The Effects of Emergency Rental Assistance During the Pandemic: Evidence from Four Cities[*]

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Abstract

Short-term rental assistance programs expanded to unprecedented scale during the COVID-19 pandemic. We evaluate these programs using applications to five assistance programs that disbursed more than $200 million via lottery. Drawing on administrative and original survey data, we estimate effects on rent payment, housing stability, financial distress, and health. Assistance led to increases in rent payment and reduced tenants' concerns about eviction. We also find suggestive evidence of improvements in self-reported mental and physical health. However, we find little effect on housing stability or financial distress. Relative to Economic Impact Payments, we find that ERA was well-targeted to high-poverty neighborhoods.

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1 Introduction

The COVID-19 pandemic disrupted economic activity and created new health risks. The federal government responded by rolling out policies to provide relief to households in the form of both direct cash assistance and expansions of traditional transfer programs, such as Unemployment Insurance benefits and the Earned Income Tax Credit. Unlike in previous economic crises, policymakers also allocated an unprecedented amount of resources to emergency rental assistance (ERA). Totaling over $50 billion, federal pandemic ERA programs represented an amount roughly equivalent to the typical annual budget for all federal rental assistance programs.[1]

Despite the remarkable expansion of the ERA, there is little, if any, evidence available on the causal effects of this type of relief program on households' housing stability and economic outcomes, and therefore on its effectiveness as a relief mechanism during the pandemic. This lack of evidence is due to several factors. First, there was no centralized data collection on the administration of ERA programs. Second, the ability to track key outcomes such as rent payment, eviction, homelessness, and households' health and financial situations is limited by the absence of comprehensive national administrative data. Third, comparisons of assisted and unassisted individuals are likely to suffer from selection bias, calling into question their causal interpretation.

In this paper, we provide the first empirical evidence on the causal impacts of ERA programs deployed in response to the pandemic. We study five ERA programs, each over-subscribed and selecting participants through a lottery, providing $1,000 to $3,400 to households in four major urban areas: Chicago, Harris County (Houston), King County (Seattle), and Los Angeles.[2] Collectively, these programs distributed approximately $200 million and received more than 200,000 applications for assistance. Figure I illustrates the backdrop against which they were implemented: Their timing coincided with the initial economic impact of the pandemic, the peak of reported rates of rental arrears, and the roll-out of other rapid-response government relief initiatives. Because these local programs provided assistance well before the large federal ERA funding rounds, they are well-suited for evaluating ERA as a crisis-response mechanism supplementing more traditional relief programs.[3]

Using data on applications to these programs linked to survey and administrative data, we

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[1]The federal government spends approximately $46 billion annually on assistance to renters, including public housing, tenant-based rent vouchers, and project-based rent vouchers (Collinson et al., 2019). A small fraction is spent on ERA.

[2]Most of the programs we study offered a flat amount of assistance that was not based on individual rent levels or arrears. The exception was the King County program, which on average offered 3 months of assistance at up to 80% of the tenant's rent.

[3]Appendix Table D.10 provides more details on timing and assistance levels for all five programs.

estimate their causal impact on several policy-relevant outcomes related to housing stability, financial distress, and mental health. We use credit bureau records and consumer reference data to track the evolution of financial stability and housing outcomes for program applicants throughout the pandemic. We augment these data with novel harmonized surveys that we administered during the pandemic to capture results that were not easily measured through administrative sources. For some sites, we also link the applications to eviction court filings and administrative data on homelessness system use to investigate impacts on measures of extreme housing instability. To learn about the causal impact of receiving assistance, we rely on exogenous variation arising from lotteries for assistance in the five programs, which were implemented due to excess demand.[4]

Receipt of assistance increased rent payment and reduced self-reported anxiety. Using harmonized surveys fielded across four of the lotteries, we find that those who received assistance were 6–13 percentage points (8–36 percent) more likely to pay their rent in full in the months shortly after the lottery. The estimated effects on rent payment are similar across sites but are somewhat larger for communities that offered more generous assistance and made payments directly to landlords.

We use the same surveys to examine the impacts of assistance on measures of mental health and on concerns about eviction. Receipt of assistance reduced self-reported anxiety by an average of 3.2 percentage points (6 percent) across sites (p-value < 0.1). We additionally find that assistance reduced concern about eviction, with a 4.7 percentage point reduction (16 percent) across sites (p-value < 0.1).

Despite the policy objective of keeping individuals and families in their homes, we find no consistent effects of the assistance on the likelihood that applicants moved. We analyze applications to all five programs linked to two separate administrative sources to draw this conclusion. First, using our panel of linked credit data, we evaluate whether recipients moved to different neighborhoods and find that treated individuals were no less likely to change ZIP code, either in the immediate aftermath of applying for assistance or in the longer run. Second, we link our lottery samples to consumer reference data that provide address histories to track moves at the address level. Here too, we find little evidence to suggest that assistance made individuals less likely to move from their application address in either the two months or the year after applying for assistance. Overall, the move rates in our samples appear similar for the period leading up to the lottery and the post-lottery period.

Next, using linked credit reports, we examine whether the assistance affected short- and

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[4]Our analysis follows a pre-specified plan. See AEA RCT Registry #0007731 and #0007167 and Appendix B for details.

longer-run measures of financial distress. While the assistance had small short-run impacts on some credit measures, these effects are not consistently present across sites and did not persist over time. Averaging across sites, individuals assisted through the lottery had approximately $74 less in collections in the two months after applying for assistance. However, these effects appear to have faded over time. The financial characteristics of applicants randomized into receiving assistance are largely indistinguishable ten months after the lottery from those of applicants who missed out.

Our last set of estimates shed light on whether receipt of assistance reduced the chances that applicants experienced more acute forms of housing instability, including eviction or homelessness. To measure the impacts on homelessness, we link the application data for three of our lotteries to homelessness system data from King County (Washington) and Chicago (Illinois). We do not find consistent evidence that receiving assistance reduced the likelihood of applicants appearing in the homelessness system.[5] We then investigate whether assistance reduced the probability of a new eviction filing in Chicago and Harris County, both shortly after assistance and after the national Centers for Disease Control (CDC) eviction moratorium was lifted. We find that the assistance had little effect on eviction filings and that baseline rates of new filings remained relatively low for applicants not assisted through the lottery.[6]

While we find generally muted effects of ERA, we nevertheless find that it was well targeted to financially distressed households. The recipients of assistance across our four sites appear more financially distressed than the typical renter in each community. We find that compared to the general population or other renters in the same community, those who received assistance had 33–141 points lower credit scores, higher collections balances, and higher levels of debt. Assisted households were also from higher-poverty neighborhoods and were more likely to be minorities. We reach similar conclusions when comparing those who received assistance to those who received Economic Impact Payments (EIP).

Taken together, our results suggest that receipt of assistance was well targeted, helped households pay their rent in the short run, and led to modest improvements in concerns about eviction, with suggestive evidence that it improved mental and physical health. However, assistance did not substantially change applicants' housing or financial stability. Furthermore, when we investigate treatment effect heterogeneity, we find little evidence that more

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[5]The only group for whom we find such evidence are applicants to a program in Chicago targeting individuals who might have limited access to other parts of the pandemic safety net.

[6]Recent studies have connected COVID-19 ERA to improvements in housing outcomes, financial well-being, and mental health, but these studies rely on comparisons of households that received assistance to those that did not (Airgood-Obrycki, 2022; Reina and Lee, 2023). Denary et al. (2021) provide evidence that that mental health improves after receiving housing subsidies using an event-study design, but focus permanent subsidies such as public housing, housing vouchers, and permanent supportive housing.

disadvantaged individuals experienced differential effects of the assistance. These conclusions stand in contrast to those drawn in prior work on pre-pandemic ERA programs that provided similarly-sized assistance to renters facing idiosyncratic shocks. While these pre-pandemic programs share design features, like generosity and targeting, with the programs we study, Evans et al. (2016) and Phillips and Sullivan (2023) find large effects on recipients' housing stability.

We interpret this discrepancy as informative about the role of ERA as a tool to respond to macroeconomic, relative to household-level, shocks. Several forces may mitigate the effectiveness of ERA during macroeconomic crises, for example, the expansion of alternative forms of assistance that is common during downturns. Alternatively or additionally, rental market slackness may lead landlords to work out private payment plans with tenants that are struggling to pay rent. Combining information from our surveys and data points from other sources, we find descriptive evidence suggestive of both channels.

Considering first the increase in receipt of social insurance and safety-net programs during the pandemic (Han et al., 2020; Blanchet et al., 2022; Raphael and Schneider, 2023), our linked credit data reveal that individuals who applied for assistance experienced rising credit scores and falling debt in the lead-up to application. These patterns likely reflect a mix of broad-based improvements in macroeconomic conditions after the initial COVID shock and the effects of other expanded government assistance during this period, including COVID relief payments, expansions of Unemployment Insurance and the Earned Income Tax Credit (EITC), the Child Tax Credit, and the Paycheck Protection Program. The improvement in household balance sheets continues post-lottery but is similar for both treatment and control applicants, consistent with our findings of small impacts on the credit measures.

Next, we consider equilibrium responses in the rental market. The early phase of the pandemic saw sharp decreases in rent prices and increases in vacancy rates. For landlords, evicting a tenant is likely a less attractive option during a widespread downturn than during normal times, when vacancies can be more easily filled at higher prices. Therefore, renegotiation or temporary agreements between landlords and tenants may be sufficient to forestall eviction without additional emergency assistance. Consistent with this mechanism, our surveys show very high rates of reported landlord agreements (greater than 70 percent) among tenants who are having trouble paying their rent. This evidence is in line with other pandemic-era surveys of landlords that find substantial increases in reported rental forbearance in 2020, relative to pre-pandemic levels (Decker, 2021; de la Campa and Reina, 2023).[7]

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[7]Data from an earlier period of macroeconomic turmoil points in a similar direction: During the 2009 financial crisis, eviction rates remained approximately constant (Gromis et al., 2022) despite an approximate

Our paper contributes to a large literature studying the effects of various policies seeking to stabilize housing markets during aggregate economic downturns. Much of this literature has focused on the owner-occupied segment of the market, where frictions in mortgage financing created substantial turmoil during the 2009 financial crisis (Agarwal et al., 2017; Piskorski and Seru, 2018; Ganong and Noel, 2020; Agarwal et al., 2022). In contrast, our paper is one of the first to study the effects of large-scale relief programs targeted specifically at renters during a time of macroeconomic distress. This emphasis is particularly relevant because renters reported significantly higher rates of missing housing payments than owner-occupants (15 percent compared to 9.5 percent) and faced substantially higher risk of losing their home (7 percent compared to 2 percent) during the pandemic (U.S. Census Bureau, 2020c). Rafkin and Soltas (2024) study landlord and tenant behavior in the context of Emergency Rental Assistance provision, they also find that ERA had small impacts on eviction using an event-study design framework. Our finding that ERA had generally small impacts on homelessness is consistent with descriptive work from Aiken et al. (2022) which found that most ERA programs targeted renters that were somewhat upstream of imminent risk of homelessness.

In focusing on renters, this paper also connects to the broader literature on housing instability and the effects of assistance to renters. One strand of the literature focuses on the effects of evictions (Collinson et al., 2024) and landlord foreclosure (Diamond et al., 2019). A second strand of this literature estimates the effects of short-term housing assistance on homelessness (Evans et al., 2016; Phillips and Sullivan, 2023).[8] These papers focus on recipients experiencing individual- or household-level shocks outside of broader economic downturns. In contrast, we provide rigorous evidence on the causal effects of ERA during a time of *aggregate* distress and concomitant large-scale policy responses. We also study a wider range of outcomes including housing stability, financial strain, and the mental and physical health of program applicants.

We contribute to a growing literature analyzing the impacts of economic policies during the COVID-19 pandemic by providing the first comprehensive analysis of the effects of the emergency assistance distributed to renters during the pandemic. Chetty et al. (2023) evaluate a range of pandemic economic policies such as the Paycheck Production Program, Pandemic Unemployment Insurance, and State-level Stay-at-home orders on spending and economic outcomes using nearly real-time data on spending from private sector data sources. Ganong et al. (2022) examine the impacts of pandemic unemployment insurance on spending

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doubling in the unemployment rate among renters (see Appendix Figure D.10), in contrast to foreclosures, which spiked during this period.

[8]Another branch of the literature examines the effects of longer-term means-tested rental assistance on labor supply and child well-being (Jacob and Ludwig, 2012; Jacob et al., 2015).

and job-finding. Karger and Rajan (2021) examine the impacts of the COVID-19 Economic Impact Payments on spending. Recent studies have analyzed the short-term effects of the 2021 expansion of the Child Tax Credit (CTC) on household financial and mental well-being (Collyer et al., 2022; Glasner et al., 2022; Kovski et al., 2023; Pignatti and Parolin, 2023; Pilkauskas et al., 2023). While past work has sought to estimate the impact of the eviction moratoriums during the pandemic on COVID-19 infections and mortality (Jowers et al., 2021) and on credit and mental health outcomes (An et al., 2021), we provide the first large-scale evidence on the causal impact of a key part of the federal economic response—the significant expansion of emergency assistance to renters—across four large urban areas. In contrast to the existing work, which uses county-level data, we also use our individual- and household-level data to study how renters' financial circumstances developed throughout the pandemic.

Finally, our work relates to recent studies of cash assistance provided during the COVID-19 pandemic. Jaroszewicz et al. (2022) compare the effects of one-time cash grants of $2,000 to those of one-time payments of $500 on bank account spending and survey measures of mental health and find the additional assistance led to small increases in spending but no improvements in mental health. Pilkauskas et al. (2022) examine the effects of one-time $1,000 payments to families receiving SNAP. They find limited effects on measures of material hardship and mental health. We study the effects of assistance targeting renters that was administered as a major component of the federal policy response to the pandemic. While, in contrast to these studies, we find some evidence for improvements in mental health, our estimates of the impacts on bill payment and financial strain appear qualitatively similar. Our results reflect program outcomes in four different metropolitan areas, feature much larger samples, and speak directly to the effects of pandemic rental assistance programs.

The rest of the paper is organized as follows. Section 2 details the assistance programs and lottery processes. Section 3 describes the data. Section 5 explains our research design and empirical strategy. Section 6 reports our main results. Section 7 further discusses our findings and concludes.

2   Program Details

We study five ERA programs administered in four different locations. This section provides information on each program's timing, eligibility requirements, application procedure, and payment amounts.[9] We also discuss relevant national and local pandemic-response policies.

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[9]Appendix Table D.10 summarizes these program details.

2.1 Chicago

We study two assistance lotteries that were run in Chicago in 2020. The first lottery was run by the City of Chicago Department of Housing (DOH). The second was organized by The Resurrection Project (TRP), a local nonprofit organization.

Chicago Department of Housing. The City of Chicago Department of Housing (DOH) partnered with UpTogether to implement an emergency financial assistance program for city residents at risk of eviction, foreclosure, or homelessness. The program opened to applications on March 27 and closed on April 5. Applications were submitted through a simple online form. The program received a total of 75,659 applications, approximately 80 percent of which were from renters, and the remainder from homeowners.

Due to the large number of applicants, grants were distributed through a lottery process. All applicants were assigned a random rank and were screened for eligibility, and offers were made in rank order until the funds were exhausted. Upon being selected, applicants had to provide proof that they were Chicago residents, that the pandemic negatively impacted their income, and that their pre-pandemic income was no greater than 60 percent of the area median income (AMI). Ultimately, 722 grants of $1,000 were distributed to eligible applicants selected by the lottery. Grants were distributed directly to applicants on a rolling basis through April and May of 2020.[10]

The Resurrection Project. The second program was run by The Resurrection Project (TRP), a local nonprofit organization, in partnership with the Chicago Resiliency Fund. The TRP program aimed to provide assistance to a population of people who were not eligible and did not receive aid from provisions of the CARES Act. Although open to all Chicago residents with incomes below 300 percent of the federal poverty line, applications from undocumented individuals, mixed-status families, dependent adults, and returning residents were particularly encouraged. Those selected had to provide identification, proof of Chicago residence, and proof of income.

The program's first round of assistance was not oversubscribed. We study its second round, which opened for applications on June 22, 2020. Like the DOH program, the TRP program was open to homeowners and renters, with 75 percent of the applications coming from renters. In the second round, 10,300 applications were submitted, and 1,607 grants of $1,000 were distributed by lottery.[11]

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[10]DOH conducted two further waves of grant programs later in 2020, but the applicant pools were smaller, leaving no, or very small, control groups. Therefore, we include only the first round in this study.

[11]In total, TRP distributed more than nine million dollars of assistance to over 9,000 people through the Chicago Resiliency Fund during the pandemic.

2.2 Harris County

In November 2020, Harris County, Texas, partnered with Catholic Charities Galveston-Houston (CCGH) to administer $60 million in assistance to households experiencing economic hardship due to the COVID-19 pandemic.[12] Eligibility was limited to individuals earning less than 60 percent of local AMI or receiving public assistance, and who could demonstrate that the pandemic negatively impacted their income. When applying online, applicants could upload proof of hardship (e.g., a letter of termination/furlough, a paystub showing a reduction in pay or hours) or self-attest to hardship using a self-certification form. Upon selection for processing, applicants underwent an income eligibility screening.

Applications for assistance opened for five days and ended on November 5, 2020. The county sought to distribute funds equally across four county precincts and therefore capped the amount of assistance going to each precinct. With this constraint, there was excess demand in the lowest-income precinct (Precinct 1). A lottery was used to select among applicants. To prioritize more vulnerable applicants, the lottery featured varying odds of receiving assistance depending on the applicant's Census tract.[13] Based on the CDC's Social Vulnerability Index, the census tracts were divided into quartiles, with the odds of selection depending on the quartile. Applicants in the top quartile had 50 percent greater odds of selection. Applicants selected through the lottery and determined eligible received $1,200 in direct cash assistance. The funds were mostly distributed in November and December 2020, with some payments going out in early 2021.

2.3 King County

In late 2020, King County, Washington, implemented an emergency financial assistance program through its Department of Community and Human Services (DCHS). DCHS operated separate programs for large-scale landlords, who could apply directly for assistance for all eligible tenants, and tenants of small-scale landlords, who could request assistance directly. We study the latter program. Tenants requested assistance through an online form that was open from August 20, 2020, to December 4, 2020.

Starting on September 22, 2020, all eligible applicants who had not been offered previous assistance were entered into a weekly lottery conducted by DCHS. The number of applicants selected weekly depended on DCHS's staff capacity. Since people who completed the interest form earlier were eligible for more weekly lotteries, the probability of treatment varies with

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[12]This was the second round of assistance distributed by the county, which administered an earlier round in July 2020.

