwig \(2012\)](#) find that winning a housing voucher lottery reduces subsequent employment, although the effect is modest—a decline of 6 percent. [Gubits et al. \(2018\)](#) find that long-term subsidies provided to families at the moment they are entering emergency shelters reduces future employment. However, there is some evidence that the work disincentive may differ when the subsidy is temporary. The same study finds that rapid re-housing subsidies, which typically phase out within 12 to 24 months, increase earnings in the short-term ([Gubits et al., 2018](#)). But the study’s power for measuring long-term effects is limited due to relatively low take-up. This is important, since one of the rationales for these temporary subsidy programs concerns their impact on future income.

Previous studies of emergency financial assistance have not focused on labor market outcomes. A series of studies examine how such assistance affects homelessness ([Evans et al., 2016](#); [Phillips and Sullivan, 2023](#)), crime ([Palmer et al., 2019](#)), and healthcare use ([Downes et al., 2022](#)) but do not measure employment outcomes. The one existing emergency assistance study that does measure employment shows large pre-treatment imbalances in employment that make inference difficult ([Rolston, Geyer, Locke, Metraux, and Treglia, 2013](#)). Perhaps the closest papers to the present study examine small, one-time income transfers during the COVID-19 pandemic. [Jaroszewicz, Jachimowicz, Hauser, and Jamison \(2022\)](#) find a small negative impact of providing \$2000 on a financial index mostly composed of employment outcomes, and [Pilkauskas, Jacob, Rhodes, Richard, and Shaefer \(2023\)](#) find little impact of a \$1000 transfer on employment. Of course, these papers study programs implemented in the unique context of a global pandemic that dramatically altered labor market outcomes, and although the transfers were targeted towards low-income households, they did not target those facing a negative income shock or other crisis.

We also contribute to the understanding of labor supply effects of cash transfers by exploring heterogeneity in this effect. Whether housing assistance encourages or discourages employment may vary across individuals. In particular, although cash transfers may lower earnings and employment through an income effect, these work disincentives might be lower for those with very little income, either because their attachment to the labor market is already weak or because the potential for improved housing stability to lead to better labor market outcomes might be greater for low-income families. In fact, previous work ([Evans et al., 2016](#)) finds that temporary financial assistance is most effective at preventing homelessness among people with the least income, and housing loss may be particularly disruptive among people facing other barriers ([Collinson et al., 2024](#)).

3. The Homelessness Prevention Call Center

Most US communities have a network of providers who make emergency assistance available to those at risk of eviction. In 2019, hotlines that provide essential community services were available to 95% of the U.S. population ([Federal Communications Commission, 2023](#)), and the most common request made to these hotlines was for help paying rent and utilities ([211.org, 2023](#)). In Chicago, the process of allocating emergency assistance is fairly centralized. Individuals and families in need of rent or utility assistance can call the city’s services hotline, 3-1-1, for help. Such calls are routed to the HPCC, which is operated by Catholic Charities and serves as the central hub for emergency financial assistance. An intake specialist at the HPCC collects contact and demographic information from the caller. This step is important for the evaluation because the HPCC collects personal identifying information and demographic characteristics before determining eligibility and regardless of whether any financial assistance is available. This step allows us to link eligible callers to outcome data regardless of whether the caller is referred to assistance or turned away because no assistance is currently available.

After collecting basic demographic information, the intake specialist collects additional information necessary to determine if the caller is eligible for assistance. To be eligible, the caller must demonstrate the presence of a crisis that (a) is on a list of eligible crises (such as the loss of a job), (b) causes imminent risk of homelessness (as evidenced by an eviction notice, for example), (c) can be solved with limited financial assistance (typically less than \$1,500), and (d) is temporary (i.e. the caller has sufficient future income to pay essential expenses). The center initially screens on these criteria based on information the caller provides, but funding agencies verify many of these eligibility criteria (e.g. with landlord and employer documentation) before funding is provided. Callers ineligible for the HPCC and callers who are not referred to funds are referred to non-financial assistance.²

The HPCC does not disburse assistance itself. Rather, it connects callers to government and private entities, or delegate agencies, that administer assistance. If a caller is determined to be eligible, the HPCC then checks to see if funding is available at one of the delegate agencies. The staff member works through a pre-set ordered list to see if any of the agencies has funds available immediately and if the caller meets any fund-specific eligibility criteria including request type (rent assistance, security deposit, or utilities), amount of assistance needed, veteran status, receipt of housing subsidies, and whether the total debt exceeds one month of rent. For example, some funds have more restrictive payment limits or may pay only for back rent, not security deposits or utilities. If an agency with funds is identified, the HPCC refers the caller to that delegate agency. The delegate agency is then tasked with meeting the household's net financial need, most frequently one month of back rent. The assistance is temporary, meeting only the immediate need and disallowing returns for more assistance in the following year. If an agency is not identified for financial assistance, the caller is referred to non-financial assistance.

On any given day, the availability of funds is sporadic and hard to predict. New delegate

²This assistance includes legal aid, domestic violence counseling, assistance with utility complaints, workforce development, senior services, disability services, public benefit screening, and other general support services (George, Hilvers, Patel, and Guelespe, 2011).

agencies come online and existing agencies shut down routinely. Also, funding may not be available continuously at currently operating agencies because they may temporarily run out of funds or are unable to distribute them immediately. Whether funds can be distributed on any given day, or time within a day, depends on many factors. For example, some delegate agencies require that callers meet with a financial counselor before receiving assistance, and a HPCC intake specialist will not refer a caller for assistance if an interview slot is not available at the time of the call. For some agencies, there are only a fixed number of appointments available each week or month, but the availability of slots may vary due to cancellations or changes in staff capacity. Variation in funding also results from the fact that some delegate agencies are supported by local or state programs that provide an inconsistent and unpredictable funding stream. Therefore, an eligible caller who calls when delegate agencies happen to have funding and staff availability will be referred to assistance, while the same caller would have been turned away had they called when funding was unavailable or staff lacked capacity to process a request.

Figure 1.a shows the weekly funding rate for all eligible callers during our full period from July 2013 through December 2015. This figure shows that the probability of funding varies considerably from week to week. While the average funding rate for this sample period was 65%, in some weeks more than 90% of eligible callers were referred to funds, while in other weeks less than 30% were referred. This variation may differ across different caller types because of fund-specific eligibility requirements. When looking at the shorter time period during which we observe fund-specific eligibility requirements (Figure 1.b), and when we restrict the sample to callers within this shorter period that share some of the same fund-specific eligibility requirements, i.e. callers who do not have other housing subsidies and are asking for more than one month of rent assistance totalling more than \$900 (1.c), we still find considerable variation in the likelihood of being referred to funds.

Because fund availability is determined by factors outside the control of the HPCC, the call center has limited information about when funds will be available. Any information they

might have about future funding is not shared with callers. The instructions for HPCC staff state, “If anyone asks, ‘when will a fund be available?’ please respond the following: ‘I do not have information on when funds will be available. Unfortunately, there are not enough funds for everyone who needs assistance and availability is sporadic.’ If anyone asks, ‘should I call back?’ please reply: ‘That is up to you.’ If anyone asks, ‘but what is the best time to call?’ please reply: ‘There is no best time to call. The need is so high in Chicago/the Suburbs, there are so many people trying to get access to the limited number of grants’” (HPCC, 2013).

As a result, the HPCC process generates a natural comparison group. Observationally identical callers are sometimes referred to funds and other times not. The unpredictable and high frequency variation in the funding rate ensures that callers who are referred to funds versus not will be similar, conditional on characteristics that affect fund-specific eligibility requirements.

4. Data

4.1. HPCC Call Center Data

This study uses a sample of call information from the HPCC that covers all calls between January 20, 2010 and March 29, 2018. Following Downes et al. (2022), we limit the sample to calls received between July 1, 2013 and December 31, 2015. Prior to matching this sample to outcome data, we exclude calls in categories unrelated to financial assistance, e.g. calls that are incomplete or do not include client interaction. The call data include personal identifiers (e.g. name) fundamental to the data linking process. They also cover various characteristics related to the program eligibility process. These variables include those related to overall eligibility (e.g. income) as well as those related to fund-specific eligibility (e.g. amount needed). They also collect general demographic information (e.g. gender) that we use as covariates and for balance tests. We also link caller address ZIP codes to 2009-2013 American

Community Survey data on ZIP-code level characteristics.

4.2. *Administrative Records and Census Data*

We use administrative and survey data to construct a panel of labor market, family structure, and residential outcomes, supplemented with additional demographic information on callers. We construct outcome measures using data from three types of tax forms: form 1040, form W-2, and various information returns (e.g., 1099 forms). In each case, we have access to a limited set of fields from the universe of records. Form 1040 is available annually starting in 1998 and provides tax unit-level information on income, filing status, presence of children, and place of residence. Because we have access to the universe of returns, the data also tell us whether a person appears on any tax return in a given year. Form W-2 is available annually beginning in 2005 and provides individual-by-employer-level information on earnings. Our primary analysis aggregates earnings across employers within person. In addition to analyzing earnings, we use data from W-2s to construct measures of employment, with people considered employed if they have earnings greater than zero, and more substantially employed if they have earnings exceeding the amount associated with half a year of full-time work at the contemporaneous federal minimum wage.

The information return data includes whether a person receives various information returns and the addresses at which forms were received. The address information is available beginning in 2003. Codes identifying the type of information return received are available consistently beginning in 2010.³ The US Census Bureau’s Numident file provides demographic information for every person with a social security number. Information provided includes date of birth, place of birth, sex, and citizenship.

For our comparisons of callers to noncallers, we also use data from the decennial census and American Community Survey (ACS) to provide other demographic data at the indi-

³The specific information returns identified by these codes are 1099-MISC, 1099-R, 1099-S, 1099-G, 1099-SSA, 1099-INT, 1099-DIV, and 1098. The file also includes an indicator for receipt of and address information associated with Form W-2.

vidual level, most notably information on race and ethnicity. This information is drawn from the 2000 (short form) and 2010 decennial censuses and all available years of the ACS, which samples one percent of households annually beginning in 2005. We determine place of residence for callers and non-callers using location information available from tax forms and the Census Bureau’s Master Address File Auxiliary Reference File (MAF-ARF) which collects person-year-address combinations from additional administrative data sources.