[13]We account for this in our analysis by including Census tract fixed effects (see Section 5.1 for more detail).

the week of application. The funds for the program were distributed from October 2020 to January 2021.

To be eligible for this program, individuals had to verify income at or below 50 percent of the local AMI during the 60 days prior to the application, demonstrate experience of financial hardship due to COVID-19 that threatened their ability to pay rent on time, and indicate risk of experiencing housing instability.

The assistance provided in King County was somewhat more generous than that provided at the other sites. Those selected received an average of three months' back rent or credit toward future rent, paid to the landlord. The maximum available support covered six months' rent. To receive this payment, the landlord needed to agree to the following conditions: (i) to be paid reduced rent equal to the lesser of 80 percent of contracted rent or HUD fair market rent, (ii) to forgive any rental debt owed by the tenant beyond six months' rent, (iii) to retain the tenant (except for cause), and (iv) to not raise rent through March 2022.

2.4 Los Angeles

In July 2020, the Los Angeles City Council approved the creation of the Emergency Rental Assistance Subsidy (ERAS) program. The program was administered by the City's Housing and Community Investment Department (HCIDLA) and allocated $103 million in federal CARES Act and city funding to be used to provide rent subsidies to low-income tenants.

To be eligible for assistance, renters needed to be city residents who could verify a pre-pandemic income at or below 80 percent of local AMI and provide documentation of a COVID-related loss of income occurring after March 13, 2020. The application period for the program spanned five days, from July 13-17, 2020. The city received approximately twice as many applications from renters as it anticipated being able to serve. To allocate funding, the city entered applicants into a randomized lottery. Those initially selected by the lottery were notified in late July 2020 and asked to submit documentation to prove their eligibility. Those not initially selected were placed on a waiting list to be contacted only after attempts were made to process the applications of all those initially selected.

Applicants who were awarded funding received rent subsidies of $2,000 per household to be applied to current or future rent payments. Initially, the rent subsidies were paid directly to landlords, who had to agree to the following three conditions to receive payment: (i) not to impose interest or late fees on rent owed, (ii) not to evict tenants during the local declaration of emergency due to COVID-19, and (iii) not to impose a rent increase during the 12-month period following the award of funding. Limited landlord participation led the city to approve a change to the policy in November 2020 that allowed the subsidy to be

paid directly to the tenant as a one-time grant in the event that the landlord opted out or did not respond. The first payment was made in September 2020 and the funds were fully exhausted at the end of December 2020. Ultimately, 56 percent of all grants were paid to landlords and 44 percent to tenants.

2.5 Program Timing

Figure I illustrates the backdrop against which the programs we study were implemented. Panel A shows that their timing coincided with the initial economic impact of the pandemic (measured using the unemployment rate). As seen in Panel C, they also coincided with the peak of rental arrears, as measured using data from the Census Household Pulse Survey. These survey data show that approximately 10 to 13 million households reported being behind on rent during the period in which these programs were rolled out. This number represents approximately 23-30 percent of renter households.[14] This statistic falls sharply to just above 7 million households (approximately 16 percent) in the spring of 2021, and subsequently does not reach a level as high as during the start of the pandemic. By early 2023, the fraction of households in arrears appears to have roughly stabilized at this level.[15]

While rental assistance programs were a primary component of local governments' pandemic response, early-phase federal relief programs tended to take the form of direct cash assistance, such as the Economic Impact Payments (EIPs), or expansions of existing transfer programs, such as Unemployment Insurance benefits. Several federal initiatives were rolled out around the same time as the programs we study. Panel B of Figure I illustrates the impact these federal initiatives had on disposable household income for households in the lower half of the income distribution, comparing disposable income before and after taxes and transfers.[16] The latter measure includes EIPs, Child Tax Credit, Earned Income Tax Credit, and Unemployment Insurance benefits (including Pandemic UI), which were implemented in the first year of the pandemic.

The federal government also provided funding specifically for emergency rental assistance in a later phase of the pandemic. Figure I shows that all of the local programs we study provided assistance well before the large federal ERA funding rounds. Given the difference in timing, as well as differences in implementation and assistance amounts, our results are

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[14]There were 42.5 million renter households in 2023 (U.S. Census Bureau, 2024).

[15]Figure I includes two other measures of renter households' distress: the number of households who are not confident in their ability to pay rent next month, and the number of households in rental arrears who report being at risk of eviction. The survey data show lower levels but very similar trends for these measures. All three measures strongly suggest that tenants had the most trouble paying rent in the early phase of the pandemic.

[16]Estimates of post-tax disposable income for the bottom have of the income distribution come from Blanchet et al. (2022).

not necessarily representative of the impact of the federal ERA programs.[17] However, the lotteries we study provide arguably the best available setting for evaluating ERA as a crisis-response mechanism during the most immediate and highest-intensity economic impact of the pandemic.

In addition to these relief programs, national and local eviction moratoria constituted an important feature of the regulatory environment for our setting. The CARES Act included a 120-day national moratorium on eviction filings for non-payment of rent and related fees for properties participating in federal assistance programs or with federally backed financing.[18] This measure was in place from March 27th to July 24th, 2020. Next, the Centers for Disease Control and Prevention (CDC) issued a national moratorium on evictions for nonpayment of rent and related fees on September 4, 2020 (McCarty and Perl, 2021), which lasted until July 31, 2021 (McCarty et al., 2021).[19] The moratorium allowed evictions for reasons other than non-payment, such as property damage, criminal activity, health and safety issues, and other contractual violations. The practical implementation of the moratorium varied by state; some judges saw it as a ban on filing new cases for non-payment, while others viewed it as a ban on enforcing eviction orders (Sudeall et al., 2023). Consequently, the impact of the federal moratorium differed by location.

In addition to the national moratorium, local moratoria were implemented in all our study sites.

Chicago. Chicago renters were covered by a state-wide eviction moratorium between March 21, 2020 and August 1, 2021. The moratorium prohibited eviction filings for nonpayment of rent, but other types of filings were allowed to continue. Chicago was also subject to an eviction sealing policy that went into effect on May 17th. The policy sealed cases filed between March 9th, 2021, and March 31st, 2022, removing the cases from the public record. These cases remained sealed after March 31st, 2022, while new filings were part of the public record (ILCS 5/9-122).

Harris County. Harris County renters were covered by a state eviction moratorium from March 19 to May 19, 2020. Eviction hearings were allowed to resume on May 19, 2020, and evictions were allowed to begin on May 26, 2020. Although the CDC moratorium covered renters in Harris County, there was significant local concern that Harris County eviction court judges were not honoring this order.[20] Even though law enforcement could not enforce

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[17]Appendix Table D.10 provides more details on timing and assistance levels for the five programs and provides a direct comparison to the federal programs.

[18]This set of properties are estimated to include 28–46% of occupied rental units (Stein and Sutaria, 2020).

[19]The federal government reinstated a more limited moratorium on August 3, 2021, which the Supreme Court struck down on August 26, 2021.

[20]Local news coverage emphasized uncertainty in how the eviction moratoria were interpreted by local

an eviction order during the national CDC eviction moratorium and new eviction orders were automatically "stayed" (delayed) (Benfer et al., 2020), new eviction cases could be filed and new judgments could be issued. Throughout the duration of the CDC moratorium, Harris County averaged more than 500 new eviction filings per week, approximately 60 percent of the pre-COVID volume (Hepburn et al., 2020).

King County. King County renters were covered by both state- and city-level eviction moratoria. A statewide moratorium was instituted from February 29, 2020, through July 31, 2021. The moratorium statute ended in July, but its protections extended through October, with landlords' ability to file evictions reinstated on November 1, 2021. Seattle, Burien, and Kenmore further extended their city-wide moratoria through January 15, 2022.

Los Angeles. LA city renters were covered by a residential eviction moratorium that was in effect from March 4, 2020, to June 31, 2022. Starting July 1, 2022, this moratorium applied only to households with income at or below 80 percent of AMI with demonstrated COVID-19-related financial hardship.

3 Data

We link administrative records from each of the five programs to five types of data sources. This section provides details on each of these data sources.

3.1 Credit Bureau Data

Our analysis of financial distress uses individual-level credit reporting data from Experian, one of the three major credit bureaus. The data contain a total of twelve monthly snapshots of consumer credit profiles observed bimonthly beginning at the end of January 2020 and running until the end of November 2021. These data allow us to track the evolution of credit outcomes throughout the early pandemic. They include information on credit scores, debt levels and delinquency status for all major forms of consumer debt.[21] In addition to these credit variables, the data also include the ZIP code of residence at the time of each snapshot, which we use to infer applicants' residential mobility.

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judges (e.g., Schuetz, 2021).

[21]Under the CARES Act, creditors were required to make a variety of hardship "accommodations" for households directly impacted by COVID-19, including deferring or forbearing payments, or reporting accounts as current, but required households to actively request relief (Fiano, 2020). Aggregate statistics suggest that delinquency on household credit continued to be reported to the credit bureaus, except for federal student loans, which were reported as current while payments were paused (*Household Debit and Credit Report*, 2023).

Experian matched the program application data to credit reporting data for all sites using the applicant's name and address. All lottery participants were eligible to be matched, except those in King County, where only survey respondents were eligible to be matched. To protect applicant confidentiality, all personally identifiable information was removed from the matched data before the latter were returned to the research team by Experian. Among people eligible to be matched, match rates across all sites are generally high, ranging from approximately 74 percent for Harris County to 81 percent for King County. Conditional on being observed in the credit data, nearly all applicants are present in every monthly snapshot. Our analysis therefore uses a balanced panel of credit outcomes.

3.2 Consumer Reference Data

As an alternative way to measure address changes, we use consumer reference data from Infutor Data Solutions. Infutor combines various information from many sources (e.g., phone bills, voter files, magazine subscriptions, and property deeds) to create a residential history for most adults in the United States. The result is a database of exact addresses that crosses state boundaries and includes start and end dates for each address. While these data were originally created for commercial applications such as identity verification and marketing, academics have recently used them to measure housing stability and migration in the wake of rent control, eviction, and new housing construction (Diamond et al., 2019; Asquith et al., 2023; Collinson et al., 2024). The Infutor data are well-suited for our study because they provide a consistent measure of housing stability across several metropolitan areas. Because the data are compiled from consumer records, they match with other data at a somewhat lower rate than records from other administrative sources and tend to miss groups of people more inclined to have shorter paper trails (e.g., young or Hispanic individuals). Even so, prior work shows that the data can measure residential mobility in similar high-risk populations; for example, address changes measured in Infutor data spike around the time people at risk of homelessness request and are denied emergency financial assistance from a large call center (Phillips, 2020).

We measure address changes among the people we are able to match to the Infutor data. The Infutor records include name, date of birth, and address, and we match on combinations of these identifiers in each location, depending on their availability in the application records for a given site. We limit our analysis to individuals who have an address in Infutor with a start date prior to their application for financial assistance. This process yields match rates of 35 percent for Chicago DOH, 21 percent for Chicago TRP, 35 percent for Harris County, 46 percent for King County, and 50 percent for Los Angeles. For this sample, we identify

the address at which the person resided when applying for assistance and measure whether Infutor later observes this person at a different address.

3.3 Survey Data

In addition to administrative data, our analysis uses surveys administered in the months following treatment from four of the five programs studied. The surveys carried out in Chicago, Harris County, and King County relied on largely harmonized survey instruments, with questions that were similar but not identical across sites.[22] When processing the survey data, we construct outcomes to align as closely as possible across sites. However, the survey questions used in Los Angeles were substantially different from the other sites. For this reason, we report the results for Los Angeles separately in the appendix. Appendix Section A provides a detailed discussion of how our survey-based outcomes are constructed.[23]

The amount of time that elapsed between assistance and the administration of the survey also varied across sites. Table D.2 reports the survey dates for each site. The surveys were administered one to six months after assistance was received. The Chicago DOH survey was administered the month after treatment, while other sites, such as Harris County, administered their surveys four to five months after assistance was received. For some of the survey outcome variables, retrospective questions were used to improve alignment across sites so as to account for differences in the elapsed time between the lottery and the completion of the survey.

The bottom panel of Table I reports survey response rates at each site. Survey response rates vary between 13 and 40 percent. For most sites, individuals who were offered assistance are more likely to respond to surveys than the those who were not. Appendix Table D.5 shows that survey nonresponse leads to modest imbalances in baseline characteristics. As we describe in the next section, our main analysis corrects for this imbalance by weighting responses by the applicant's inverse probability of responding to the survey as predicted from baseline characteristics observed for all applicants (Wooldridge, 2007).

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[22]This research began as three independent projects. Site-specific surveys were initially developed independently and in collaboration with partner organizations. The research teams eventually shared the survey instruments and, to the extent possible, aligned them. The full survey instruments can be found at https://github.com/robcollinson/covid_era_surveys/.

[23]Even among the sites where survey questions were largely aligned, one notable exception is the "COVID Positive" outcome, the Chicago DOH survey codes this outcome as one if the respondent selects "I got sick" to the multiresponse question "How has the COVID-19 epidemic impacted you?" The other sites' surveys specifically ask if the respondent suspected that she was infected with COVID-19 or had a positive self-test.

3.4 Evictions Data

We supplement the data sources above with eviction data from Harris County and Cook County. These data, and the homelessness data described in the next subsection, allow us to track more extreme forms of housing instability that we cannot measure across all sites.

Data on eviction filings and judgments were collected from the Harris County Justice of the Peace, the court entity that handles eviction cases, for calendar years 2019–2023. The eviction records contain basic case details, such as filing date, amount owed, and disposition or judgment details. We link these to the Harris County application data using names and addresses as described in Appendix C.

Eviction court records for Cook County were shared by the Cook County Circuit Court and supplemented with data from Record Information Services. Combined, the data span the years 2019-2024. The data contain filing date, name, and address, and include filings that were sealed from the public record as part of the state's pandemic-related tenant protection measures. Appendix C provides details on the linkage process. A limitation of both eviction datasets is that we can link only to evictions occurring *at the application address*, which undercounts total exposure to eviction.

3.5 Homelessness Data

We measure homeless services use in King County and Chicago using local Homeless Management Information System (HMIS) data. These databases systematically record the use of homeless programs in a community, following the guidelines of the US Department of Housing and Urban Development.

Starting from the set of all HMIS program enrollments between March 2019 and September 2021, King County staff extracted records that fuzzy matched with lottery applicants based on name, date of birth, and ZIP code. We limit the data to program types offered only to people who are already homeless (e.g., we do not include homelessness prevention programs) so that program use indicates that the individual both receives services and is homeless at the point of program entry.[24] The existing literature uses similar measures to evaluate the impact of rental assistance and eviction on homelessness (Evans et al., 2016; Phillips and Sullivan, 2022, 2023; Collinson et al., 2024).

The DOH and TRP applicant records were similarly matched on name and date of birth to Chicago HMIS program enrollments spanning January 2017 to December 2023 through a

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[24]The categories of programs we consider include emergency shelter, street outreach for people living unsheltered, coordinated entry (entries for requesting but not yet accessing oversubscribed services), diversion programs provided to people who have just become homeless, transitional housing, permanent supportive housing, and rapid rehousing.

probabilistic linkage procedure. In the case of multiple viable matches to a single applicant, HMIS service utilization histories were reconciled to take the highest level of engagement on any given day. All outcomes for King County and Chicago were constructed to align with HUD project types, except diversion services, which are only available in the King County HMIS.

4   Who Were the Program Recipients?

4.1   Lottery Applicants

Table I provides summary statistics for each of the program sites. We report means separately for applicants who were offered assistance ($Z = 1$) and those who were not ($Z = 0$). The table summarizes applicant characteristics, which we group into four broad areas. The first panel uses the complete lottery sample and provides information on demographics (or imputed demographics) derived from the applications for assistance.[25] The second panel provides details on baseline financial characteristics, such as income and amount of rent owed, collected at the time of application. The third panel reports ZIP code characteristics of applicants from the American Community Survey. Finally, for those who match to credit records, we report baseline credit measures from January 2020.

Applicants were, on average, 39 to 41 years old, and 54-64 percent of applicants were female. The racial composition differs across lotteries. Black individuals account for over one-half of applications in Harris County, and around a third in King County and Chicago DOH. For Los Angeles and Chicago TRP, over 50 and 80 percent of applicants are Hispanic, respectively. The median rent in applicants' ZIP codes is between $1,000 and $1,500 across sites, and poverty rates range from 11% to 21%. The average credit scores are low across sites, ranging from 550 to 650, and applicants have relatively large balances in delinquency or collections. Overall, the racial compositions differ across lotteries; otherwise, applicants across sites are broadly similar.

Figure III extends the descriptive statistics from Table I to plot the evolution of several key measures of financial distress: credit scores, total balances in delinquent accounts, and total balances in collections for utility bills. Each panel reports the raw means (and standard errors) for a given outcome and site separately for applicants who were and were not offered assistance.[26] Means are plotted for all months with available credit reporting data. The

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[25]For Harris County, we impute gender and race using the R packages *gender*, *genderdata*, and *wru*.

[26]We report standard errors for each mean separately rather than their difference to provide a sense of the overall variability in the data. Formal tests for differences in means between applicants who were and were not offered assistance are discussed in Section 6.

vertical dashed line denotes the month in which the lottery was conducted for each site. The vertical red line marks the beginning of the pandemic (March 2020).[27]

Three features of this figure stand out. First, the balance between applicants who were and were not offered assistance, which is documented in Table I for January 2020, persists across all pretreatment months. The gap is somewhat larger in King County, where assistance was randomly assigned but we only observe credit records for survey respondents, as described in Section 3.1. Second, the overall trend for applicants across all sites is one of generally improving financial distress. Credit scores trend upward throughout the sample period, while delinquent balances and utilities collections trend downward. This finding is consistent with evidence from other work showing that various measures of financial well-being improved for most households during the early pandemic (Han et al., 2020). Third, there is no meaningful divergence in outcomes between applicants who were and were not offered assistance either at the onset of the pandemic or in the months following assistance. This finding, which foreshadows our main results, is consistent with the idea that the emergency assistance grants we study did not have meaningful effects on financial distress.

4.2   Did ERA Programs Target Those in Need?

As noted in Section 2, the ERA programs required proof of eligibility, including income limits and a need to show an inability to pay rent or pandemic-related income loss. These criteria may have led to the programs being accessed by lower-income or more financially strained households compared to other pandemic-relief initiatives. To assess the extent to which ERA programs targeted those in greater need, we first compare program recipients with other renters in the same cities. Then, we compare ERA recipients to those who received federal Economic Impact Payments (EIP), which were distributed around the same time.

Table II compares the characteristics of those who received assistance to the characteristics of all renters who live within the relevant city or county. We compare demographic characteristics (top panel), ZIP code characteristics (middle panel), and credit characteristics (bottom panel). The first two panels use data on renters in the ACS in 2019.[28] The final panel uses data from a 10 percent random sample of individuals from Equifax. We restrict to renters who live within one of the catchment areas for the programs in the months the

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[27] In King County, the applications were made and lotteries conducted over time. Thus, we display the data by relative time, limiting to time periods for which data are available for the full sample. We indicate the start of the pandemic using the average for the sample.

[28] The first panel uses the 2019 ACS public-use micro-data and is a subset of all renters in each area. The second panel uses aggregate ZIP code (ZCTA) characteristics from the 5-year 2015-2019 ACS, where ZIP-level characteristics are weighed by the number of renters in the ZIP or the number of applicants in the ZIP.

lotteries took place. We focus on credit scores (VantageScore 4.0), balance in delinquent accounts, and balance in collections, as these outcomes can be best aligned between the Equifax and Experian data.

Across all sites, those assisted are less likely to be White, and more likely to be Black or Hispanic than renters on average. Those assisted are also from ZIP codes with higher poverty rates, a lower share of White residents, and moderately lower median rent. Finally, those assisted have notably lower credit scores, higher balances in collections or delinquency, and are less likely to have a revolving line of credit (e.g., a credit card).

We further compare trends in the financial characteristics of those assisted compared to all renters using the panel nature of the Equifax and Experian data. Appendix Figure D.7 plots the outcome trajectories for applicants who were and were not offered assistance and the random samples of renters over time relative to the treatment month for all five programs. Across all sites, we see large gaps between the random sample of renters and those who participated in the lottery. For example, in Harris and King Counties, the credit score gap is more than 100 points in all periods, while the gap is 50 or more points in all periods in Los Angeles and Chicago DOH. The lottery participants also have low average baseline credit scores ranging between 550 and 640 (with the standard cut-off for subprime being 600), with a smooth rise of approximately 25 points during the pandemic.

Similar gaps are present for the balances in delinquent accounts and in collections, with those participating in the lottery having average balances in collections ranging from approximately $3,000 in Harris County and $1,400 to $1,800 in King County to $1,000 in Los Angeles and $500 to $1,100 in Chicago. The trends are not widely different between lottery participants and the random sample of renters, though on average, the gaps between the two groups close somewhat over time. The random samples of renters have largely flat trajectories, while both applicant groups have rising credit scores and flat or decreasing balances over the whole time period.

Our second benchmark to evaluate the targeting properties of the ERA programs are the recipients of the first round of federal Economic Impact Payments – cash checks provided under the CARES Act. Figure II provides a comparison between recipients of the ERA programs we study and EIP Round 1 recipients, based on ZIP-level poverty rates.[29] Economic Impact Payments were the federal government's most immediate response to the economic impact of the pandemic and the first round consisted of checks in the amount of

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[29]We make comparisons based on ZIP-level characteristics because we observe ZIP codes for all recipients in the programs we study, and counts of EIP recipients by ZIP code are available from the Internal Revenue Service Statistics of Income (Internal Revenue Service, 2020, 2021). We focus on EIP round 1 recipients because recipients in rounds 2 and 3 have nearly identical ZIP-level characteristics, as can be seen in Appendix Figures D.3 and D.4.

$1,200 per adult plus $500 per qualifying child under age 17, sent to individuals with less than $75,000 ($150,000 for married couples filing a joint return) in income reported on their 2018 or 2019 federal tax returns. Payment amounts were reduced for eligible individuals with higher adjusted gross income. Across all sites, ERA recipients live in ZIP codes with higher poverty rates as compared to EIP recipients.[30]

Appendix Figures D.1 and D.2 make similar comparisons based on ZIP-level minority and Hispanic population shares for ERA recipients and EIP recipients. With the exception of Los Angeles, all sites distributed assistance to recipients in neighborhoods with higher minority shares. As expected given that it was designed to target undocumented immigrants, recipients in the Chicago TRP program were substantially more likely to be from neighborhoods with high Hispanic shares.

Overall, the evidence suggests that the ERA programs targeted renters who were substantially more financially distressed, and who were living in higher-poverty and higher-minority share neighborhoods, relative to renters not assisted by the programs. These findings are in line with the results in Figinski et al. (2024), who find that the federal ERAP payments that were implemented in a later phase of the pandemic (see Figure I) disproportionately went to Census tracts with more disadvantaged renters.

5   Using Lotteries to Study the Impact of ERA

5.1   Regression Specifications

Our empirical analysis aims to estimate the causal effects of receiving ERA on various outcomes of interest. However, simply comparing average outcomes across those who did and did not receive assistance may yield biased estimates of this effect. Most financial assistance programs select clients based on their vulnerability or their recent experience of a large negative shock. Even in settings where assistance is administered via lottery, take-up of assistance is typically endogenous. Households that do not take up the assistance may differ along dimensions unobservable to the econometrician. For example, they might have more tumultuous lives, making it difficult to submit necessary paperwork or respond to attempts to contact them. Alternatively, they might not take up the assistance because they have relatively less need for it or have access to other financial support.

We address these challenges by estimating treatment effects using random variation in *offers* of assistance. Specifically, we limit our sample to people who applied for assistance

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[30]Karger and Rajan (2021) provide evidence that those with lower income and less savings had higher marginal propensities to consume from the EIP payments. This suggests that ERA may have targeted those with higher marginal propensities to consume.

and study contexts in which local jurisdictions rationed oversubscribed assistance by lottery. To measure the effect of being offered assistance (which we will refer to as "intent-to-treat effect," or ITT), we estimate simple linear regressions of the following form:

$$Y = \gamma_0 + \gamma_1 Z + \mathbf{X}'\phi + U, \tag{1}$$

where Y is an outcome of interest, such as credit score, γ_1 is the intent-to-treat effect, Z is an indicator for whether the applicant was selected by lottery to receive an assistance offer, and $\mathbf{X}$ is a set of control variables.[31]

As discussed in Section 2, several jurisdictions administered their lotteries in a way that resulted in offers that were random conditional on observable information, such as time of application or Census tract. We include controls for these "site-specific design features" in $\mathbf{X}$ in equation (1). In particular, we include week-of-application fixed effects for King County and Census tract fixed effects for Harris County. For Chicago, we include application-count fixed effects to account for a small number of individuals applying more than once. To increase precision, we additionally control for individual-level gender and race indicators. When analyzing credit report data, we also control for lagged credit outcomes for the period prior to lottery application and for January 2020.[32]

Not everyone initially offered funding actually received it. There are several reasons those selected for funding may not have received it, such as program administrators not being able to contact the applicant, the applicant being determined ineligible, or the applicant failing to complete the required forms. It is also possible that applicants not originally selected for assistance via the lottery nonetheless ended up receiving it. To account for both directions of imperfect take-up, our analysis focuses on instrumental variables estimates. We calculate these estimates using two-stage least squares (TSLS) regressions, with the first and second stages given by:

$$R = \alpha_0 + \alpha_1 Z + \mathbf{X}'\delta + V \tag{2}$$
$$Y = \beta_0 + \beta_1 \widehat{R} + \mathbf{X}'\lambda + W, \tag{3}$$

where R is an indicator variable for whether an applicant received assistance, and all other variables are as previously defined. The coefficient β_1 is our parameter of interest, and

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[31]Below, we use the terminology "offered treatment" and "selected for an offer of treatment" interchangeably, even though not all applicants selected through the lottery were offered assistance, for example due to difficulties contacting the applicant.

[32]The lagged credit outcomes are credit score, total debt balance, balance in collections, balance delinquent, utility balance in collections, and indicators for any delinquency, any revolving credit account, and any auto loan.

represents a local average treatment effect (LATE) of assistance receipt if the standard IV assumptions (Imbens and Angrist, 1994) are satisfied and (2)–(3) are correctly specified (Blandhol et al., 2022).

Table III reports estimates of α_1 from the first-stage regression for each site. The table also reports the partial F-statistic on that coefficient, the control-group mean, and the share offered assistance. For each site, we observe a large and statistically significant first stage (with the F statistics ranging between 2,442 and 47,977). The size of the first-stage coefficients differ as there were differential take-up rates across sites. Some of these differences come from how the lotteries were implemented and, specifically, how much screening took place at the time of the application versus upon selection as a lottery winner. For example, Chicago's initial application process was easy to complete, and candidates were screened more rigorously upon being selected. Programs also differed in the extent to which assistance required the agreement of landlords. In King County and during the early stages of the Los Angeles program, the assistance was paid to landlords, some of whom did not accept the program's limits on future evictions or rent increases. In contrast, Harris County made payments directly to the household applying for assistance.

We estimate all treatment effects site by site. For example, when measuring local average treatment effects, we estimate equations (2) and (3) separately for each site. We then compute the simple, unweighted average of the estimates across sites. We estimate heteroskedasticity-robust standard errors for each site and compute a full-sample standard error assuming independence across sites.

5.2   Balance Tests

We check whether the data is consistent with randomization of offers of assistance by program administrators. Table I shows the results of tests for balance on observable characteristics between the groups offered and not offered assistance. For each site, we report the difference between these group means ("Diff"), adjusted using an ordinary least squares (OLS) regression of equation (1) that controls for any site-specific design features (see Section 5.1).

Overall, the applicants selected for assistance are observably similar at baseline to applicants not selected on nearly all variables. Across the demographic and credit characteristics, the two groups are generally balanced. Where there are some statistically significant differences between the two groups' populations, the differences are quantitatively small. Credit report characteristics in King County show somewhat larger gaps between the two groups. This is likely the result of the fact that we can only access Experian records in King County for people who respond to the survey, as discussed in Section 3. This sample selection gen-

erates the somewhat larger baseline differences in attributes measured in credit reports, the largest difference in credit scores across sites, 8.5 points. Reassuringly, the top two panels of Table I use the full lottery sample for King County and show balance, suggesting that the imbalance in Experian data is indeed due to selection into the survey in King County. Appendix Table D.1 reports balance for additional baseline applicant characteristics available in Los Angeles, but not the other sites.

For most sites, survey response rates were not equal across the groups offered and not offered assistance. To address potential bias due to differential selection into responding to the survey, in any analysis of survey outcomes, we always weight the answers by the applicant's inverse probability of responding to the survey (Wooldridge, 2007). To calculate these weights, we first estimate site-specific logit regressions of whether an applicant responded to the survey, using a dummy for being offered assistance (Z) and a host of baseline control variables. For all sites except King County, these controls include ZIP code-level median rent, poverty rate, share high-school educated, share Hispanic, share White, share Black, and share Asian. Additional applicant-level controls vary across sites depending on data availability.[33] We then predict an applicant's probability of responding if they had not been offered assistance (i.e., setting $Z = 0$) and use the inverse of this predicted probability as the weight in our regressions. As discussed in Section 6.1, we obtain similar results with and without these weights.

6   Results

In this section, we report estimates of treatment effects from receiving assistance on outcomes measured in our surveys, financial distress measures observed in the administrative data from Experian, residential mobility as measured in both the Infutor and Experian data, and eviction and homelessness data as measured from court records and local homeless services administrative systems. We report both site-specific estimates and equal-weighted averages across sites.

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[33]For Harris County, the controls include language (English speaking vs non-English speaking), contact information (valid email, two phone numbers, etc.), public assistance type, income eligible, gender, race, and ethnicity. For King County, they include indicators for race, gender, and primary language, and for both Chicago lotteries, they include age and indicators for race, gender, missing age, and if the applicant applied to the lottery more than once. For Los Angeles, these controls include age, household size, gender, language (English speaking vs non-English speaking), ethnicity, race, income, monthly rent, total rent owed, months' rent owed, and COVID hardship reason.

6.1 Impacts on Survey Outcomes

Table IV reports IV estimates of the effect of assistance receipt on survey measures of rent and bill payment, mental and physical health, material hardship, and feelings of economic insecurity. Most of our survey questions ask about the month prior to survey collection. However, the questions about rent payment ask about specific months following the month of the lottery.[34] Columns (1)–(4) report estimates separately by location, and column (5) combines estimates across sites. Control group means (i.e., means for the group not selected for assistance) are reported in brackets. While Table IV reports estimates from the weighted regressions that adjust for survey nonresponse, the unweighted results are qualitatively similar (Appendix Table D.3).

The survey data reveal three key results. First, assistance receipt led to higher rates of rent payment at the time of follow-up. Consistently across Harris County, King County, and Chicago (both DOH and TRP), recipients are 5.8–13.4 percentage points more likely to have paid their rent in full in the month prior to the survey. Across these three sites, the combined increase in the likelihood of rent payment is 8.2 percentage points, a 15 percent increase over the control group mean. The effects of assistance on other types of bill payment appear more mixed. Across the four lotteries, we find no evidence of impacts of the assistance on other bill payments. Due to the substantive differences in the questions asked in the Los Angeles survey, we report estimates separately for L.A.in Appendix Table D.4.[35]

Second, recipients are less likely to report feeling worried about being evicted (a 4.7 percentage-point decrease, or 16 percent). The point estimates for experiencing homelessness (self-reported) are consistently negative, but none are statistically significant. The combined estimate for staying in a homeless shelter is not statistically significant overall. However, we do find a statistically significant decrease in self-reported sheltered homelessness in Harris County (where the CDC moratorium was not as stringently enforced). The other sites have a mixture of negative and positive point estimates which are not significant.[36] We also find no statistically significant evidence of reduced food insecurity.

Finally, there is suggestive evidence of improved physical and mental health among recipients. Recipients in the Chicago DOH lottery experienced a 5.1 percentage-point decline in their likelihood of becoming sick in the previous month as a consequence of COVID-19, and the point estimates for King County and Harris County are of similar magnitude, albeit

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[34]See Appendix A for details about the survey questions across each site.

[35]The effects are noticeably different for Los Angeles, likely due to difference in the wording of the survey question, which focused on cumulative rent payment. At the same time, there is some indication in LA that receipt of assistance resulted in increased payment of bills other than rent, though the estimates are somewhat imprecise.

[36]We consider impacts on homelessness as measured by administrative records in Section 6.4.

measured with less precision. Across all three sites, we estimate a marginally significant 5.6 percentage point reduction. Similarly, recipients are less likely to have reported feelings of anxiety or depression, a 3.2-percentage-point (6.3 percent) decrease across Harris County, King County, and Chicago, which is marginally significant.

Overall, the results based on the survey data suggest that recipients were more likely to pay rent and to be less worried about being evicted. The point estimates for staying in shelter also suggest reductions in housing instability, but are generally not significant. Lastly, we find suggestive evidence that assistance modestly improved recipients' physical and mental health.

6.2   Impacts on Credit Measures

Next, we consider how financial assistance affected financial health using panel data from Experian. Figure IV depicts reduced-form (ITT) and IV estimates, constructed as described in Section 5.1, for a subset of our credit outcomes. Each column reports effects on a different outcome: credit score (left column), balance in delinquent accounts (middle column), and balance in utilities collections (right column). The reduced-form (ITT) and IV estimates are depicted by navy diamonds and gold circles, respectively. Across outcomes and locations, there is a consistent pattern in the results—namely, that being selected to receive assistance (ITT) or receiving assistance (IV) did not meaningfully improve applicants' financial well-being.

Table V summarizes the IV estimates of the effects of assistance across a broad range of credit outcomes measured two months and ten months after receipt. There is some evidence that recipients used the additional resources to pay down some of their debt in the short run. Receipt of assistance led to a $74 decrease in the debt balance in collections (column (6)), driven by declines in the King County and Los Angeles samples. However, there are no consistent effects on credit score, total balances, balance in utility collections, delinquent accounts, or bankruptcy. Recipient households are no more likely to have increased their durable consumption by taking out a car loan/lease and no more likely to have used a revolving line of credit. Within ten months of assistance receipt, there are no statistically significant differences in the administrative credit outcomes.

The overall effects on credit outcomes are small and precisely estimated. For example, the 95 percent confidence interval for the short-run effect on credit scores ranges from -3.1 to 1.8. Thus, we can rule out large effects on credit scores like the 16.5-point decrease in response to an eviction estimated in Collinson et al. (2024) or the 9.4-point increase in response to the removal of a bankruptcy flag estimated in Dobbie et al. (2020). Similarly, the 95 percent

confidence interval on the 10-month balance in collections, which ranges from -$175 to $196, allows us to rule out effects of the magnitude of the $302 increase in collections balances 4 years after a hospitalization among nonelderly insured adults estimated in Dobkin et al. (2018).

One possible explanation for these modest effects is that they mask larger effects across some subgroups. We investigate this possibility by examining several subgroups based on financial stability in the lead-up to their applying for assistance. We divide the subgroups based on both levels and trends in credit measures, including groups with credit scores below (above) 580, delinquent account balances above (below) $5,000, decreasing (increasing) credit scores, and increasing (decreasing) delinquent account balances. Figure D.6 plots the standardized IV estimates for the effects of assistance on credit scores and balances in delinquent accounts and utility collections separately by subgroup and site.[37] Within sites, there are few meaningful differences among the subgroups. Moreover, there is no consistent pattern *across* sites. Taking these results together, we find little evidence that the more disadvantaged individuals in our sample experienced larger gains from the assistance.

6.3   Impacts on Residential Mobility

We find no consistent evidence that residential mobility changed as a result of receiving emergency rental assistance. Table VI reports our IV estimates of the effects of assistance on residential mobility. We measure address changes in two administrative data sets in the short run (two months post-lottery) and long run (ten months post-lottery). Using the Infutor data, we code a change of address if an applicant's current address differs from her address at the time of application. In the Experian data, address changes are measured by changes in ZIP code relative to the application ZIP code. Move rates do not differ noticeably with receipt of assistance. For example, 10-month move rates in the Infutor data decrease by a statistically insignificant 0.8 percentage points from a mean of 9.3, and the 95 percent confidence interval on this estimate ranges from -2.7 to 1.2 percentage points. For context, an eviction order is estimated to increase the likelihood of a changed address one year later by 8.2 percentage points (Collinson et al., 2024).

6.4   Impacts on Eviction and Homelessness

Next, we investigate whether the assistance reduced other measures of acute housing instability, including evictions and homelessness. We are not able to track these outcomes across

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[37]We standardize the IV estimates by dividing the point estimates by the control group standard deviation of the outcome.

all sites, so we draw on evidence from individual locations. In particular, we study effects on homelessness in Chicago and King County and effects on eviction activity in Chicago and Harris County.