4.3. *Data Linkage*

The HPCC data are linked to outcome data at the individual level using the Census Bureau’s Protected Identification Keys (PIKs), assigned using personally identifiable information (PII) by the Person Identification Validation System (PVS).⁴ Each PIK is associated with a unique social security number (SSN) or individual taxpayer identification number (ITIN). For this reason, files that include information on people’s SSNs/ITINs (e.g. administrative records such as data from tax forms) typically have extremely high PIK assignment rates (97 percent or higher). PIK assignment rates for the decennial census and ACS, which do not contain SSN/ITIN information, are typically somewhat lower but still high in absolute terms at about 90 to 93 percent (Mulrow, Mushtaq, Pramanik, and Fontes, 2011). PVS’s false match rates are generally extremely low (Layne, Wagner, and Rothhaas, 2014).

In the HPCC data, about 95 percent of records are successfully assigned a PIK, in line with the high PIK assignment rates for the other data we are using. For callers who meet the criteria to be included in our main analysis sample, Table A.1 compares those who are assigned a PIK to those who are not, using information collected by the HPCC. In general, the differences between the two groups are fairly small. One notable exception is that the people not assigned a PIK are nearly three times as likely to be Hispanic as people who are assigned a PIK (21 percent vs. 7.5 percent). However, given the small size of the group not assigned PIKs, their exclusion from the sample does little to shift the baseline characteristics

⁴See Wagner and Layne (2014) for details.

of the HPCC callers whose subsequent outcomes we are able to analyze.

4.4. *Sample for Analysis*

Because we have access to the universe of records from the data sources described in Section 4.2, we can compare HPCC callers to non-callers from the same narrow geographic area based on contemporaneous and pre-call characteristics. This comparison, which has not been feasible in prior studies of this program, improves our understanding of who seeks emergency financial assistance, and specifically who calls the HPCC.

We start broadly, comparing all callers, regardless of whether they are eligible for assistance, to non-callers. The first two columns of Table 1 compare HPCC callers from 2013 through 2015 to non-callers who were living in the same set of Census blocks at the time.⁵ The comparison must be based on information that is available for both groups and so is limited to demographic characteristics obtained from full population data available through the Census Bureau. There are large differences on several characteristics between callers and their geographic neighbors. Callers are three years younger on average, 25 percentage points more likely to be women, and nearly 21 percentage points more likely to be Black than are non-callers living in the same Census blocks. Callers are also nearly 14 percentage points less likely to have been born outside the United States, and correspondingly more than 16 percentage points more likely to be citizens.

Columns 3 through 5 show how we construct our analysis sample from the call data and how caller characteristics change as we narrow the sample. These restrictions are identical to those in Downes et al. (2022). We first limit the sample in column 3 to people who meet general eligibility requirements: experienced a crisis, at imminent risk of homelessness, solvable with limited financial assistance, and demonstration of future income (see program description above). Because people can call repeatedly and likely do so non-randomly, we

⁵Census blocks are the smallest geographic unit used by the Census Bureau for official data tabulations. Their boundaries are generally formed by streets and highways, especially in more urban areas where they often consist of city blocks, but may also consist of landscape features such as bodies of water or political borders, such as county/city/town boundaries.

limit our sample to calls with no prior call in the past 6 months. This restriction leads to the main analysis sample in column 4. Finally, at times we analyze data separately for callers with the lowest pre-period wages; column 5 shows the sample of callers with pre-period wages below the median. While there are some small fluctuations on these characteristics across subsets of callers, these changes are small compared to the gaps between the full set of callers and non-callers living in the same places. Even when we restrict the sample to those with low earnings, which is a sample we focus on in our analysis, the observable characteristics are quite similar to those for the full sample of eligible callers.

The final column of Table 1 shows characteristics of non-callers matched one-to-one with eligible callers in the low-earnings sample using propensity score matching. Propensity scores are estimated using a logistic regression of calling HPCC on the characteristics shown in the table. Matches are drawn without replacement. Where possible, each caller’s match is selected from the same Census block as the caller.⁶ As one might expect, the differences between the HPCC callers and the matched sample on the characteristics used in the matching process are fairly small.

We use similarly identified matched samples to examine differences between callers and observably similar non-callers on time-varying, pre-call characteristics. Figure 2 shows trends in select outcomes for all HPCC callers in 2013–2015 and matched non-callers, beginning at least ten years before a call.⁷ There are clear differences between these two groups: HPCC callers are less likely to be employed (i.e. to have any income reported on a W-2), have lower AGI, claim more children as dependents on their tax returns, and change addresses more frequently than demographically similar non-callers living in the same parts of Cook County. These trends do not point to particularly sharp changes in circumstances preceding callers’ interactions with the HPCC, though the number of children claimed on tax returns does trend up for callers over the preceding years, with a notable jump up five years prior,

⁶If matching within block is not possible, the match is selected from the same tract. If matching within tract is not possible, the match is selected randomly from non-callers living in the union of all blocks that were home to HPCC callers that year.

⁷For non-callers, the year of the call is the year in which they are matched to a caller.

while trending down for matched non-callers, suggesting that the presence of children could contribute to financial need for people seeking assistance from HPCC. Trends are similar for our full analysis sample and the corresponding matched non-callers (Figure 3), though the difference in the likelihood of being employed is notably smaller for this sample. The smaller gap between callers in our analysis sample and matched non-callers with respect to employment likely reflects the screening done by the HPCC to ensure that aid is provided to people facing a temporary crisis that causes an imminent risk of homelessness but can be solved with limited financial assistance. The fact that potential contributors to financial need such as the presence of children do not meaningfully change relative to non-callers between Figure 2 and 3 while employment gaps close suggests that callers with relatively weak employment prospects are screened out by the HPCC, likely because a modest amount of financial assistance is less likely to fully meet their financial obligations.⁸

Altogether, HPCC callers appear to be negatively selected based on characteristics that could affect labor market success. This is not surprising given that the HPCC program is intended for individuals facing difficult economic circumstances. However, if one were to estimate the effects of assistance by comparing people referred to financial assistance to noncallers, the comparison could confound the effects of assistance with these underlying characteristics. Instead, our empirical approach will focus on callers, and more specifically callers eligible for assistance, to measure how assistance matters. The next section describes our empirical strategy.

⁸Hungerman, Phillips, Rinz, Sullivan, and Wasser (2025) has a brief discussion of callers and noncallers to the HPCC, but that discussion does not permit this same analysis of the role of screening as (a) it does not include economic outcomes like employment & AGI (b) it does not include the sample used in Figure 2 and (c) it is limited to a single year prior to the year of the call.

5. Empirical Strategy

5.1. Regression Specifications

We focus on callers to the HPCC for our estimates. If funding were randomly assigned by the HPCC, the causal effect of being referred to emergency financial assistance could be determined through OLS estimation of the following:

$$Y_i = \alpha + Funds_i\beta + \epsilon_i \tag{1}$$

where Y_i is an outcome such as subsequent earnings for individual i ; $Funds_i$ is an indicator for whether the person was referred to funds, and ϵ_i is an error term.⁹ The estimate of β would reflect the difference in average outcomes for those referred to funds and those not referred to funds.

As indicated earlier, multiple levels of selection mean that referral to funds by the HPCC is not unconditionally exogenous, but depends on observable factors. First, people select into calling because they face greater challenges than their neighbors. Second, the HPCC limits assistance based on eligibility rules. We address these levels of selection by limiting the sample to eligible callers. However, agencies may go beyond the HPCC’s eligibility criteria and use fund-specific criteria, such as caps on the amount of need for eligible callers. Some callers are eligible for aid from more delegate agencies than others, and this can increase the likelihood of referral; the probability of treatment can thus depend on these observable characteristics.

Addressing the fact that referral varies with these characteristics is a central focus of our methodology. The call center takes into account certain observable characteristics so that, for example, referred clients are less likely to be recipients of other housing subsidies (see Appendix Table A.2). To account for the fact that some groups are more likely to be referred

⁹For simplicity and consistency we refer to i as an individual caller, but some outcomes Y_i below could be household-level outcomes (such as AGI), in which case the subscript i could be taken as representing the household of the caller.

to funds, we focus on variation in funding access after controlling for fund specific criteria. The HPCC is the central screening point for the delegate agencies, so one can observe and control for the factors that explicitly affect funding. We can thus estimate:

$$Y_i = \alpha + Funds_i\beta + X_i\Gamma + Z_i\Pi + \epsilon_i \quad (2)$$

where Z_i is the set of caller characteristics that affect fund-specific eligibility and the probability of referral. These controls include request type (i.e. rent assistance, security deposit, etc.), controls for need amount, whether the caller is a military veteran, receipt of housing subsidies, and whether the individual’s debt exceeds one month of rent. Controls in Z_i also capture call characteristics including the rank of the call within the day, the day of the week and month of the call, the time within the month (first five days, last five days, and middle days), and a set of year-quarter interactions. We also include interactions of need amount with year and quarter indicators to capture the fact that the maximum amount offered by different delegate agencies changes over the sample period. We further include a set of controls for caller characteristics X_i including age, gender, race, ethnicity, income, and receipt of benefits, to reduce residual variance in the outcome.

Table 2 compares those referred and not referred to funds.¹⁰ The sample is restricted to eligible callers, with a PIK, who have not called in the prior six months and with nonmissing characteristic information. The last column in Table 2 shows differences in characteristics after controlling for characteristics related to fund-specific eligibility and the timing of the call, Z_i . In the first two rows of the table, we compare predicted (pre-call) earnings and income for those referred and not referred. Using the non-referred group only, we regress pre-call earnings and AGI on all the baseline caller characteristics in the table. We then use these regressions to predict earnings and AGI for the treatment and control groups. Comparisons of these predicted outcomes provide a summary measure of balance, as they capture a weighted average of how differences in observable characteristics across groups

¹⁰See Appendix Table A.3 for a more complete set of baseline characteristics.

might affect our key outcomes. As the last column shows, the differences in predicted earnings or AGI are small and not statistically significant after characteristics related to fund-specific eligibility are accounted for.

The remainder of the table shows how specific baseline characteristics vary with fund referral in more detail. The table shows that monthly rent averages \$705 among calls referred to assistance compared to \$457 for calls not referred. This gap is expected because referral depends on known, observable characteristics. For example, many delegate agencies only accept referrals to pay back rent, excluding callers requesting security deposits or utility payments who tend to owe lower rent. For similar reasons, those referred to funds have higher monthly income at the time of the call. However, the last columns shows that after controlling for Z_i this and most other differences are much smaller (closer to zero) than the raw differences. The difference in monthly rent reported by callers at the time of the call flips signs; those referred to funds have \$248 greater monthly rent but conditional on fund characteristics this difference becomes $-\$20$. Similarly, the difference in reported monthly earnings goes from \$260 to $-\$57$. These figures are based on information taken during calls to the HPCC, but we can verify this information by looking at pre-call earnings data from linked W-2s. Pre-call average earnings and AGI data are reported near the bottom of the table. These pre-period differences also become smaller after the controls in Z_i are included.