In Table VII, we report the effects of receiving assistance on homelessness system use in the 9 months after the lottery for three of the lotteries that we study: King County, Chicago DOH, and Chicago TRP. We examine the impacts on any homelessness system use as in Collinson et al. (2024) and Phillips and Sullivan (2023) and the impacts on the types of services used. The effects of assistance on homelessness are mixed. In King County, receipt of assistance *increased* interactions with the homelessness system by 2 percentage points. Descriptively, this result appears to be driven primarily by unassisted members of the assigned treatment group being made *more* likely to show up in the homelessness system, as we explore in Appendix Figure D.8. This finding could be due to applicants whose applications were incomplete or who were found to be ineligible being steered to other resources in the homelessness system by program staff.

In Chicago, applicants who received assistance through the TRP lottery were 0.35 percentage points less likely to appear in the homelessness system in the 9 months after the lottery. This decline is a small absolute reduction but a large relative reduction of 65 percent since homelessness system interactions are rare among the TRP applicants not selected for assistance via lottery (only 0.55 percent of control group applicants end up in the homelessness system). Applicants who received assistance through the Chicago DOH lottery are slightly less likely to have interacted with the homelessness system, but the difference is not statistically significant.

Our results on homelessness from King County and Chicago DOH contrast with other evidence on emergency rental assistance programs from outside the pandemic context. Prior work finds that emergency rental assistance decreases rates of homelessness by approximately three-quarters in Chicago (Evans et al., 2016) and San Jose (Phillips and Sullivan, 2023). This contrast between our results and others from the literature does not arise from major differences in the interventions being studied. The emergency financial assistance programs offered during COVID were largely designed based on existing programs and in most cases were even operated by the same agencies. The traditional and COVID-era programs both feature temporary assistance in relatively modest amounts. For example, in Evans et al. (2016), Phillips and Sullivan (2023), and Phillips and Sullivan (2022), the clients offered financial assistance received an average of 0.7, 1.0, and 0.7 months of rent, respectively, which are magnitudes similar to those of the programs that we study in Chicago, Harris County, and Los Angeles, though the King County program is somewhat more generous.

The programs that we study also target clients who appear largely similar to the par-

ticipants in pre-COVID-era rental assistance programs. The King County COVID rental assistance lottery and the pre-COVID homelessness prevention program studied in Phillips and Sullivan (2022) were operated by the same agency, are evaluated using the same data sources and methods, and had enrollment periods separated by only 5 months, providing an ideal comparison. In the King County COVID program, 19.7 percent of the sample had moved in the 12 months prior to the onset of the pandemic in March 2020, compared to 18.1 percent for the sample in Phillips and Sullivan (2022). Homelessness service usage differs slightly between the two samples, at 4.8 and 7.9 percent, respectively, but both are high. Similarly, the DOH lottery population in Chicago has rates of prior homelessness comparable to those studied in (Evans et al., 2016). An exception is the Chicago TRP lottery, which served a population with much lower pre-COVID rates of homelessness system use than those of the populations studied in prior work.

In contrast to King County and Chicago DOH, our results on homelessness for the Chicago TRP lottery are qualitatively similar to the findings from prior studies of pre-COVID emergency rental assistance programs (Evans et al., 2016; Phillips and Sullivan, 2023), showing a sharper reduction in homelessness for those who received assistance through this lottery than for those treated by the other lotteries that we evaluate here. A plausible explanation for this difference is that the TRP program targeted populations who might have more limited access to other aspects of the pandemic safety net, such as expanded unemployment insurance or COVID Economic Impact Payments, either because they were undocumented immigrants or lacked formal sector employment. In Appendix Table D.12, we report the fraction of applicants receiving government assistance across lotteries. Consistent with programmatic differences in target populations, we find that TRP applicants report much lower rates of assistance from government sources in our survey than Chicago DOH applicants or applicants in King County.

Finally, we examine impacts on eviction. As discussed in Section 2, new eviction cases could be initiated and new judgments issued in Harris County throughout the studied period, including the period covered by the CDC moratorium. However, enforcement of eviction orders by law enforcement was stayed during the moratorium. In contrast, eviction moratoria cover the entire sample period in King County and Chicago, so use of homelessness programs serves as a more useful outcome measure for these locations. To examine the impacts on filing of evictions and related judgment activity, we link the sample of Harris County assistance applicants to eviction data, as described in Appendix C.

Table VIII reports the effects of receipt of assistance on eviction filing (initiation of a new case), which we only observe in Harris County and Chicago (both DOH and TRP). One limitation of this analysis is that we can only consider evictions occurring at the same address

listed on the application for assistance. The top panel considers 2SLS on any eviction filing within two, six, and ten months after the lottery. Given that the CDC moratorium was in place at the time, we also consider any eviction filings within two, six, and ten months after the eviction moratorium was lifted. The first column for each lottery reports the control mean. As expected, the baseline means during the moratorium are quite low, especially in Chicago.[38] After the moratorium, baseline means remain low, potentially partly due to applicants no longer living at the same address, but are several times higher than during the moratorium.

The second column for each site in Table VIII reports the IV estimates for the effects of the assistance. For Harris County, we find no statistically significant effects, with small negative point estimates in all periods. For Chicago DOH, we find some suggestive evidence of reduced evictions. During the moratorium, we find a reduction two months after the lottery. Yet, the control mean (0.0004) and treatment effect (-0.0004) are so small that this is based only on an extremely small difference in filings and should be interpreted cautiously. After the moratorium the estimates for Chicago DOH are also negative, with a weakly statistically significant reduction of -0.003 after two months, off a baseline mean of 0.005. The estimates for Chicago TRP are all statistically insignificant and small. In summary, the results are consistent with a small reduction in eviction filings during and after the moratorium, but the estimates are small and imprecise.

Taking the above results together, we find little evidence that applicants who received emergency rental assistance through the lottery were less likely than nonselected applicants to experience extreme housing instability in the months after applying. These results are consistent with our finding of limited to no effects of assistance on residential mobility or credit market outcomes.

7   Discussion and Concluding Remarks

This paper studies the unprecedented expansion of emergency rental assistance in response to the economic disruption caused by the COVID-19 pandemic. Using application data from five program lotteries conducted in four large cities linked to credit records, administrative homeless system data, and novel surveys, we provide the first experimental evidence on the effects of pandemic-era ERA on a wide range of policy-relevant outcomes.

We show that these programs were relatively well-targeted. Compared to other renters

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[38]In Appendix Figure D.9 we plot monthly eviction filings in Harris County. Filing volumes drop with the onset of COVID-19 and the CARES Act Moratorium. Filings remain roughly 50 percent lower than pre-pandemic levels (though still average about 2,000 cases per month) through the CDC moratorium. In contrast, the number of filings in Chicago remains low during the CDC moratorium.

in the area, applicants were more financially distressed, more likely to live in high-poverty neighborhoods, and more likely to be minorities. Similar conclusions are reached when comparing applicants to EIP recipients. Lastly, the assistance went out relatively early in the pandemic while unemployment rates and rental arrears were still quite high, and well before the federal ERA programs.

We find that rental assistance was successful in reducing rental arrears, reducing self-reported concern about eviction, and may have improved self-reported physical and mental health. However, it had little detectable short- or longer-run effect on broader measures of financial security, including evictions, homelessness, residential mobility, credit scores, indebtedness, or delinquency.

The key question raised by these findings is: why did these programs not have more of a detectable impact? Several pieces of evidence suggest that the modest effects that we see are unlikely to be a result of poor targeting or insufficient support. The program applicants were substantially more financially distressed than the average renter in their communities, and the null effects that we find persist even in subsamples of applicants with severe financial distress at the time of application. The size of the grants are also similar to that of other smaller-scale assistance programs that have been shown to have large effects (Phillips and Sullivan, 2023; Evans et al., 2016). Moreover, we find little heterogeneity across sites, even though the assistance was significantly more generous in some places (e.g., King County).

These results suggest that the broader economic and policy context, rather than program design or targeting, was responsible for the modest size of the effects. Unlike other ERA programs, which target shocks faced by individual renters, the programs that we study were created with the specific aim of responding to a macroeconomic shock. There are two natural explanations for why ERA could be less impactful during a macroeconomic downturn. First, macro-level shocks tend to be accompanied by other fiscal stimulus that provides additional support to low-income households, which tend to be renters. The COVID pandemic, in particular, featured a massive expansion of nearly every aspect of the social safety net, and created unprecedented limits on landlords' ability to evict, which may have muted the marginal effectiveness of additional rental assistance. Consistent with this conjecture, we find that individuals who applied for assistance—regardless of whether they actually received it—experienced broad-based improvements in their financial circumstances in the post-application period.

A second explanation is that, even in the absence of expanded fiscal stimulus, general equilibrium market responses to aggregate shocks may limit the impact of additional rental assistance. For landlords, evicting a tenant is likely a less attractive option during a widespread downturn than during normal times, when vacancies can be more easily filled at

higher prices. Thus, renegotiation or temporary agreements between landlords and tenants may be sufficient to forestall eviction without additional emergency assistance. Consistent with this possibility, we find that more than 70 percent of the lottery applicants who missed rental payments reported having some type of agreement with their landlord (Appendix Table D.11). This evidence is in line with other pandemic-era surveys of landlords that find substantial increases in reported rental forbearance in 2020, relative to pre-pandemic levels (Decker, 2021; de la Campa and Reina, 2023).[39] In such a setting, rental assistance may reduce rental arrears without changing tenants' longer-run housing stability, because these arrears would not have led to eviction or homelessness even in the absence of assistance.

While extensive evidence from the Great Recession has yielded lessons on the effectiveness of foreclosure prevention policies during macroeconomic downturns, far less is known about policies for renters. Our lottery-based estimates of the impact of ERA allow us to measure the effects of one such policy and offer a potentially valuable lesson about the effectiveness of these programs as macroeconomic stabilizers. Whether our results generalize to subsequent rounds of ERA (which were typically more generous, prioritized paying-down arrears, and were implemented during the tail end of the pandemic), is an open question. Future work should seek to study the effects of these programs on both tenants and landlords.

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[39]Data from an earlier period of macroeconomic turmoil points in a similar direction: during the 2009 financial crisis, eviction rates remained approximately constant (Gromis et al., 2022) despite an an approximate doubling in the unemployment rate among renters (see Appendix Figure D.10), in contrast to foreclosures, which spiked during this period.

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Tables and Figures

TABLE I
SUMMARY STATISTICS AND BALANCE

	Harris County			King County			Los Angeles			Chicago DOH			Chicago TRP		
	Z=0 (1)	Z=1 (2)	Diff (3)	Z=0 (4)	Z=1 (5)	Diff (6)	Z=0 (7)	Z=1 (8)	Diff (9)	Z=0 (10)	Z=1 (11)	Diff (12)	Z=0 (13)	Treat (14)	Z=1 (15)
Demographics															
Age	–	–	–	38.729	38.528	0.098	41.577	41.315	−0.262	38.367	38.741	0.374	38.991	38.944	−0.046
Female	0.648	0.642	0.013	0.618	0.618	0.005	0.546	0.541	−0.005	0.610	0.592	−0.019	0.562	0.560	−0.002
Household Size	–	–	–	–	–	–	2.660	2.664	0.005	2.990	3.002	0.012	4.050	4.004	−0.047
White	0.061	0.051	−0.003	0.231	0.235	0.007	0.213	0.217	0.003	0.218	0.223	0.004	0.039	0.034	−0.006
Black	0.607	0.629	−0.007	0.325	0.345	−0.027*	0.116	0.115	−0.001	0.333	0.336	0.003	0.120	0.112	−0.008
Hispanic	0.259	0.253	0.015**	0.177	0.153	0.008	0.535	0.540	0.005	0.406	0.390	−0.016	0.800	0.821	0.021*
Asian	0.024	0.025	−0.007***	0.074	0.073	−0.001	0.109	0.105	−0.004	0.043	0.052	0.009*	0.041	0.032	−0.009
ACS Zip Code Data															
Median Rent	1.005	1.005	−0.001	1.485	1.484	−0.000	1.419	1.424	0.005	1.050	1.057	0.007	1.004	1.000	−0.004
Poverty Rate	0.214	0.215	0.001*	0.115	0.116	−0.001	0.198	0.197	−0.001	0.205	0.204	−0.000	0.199	0.200	0.001
% with High School Diploma	0.766	0.758	−0.000	0.902	0.902	0.001	0.753	0.756	0.003	0.818	0.818	−0.001	0.767	0.768	0.000
% Hispanic	0.431	0.450	−0.000	0.123	0.123	−0.001	0.487	0.483	−0.005	0.322	0.319	−0.003	0.487	0.485	−0.002
%Non-Hispanic White	0.130	0.121	−0.000	0.519	0.518	0.000	0.264	0.268	0.004	0.256	0.257	0.001	0.207	0.208	0.001
% Black	0.374	0.373	−0.000	0.101	0.102	−0.000	0.090	0.089	−0.001	0.346	0.345	−0.001	0.236	0.239	0.003
% Asian	0.050	0.041	0.000	0.176	0.176	0.000	0.128	0.130	0.002	0.056	0.058	0.003	0.053	0.052	−0.001
Experian Linked: Jan 2020															
Credit Score	554	553	−1.798	583	575	8.510*	637	636	−0.961	603	610	6.096**	644	651	4.399
Balance Across All Trades	21.430	23.168	−1.899**	19.314	18.346	2.624	19.775	20.011	0.236	32.008	34.483	2.320	19.114	22.391	2.913
Balance in Collections	3.212	3.264	0.007	1.436	1.829	−0.398**	0.917	0.932	0.015	1.121	1.133	0.001	0.491	0.432	−0.046
Balance in Utility Collections	0.576	0.566	0.025	0.298	0.386	−0.084**	0.125	0.120	−0.005	0.306	0.311	0.005	0.147	0.114	−0.029
Balance in Delinquent Accts.	10.225	9.911	0.410	7.776	8.355	−0.567	4.986	4.988	0.003	6.753	6.774	−0.040	2.271	2.136	−0.061
Auto Loan or Lease	0.293	0.299	−0.003	0.308	0.334	−0.019	0.279	0.274	−0.005	0.306	0.338	0.031*	0.214	0.227	0.010
Personal Bankruptcy	0.020	0.019	0.001	0.067	0.087	−0.016	0.050	0.043	−0.007**	0.143	0.151	0.008	0.032	0.030	−0.000
Rev. Line of Credit	0.347	0.343	−0.003	0.529	0.499	0.035	0.656	0.658	0.003	0.569	0.594	0.018	0.553	0.569	0.011
Survey															
Response Rates	0.185	0.221	0.035***	0.235	0.264	0.016	0.129	0.148	0.020***	0.283	0.409	0.126***	0.175	0.311	0.136***
N†	4,911	13,460	18,390	6,868	5,087	11,955	13,062	11,315	24,377	73,126	1,537	68,075	4,688	1,765	6,414

Notes: Data come from program applications, the 2015-2019 American Community Survey, and credit records from Experian. The sample includes all program applicants for all variables except credit attributes, for which the sample is restricted to individuals linked to the balanced panel of Experian records. For each site, we report the average characteristics for individuals not selected by the lottery ($Z = 0$) and selected by the lottery ($Z = 1$). Conditional differences in average characteristics between these two groups come from regressions that control for site-specific design features. See Section 5. All monetary values expressed in 2020 U.S. dollars divided by 1000. Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$. †We report the maximum observation counts. Observation counts for Experian characteristics are lower than those for the rest of the characteristics.

TABLE II
ASSISTANCE RECIPIENTS AND TARGETING

| | Harris County | | King County | | Los Angeles | | | Chicago DOH | TRP |
| | Renters | Assisted | Renters | Assisted | Renters | Assisted | Renters | Assisted | Assisted |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Demographics:									
Age	39.447	.	39.288	39.433	41.659	41.367	40.986	37.969	39.428
Female	0.514	0.669	0.485	0.643	0.510	0.545	0.523	0.601	0.562
Household Size	2.869	2.470	2.252	.	2.856	2.535	2.303	2.886	3.994
White	0.517	0.053	0.580	0.239	0.487	0.250	0.473	0.224	0.033
Black	0.273	0.667	0.112	0.359	0.099	0.114	0.341	0.359	0.100
Hispanic	0.441	0.220	0.120	0.147	0.494	0.494	0.249	0.349	0.837
Asian	0.062	0.020	0.187	0.073	0.127	0.114	0.071	0.068	0.029
ACS Zip Code Data:									
Median Rent	1.139	1.008	1.598	1.479	1.521	1.443	1.177	1.052	0.999
Poverty Rate	0.163	0.214	0.098	0.111	0.180	0.193	0.192	0.209	0.199
% with High School Diploma	0.786	0.760	0.894	0.895	0.772	0.769	0.830	0.821	0.765
% Hispanic	0.408	0.446	0.111	0.135	0.436	0.462	0.247	0.307	0.492
% Non-Hispanic White	0.310	0.121	0.558	0.508	0.318	0.289	0.350	0.253	0.206
% Black	0.184	0.377	0.072	0.099	0.091	0.083	0.308	0.354	0.234
% Asian	0.077	0.041	0.187	0.176	0.122	0.134	0.072	0.065	0.051
Credit Characteristics:									
Credit Score	684	566	725	584	710	649	691	613	658
Balance Across All Trades ($1000s)	19.1	27.9	15.4	21.4	16.7	22.1	19.5	30.7	23.6
Balance in Collections ($1000s)	0.721	3.320	0.219	1.651	0.292	0.918	0.327	1.226	0.419
Balance In Delinquent Accounts	1.661	9.426	0.709	7.428	1.167	4.671	1.126	6.626	1.821
Any Auto Loan or Lease	0.355	0.326	0.261	0.349	0.322	0.279	0.250	0.305	0.214
Any Personal Banckruptcy	0.012	0.019	0.026	0.100	0.031	0.046	0.061	0.140	0.031
Any Open Revolving Line of Credit	0.807	0.384	0.906	0.505	0.870	0.703	0.848	0.599	0.583
N		8,245		2,532		10,794		722	1,607

Notes: This table reports mean characteristics for renters and those who received assistance at each of our four sites. For Chicago those assisted through the DOH program and the TRP program are reported separately. The first panel reports demographic characteristics. The Assisted include those who received assistance despite not being selected through the lottery. Renter characteristics are from the 2019 American Community Survey, restricted to renters in Harris County, King County, Los Angeles, and Chicago. The second panel reports ZIP code characteristics. For renters, these are the weighted average of aggregate ZIP (ZCTA) code characteristics for ZIP codes in the county/city from the 2015-2019 ACS, weighted by the number of renters in the ZIP code. For those assisted, it is the same, but weighted by the number of applicants. The third panel reports credit characteristics. For the renter columns, these are from a 10% sample from Equifax restricted to renter in the relevant county/city. For those assisted, these are for those who were linked to Experian. Both are from January 2020.

TABLE III
First Stage

	Received Assistance				
	Harris County (1)	King County (2)	Los Angeles (3)	Chicago DOH (4)	Chicago TRP (5)
Selected by Lottery	0.590***	0.372***	0.207***	0.431***	0.910***
	(0.005)	(0.008)	(0.006)	(0.013)	(0.007)
Control Mean	0.000	0.046	0.347	0.001	0.000
Frac. Selected for Assistance	0.742	0.426	0.464	0.010	0.249
F Statistic	17,096	2,442	1,093	47,977	47,332
N	18,439	12,062	24,377	74,663	6,453

Notes: This table reports OLS estimates of α_1 in equation (2). The sample includes all program applicants from Harris County (column (1)), King County (column (2)), Los Angeles (column (3)), Chicago DOH (column (4)) and Chicago TRP (column (5)). Regressions include site-specific design controls described in Section 5. The control mean reports the share who received assistance among individuals not selected by the lottery. "Frac. Selected for Assistance" reports the share of applicants offered treatment. Robust standard errors are reported in parentheses. Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

TABLE IV
Survey Outcomes

	Harris County (1)	King County (2)	Chicago: DOH (3)	Chicago: TRP (4)	Combined (5)
In the Last Month:					
Expenditures					
All Rent Paid	0.076*	0.134**	0.058*	0.059**	0.082***
	(0.040)	(0.053)	(0.031)	(0.028)	(0.020)
	[0.497]	[0.368]	[0.649]	[0.678]	[0.548]
All Bills Paid	−0.022	0.026	−0.025	0.023	0.001
	(0.032)	(0.042)	(0.033)	(0.033)	(0.018)
	[0.284]	[0.203]	[0.358]	[0.496]	[0.335]
Health					
COVID Positive (self-tested)	−0.110	−0.064	−0.051***	0.002	−0.056*
	(0.105)	(0.074)	(0.017)	(0.018)	(0.033)
	[0.182]	[0.074]	[0.101]	[0.095]	[0.113]
Feeling Anxious	−0.069*	0.014	−0.075**	0.002	−0.032*
	(0.036)	(0.050)	(0.033)	(0.028)	(0.019)
	[0.525]	[0.633]	[0.549]	[0.319]	[0.506]
Economic Insecurity					
Worried about Eviction	−0.082**	−0.056	−0.029	−0.022	−0.047***
	(0.034)	(0.053)	(0.030)	(0.020)	(0.018)
	[0.320]	[0.443]	[0.287]	[0.121]	[0.293]
Experienced Homelessness	−0.031	−0.008	−0.022	−0.005	−0.016
	(0.030)	(0.037)	(0.014)	(0.017)	(0.013)
	[0.241]	[0.146]	[0.063]	[0.079]	[0.132]
Stayed in a Homeless Shelter	−0.016**	−0.003	0.008	−0.000	−0.003
	(0.008)	(0.013)	(0.007)	(0.003)	(0.004)
	[0.015]	[0.014]	[0.005]	[0.001]	[0.009]
Was Food Insecure	−0.048	0.025	−0.039	−0.016	−0.019
	(0.033)	(0.049)	(0.029)	(0.026)	(0.018)
	[0.335]	[0.325]	[0.270]	[0.256]	[0.297]
N	1,671	2,621	14,681	1,352	20,325

Notes: This table reports TSLS estimates of β_1 in equation (3), for several outcomes: expenditures, health, and economic insecurity. Outcomes are derived from the surveys as described in Section 3 and Appendix A. Survey timing and treatment dates appear in Appendix Table D.2. Columns (1)–(5) report the TSLS estimates for each site, reweighting to adjust for survey nonresponse as described in Section 3. Columns (6) and (7) report the combined averages across all sites and all sites excluding LA, respectively. Robust standard errors are reported in parentheses, and the control group mean is reported in brackets (this corresponds to the mean for the group not offered assistance, i.e., $Z = 0$). Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

TABLE V
Impacts on Credit Outcomes

	Harris County (1)	King County (2)	Los Angeles (3)	Chicago DOH (4)	Chicago TRP (5)	Combined (6)
Short Run: 2 months after lottery						
Credit Score	2.863**	−3.413	0.854	−3.494	0.155	−0.607
	(1.235)	(4.511)	(2.480)	(2.755)	(1.566)	(1.234)
	[565]	[597]	[649]	[612]	[654]	[615]
Balance Across All Trades ($1000s)	0.259	0.113	0.929	1.655	−1.351*	0.321
	(0.500)	(2.392)	(1.086)	(1.937)	(0.742)	(0.677)
	[24.825]	[21.318]	[19.628]	[33.758]	[20.784]	[24.063]
Balance in Collections ($1000s)	0.003	−0.233	−0.157**	0.026	−0.008	−0.074*
	(0.058)	(0.161)	(0.070)	(0.067)	(0.029)	(0.040)
	[3.258]	[1.371]	[0.965]	[1.120]	[0.489]	[1.441]
Balance in Utility Collections ($1000s)	0.013	−0.024	−0.000	−0.030	−0.020**	−0.012
	(0.019)	(0.048)	(0.015)	(0.031)	(0.010)	(0.013)
	[0.617]	[0.255]	[0.121]	[0.322]	[0.150]	[0.293]
Balance in Delinquent Accounts ($1000s)	−0.230	0.639	0.132	−0.384	−0.146	0.002
	(0.218)	(0.850)	(0.374)	(0.559)	(0.208)	(0.225)
	[9.459]	[6.315]	[4.556]	[5.812]	[2.152]	[5.659]
Any Auto Loan or Lease	−0.004	−0.013	0.007	−0.004	0.007	−0.001
	(0.007)	(0.024)	(0.015)	(0.016)	(0.009)	(0.007)
	[0.300]	[0.311]	[0.277]	[0.293]	[0.212]	[0.279]
Any Personal Bankruptcy	0.001	−0.003	−0.007*	−0.005	0.000	−0.003
	(0.001)	(0.006)	(0.004)	(0.007)	(0.002)	(0.002)
	[0.019]	[0.065]	[0.047]	[0.144]	[0.032]	[0.061]
Any Open Revolving Line of Credit	0.009	−0.023	0.007	0.026	−0.008	0.002
	(0.007)	(0.028)	(0.012)	(0.016)	(0.008)	(0.007)
	[0.372]	[0.536]	[0.667]	[0.576]	[0.571]	[0.544]
Long Run: 10 months after lottery						
Credit Score	0.881	−2.633	−0.932	−6.940*	1.253	−1.674
	(1.597)	(6.344)	(3.713)	(2.077)	(3.279)	(1.693)
	[575]	[604]	[659]	[624]	[663]	[625]
Balance Across All Trades ($1000s)	−0.243	−3.166	2.237	−1.329	−0.732	−0.647
	(0.830)	(4.300)	(2.054)	(2.623)	(1.256)	(1.129)
	[26.756]	[23.879]	[20.659]	[35.893]	[21.809]	[25.799]
Balance in Collections ($1000s)	0.007	0.011	0.013	0.065	0.006	0.020
	(0.084)	(0.250)	(0.110)	(0.101)	(0.043)	(0.061)
	[3.085]	[1.385]	[0.969]	[1.124]	[0.501]	[1.413]
Balance in Utility Collections ($1000s)	−0.005	−0.016	−0.009	−0.044	−0.011	−0.017
	(0.022)	(0.059)	(0.020)	(0.038)	(0.014)	(0.015)
	[0.590]	[0.229]	[0.109]	[0.286]	[0.129]	[0.269]
Balance in Delinquent Accounts ($1000s)	0.116	−0.687	0.574	0.381	−0.103	0.056
	(0.262)	(1.019)	(0.482)	(0.669)	(0.222)	(0.271)
	[8.473]	[6.176]	[4.275]	[5.267]	[1.973]	[5.233]
Any Auto Loan or Lease	0.001	−0.027	−0.013	0.003	−0.001	−0.007
	(0.010)	(0.039)	(0.022)	(0.022)	(0.014)	(0.011)
	[0.314]	[0.320]	[0.285]	[0.328]	[0.224]	[0.294]
Any Personal Bankruptcy	−0.001	0.010	−0.014*	−0.024**	0.005*	−0.005
	(0.002)	(0.013)	(0.008)	(0.010)	(0.003)	(0.004)
	[0.019]	[0.059]	[0.046]	[0.141]	[0.030]	[0.059]
Any Open Revolving Line of Credit	−0.018	−0.019	0.021	0.009	−0.012	−0.005
	(0.011)	(0.042)	(0.019)	(0.022)	(0.011)	(0.011)
	[0.435]	[0.582]	[0.676]	[0.603]	[0.587]	[0.577]
N	14,159	1,889	18,559	45,853	2,577	83,037

Notes: This table reports TSLS estimates of β_1 in equation (3), for short-run (2 months) and longer-run (10 months) credit outcomes. Columns (1)–(4) report the TSLS estimates for each site. Column (5) reports the combined results across all of the locations. The sample is restricted to lottery applicants linked to Experian credit data. All monetary values are expressed in thousands of 2020 U.S. dollars. Robust standard errors are reported in parentheses, and the control group mean is reported in brackets (this corresponds to the mean for the group not offered assistance, i.e. $Z = 0$). Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

TABLE VI
Impacts on Residential Mobility

	Harris County (1)	King County (2)	Los Angeles (3)	Chicago DOH (4)	Chicago TRP (5)	Combined (6)
Short Run: 2 months after lottery						
Change of Address(Infutor)	0.002	−0.002	0.002	0.000	−0.002	0.000
	(0.006)	(0.016)	(0.009)	(0.009)	(0.003)	(0.004)
	[0.011]	[0.057]	[0.012]	[0.009]	[0.004]	[0.019]
Change of Address(Experian)	−0.007	0.040	−0.008	0.001	−0.003	0.005
	(0.010)	(0.036)	(0.017)	(0.019)	(0.008)	(0.009)
	[0.102]	[0.105]	[0.066]	[0.080]	[0.034]	[0.077]
Long Run: 10 months after lottery						
Change of Address(Infutor)	−0.012	0.012	−0.016	−0.022	−0.018***	−0.011
	(0.010)	(0.029)	(0.022)	(0.018)	(0.007)	(0.008)
	[0.044]	[0.209]	[0.069]	[0.049]	[0.025]	[0.079]
Change of Address(Experian)	−0.003	0.046	−0.007	−0.000	0.016	0.010
	(0.014)	(0.053)	(0.027)	(0.028)	(0.014)	(0.014)
	[0.250]	[0.303]	[0.187]	[0.202]	[0.092]	[0.207]
N (Infutor)	6,562	5,570	11,864	26,373	1,616	51,985
N (Experian)	14,159	1,889	18,559	45,853	2,577	83,037

Notes: This table reports TSLS estimates of β_1 in equation (3), for residential moves in the short run (2 months) and long run (10 months). Change of address is measured in two ways: by a direct measure of change of address via Infutor, and by a change in ZIP code in the Experian linked data. The sample consists of the application sample linked to the respective outcome data source, and varies by outcome. Columns (1)–(4) report TSLS estimates for each site. Column (5) reports the combined results across all of the locations. Robust standard errors are reported in parentheses, and the control group mean is reported in brackets (this corresponds to the mean for the group not offered assistance, i.e. $Z = 0$). Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

TABLE VII

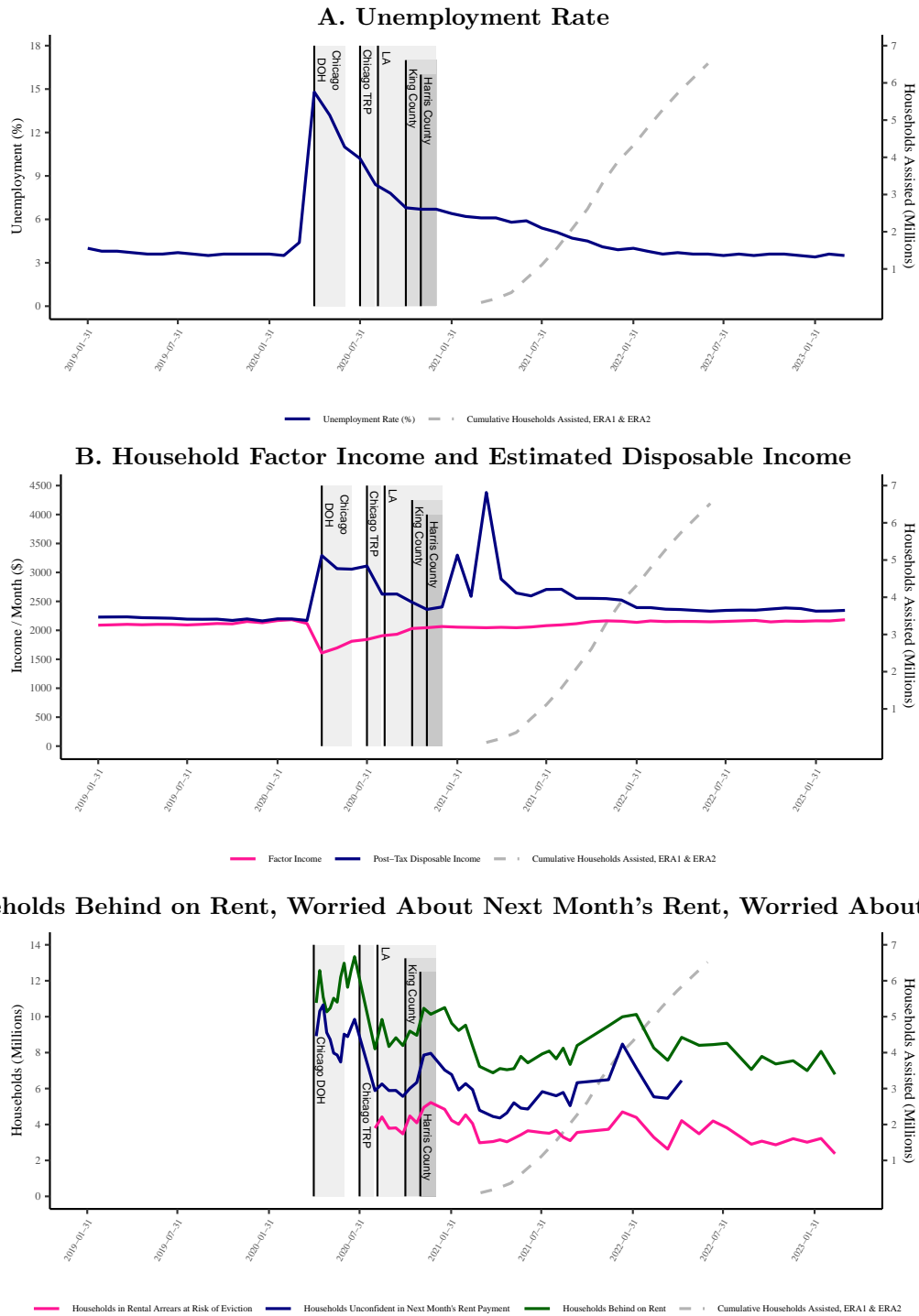|	King County (1)	Chicago DOH (2)	Chicago TRP (3)
Any Homeless Services	0.020**	−0.0021	−0.0035**
	(0.0083)	(0.0055)	(0.0017)
	[0.027]	[0.0092]	[0.0055]
	{0.048}	{0.0109}	{0.0045}
Emergency Shelter	0.0028	−0.0003	−0.0003
	(0.0039)	(0.0015)	(0.0004)
	[0.0064]	[0.0008]	[0.0085]
	{0.018}	{0.0024}	{0.0015}
Street Outreach	0.0067*	0.0016	−0.0007*
	(0.0036)	(0.0021)	(0.0004)
	[0.0037]	[0.0006]	[0.0006]
	{0.0091}	{0.0021}	{0.0014}
Diversion/Prevention	0.0081*	−0.0019	−0.0022
	(0.0045)	(0.005)	(0.0015)
	[0.0070]	[0.0078]	[0.0038]
	{0.019}	{0.007}	{0.0017}
Long-Term Subsidies	0.0012	−0.00097***	−0.00065*
	(0.0059)	(0.0002)	(0.0004)
	[0.015]	[0.00042]	[0.0006]
	{0.021}	{0.0006}	{0.0006}
Coordinated Entry	0.0010		
	(0.0024)		
	[0.0024]		
	{0.0078}		
N	12,148	74,663	6,453

Notes: This table reports TSLS estimates of β_1 in equation (3), for measures of homelessness system use in the 9 months after the lottery in three lottery samples: King County, Chicago DOH, and Chicago TRP. The first row reports impacts on any appearance in the homelessness system ("Any Homeless Services"), and the subsequent rows report impacts on specific types of system use. We assign project types to categories to align with local differences in the nature of services and how the data were provided. "Emergency Shelter" includes Emergency Shelter, Transitional Housing and Safe Haven in Chicago and Emergency Shelter and Day Shelter in King County. "Diversion/Prevention" refers to diversion programs in King County and homelessness prevention projects in Chicago. "Long-term Subsidies" includes Rapid Rehousing and Permanent Supportive Housing in both sites and also includes Transitional Housing in King County. Information on participation in Coordinated Entry is only available for King County. Columns (1)–(3) report TSLS estimates for each site. Robust standard errors are reported in parentheses, and the control group mean of the outcome is reported in brackets (this corresponds to the mean for the group not offered assistance, i.e. $Z = 0$). The pre-COVID means from March 2019 to February 2020 for the listed measures are reported in braces. Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

TABLE VIII
Impacts on Eviction Filings

|	Harris County		Chicago: DOH		Chicago: TRP	
	Control Mean (1)	Treatment Effect (2)	Control Mean (3)	Treatment Effect (4)	Control Mean (5)	Treatment Effect (6)
Evictions Post Lottery:						
Two Months	0.0032	−0.0008 (0.0018)	0.0004	−0.0004*** (0.0001)	0.0000	−0.0002 (0.0002)
Six Months	0.0097	−0.0017 (0.0029)	0.0012	0.0004 (0.0018)	0.0002	−0.0004 (0.0003)
Ten Months	0.0121	−0.0022 (0.0033)	0.0019	−0.0004 (0.0018)	0.0002	−0.0004 (0.0003)
Evictions Post Moratorium:						
Two Months	0.0129	−0.0022 (0.0034)	0.0051	−0.0030* (0.0022)	0.0004	0.0000 (0.0007)
Six Months	0.0144	−0.0023 (0.0036)	0.0078	−0.0024 (0.0033)	0.0004	0.0007 (0.0010)
Ten Months	0.0156	−0.0029 (0.0037)	0.0118	−0.0050 (0.0038)	0.0011	0.0007 (0.0012)
N		18,390		55,519		6,414