As foreshadowed by the highly similar predicted wage and income results at the top of the table, the differences in column 4 have countervailing implications for how referred and non-referred households differ. With controls, referred individuals have slightly lower monthly income and rent, and are less likely to receive SNAP. But (as shown in the appendix) they report higher EITC participation and earnings.

The version of Table 2 for our sample of the lowest earners (a group defined momentarily) is reported in Table 3; the higher-earners version is in Appendix Table A.4. Notably, below we find stronger evidence that assistance increases earnings for low-earnings households. Table 3 shows stronger balance across treatment and control in the low-wage group for several

baseline characteristics, both before and after controlling for Z_{it} characteristics. For example, in the low-wage group pre-call adjusted gross income differs by a statistically insignificant \$925 in raw means and \$1,265 after adjusting for Z_{it} , about one-quarter and one-half of the respective gaps in the full sample. As in the full sample, any such differences tend to be offsetting and aggregate to negligible differences in predicted outcomes.

The availability of pre-period administrative tax and earnings data used in these tables raises the fact that we can track individuals over time to further address differences in observables. Our main estimation equation will be

$$Y_{it} = \alpha + Funds_{it}\beta + X_{it}\Gamma + Z_{it}\Pi + Y_{i,-1}\delta + \epsilon_{it} \quad (3)$$

where time period is indexed by t , $Y_{i,-1}$ denotes the outcome observed for individual i in the year prior to calling (thus it is for the year $t = -1$, where year zero is the year of the call, rather than year $t - 1$), and the variable $Funds_{it}$ is an indicator for whether an individual was referred to funds at the time of the call.¹¹ This specification pools all time periods starting with the year of the call. The results can thus control for differences in outcomes prior to referral. We will also pursue event-study approaches that limit the sample to a single treatment year and allow the effects of funds β_t to vary over time. Additionally, since our administrative tax data allows us to track individuals over time, we can also consider individual-fixed-effect specifications:

$$Y_{it} = \alpha + Funds_{it}\beta + X_{it}\Gamma + Z_{it}\Pi + \mu_i + \epsilon_{it} \quad (4)$$

where the individual-specific effects μ_i will preclude estimation of coefficients for the $Y_{i,-1}$ control along with many of the X and Z controls. Equation (4) can account for any fixed differences, observed or unobserved, between individuals referred to funds and other individ-

¹¹When a caller has made multiple calls that satisfy our sample conditions within our analysis period, each call record is included in our analysis. For the purposes of event study analysis, each call has relative year set to zero in the calendar year it was made.

uals. The administrative tax data further allows a comparison of the outcome variables for the treatment and control groups in the years leading up to contact with the HPCC. Similar to the results in Table 2, we find below consistent and growing differences in pre-treatment outcomes in the raw data, but this is driven by observable differences in fund characteristics and is largely eliminated after controls are included.

To test whether the lowest-income households benefit most from intervention, we also use the panel data to break our estimates of (3) and (4) apart for low- and high-earnings households using pre-period earnings. For each individual, we take average earnings over the five years prior to contacting the call center; we split the sample into low-earnings and high-earnings groups based on whether individuals’ average pre-call earnings are below or above the sample median of about \$6,000. (Below we discuss effects across a range of earnings values beyond the median.) As noted above, we find stronger evidence that assistance increases earnings for low-earnings households; not only do these households have more balanced observables across treatment and control than the overall sample, both before and after controlling for Z_{it} characteristics, but pre-call outcomes for this group are also extremely balanced in an event-study analysis, as shown below.

Overall, callers differ from noncallers; we focus on callers eligible for fund referral. While delegate agencies’ ability to target the aid they provide means that referral to funds should and does vary by observable characteristics among eligible callers, we address these differences by controlling for these characteristics and exploiting the panel nature of the data, and after doing so we find that referral occurs for similar looking households, with similar pre-trends and similar predicted future values (absent treatment) in outcomes, and that this is true for overall callers and for those who benefit most from the intervention.

5.2. *Take-Up*

Our empirical model estimates the (regression-adjusted) difference in mean outcomes between those who are referred to financial assistance and those who are not, which can be

thought of as an intent-to-treat (ITT) effect. For interpreting the magnitude of our estimates it is important to note that we are not estimating the impact of actual receipt of financial assistance for two reasons. First, not all callers who are initially deemed eligible and offered assistance ultimately receive assistance either because the caller does not follow through with the application process or the delegate agency determines that the caller is not eligible. Second, callers who are initially denied funds may subsequently receive assistance, either because they call the HPCC back and ultimately receive assistance, or they subsequently receive assistance from some entity besides the HPCC. Despite this imperfect compliance, follow-up information on eligible callers indicates significant contrast in the probability of assistance between those initially referred to assistance and those who are not.

Evidence from the Center for Urban Research and Learning (CURL) at Loyola University, which conducted a descriptive evaluation of the HPCC ([George et al., 2011](#)), indicates that most callers to the HPCC who are referred to assistance do actually receive help. Their survey of HPCC callers who had been approved for funding showed that of 105 people in the survey, 71 percent had already received assistance, expected to receive assistance, or had a request in process within 7 days of the initial call. The remainder had either not been contacted (18 percent) or had been denied as ineligible (10 percent).

In addition, we observe that relatively few households that are initially not referred to funding subsequently succeed in being referred in the future. Using our HPCC data on callers, we find that among those who call when funds are not available in our sample of first-time eligible callers, only 5.4% call back at some later date and are referred to funds. Assuming that actual receipt of funds occurs at the same rate as the full sample of callers who are referred to funds (71%), approximately 4% of our control group would receive assistance through repeat calling. It is also possible for rejected callers to receive assistance from other sources, such as small charities, friends, and family, but these alternative sources are less of a concern in our setting because the HPCC coordinates the distribution of such assistance for all major providers of emergency rental assistance in Chicago. [George et al. \(2011\)](#) find that

the call center “operates under the assumption that they are screening for all homelessness prevention funds [in the city]” and that only 8.4% of callers turned away by HPCC had their need met elsewhere. Taken together, this suggests that roughly 12% of those initially turned down for assistance eventually receive some assistance either from repeat calls to the HPCC or from other organizations.

Overall, these estimates suggest that those who are initially referred to assistance are 59% more likely to actually receive assistance than those not referred. We estimate this rate as the difference between our best estimates of take-up among treated in the CURL survey (71%) and fund receipt among the control group (12%). As shown in Table 2, the average household’s net need is \$936; since the program fully meets the net need for treated households, the average referral receives \$552 in assistance. Similarly, a 59% first stage would imply that a 2SLS estimate of treatment effects would be about 69% (or $1/0.59$) larger than the ITT effects we report.

6. Results

6.1. *Trends in Outcomes*

Figure 4 shows trends in earnings in the five years prior to an individual calling the HPCC (denoted year 0) and in the four years after. Panels a and b show raw means for all individuals. The remaining panels split on median pre-period earnings with panels c and d showing results using the low-earnings sample and panels e and f using the high-earnings sample.

The three figures on the left report sample means for eligible callers referred to funds and eligible callers not referred. These figures show rising earnings over time for all groups, but differences in the levels and the trends in pre-call earnings, especially for the high earnings group. Those referred to funds have higher annual earnings than those not referred, as suggested earlier by Table 2, and earnings that rise faster. The flattening of earnings for

the treatment group in period zero in the upper left figure is driven entirely by the high-earnings sample, where there is a large drop in earnings in year zero. This drop resembles the “Ashenfelter dip” in earnings observed for evicted individuals in [Collinson et al. \(2024\)](#), though they compare evicted to non-evicted individuals, whereas the comparison here is to individuals who (voluntarily) call the HPCC and are referred to funds against callers who are not referred. Finally, both this pre-trend and the period-0 decline are absent for the low earnings group.

The rightmost three figures present event-study-style estimations based off of year-by-year regressions of equation 3. Each coefficient is the estimate β taken from a regression of the outcome Y_{it} on a dummy for whether an individual is ever referred to funds, along with the controls X_{it} , Z_{it} , and $Y_{i,-1}$. A separate regression is done for each t . Robust standard errors are used to construct the confidence intervals.

Several things are noteworthy. First, following Table 2 earlier, the results are much different after controls are introduced. The increasing pre-trend for the high earnings group in the bottom row is eliminated, and the pre-treatment gap in earnings between those referred and not-referred to funds is much smaller and insignificant. Next, there are no significant differences in post-treatment earnings for the high-earnings group, but there are for the low-earnings group, where earnings appear to be higher following referral even five years later. The large gains in earnings two years after referral indicate a *positive* effect on earnings for this group.

These results appear consistent with a view that significant disemployment effects of housing assistance are limited to more generous programs. Studies of housing vouchers for general applicants in [Jacob and Ludwig \(2012\)](#) and homeless families in [Gubits et al. \(2018\)](#) both find that housing assistance reduces employment, but both of these studies focus on ostensibly permanent vouchers. More temporary interventions may have different effects. For example, the time-limited subsidy arm of [Gubits et al. \(2018\)](#) increased employment, though only temporarily. Our two-year result for the low earnings group is similar in sign

and magnitude to these rapid re-housing estimates. Similarly, the dip in earnings observed around the time of the call is very close in magnitude to what is reported in [Collinson et al. \(2024\)](#) (accounting for the fact that our result uses annual data and theirs uses quarterly data), though they observe more persistent effects.

6.2. *Effects on Labor Supply*

Table 4 consolidates these treatment results using several different specifications. The first column, which reports estimates from equation (3), combines all post-treatment years into one sample, while including the controls X_{it} , Z_{it} and the pre-calling control $Y_{i,-1}$; the resulting coefficient is an aggregate treatment effect that combines the post-treatment event-study estimates in Figure 4. Standard errors are clustered by PIK, and each reported number of observations is rounded to preserve anonymity. Column 2, which reports estimates from equation (4), uses individual fixed effects and includes the full sample (i.e. all years) of observations. The inclusion of fixed effects produces stronger results than the baseline estimates; here the overall sample estimate now indicates gains in earnings.

Column 3 uses inverse propensity weights; we estimate a logit model of the probability of referral on the full sample and use this regression to predict referral for each caller in the sample. We then weight both referred and non-referred observations by the inverse of the probability that the logit assigned to the caller’s true referral status.¹² Column 4 uses both fixed effects and inverse propensity weights. The final column repeats the baseline specification except that the year $t = -1$ earnings are omitted.