Notes: This table reports TSLS estimates of β_1 in equation (3), for measures of eviction filings in three lottery samples: Harris County, Chicago DOH, and Chicago TRP. The top panel reports impacts on cumulative eviction filings by month relative to the lottery. The bottom panel summarizes impacts on cumulative eviction filings by month relative to the expiration of the CDC eviction moratorium. Columns (1), (3), and (5) report the mean among those assigned to the control group (i.e., those for whom $Z = 0$). Columns (2),(4), and (6) report TSLS estimates for each site. Robust standard errors are reported in parentheses, and the control group mean of the outcome is reported in brackets (this corresponds to the mean for the group not offered assistance, i.e. $Z = 0$). Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

FIGURE I
Timing of ERA Programs Relative to Macroeconomic Trends

A. Unemployment Rate

B. Household Factor Income and Estimated Disposable Income

C. Households Behind on Rent, Worried About Next Month's Rent, Worried About Eviction
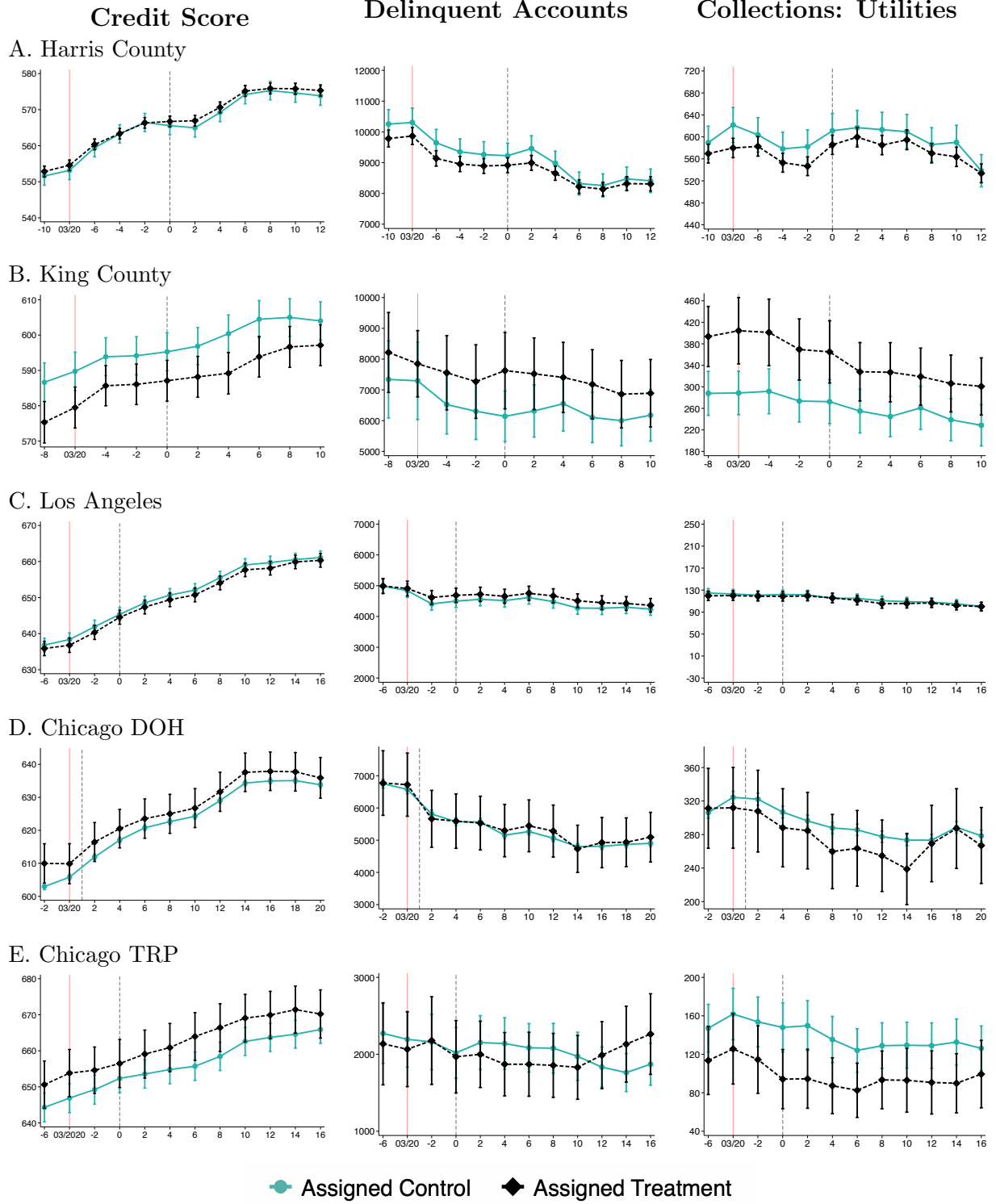

Notes: This figure shows the timing of the ERA programs we study relative to macroeconomic indictors. Panel A plots the civilian unemployment rate as measured by Current Population Survey (CPS). Panel B shows Factor Income and Post-Tax disposable income using estimates from Blanchet et al. (2022). Panel C is based on the authors calculations from the Census Pulse Surveys. ERA1 and ERA2 cumulative households assisted are constructed from the U.S. Treasury Department's ERA1 and ERA2 Grantees Compliance Reports.
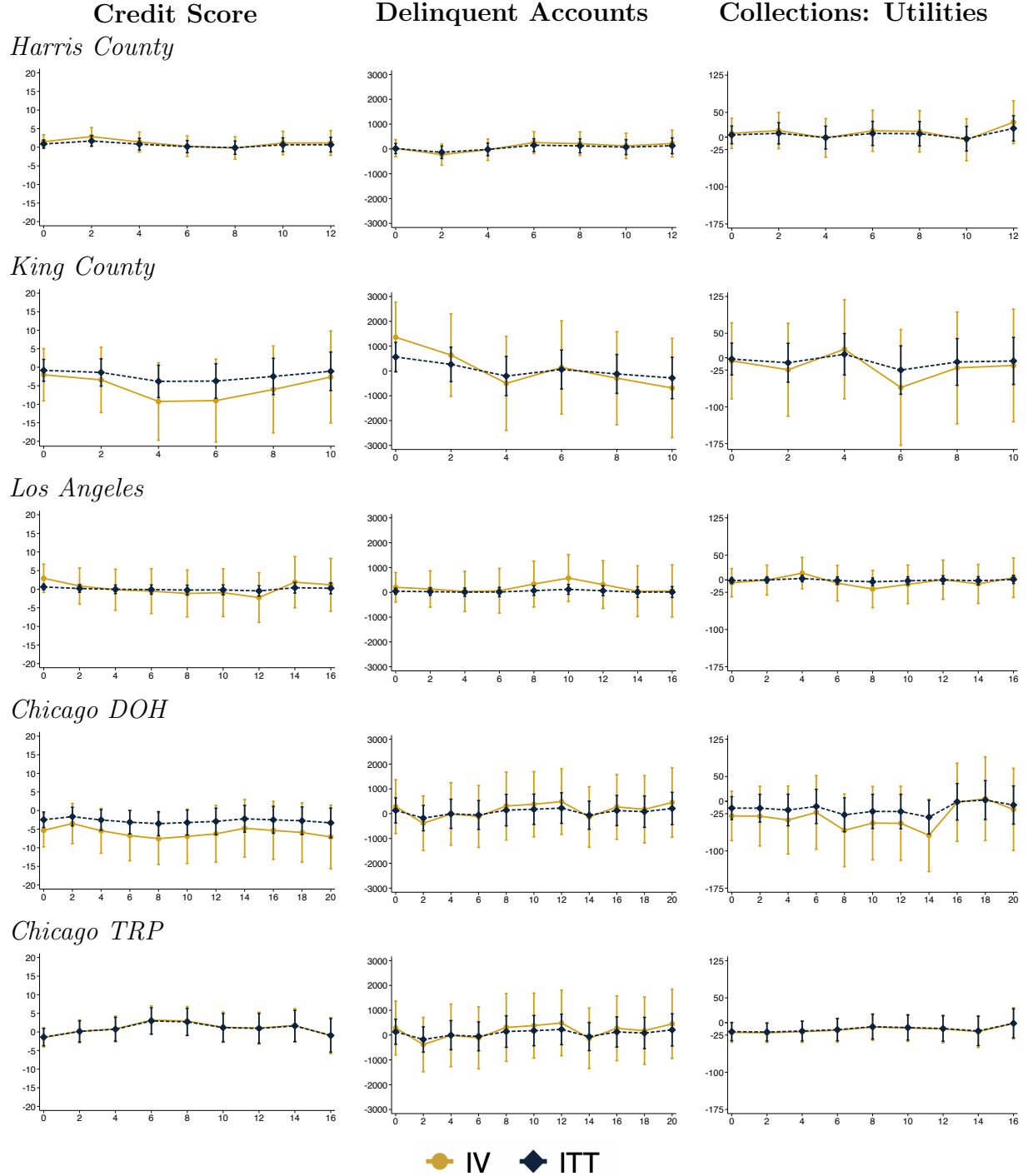
FIGURE II
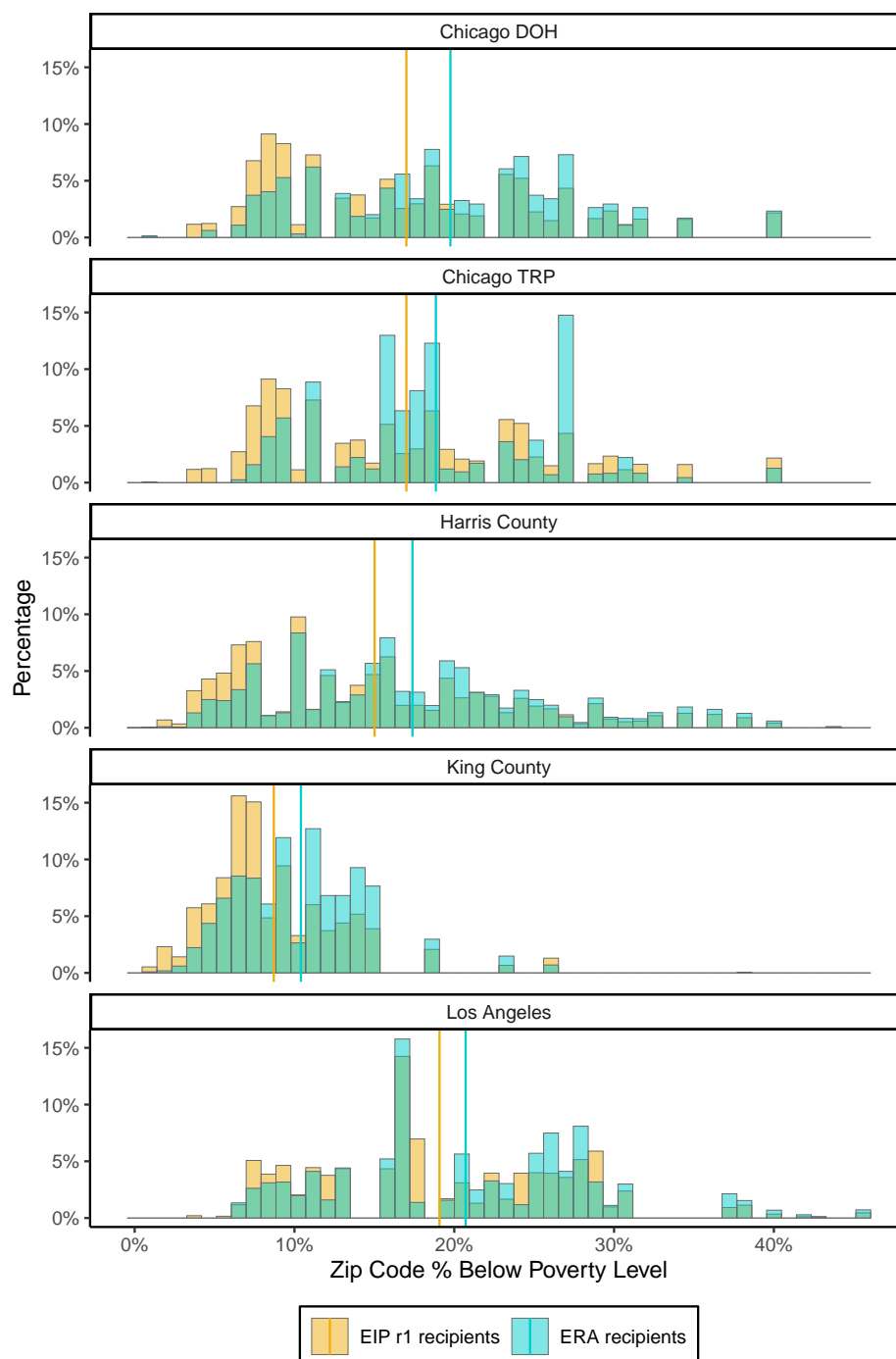
Notes: This figure shows the distribution of ZIP-level population poverty status rates for Emergency Rental Assistance recipients (cyan) and Economic Impact Payments Round 1 recipients (yellow). The poverty rate measure is from the 2020 American Community Survey (ACS) 5-Year Estimates and is the percentage of the population for whom poverty status is determined (U.S. Census Bureau, 2020b). EIP r1 data is from the 2020 Internal Revenue Service Statistics of Income and measures the number of income tax returns filed in 2020 that received round one EIP provided under the CARES Act (Internal Revenue Service, 2020). The vertical lines indicate the mean poverty rate for each group within each site.

FIGURE III
Credit Measure by Month Relative to Application

Credit Score **Delinquent Accounts** **Collections: Utilities**

A. Harris County

B. King County

C. Los Angeles

D. Chicago DOH

E. Chicago TRP

● Assigned Control   ◆ Assigned Treatment

Notes: This figure shows the average credit outcome for the group selected for treatment (black diamonds, $Z = 1$) and the group not selected for treatment (teal circles, $Z = 0$), by month relative to the time of application. Month 0 represents the site's application month. The dashed vertical line indicates the month of application, and the red vertical line indicates March 2020. The sample includes applicants linked to Experian credit data. Vertical bars plot the 95 percent confidence intervals of the estimates.

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FIGURE IV
Reduced-form (ITT) & TSLS Estimates by Month Relative to Application

Credit Score   **Delinquent Accounts**   **Collections: Utilities**

Harris County

King County

Los Angeles

Chicago DOH

Chicago TRP

IV   ITT

Notes: This figure shows the reduced-form (ITT) and TSLS estimates for different credit outcomes by month relative to the application date. The former corresponds to OLS estimates of γ_1 in equation (1), while the latter corresponds to TSLS estimates of β_1 in equation (3). The sample includes applicants linked to Experian credit data. Vertical bars plot the 95 percent confidence intervals of the estimates.

A Construction of Survey Outcomes

This appendix describes how each of the survey outcomes studied in this paper is constructed. Although similar surveys were administered across sites, they were not identical. Below, we provide exact definitions and across-site harmonization procedures for each survey outcome variable we consider (i.e., for each survey variable included in Table IV). Our discussion references question numbers in the survey instruments, which are provided at https://github.com/robcollinson/covid_era_surveys/.

All Rent Paid

- For King County, this outcome is based on Q30 and Q31 and is the amount of rent paid in January 2021 divided by the amount of rent owed in January 2021. The "All Rent Paid" variable is coded as 1 if this ratio is 1, and 0 otherwise.

- For Harris County, this outcome is based on Q29, for which the response is provided through a sliding percentage bar indicating the proportion of rent paid in January 2021. The "All Rent Paid" variable is coded as 1 if the bar was set to 100%, and 0 otherwise.

- For Chicago DOH and Chicago TRP, this outcome is based on a question about whether the individual paid the full amount of rent due (on time or late). For DOH, the reference month is May 2020 and is based on Q147. For TRP, the reference month is March 2021 and is based on Q229.

All Bills Paid

- For King and Harris Counties, this outcome is based on Q68, which asks separately if the respondent paid all of their gas, electric, phone, TV/cable, car payment, car insurance, health insurance, and student loan bills in the past month. An index is then created with "yes" coded as 1, "some" as 0.5, and "none" as 0. Bills for which the respondent answered "did not have bill" are omitted from the index.

- For Chicago DOH and TRP, this outcome is based on Q67 and Q68, which ask "In the past month, did you or your household pay all of your utility bills such as internet, phone, gas, electricity?" and "In the past month, did you or your household pay all of your other bills such as care payments, car insurance, health insurance, or student loans?" We code the outcome as 1 if the answer is "Yes" to both questions.

COVID Positive (Self-Tested)   For this outcome, we use the same two questions across sites: "Have you suspected that you were infected with COVID-19?" and "Have you tested positive for COVID-19?" The exact time period to which the question refers varies slightly across sites. For King and Harris Counties, this question begins with "Since March 1st," while for Los Angeles, it begins with "Since May," and for the Chicago TRP survey, it is "Since March 13th". The Chicago DOH survey did not ask these questions; instead, we code this outcome as 1 if the respondent selects "I got sick" in response to the question "How has the COVID-19 epidemic impacted you?"

Feeling Anxious or Depressed   Across all sites, the question "How often have you felt nervous, anxious, or on edge?" from the PHQ4 is used for this outcome, which is coded as 1 if the respondent reports "more than half the days" or "nearly every day". For Harris County, King County, and Chicago, the question refers to the last week, while for Los Angeles, the question asks about the last two weeks.

Worried about Eviction   For King and Harris Counties, we use the question "How worried are you about being evicted or foreclosed on in the next three months?" We code the outcome as 1 if the respondent reports "very worried" and zero otherwise. For all other sites, we use the same question, but it asks about the next two rather than three months.

Experience Homelessness   Across all sites, this outcome is based on a question that asks whether the respondent has spent any nights couchsurfing, in a homeless shelter, on the street, in an abandoned building, in a car or van, or in a hotel or motel (for nontravel reasons). The outcome is coded as "yes" if the respondent answers "yes" to any of the the above options. For King County, Harris County, Chicago DOH, and Chicago TRP, this question refers to "the last month". For Los Angeles, the question is phrased as "Since May, ...".

Stayed in Shelter   This outcome is constructed the same as the "Experience Homelessness" outcome, but it is coded as 1 only if the respondent answers "yes" to the "in a homeless shelter" option. Similarly to the "Experience Homelessness" outcome, for Los Angeles, the phrasing refers to "since May", while for all other sites, the question asks about the last month.

Was Food Insecure   The question "For the past month, which of these statements best describes the food eaten in your household?" was asked across all locations and coded as 1 if the responded selected "sometimes not enough to eat" or "often not enough to eat".

B   Pre-Analysis Plan

The lotteries analyzed in this paper were originally studied by three independent research teams. The studies were combined and attempts were made to harmonize approaches across sites as much as possible. Once linked data became available for analysis, pre-registrations existed for three out of five lotteries. These can be found in the American Economic Association's RCT Registry: the study IDs are AEARCTR-0007731 (Chicago) and AEARCTR-0007167 (King County). Of these, the King County registration had a detailed pre-analysis analysis plan (PAP), which can be downloaded from the registry.

   The analysis in this paper follows the PAP for King County. Given the urgency in getting surveys to respondents once a lottery was implemented by the local partner, it was not always possible to field the exact same questions across all sites. To facilitate harmonizing survey outcomes across sites, we deviated in constructing outcomes in the following ways:

- *All Rent Paid*: While the PAP specified using the fraction of rent paid as a primary outcome, we use a binary variable indicating whether rent was paid in full. This was done to create a harmonized measure of rent payment across sites. As described in Appendix A, three out of five surveys asked about full rent payment (a yes/no question), while the others asked about the fraction of rent paid. To present a single measure across the different sites, the fraction of rent was binarized.

- *Housing Stability Outcomes*: This paper presents estimates for homelessness and address changes separately, while the PAP specified as the primary outcome a binary variable that indicated either of these two outcomes. Because homelessness data was not available in all sites, it was not possible to construct such an outcome everywhere. Hence, we opted to present the outcomes separately. Each outcome was listed as a secondary outcome in the PAP.

- *Bills Paid*: The PAP designated as our primary outcome the fraction of bills paid. Similar to the *All Rent Paid* variable, we instead used a binary outcome indicating whether all bills were paid, so that we could harmonize across sites. The construction of this variable is described in Appendix A.

- *Feeling Anxious or Depressed*: As described in Appendix A, we construct a binary variable based on multiple choice responses. By contrast, the PAP describes using the number of days during which the respondent indicated feeling anxious or depressed as the outcome. Because surveys in different sites asked about different time spans, and to make the outcome easier to interpret, we harmonized these outcomes across sites by binarizing them as described in A.

We also harmonized control variables across sites. The King County PAP indicated that, beyond design-based controls, we would select additional covariates from the following: lagged outcomes, gender, race/ethnicity, age, city, disability status, and preferred language. We have limited these additional controls to those which overlap across sites: gender and race.

C Linking Eviction Data

Harris County. We collect eviction case data from 2019 to December 2023 from the Harris County Justice of the Peace. These data include case information such as case date and judgment, along with defendant name and address.

We link the lottery applications to eviction records using the following process:

1. Geocode lottery applications and eviction records

2. Construct soundex of first names and last names in lottery applications and eviction records

3. Exact match on 9-digit ZIP code, soundex of last name and soundex of first name

Approximately 2.65 percent of applicants can be linked to one or more eviction records from 2019 to 2023. Our analysis focuses on the linking to any eviction filing at 2 months, 6 months, and 10 months after the lottery, and 2, 6, and 10 months after the expiration of the CDC moratorium.

Cook County. Our data is a combination of data from Record Information Services and data received from the Cook County Clerk's office, collectively covering the period between 2019 and April 2024, and including case filings that were sealed from the public record during the eviction moratorium. The data include filing date, each defendant's name, and the address of the filing.

We link the records to applications to the DOH and TRP programs as follows:

1. Clean name fields by removing prefix/suffixes and omitting initials.

2. Geocode addresses via ArcGIS Street maps Premium (geocode rates ¿ 97%).

3. Block data by latitude/longitude match up to three decimal places (equal to 1 km) and conduct fuzzy matching algorithm using Jaro-winkler string distance.

4. Retain only matches with sufficiently similar name field and where geocoordinates are within 33 meters.

5. Take best match for each eviction filing by name distance and geodistance.

D Additional Tables and Figures

Summary and Balance: LA Financial

| | Los Angeles | | |
| | Z=0 | Z=1 | Diff |
	(1)	(2)	(3)
Financial Characteristics			
Income	29.533	29.835	0.301
Rent	1.614	1.624	0.009
Rent Owed	2.509	2.580	0.071*
N	13,062	11,315	24,377

Notes: Data on financial characteristics come from applications to the LA program. The sample includes all program applicants. We report the average characteristics for individuals selected by the lottery in column (1) ($Z = 1$), and the average characteristics for individuals not selected by the lottery in column (2) ($Z = 0$). Conditional differences (column (3)) in average characteristics between these two groups come from regressions that control for design features specific to the LA program. Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$. We report the maximum observation counts.

Treatment and Survey Timing

Site	Treatment dates	Survey dates
King County	09/2020–12/2020	02/2021–03/2021
Harris County	11/2020–01/2021	05/2021–06/2021
Los Angeles	09/2020–12/2020	01/2021–02/2021
Chicago DOH	04/2020–05/2020	05/2020–06/2020
Chicago TRP	08/2020–10/2020*	02/2021–04/2021

Notes: This table documents the program and survey timing for each site. For Harris County, we study the second round of assistance that was offered in November 2020 rather than the earlier round distributed in July 2020. For Chicago, we study the first round of the Department of Housing (DOH) program, which provided grants between April and May 2020, and the second round of The Resurrection Project (TRP) grants program, which opened to applications in late June 2020.

	Harris County (1)	King County (2)	Chicago: DOH (3)	Chicago: TRP (4)	Combined (5)
In the Last Month:					
Expenditures					
All Rent Paid	0.056	0.125**	0.057*	0.051*	0.072***
	(0.036)	(0.052)	(0.030)	(0.027)	(0.019)
All Bills Paid	−0.007	0.023	−0.024	0.024	0.004
	(0.029)	(0.042)	(0.033)	(0.032)	(0.017)
Health					
COVID Positive (self-tested)	−0.091	−0.066	−0.051***	−0.003	−0.053**
	(0.084)	(0.063)	(0.016)	(0.017)	(0.027)
Feeling Anxious	−0.049	0.007	−0.072**	0.006	−0.027
	(0.032)	(0.049)	(0.032)	(0.027)	(0.018)
Economic Insecurity					
Worried about Eviction	−0.072**	−0.061	−0.029	−0.015	−0.044**
	(0.030)	(0.052)	(0.029)	(0.020)	(0.017)
Experienced Homelessness	−0.027	−0.006	−0.022*	−0.003	−0.015
	(0.026)	(0.036)	(0.013)	(0.016)	(0.012)
Stayed in a Homeless Shelter	−0.011*	−0.004	0.009	0.001	−0.001
	(0.007)	(0.012)	(0.007)	(0.003)	(0.004)
Was Food Insecure	−0.042	0.022	−0.038	−0.013	−0.018
	(0.030)	(0.048)	(0.028)	(0.025)	(0.017)
N	1,671	2,626	14,681	1,352	20,330

Notes: This table reports the effects of assistance on expenditures, health, and economic insecurity with no reweighting of the survey responses. Outcomes are derived from the surveys described in Section 3. Survey timing and treatment dates appear in Appendix Table D.2. See Appendix A for details on the survey questions. Columns (1)–(5) report separately by site the IV estimates of the effects of assistance on the measure listed in the row, as described in Section 3. Columns (6) and (7) report the combined averages of all sites and all sites excluding LA, respectively. Robust standard errors are reported in parentheses, and the control group mean is reported in brackets. Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

LA Survey Outcomes – Weights and No Weights

|	Los Angeles	
	Weights (1)	No Weights (2)
In the Last Month:		
Expenditures		
All Rent Paid	−0.264*	−0.215
	(0.136)	(0.134)
	[0.385]	[0.385]
All Bills Paid	0.246*	0.239*
	(0.140)	(0.135)
	[0.361]	[0.361]
Health		
COVID Positive (self-tested)	0.065	0.117
	(0.135)	(0.129)
	[0.263]	[0.263]
Feeling Anxious	0.040	0.041
	(0.140)	(0.136)
	[0.543]	[0.543]
Economic Insecurity		
Worried about Eviction	0.141	0.115
	(0.137)	(0.130)
	[0.343]	[0.343]
Experienced Homelessness	−0.095	−0.083
	(0.079)	(0.075)
	[0.086]	[0.086]
Stayed in a Homeless Shelter	0.000	0.002
	(0.016)	(0.014)
	[0.003]	[0.003]
Was Food Insecure	−0.004	−0.053
	(0.130)	(0.122)
	[0.291]	[0.291]
N	3,360	3,360

Notes: Robust standard errors are reported in parentheses, and the control group mean is reported in brackets. Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

Appendix Table D.5

Balance Table – Survey Response

|	Harris County			King County			Los Angeles			Chicago DOH			Chicago TRP		
	$Z=0$ (1)	$Z=1$ (2)	Diff (3)	$Z=0$ (4)	$Z=1$ (5)	Diff (6)	$Z=0$ (7)	$Z=1$ (8)	Diff (9)	$Z=0$ (10)	$Z=1$ (11)	Diff (12)	$Z=0$ (13)	$Z=1$ (14)	Diff (15)
Demographics															
Age	–	–	–	37.175	37.705	0.530	42.070	41.082	0.988**	38.731	39.028	0.297	39.854	39.122	−0.732
Household Size	–	–	–	–	–	–	2.605	2.654	−0.049	2.980	2.802	−0.178**	4.043	4.004	−0.039
White	0.071	0.073	−0.008	0.297	0.286	−0.011	0.240	0.237	0.003	0.131	0.132	0.001	0.036	0.022	−0.013
Black	0.616	0.588	0.012	0.268	0.313	0.045**	0.127	0.101	0.026**	0.383	0.333	−0.050**	0.097	0.089	−0.008
Hispanic	0.239	0.272	0.004	0.157	0.151	−0.005	0.519	0.543	−0.024	0.412	0.450	0.038*	0.843	0.857	0.015
Asian	0.014	0.030	0.016**	0.078	0.072	−0.006	0.095	0.089	0.006	0.039	0.060	0.021**	0.025	0.032	0.007
N†	804	536	1,410	1,456	1,170	2,626	1,680	1,680	3,360	14,114	567	14,681	813	539	1,352

Notes: This table reports separately by site the average of demographic characteristics for applicants not selected by the lottery ($Z=0$) and applicants selected by the lottery ($Z=1$). Conditional differences in average characteristics (Diff) between these two groups come from regressions that control for site-specific design features. See Section 5. The sample includes only applicants who completed the survey. The Harris County survey did not ask about age or household size, and the King County survey did not ask about household size.   X Was there another reason why we had the note on observations? X Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

APPENDIX FIGURE D.1
TARGETING: ERA RECIPIENTS VS. ECONOMIC IMPACT PAYMENTS ROUND 1 RECIPIENTS
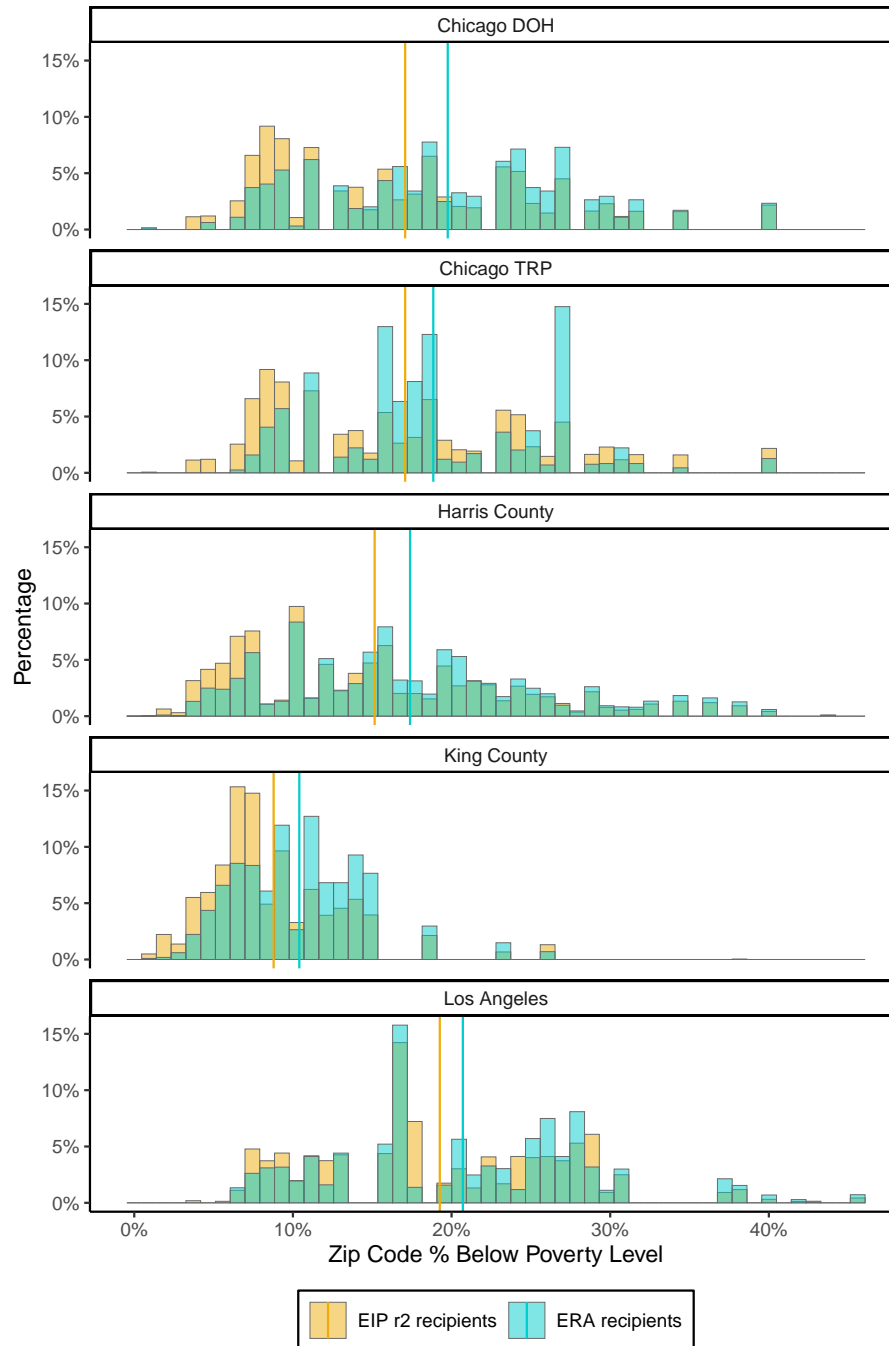(ZIP-LEVEL MINORITY SHARE)
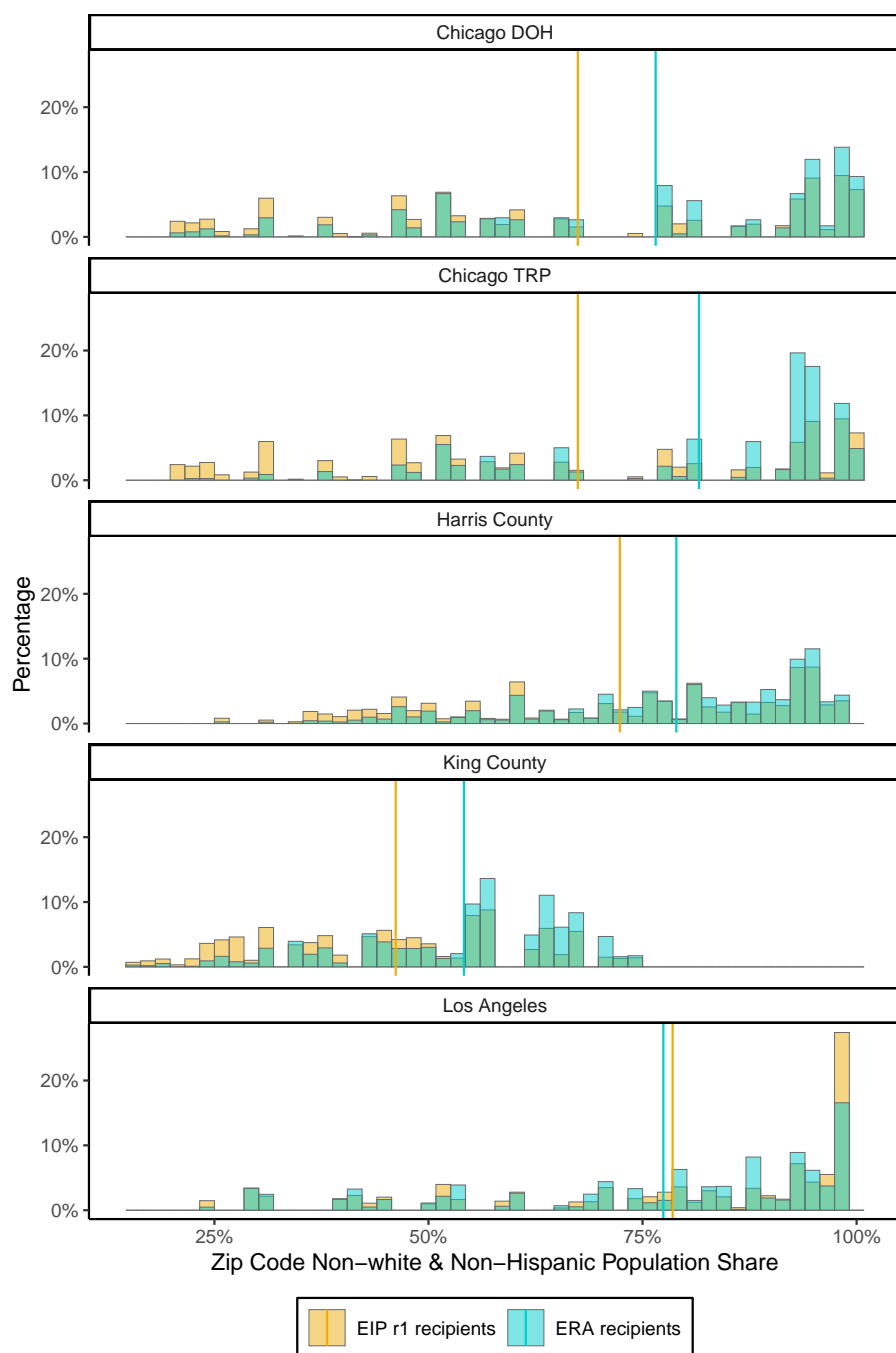
Notes: This figure shows the distribution of ZIP-level minority share for Emergency Rental Assistance recipients (cyan) and Economic Impact Payments Round 1 recipients (yellow). The minority share measure is from the 2020 Census Demographic and Housing Characteristics File and is calculated as the percentage of the population within a ZIP code that identifies as a minority (U.S. Census Bureau, 2020a). Minority status is determined based on self-reported race and ethnicity, with individuals identifying as non-white or Hispanic considered to be minorities. EIP r1 data is from the 2020 Internal Revenue Service Statistics of Income and measures the number of income tax returns filed in 2020 that received round one EIP provided under the CARES Act (Internal Revenue Service, 2020). The vertical lines indicate the mean minority share for recipients in each group within each site.