These various specifications consistently reject large decreases in earnings. In the overall sample, whether being referred to assistance increases earnings is sensitive to the specification. The significant positive effect when we omit a control for lagged earnings is consistent with some callers (as suggested by Figure 4.e) who have higher earnings in period -1 being

¹²The controls used in the logit include earnings in year -1, earnings averaged across the pre-period, monthly income reported to the HPCC, and indicators for caller need amount category, year-quarter of call, need type, and the presence of missing data for any of the prior variables.

more likely to see referral. This is also suggested by the negative weighted result for high-earnings callers in column 3, although this result becomes positive and insignificant when fixed effects are used in column 4. In this main specification, we can reject that earnings decrease by more than \$353, or 3% of average pre-call earnings. The fixed effect specification can reject any decline and the most demanding specification with weight and fixed effects can reject declines of \$239 (2%).

Any positive earnings effects we observe from referral are driven by low-earnings callers. For this group, the effects are positive for all specifications and suggest long-term increased earnings of \$400-\$500 from referral, consistent with Figure 4. This represents nearly 10% of the control group mean for low earners and about 55% of the total long-term effect of eviction on earnings in Collinson et al. (2024).¹³ All of the estimates are at or near statistical significance (the p-value in the first column is about 0.104) and for all specifications we can reject the hypothesis that being referred to funds leads to a decline in earnings, which is an important result.

Figure 5 explores heterogeneity by earning status further. The figure depicts two plots, each made up of 101 regressions. In each regression, the dependent variable is an indicator for whether an individual has earnings of at least x for varying amounts of x in increments of \$1,000, from \$0 to \$100,000. The plot in panel (a) uses the main specification given in equation (3), while the panel-(b) plot uses individual fixed effects as in equation (4). The plot in panel (b) is negative to the left of the figure, suggesting that individuals who are referred are less likely to report low levels of earnings or, for an x-axis value of zero, any earnings. The panel-(a) results to the left are smaller, positive at zero, and highly insignificant, suggesting that this panel-(b) negative effect is not robust; this is confirmed further in Table 5 below. Both plots become positive around \$15,000, suggesting a higher likelihood of earnings above this amount. Both plots unsurprisingly approach zero for values

¹³Collinson et al. (2024) report quarterly effects of \$323 in the first year, \$613 in the second (Table 6), and \$217 in the third & fourth (Appendix table H6), for an average of \$342.5. Adjusting a \$450 ITT effect by a factor of 1.69 to make it TOT and dividing by 4 to make it quarterly produces \$191.1; $191/343 \approx .55$.

around \$40,000 and above, but both panels continue to show positive effects and, in both cases, estimates at very high levels (near \$80,000) are marginally significant, suggesting a small (about 0.2 percent) probability of large earnings gains (or, equivalently, the avoidance of large earnings losses) from emergency assistance.

We next measure treatment effects on other labor market outcomes. Table 5 shows our main specification and individual-fixed-effect specification for a number of outcomes beyond earnings. The table presents first a set of three columns using our main specification on combined, low-earnings, and high-earnings samples. The last three columns use individual fixed effects. The first row of this panel repeats our main estimates from Table 4, and below that we report estimates for two indicators of employment: first, any employment, as measured by receiving any W-2 earnings. Next, we look at whether earnings on a W-2 are equal to or above what would be earned for half-time (20 hours a week) work at minimum wage for one quarter. For individuals with low earnings, the fixed-effect estimates suggest gains in both measures of employment, although the increase is only significant in the fixed-effects specification. Notably, even the imprecise estimates here can rule out sizeable declines in employment, with confidence intervals generally excluding even a decline of 2 percentage points. This suggests that referral to funds does not have sizeable disemployment effects.

The next row reports results on Adjusted Gross Income. Relative to the baseline estimates on earnings, AGI both combines outcomes for multiple earners in the tax unit and includes non-wage sources of taxable income, such as unemployment compensation or any state tax credit (AGI will exclude cash assistance such as TANF, SSI, and child support payments). By comparing these results to the prior tax-unit estimates, one can observe how the AGI's broader income base affects the results. There is some suggestive evidence of larger effects, especially for the low earners, although the difference between the low- and high-earnings groups is not statistically significant. Also, both specifications return a positive and significant coefficient on the likelihood of filing a 1040 for low-earnings households.

The last two rows report results for effects on whether an individual receives a 1099-G

(which captures local government payments, such as for unemployment compensation or state tax refunds) and 1099-MISC (which prior to 2020 included business payments to a non-employee). For low-earnings workers the estimates show an increase in the likelihood of receiving a 1099-G. These results, like the AGI results, indicate stable or perhaps modestly increasing income from government payments for low-income households referred to financial assistance. A key issue of many low-income housing programs is to promote self-sufficiency (e.g., Gubits, 2015); one might wonder whether these results are evidence that HPCC referral decreases self-sufficiency. This interpretation seems inconsistent with the fact that the primary driver of the increase in AGI is from earnings, and this is driven by a group (initially low earners) that if anything appears to have gains in employment after referral.

An alternate story could involve unemployment compensation: individuals who are more likely to work are, mechanically, more likely to receive UI, and this compensation would lead to both higher AGI and receipt of form 1099-G. But this mechanical mechanism would not explain higher earnings, which are robustly documented for low-income workers.

Combined with null/positive employment effects and positive earnings effects, the results on AGI, 1040 filing, and 1099-G are consistent with financial assistance leading to positive labor market outcomes and greater likelihood of accessing ancillary income (such as UI, refundable state tax credits, or SNAP) for low-earnings individuals. None of these effects are observed for the ex-ante high-earnings group, although the estimates rule out large negative effects for this group. Again, our use of the terms “low earnings” and “high earnings” are relative, as the sample overall is disadvantaged. But the strongest evidence of benefits in Tables 4 and 5 comes from effects of assistance on the poorest of the poor.

6.3. *Heterogeneous Effects*

Tables 6 and 7 report results for several subgroups. Table 6 uses the main specification and Table 7 uses fixed effects. In both tables, the first three columns are for the full sample (both low- and high-wage callers) and the last three columns are just the low-wage sample.

The dependent variables for each sample are earnings, AGI, and (any) employment. For each table, the first row shows the main result. The next two rows split the sample by reason for calling the HPCC—job loss versus any other reason. The last two rows break the result down by having kids or not having kids, as reported to the call center at the time of the call.¹⁴

Splitting the sample unsurprisingly lowers the precision of the estimates. Looking at rows two and three in each table, the results do not show a clear pattern of heterogeneity by the type of shock callers have experienced. Across the two tables, half of the coefficients indicate larger benefits of referral for those facing a job shock and half indicate smaller.

Perhaps the most suggestive result across the two tables is a more positive effect of referral for those without kids; all but one of the twelve specifications are consistent with this result. Our balance table for low wage earners earlier (Table 3) shows that the low wage sample have a similar number of minors present on average compared to the full sample. It also shows that those referred have more kids than those not referred, but that this difference becomes much smaller and insignificant after fund eligibility characteristics are controlled for. This implies, first, that differences in number of children are not driving the stronger earnings results for the low-wage sample relative to the full sample. Second, it raises the possibility that greater fund availability to those without kids could have relatively large economic benefits. This result parallels prior work by [Palmer et al. \(2019\)](#) showing that the same intervention’s violent crime reduction benefits operate primarily through households without children.

In summary, the results continue to indicate earnings gains for those with initially low earnings, with some evidence for heterogeneity by presence of children.

¹⁴We have considered other dimensions of heterogeneity including marital status, gender, age, receipt of benefits, and whether it is a first-time call, among others. These results do not generate clear differences in the effect of assistance across groups.

7. Conclusion

This study finds that a temporary financial transfer aimed at preventing homelessness has minimal disemployment effects and in fact facilitates increased earnings for people with the lowest baseline income. We use federal tax records to measure earnings for people who request assistance from a call center after they have experienced a negative shock that puts their housing at risk. Due to external constraints on funding and staffing, the call center refers some callers to temporary financial assistance but not others. We compare these two groups and find that average earnings do not differ statistically between callers referred to assistance versus those not referred to assistance, conditional on observable factors that affect eligibility for funding. We can reject that earnings fall by more than 3% of the baseline mean. The full-sample point estimate is positive, and we find evidence that temporary financial assistance encourages work among the lowest-income participants, increasing earnings by \$400-\$500 among people with earnings below the sample median at baseline.

Our results imply that existing analyses of homelessness prevention programs underestimate their benefits. Existing studies ([Rolston et al., 2013](#); [Evans et al., 2016](#); [Phillips and Sullivan, 2023](#)) demonstrate that such programs stabilize housing. While studies of other housing subsidies might lead to concerns of disemployment effects ([Jacob and Ludwig, 2012](#)), our results suggest any disemployment effect is small for temporary assistance. In fact, our results suggest that temporary assistance encourages employment for many beneficiaries. For this group, the present value of increased earnings far exceeds the cost of the program. As a result, existing cost-benefit analyses ([Phillips and Sullivan, 2023](#)) that value the private benefits of financial assistance at the payment amount are conservative.

More generally, our results suggest that many low-income households are underinsured against shocks to their income. If future labor market earnings can pay for the cost of temporary financial assistance, then households likely face barriers to credit and insurance that would otherwise allow them to move resources across time or states of the world. Some have argued that housing is a necessary platform for stable employment, and temporary

disruptions to housing can permanently shift people into poverty ([Desmond, 2016](#)). Our results suggest that, to the extent that this is true, providing insurance against temporary shocks can help to undo such a poverty trap.

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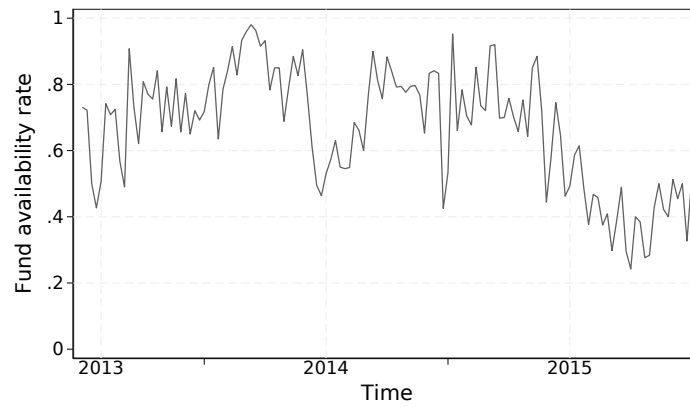
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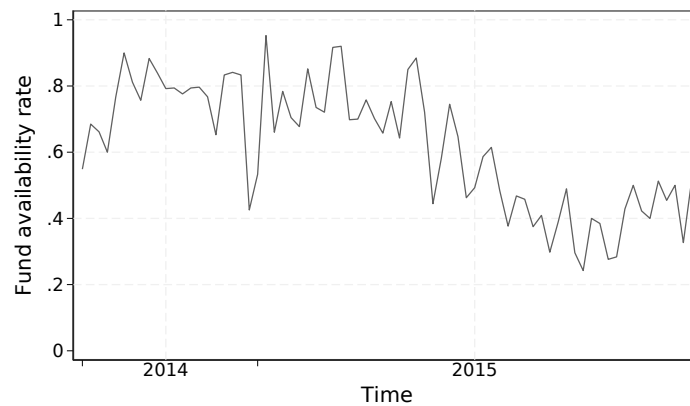
Tables and Figures

Fig. 1. Funding Rate by Week

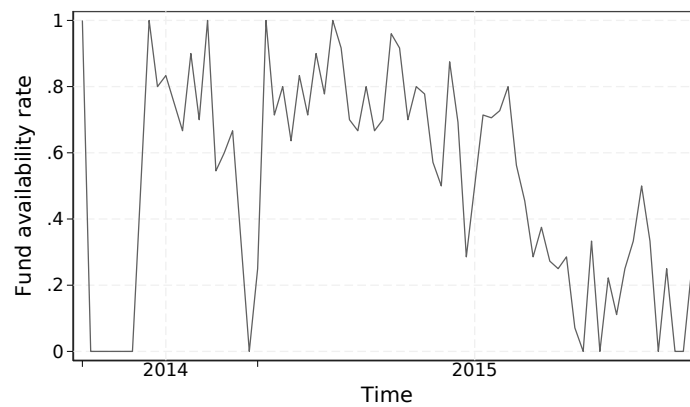
(a) Longer Sample - All



(b) Shorter Sample - All



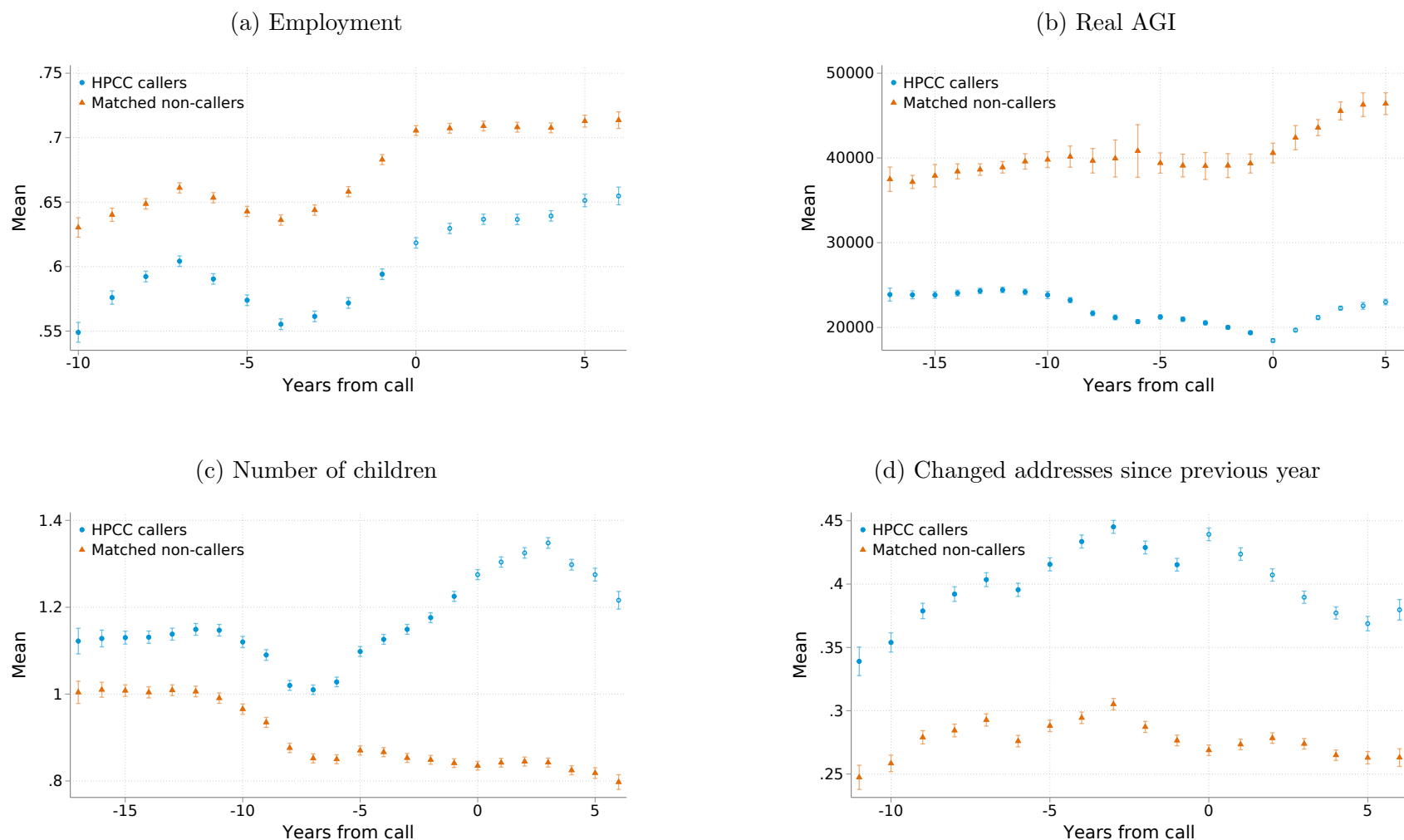
(c) Shorter Sample - Needs rent, need ≥ 1 month rent, need $> \$900$, no other housing subsidy



Source: Homelessness Prevention Call Center data and authors' calculations.

Note: Figure shows availability of funding by week for three samples of interest. Panel (a) is based on the sample of all eligible callers between mid-2013 and the end of 2015. Panel (b) is based on callers from August 2014 through December 2015, the period for which the data contain complete information on the reason for and amount of callers' needs. Panel (c) is based on the same period as panel (b) but limits the sample to callers with the characteristics indicated in the figure title.

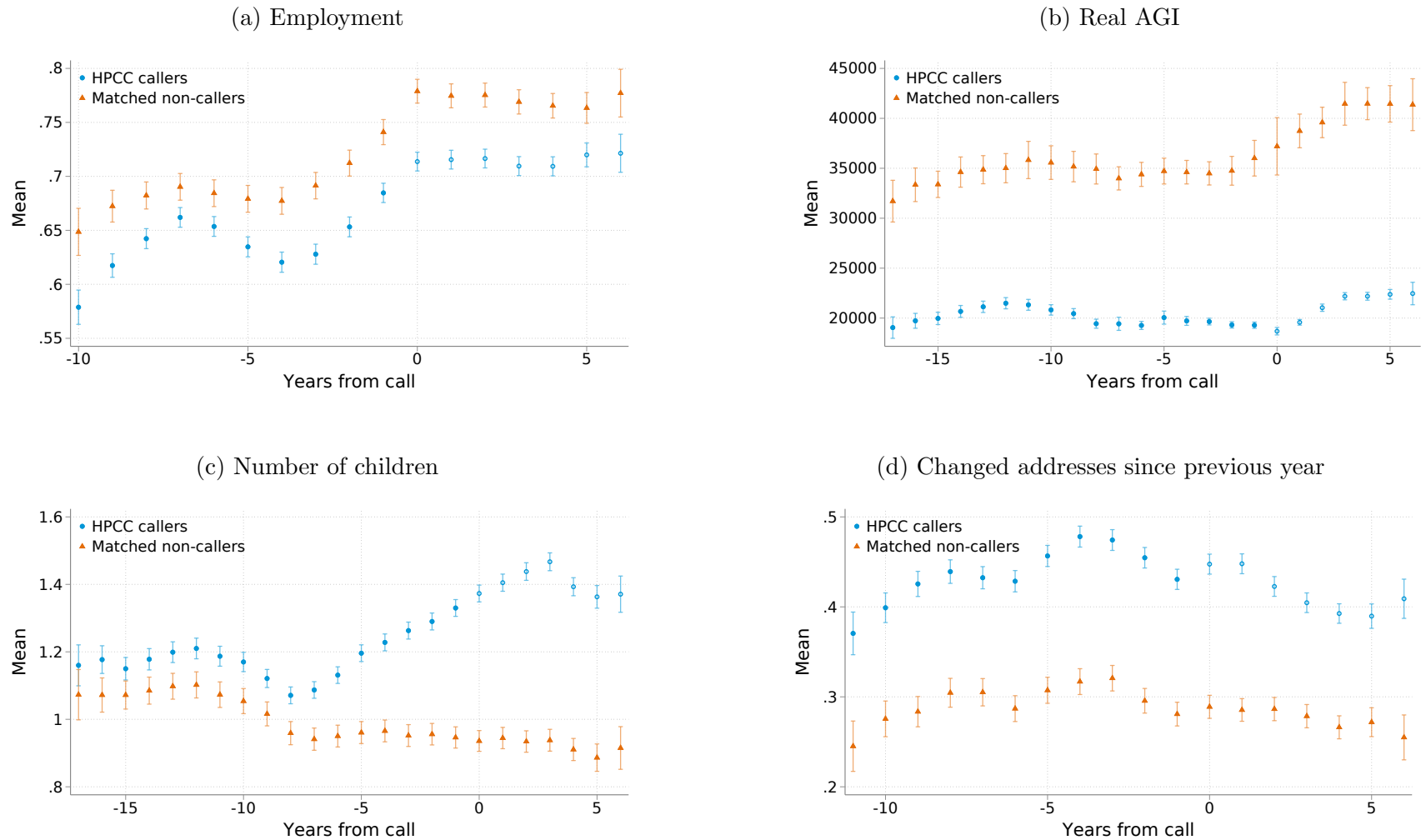
Fig. 2. Selection into Calling, All Callers



Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: Figure plots average outcomes for all callers to the Homelessness Prevention Call Center between mid-2013 and 2015 and matched non-callers. Callers are matched to non-callers based on demographic characteristics and place of residence in the year of the call, with matches drawn from the same Census block as callers where possible. Bars extending from plotted points represent 95 percent confidence intervals. Release authorization CBDRB-FY24-0033.

Fig. 3. Selection into Calling, Full Analysis Sample



Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

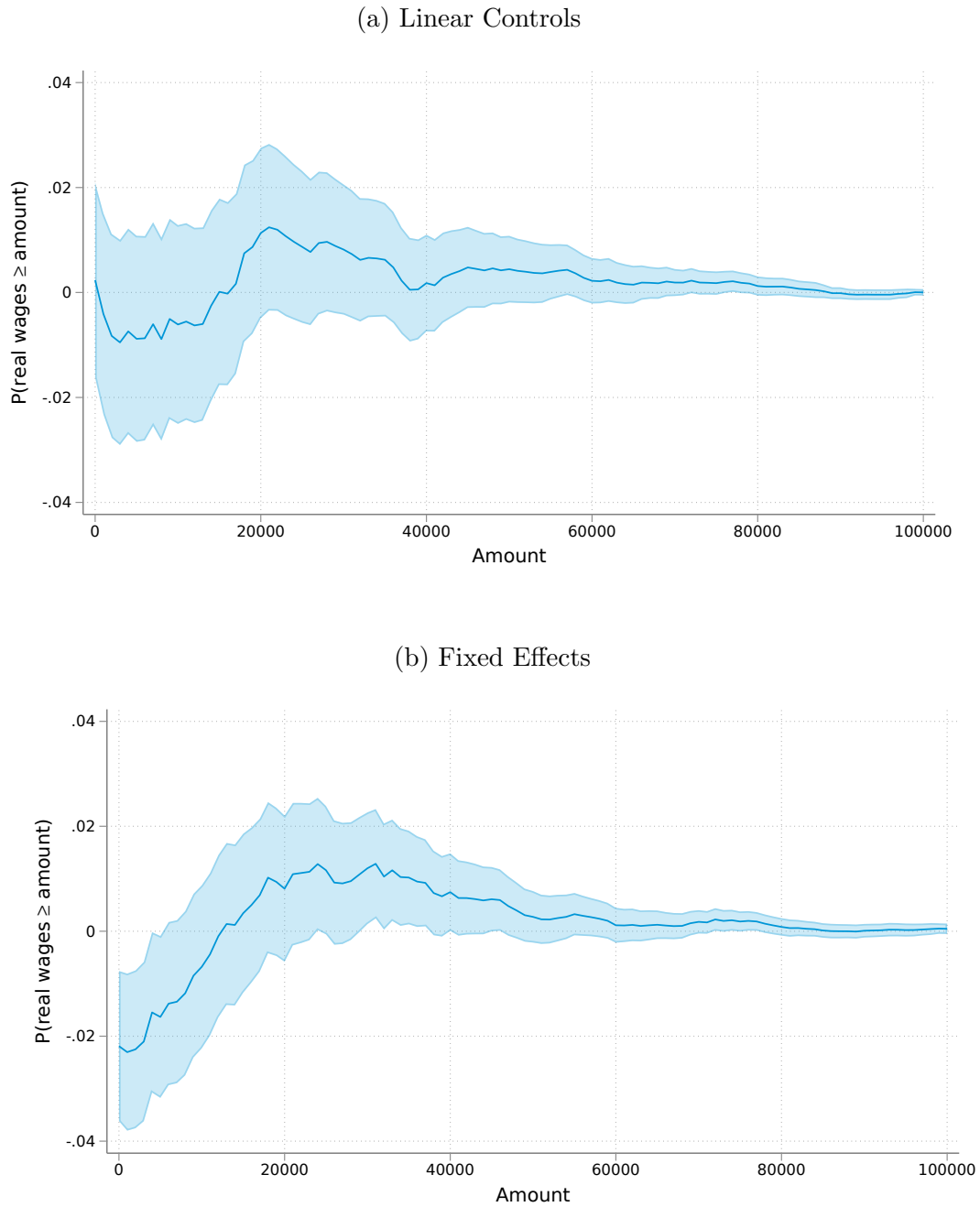
Note: Figure plots average outcomes for all callers in our main analysis sample and 2015 and matched non-callers. Callers are matched to non-callers based on demographic characteristics and place of residence in the year of the call, with matches drawn from the same Census block as callers where possible. Bars extending from plotted points represent 95 percent confidence intervals. Release authorization CBDRB-FY24-0033.

Fig. 4. Wages, Trends in Means and Event Studies



Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations. Note: Figure presents sample means and event study estimates comparing callers referred to funds and callers not referred. Event study estimates are based on equation (3). Shaded regions represent 95 percent confidence intervals. Release authorization CBDRB-FY23-0267.

Fig. 5. Treatment Effects Across the Income Distribution



Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: Figures report estimates of the effect of being referred to funds by the Homelessness Prevention Call Center on the probability of having wage and salary income at least great as various amounts between \$0 and \$100,000. Shaded regions represent 95 percent confidence intervals. Release authorization CBDRB-FY23-0267 and CBDRB-FY24-0033.

Table 1: Sample Composition under Various Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)
	Neighbors	Callers	Eligible Callers	Eligible Callers full sample	Eligible Callers low-wage sample	Matched non-callers low-wage sample
Age	43.42 (0.0135)	40.16 (0.0598)	38.41 (0.0864)	38 (0.124)	38.82 (0.226)	40.21 (0.231)
Male	0.466 (0.000356)	0.221 (0.00176)	0.187 (0.00265)	0.188 (0.00384)	0.216 (0.00646)	0.221 (0.00652)
Citizen	0.796 (0.000287)	0.960 (0.000831)	0.975 (0.00107)	0.972 (0.00163)	0.974 (0.00249)	0.965 (0.00289)
Foreign-born	0.171 (0.000269)	0.0336 (0.000765)	0.0209 (0.000972)	0.0248 (0.00153)	0.0252 (0.00246)	0.0254 (0.00248)
White	0.199 (0.000285)	0.0618 (0.00102)	0.0458 (0.00142)	0.0433 (0.00200)	0.0479 (0.00336)	0.0383 (0.00302)
Black	0.521 (0.000356)	0.729 (0.00189)	0.764 (0.00289)	0.770 (0.00413)	0.749 (0.00681)	0.770 (0.00661)
Asian	0.0343 (0.000130)	0.00274 (0.000222)	0.00199 (0.000303)	0.00202 (0.000441)	0.000988 (0.000494)	0.00173 (0.000653)
Hispanic	0.134 (0.000243)	0.0956 (0.00125)	0.0767 (0.00181)	0.0795 (0.00266)	0.0785 (0.00423)	0.0837 (0.00435)
Other race	0.0152 (8.72e-05)	0.0166 (0.000543)	0.0176 (0.000894)	0.0162 (0.00124)	0.0156 (0.00195)	0.0166 (0.00201)
Observations	1,966,000	55,500	21,500	10,500	4,000	4,000

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: Table reports simple mean demographic characteristics of callers from 2013-2015 in various samples, their neighbors (people living in the same set of Census blocks), and a sample of matched non-callers. The sample changes across columns. Column 1 covers people living in the same Census block as any HPCC caller. Column 2 covers all HPCC callers. Column 3 covers callers identified as meeting general eligibility at the time of their call. Column 4 displays our analysis sample, eligible calls with no prior call in the past 6 months. Column 5 limits the analysis to the sample of callers with below median pre-call wages. Column 6 covers a subset of non-callers that are 1-to-1 matched to callers based on the characteristics in this table. Age is in years. Other rows report the share of callers having the indicated demographic characteristic. Standard errors are in parentheses. Release authorization CBDRB-FY24-0033.

Table 2: Select Baseline Characteristics, by Referral Status

	Referred to Funds	Not Referred	Difference	Adjusted Difference
<u>Predicted outcomes:</u>				
Predicted wages, 2 years post call	13320	10420	2900*** (151.4)	-20.6 (157.2)
Predicted AGI, 2 years post call	20260	18570	1687*** (101.2)	109 (106.3)
<u>Particular characteristics:</u>				
Monthly rent	704.8	456.9	247.9*** (7.91)	-20.1*** (6.74)
Net dollars owed	935.8	981.2	-45.4* (25.1)	75.7*** (23.3)
Monthly income (thousands)	1.37	1.11	0.26*** (0.016)	-0.057*** (0.017)
Nbd median income	39760	38970	795.2*** (297.3)	1185*** (410.1)
Nbd pct Black	0.64	0.67	-0.021*** (0.0077)	-0.021** (0.011)
Number of adults	1.39	1.45	-0.059*** (0.017)	-0.049** (0.022)
Number of minors	1.30	1.53	-0.23*** (0.035)	-0.16*** (0.046)
Age	38.6	40.6	-1.95*** (0.30)	0.59* (0.34)
Female	0.79	0.84	-0.052*** (0.0089)	-0.028** (0.012)
Black	0.87	0.92	-0.043*** (0.0069)	-0.025*** (0.0094)
Rents home	0.86	0.84	0.019** (0.0083)	0.037*** (0.010)
Pre-call average wages	11510	7394	4112*** (254.9)	1416*** (340.7)
Pre-call average AGI	20290	16740	3551*** (394.8)	2042** (999.9)

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: The sample consists of 5300 callers referred to funds and 2800 callers not referred to funds. Sample sizes are rounded in compliance with disclosure restrictions. The sample is restricted to eligible callers who have not called in the prior six months with non-missing characteristic information. The first two columns present means for each group. The third column reports the difference in means, and the last column reports this difference after controlling for a vector of caller characteristics Z_i related to fund eligibility; robust standard errors in parentheses. Statistical significance at the 10, 5, and 1% levels are denoted by *, **, and ***, respectively. The full set of baseline characteristics considered is reported in Table A.3. Release authorization CBDRB-FY23-0267.

Table 3: Select Baseline Characteristics, by Referral Status, Low Wage Sample

	Referred to Funds	Not Referred	Difference	Adjusted Difference
<u>Predicted outcomes:</u>				
Predicted wages, 2 years post call	10760	8176	2586*** (200)	57.5 (208.6)
Predicted AGI, 2 years post call	18780	17390	1389*** (131.9)	126.1 (136.2)
<u>Particular characteristics:</u>				
Monthly rent	623.5	389.4	234*** (10.5)	-10.8 (8.60)
Net dollars owed	859.4	877.4	-18.0 (22.0)	64.8** (28.9)
Monthly income (thousands)	1.22	0.98	0.24*** (0.020)	-0.053** (0.022)
Nbd median income	39450	38480	969** (406.9)	1652*** (546.9)
Nbd pct Black	0.65	0.68	-0.022** (0.011)	-0.025* (0.014)
Number of adults	1.38	1.44	-0.060*** (0.023)	-0.030 (0.030)
Number of minors	1.37	1.52	-0.15*** (0.051)	-0.083 (0.067)
Age	38.9	41.8	-2.95*** (0.46)	0.19 (0.50)
Female	0.77	0.82	-0.055*** (0.013)	-0.034** (0.017)
Black	0.87	0.91	-0.039*** (0.0096)	-0.018 (0.013)
Rents home	0.83	0.83	-0.0031 (0.012)	0.038** (0.015)
Pre-call average wages	1726	1320	406.1*** (57.4)	210.7*** (76.6)
Pre-call average AGI	14210	13290	925 (672.6)	1265 (1678)

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: The sample consists of the subset of our main analysis sample with below median pre-period wages. The first two columns present means for each group. The third column reports the difference in means, and the last column reports this difference after controlling for a vector of caller characteristics Z_i related to fund eligibility; robust standard errors in parentheses. Statistical significance at the 10, 5, and 1% levels are denoted by *, **, and ***, respectively. The full set of baseline characteristics considered is reported in Table A.3. Release authorization CBDRB-FY23-0267.

Table 4: Effects on Earnings

	Main	Individual Fixed Effects	Weighted	Fixed Effects and Weighted	No Control for Lag Wages
Full Sample	197.4 (280.8)	574.3** (252.2)	-358.9 (380.1)	851.3 (556.5)	871** (358)
Call Center Controls	Yes	No	Yes	No	Yes
Lagged Outcome	Yes	No	Yes	No	No
Fixed Effects	No	Yes	No	Yes	No
Control Mean	10380	10380	10380	10380	10380
N	40500	81500	40500	81500	40500
Low Wage	430.6 (265.1)	1410*** (232.6)	460.5* (267.7)	669.3** (285.5)	483.9* (292.2)
Call Center Controls	Yes	No	Yes	No	Yes
Lagged Outcome	Yes	No	Yes	No	No
Fixed Effects	No	Yes	No	Yes	No
Control Mean	4944	4944	4944	4944	4944
N	20000	40500	20000	40500	20000
High Wage	49.78 (510.2)	310.5 (481.3)	-1147* (649.3)	1106 (1061)	803.2 (579.7)
Call Center Controls	Yes	No	Yes	No	Yes
Lagged Outcome	Yes	No	Yes	No	No
Fixed Effects	No	Yes	No	Yes	No
Control Mean	18140	18140	18140	18140	18140
N	20500	41000	20500	41000	20500

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: Table reports effects of being referred to funds by the Homelessness Prevention Call Center on earnings for various samples and specifications. The main specification includes controls for various characteristics of callers, as well as a measure of earnings from the year before a person called, and is estimated using data from the four years following each call. 'Call center controls' include both Z and X , specifically, linear controls for rank of the call within the day, age, and income as well as indicators for the day of the week, month, the time within the month (first five days, last five days), interactions of year-quarter with need amount category, gender, race, ethnicity, and receipt of public benefits. The fixed effects specifications include individual, calendar year, age, and relative year fixed effects and are estimated using data from five years prior through four years after each call. Weighted specifications use inverse propensity score weights to further adjust for observable differences between callers who are referred and not referred to funds. Statistical significance at the 10, 5, and 1% levels are denoted by *, **, and ***, respectively. Release authorization CBDRB-FY24-0033.

Table 5: Effect of Referral to Funds on Other Outcomes

	Ctrl Mean	Main Specification			Fixed Effects Specification		
	Full Sample	Full Sample	Low Wage	High Wage	Full Sample	Low Wage	High Wage
Individual Wages	10380	197.4 (280.8)	430.6 (265.1)	49.78 (510.2)	574.3** (252.2)	1410*** (232.6)	310.5 (481.3)
Employed	.6401	.007568 (.008696)	.007342 (.01282)	.008567 (.01046)	-.01341* (.007906)	.02053* (.01159)	.01412 (.009421)
Employed > Half Time Min Wage	.4278	-.0003555 (.009743)	.002892 (.01249)	-.00284 (.01435)	-.0003092 (.008667)	.05109*** (.01071)	.001784 (.01372)
Tax Unit Wages	15660	344 (376.3)	609.6 (444.1)	240.3 (581.7)	25.02 (344.8)	909.6** (440.4)	-182.2 (497.8)
Adj Gross Income	19130	714.2* (369.2)	811.3** (395.8)	692.9 (578.7)	96.25 (313.6)	1155*** (433.6)	-412.6 (448.6)
Filed 1040	.6206	.01157 (.008368)	.02198* (.01148)	.002456 (.01203)	-.007525 (.007854)	.02317** (.01133)	-.005436 (.01077)
Received 1099-Misc	.09356	-.001634 (.006081)	-.0009758 (.007773)	.0000881 (.00958)	.006595 (.005727)	.003293 (.007564)	-.001414 (.009014)
Received 1099-G	.4127	.01525 (.009418)	.0225* (.01179)	.0023 (.01455)	.01344 (.009057)	.04411*** (.01154)	.02249 (.01428)

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, and authors' calculations. Note: Other than the first column, which reports mean outcomes for non-referred callers, the table reports the effect of being referred to funds by the Homelessness Prevention Call Center on assorted outcomes for various samples and OLS specifications. The main specification includes controls for various characteristics of callers, as well as a measure of earnings from the year before a person called. The fixed effects specifications include individual, calendar year, age, and relative year fixed effects. Statistical significance at the 10, 5, and 1% levels are denoted by *, **, and ***, respectively. Release authorization CBDRB-FY24-0033.

Table 6: Heterogeneous Effects, Linear Controls

	Full Sample			Low Wage		
	Wages	AGI	Employed	Wages	AGI	Employed
Full Sample	197.4 (280.8)	714.2* (369.2)	0.00757 (0.00870)	430.6 (265.1)	811.3** (395.8)	0.00734 (0.0128)
Lost Job	1257 (912)	2818*** (1094)	-0.00894 (0.0216)	1970** (936.1)	1643 (1338)	-0.00687 (0.0366)
Other Shock	-160.4 (424.4)	609.5 (565.5)	0.0174 (0.0143)	163.5 (398.6)	631.9 (531.9)	0.0274 (0.0206)
Has Kids	63.49 (361.1)	505.1 (382)	0.00174 (0.0106)	319.7 (354)	280.7 (342.6)	-0.00104 (0.0168)
No Kids	570.4 (440.2)	1733* (984.9)	0.0179 (0.0149)	758.8* (400.7)	1705 (1526)	0.0261 (0.0198)

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: Table reports effects of being referred to funds by the Homelessness Prevention Call Center on income and employment outcomes for various samples using the specification described in equation (3). Statistical significance at the 10, 5, and 1% levels are denoted by *, **, and ***, respectively. Release authorization CBDRB-FY24-0033.

Table 7: Heterogeneous Effects, Fixed Effects

	Full Sample			Low Wage		
	Wages	AGI	Employed	Wages	AGI	Employed
Full Sample	574.3** (252.2)	96.25 (313.6)	-0.0134* (0.00791)	1410*** (232.6)	1155*** (433.6)	0.0205* (0.0116)
Lost Job	-314.9 (706.6)	658 (835.3)	-0.0432** (0.0203)	1053 (699.2)	2338 (1660)	-0.0413 (0.0334)
Other Shock	465.1 (401.9)	-101.5 (479.3)	-0.00428 (0.0124)	1256*** (359.8)	556.3 (541.4)	0.0411** (0.0177)
Has Kids	541.3* (302)	270.4 (296.5)	-0.0144 (0.00970)	1160*** (290)	781.8** (323.8)	0.0131 (0.0148)
No Kids	1052** (450.3)	104.7 (942.4)	0.00275 (0.0134)	1983*** (381.8)	2369 (1702)	0.0425** (0.0179)

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: Table reports effects of being referred to funds by the Homelessness Prevention Call Center on income and employment outcomes for various samples using the specification described in equation (4). Statistical significance at the 10, 5, and 1% levels are denoted by *, **, and ***, respectively. Release authorization CBDRB-FY24-0033.

Appendix A. Additional Tables

Table A.1: Representativeness of the Analysis Sample

	Has PIK	No PIK	Dif.	Adj. Dif.
Number of adults	1.41	1.54	-0.13*** (0.046)	-0.093** (0.045)
Number of minors	1.38	1.44	-0.066 (0.075)	-0.11 (0.073)
Monthly rent	618.2	705.4	-87.1*** (18.7)	-18.4* (11.0)
Net dollars owed	951.6	998.2	-46.6 (31.8)	28.6 (20.3)
Monthly income (thousands)	1.28	1.44	-0.15*** (0.037)	-0.069** (0.030)
Veteran	0.016	0.025	-0.0088 (0.0078)	6.2e-18** (2.6e-18)
Senior	0.038	0.025	0.013 (0.0080)	-3.3e-18 (2.1e-18)
Nbd median income	39480	36970	2511*** (848.3)	2377*** (832.2)
Nbd pct Black	0.65	0.53	0.12*** (0.019)	0.12*** (0.020)
Age	39.3	39.2	0.14 (0.64)	-0.034 (0.57)
Reason missing	0.44	0.47	-0.033 (0.025)	-0.0070 (0.0051)
Reason: lost job	0.17	0.18	-0.0062 (0.020)	-0.0098 (0.017)
Reason: job cut hours	0.062	0.044	0.018* (0.011)	0.015 (0.011)
Reason: medical work absence	0.058	0.057	0.00081 (0.012)	0.0030 (0.012)
Reason: health	0.023	0.022	0.00077 (0.0075)	-0.00098 (0.0074)
Reason: housing change	0.13	0.10	0.028* (0.015)	0.018 (0.013)
Reason: lost benefits	0.055	0.049	0.0055 (0.011)	-0.00039 (0.011)
Reason: other	0.060	0.074	-0.014 (0.013)	-0.018 (0.013)
Female	0.81	0.81	-0.0037 (0.020)	-0.021 (0.020)
Hispanic	0.075	0.21	-0.13*** (0.020)	-0.13*** (0.020)
White	0.074	0.14	-0.064*** (0.017)	-0.060*** (0.017)
Black	0.89	0.77	0.12*** (0.021)	0.11*** (0.021)
Other	0.032	0.074	-0.043*** (0.013)	-0.040*** (0.013)
Receives housing subsidy	0.33	0.20	0.12*** (0.021)	-2.6e-17 (1.7e-17)
Receiving SNAP	0.50	0.40	0.10*** (0.025)	0.087*** (0.020)
Receives income from disability	0.047	0.035	0.012 (0.0094)	-2.4e-17*** (7.1e-18)
Receiving child support	0.022	0.030	-0.0074 (0.0086)	-0.0056 (0.0087)
Receiving EITC	0.26	0.33	-0.075*** (0.024)	-0.030** (0.015)
Receiving disability	0.047	0.035	0.012 (0.0094)	-2.4e-17*** (7.1e-18)
Receiving SSI	0.067	0.079	-0.012 (0.014)	-0.014 (0.013)
Receiving TANF	0.037	0.012	0.024*** (0.0059)	0.022*** (0.0063)
Receiving UI	0.034	0.025	0.0097 (0.0080)	0.013 (0.0083)
Owns home	0.018	0.030	-0.012 (0.0086)	-3.3e-18 (4.0e-18)
Lives with family or friends	0.13	0.13	0.00053 (0.017)	0.0011 (0.016)
Rents home	0.86	0.84	0.011 (0.018)	-0.0011 (0.016)

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: The table compares callers who do and do not have a PIK (protected identification key) from the US Census Bureau. The sample includes about 8200 individuals with a PIK and about 400 individuals without a PIK. Sample sizes are rounded in compliance with disclosure restrictions. The first two columns present means for each group. The third column reports the difference in means, estimated via linear regression; *, **, and *** denote significance at the 10%, 5% and 1% levels. The last column reports this difference after controlling for a vector of caller characteristics Z_i related to fund eligibility. Robust standard errors in parentheses. Release authorization CBDRB-FY23-0267.

Table A.2: Select Fund-Specific Eligibility Criteria at Baseline, by Referral Status

	Referred to Funds	Not Referred	Difference	Adjusted Difference
Receives housing subsidy	0.19	0.58	-0.40*** (0.011)	—
Veteran	0.015	0.018	-0.0036 (0.0030)	—
Senior	0.027	0.058	-0.031*** (0.0049)	—
Receives income from disability	0.045	0.051	-0.0062 (0.0050)	—
Owns home	0.018	0.018	-0.000071 (0.0031)	—

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: The sample consists of 5300 callers referred to funds and 2800 callers not referred to funds. Sample sizes are rounded in compliance with disclosure restrictions. The sample is restricted to eligible callers who have not called in the prior six months with non-missing characteristic information. The first two columns present means for each group. The third column reports the difference in means, and the last column would report this difference after controlling for a vector of caller characteristics Z_i related to fund eligibility but is blank because the outcome variables are part of the same vector Z_i . Robust standard errors in parentheses. Statistical significance at the 10, 5, and 1% levels are denoted by *, **, and ***, respectively. Release authorization CBDRB-FY23-0267.

Table A.3: Baseline Characteristics, by Referral Status

	Referred to Funds	Not Referred	Difference	Adjusted Difference
Number of adults	1.39	1.45	-0.059*** (0.017)	-0.049** (0.022)
Number of minors	1.30	1.53	-0.23*** (0.035)	-0.16*** (0.046)
Monthly rent	704.8	456.9	247.9*** (7.91)	-20.1*** (6.74)
Net dollars owed	935.8	981.2	-45.4* (25.1)	75.7*** (23.3)
Monthly income (thousands)	1.37	1.11	0.26*** (0.016)	-0.057*** (0.017)
Veteran	0.015	0.018	-0.0036 (0.0030)	-1.7e-18 (2.2e-18)
Senior	0.027	0.058	-0.031*** (0.0049)	-4.1e-18*** (7.3e-19)
Nbd median income	39760	38970	795.2*** (297.3)	1185*** (410.1)
Nbd pct Black	0.64	0.67	-0.021*** (0.0077)	-0.021** (0.011)
Age	38.6	40.6	-1.95*** (0.30)	0.59* (0.34)
Reason missing	0.47	0.37	0.10*** (0.011)	-0.0058*** (0.0020)
Reason: lost job	0.18	0.16	0.020** (0.0087)	0.011 (0.010)
Reason: job cut hours	0.068	0.051	0.017*** (0.0054)	-0.0069 (0.0067)
Reason: medical work absence	0.065	0.044	0.022*** (0.0051)	0.0082 (0.0063)
Reason: health	0.017	0.034	-0.018*** (0.0038)	-0.0026 (0.0048)
Reason: housing change	0.096	0.19	-0.095*** (0.0084)	0.016* (0.0093)
Reason: lost benefits	0.053	0.059	-0.0062 (0.0054)	-0.00084 (0.0063)
Reason: other	0.045	0.090	-0.045*** (0.0061)	-0.019*** (0.0066)
Female	0.79	0.84	-0.052*** (0.0089)	-0.028** (0.012)
Hispanic	0.084	0.058	0.026*** (0.0058)	0.018** (0.0076)
White	0.085	0.053	0.032***	0.012

			(0.0057)	(0.0080)
Black	0.87	0.92	-0.043***	-0.025***
			(0.0069)	(0.0094)
Other	0.035	0.026	0.0086**	0.010**
			(0.0039)	(0.0052)
Receives housing subsidy	0.19	0.58	-0.40***	-1.1e-18
			(0.011)	(7.4e-18)
Receiving SNAP	0.54	0.42	0.13***	-0.018*
			(0.011)	(0.010)
Receives income from disability	0.045	0.051	-0.0062	1.2e-18
			(0.0050)	(3.2e-18)
Receiving child support	0.024	0.019	0.0051	0.0017
			(0.0033)	(0.0045)
Receiving EITC	0.31	0.16	0.15***	0.026***
			(0.0093)	(0.0097)
Receiving disability	0.045	0.051	-0.0062	1.2e-18
			(0.0050)	(3.2e-18)
Receiving SSI	0.064	0.071	-0.0069	-0.020**
			(0.0059)	(0.0080)
Receiving TANF	0.035	0.040	-0.0051	-0.0048
			(0.0045)	(0.0065)
Receiving UI	0.039	0.025	0.014***	0.0057
			(0.0040)	(0.0056)
Owns home	0.018	0.018	-0.000071	2.7e-19
			(0.0031)	(1.8e-18)
Lives with family or friends	0.12	0.14	-0.019**	-0.037***
			(0.0079)	(0.010)
Rents home	0.86	0.84	0.019**	0.037***
			(0.0083)	(0.010)
Pre-call average wages	11510	7394	4112***	1416***
			(254.9)	(340.7)
Pre-call average AGI	20290	16740	3551***	2042**
			(394.8)	(999.9)
Predicted wages, 2 years post call	13320	10420	2900***	-20.6
			(151.4)	(157.2)
Predicted AGI, 2 years post call	20260	18570	1687***	109
			(101.2)	(106.3)

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: The sample consists of 5300 callers referred to funds and 2800 callers not referred to funds. Sample sizes are rounded in compliance with disclosure restrictions. The sample is restricted to eligible callers who have not called in the prior six months with non-missing characteristic information. The first two columns present means for each group. The third column reports the difference in means, and the last column reports this difference after controlling for a vector of caller characteristics Z_i related to fund eligibility; robust standard errors in parentheses. Release authorization CBDRB-FY23-0267.

Table A.4: Baseline Characteristics for High Wage Group, by Fund Availability

	Referred to Funds	Not Referred	Dif.	Adj. Dif.
Predicted wages, 2 years post call	15420	13700	1715*** (200.5)	-181.6 (222.4)
Predicted wages, 2 years post call	21470	20300	1174*** (144.3)	67.0 (159.6)
Number of adults	1.39	1.45	-0.062** (0.025)	-0.056* (0.031)
Number of minors	1.24	1.54	-0.30*** (0.049)	-0.22*** (0.063)
Monthly rent	771.4	556.4	215*** (11.8)	-25.5** (10.4)
Net dollars owed	997.9	1133	-135.4** (52.8)	74.9 (47.9)
Monthly income (thousands)	1.50	1.31	0.19*** (0.024)	-0.055** (0.026)
Veteran	0.015	0.014	0.00074 (0.0041)	1.7e-18 (2.4e-18)
Senior	0.010	0.021	-0.011** (0.0046)	1.6e-18 (3.1e-18)
Nbd median income	40010	39680	334.3 (447.7)	637.4 (629.1)
Nbd pct Black	0.64	0.65	-0.013 (0.012)	-0.021 (0.016)
Age	38.4	38.8	-0.31 (0.38)	0.91* (0.48)
Reason missing	0.47	0.36	0.10*** (0.017)	-0.010*** (0.0031)
Reason: lost job	0.21	0.21	0.0049 (0.014)	0.016 (0.016)
Reason: job cut hours	0.084	0.091	-0.0068 (0.0099)	-0.028** (0.012)
Reason: medical work absence	0.087	0.069	0.018** (0.0091)	0.020* (0.011)
Reason: health	0.014	0.011	0.0023 (0.0038)	-0.0021 (0.0054)
Reason: housing change	0.063	0.15	-0.089*** (0.011)	0.011 (0.012)
Reason: lost benefits	0.044	0.046	-0.0018 (0.0073)	0.0010 (0.0092)
Reason: other	0.032	0.061	-0.028*** (0.0078)	-0.0083 (0.0086)
Female	0.81	0.87	-0.062*** (0.012)	-0.019 (0.017)
Hispanic	0.087	0.070	0.017* (0.0092)	0.013 (0.012)
White	0.084	0.049	0.035*** (0.0081)	0.014 (0.012)
Black	0.87	0.92	-0.048*** (0.010)	-0.035** (0.014)
Other	0.035	0.026	0.0093 (0.0058)	0.016** (0.0080)
Receives housing subsidy	0.13	0.53	-0.40*** (0.016)	9.0e-17*** (1.2e-17)
Receiving SNAP	0.48	0.36	0.11*** (0.017)	-0.026 (0.017)
Receives income from disability	0.016	0.020	-0.0036 (0.0047)	-6.5e-18* (3.4e-18)
Receiving child support	0.022	0.021	0.0016 (0.0050)	-0.00024 (0.0070)
Receiving EITC	0.35	0.23	0.12*** (0.015)	0.018 (0.014)
Receiving disability	0.016	0.020	-0.0036 (0.0047)	-6.5e-18* (3.4e-18)
Receiving SSI	0.031	0.032	-0.0012 (0.0061)	-0.0071 (0.0089)
Receiving TANF	0.011	0.023	-0.012** (0.0048)	-0.014** (0.0067)
Receiving UI	0.057	0.046	0.011 (0.0075)	0.0033 (0.011)
Owns home	0.023	0.022	0.0014 (0.0051)	-9.1e-21 (5.6e-18)
Lives with family or friends	0.086	0.12	-0.029*** (0.011)	-0.024* (0.014)
Rents home	0.89	0.86	0.028** (0.012)	0.024* (0.014)
Pre-call average wages	19470	16360	3113*** (373.2)	1582*** (519.9)
Pre-vall average AGI	24250	20540	3708*** (466.8)	1910*** (654.6)

Source: Homelessness Prevention Call Center data, American Community Survey, Decennial Census, IRS Form 1040, Form W-2, IRS information returns, Census Numident, Master Address File Auxiliary Reference File, and authors' calculations.

Note: The table compares callers who are and are not referred to funds within the sample of people with above-median pre-call wage and salary income. The first two columns present means for each group. The third column reports the difference in means; *, **, and *** denote significance at the 10%, 5% and 1% levels. The last column reports this difference after controlling for a vector of caller characteristics Z_i related to fund eligibility; robust standard errors in parentheses. Release authorization CBDRB-FY23-0267.