Targeting: ERA Recipients Vs. Economic Impact Payments Round 1 Recipients
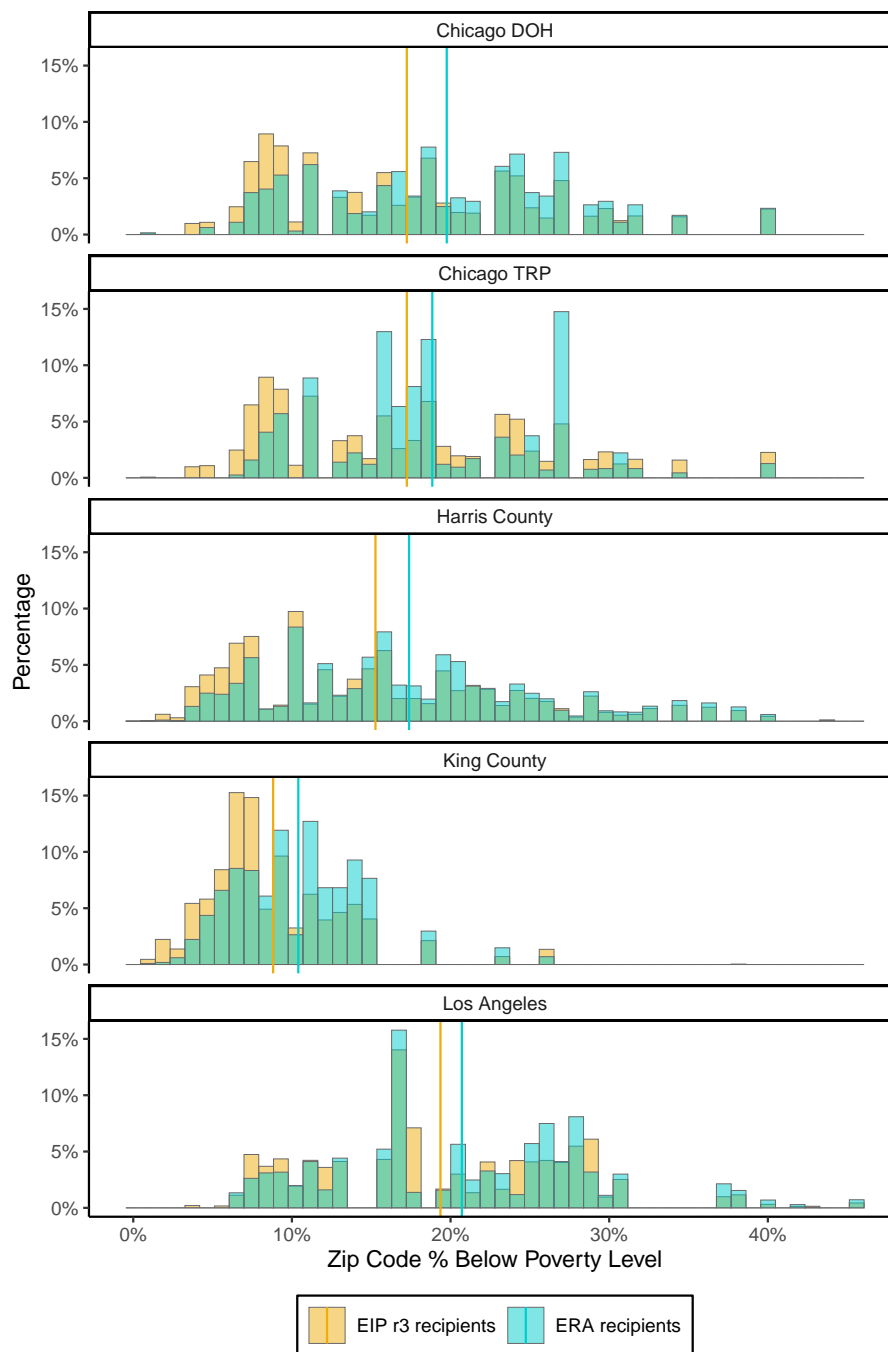(ZIP-Level Hispanic Share)
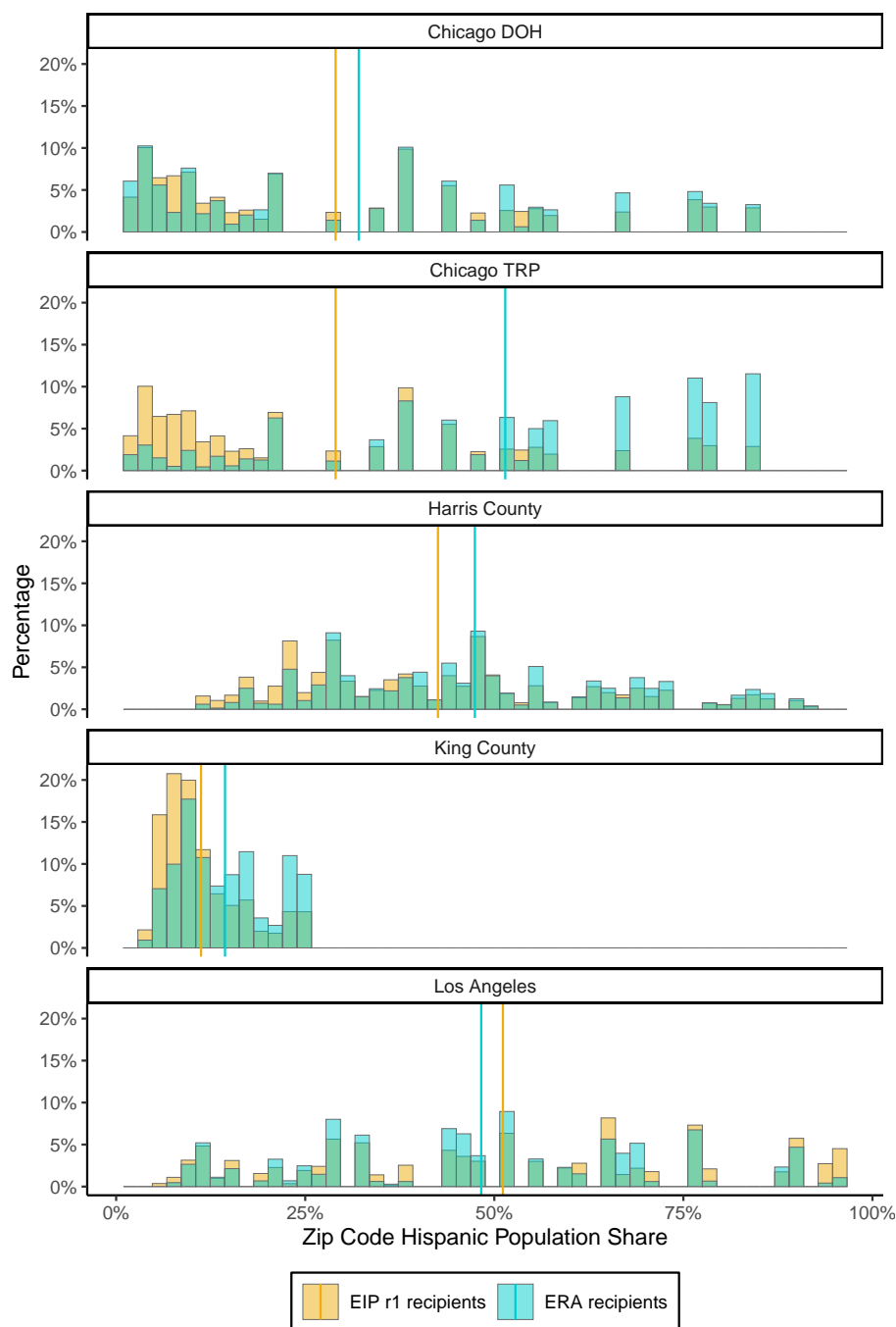
Notes: This figure shows the distribution of ZIP-level Hispanic share for Emergency Rental Assistance recipients (cyan) and Economic Impact Payments Round 1 recipients (yellow). The Hispanic share measure is from the 2020 Census Demographic and Housing Characteristics File and is calculated as the percentage of the population within a ZIP code that identifies as Hispanic (U.S. Census Bureau, 2020a). Hispanic status is determined based on self-reported ethnicity. EIP r1 data is from the 2020 Internal Revenue Service Statistics of Income and measures the number of income tax returns filed in 2020 that received round one EIP provided under the CARES Act (Internal Revenue Service, 2020). The vertical lines indicate the mean Hispanic share for recipients in each group within each site.

Appendix Figure D.3
Targeting: ERA Recipients Vs. Economic Impact Payments Round 2 Recipients (ZIP-Level Poverty Rate)
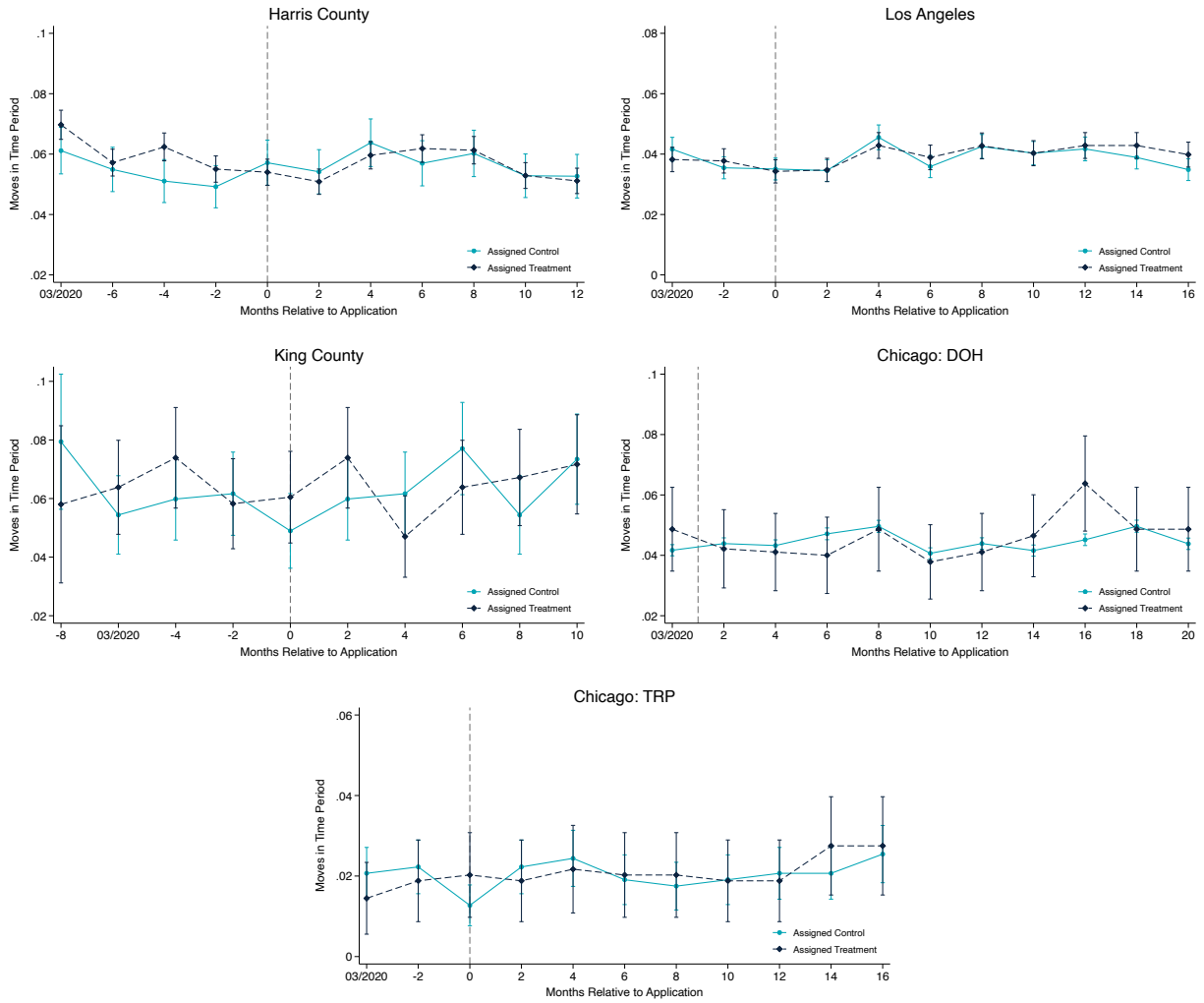

Notes: This figure shows the distribution of ZIP-level population poverty status rates for Emergency Rental Assistance recipients (cyan) and Economic Impact Payments Round 2 recipients (yellow). The poverty rate measure is from the 2020 American Community Survey 5-Year Estimates and is the percentage of the population for whom poverty status is determined (U.S. Census Bureau, 2020b). EIP r2 data is from the 2020 Internal Revenue Service Statistics of Income and measures the number of income tax returns filed in 2020 that received round two EIP provided under the COVID-related Tax Relief Act of 2020 (Internal Revenue Service, 2021). The vertical lines indicate the mean poverty rate for recipients in each group within each site.

TARGETING: ERA RECIPIENTS VS. ECONOMIC IMPACT PAYMENTS ROUND 3 RECIPIENTS
(ZIP-LEVEL POVERTY RATE)

Notes: This figure shows the distribution of ZIP-level population poverty status rates for Emergency Rental Assistance recipients (cyan) and Economic Impact Payments Round 3 recipients (yellow). The poverty rate measure is from the 2020 American Community Survey 5-Year Estimates and is the percentage of the population for whom poverty status is determined. EIP r3 data is from the 2021 Internal Revenue Service Statistics of Income and measures the number of income tax returns filed in 2021 that received round three EIP provided under the American Rescue Plan Act of 2021 (Internal Revenue Service, 2021). The vertical lines indicate the mean poverty rate for recipients in each group within each site.
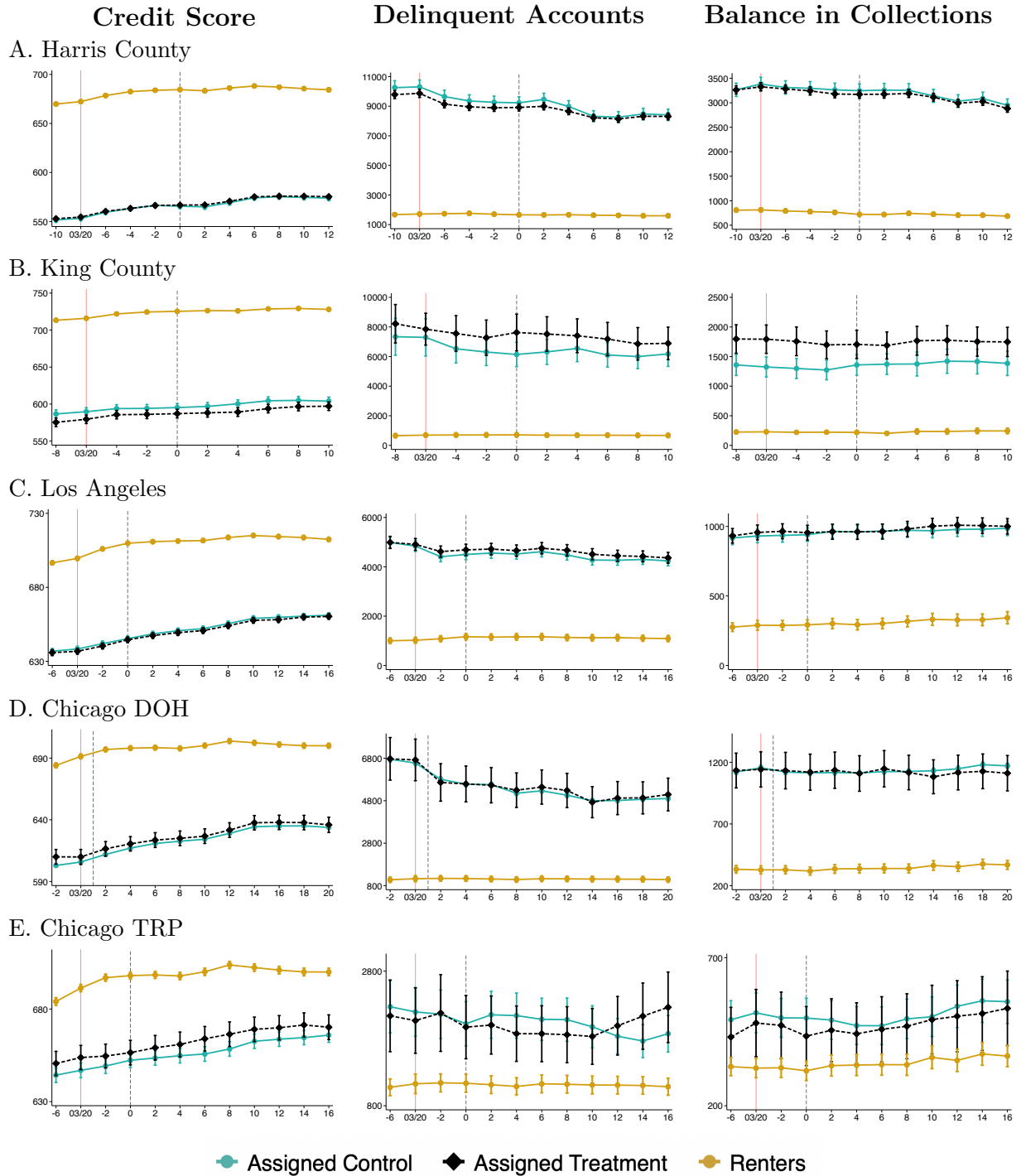
Notes: This figure plots the average number of moves for the treatment and control groups against the number of months since application. Moves are derived from address changes observed in the Experian data. The dashed vertical line indicates the month of application (month 0). Applications were submitted at different times across sites. March 2020 is marked on the horizontal axis.
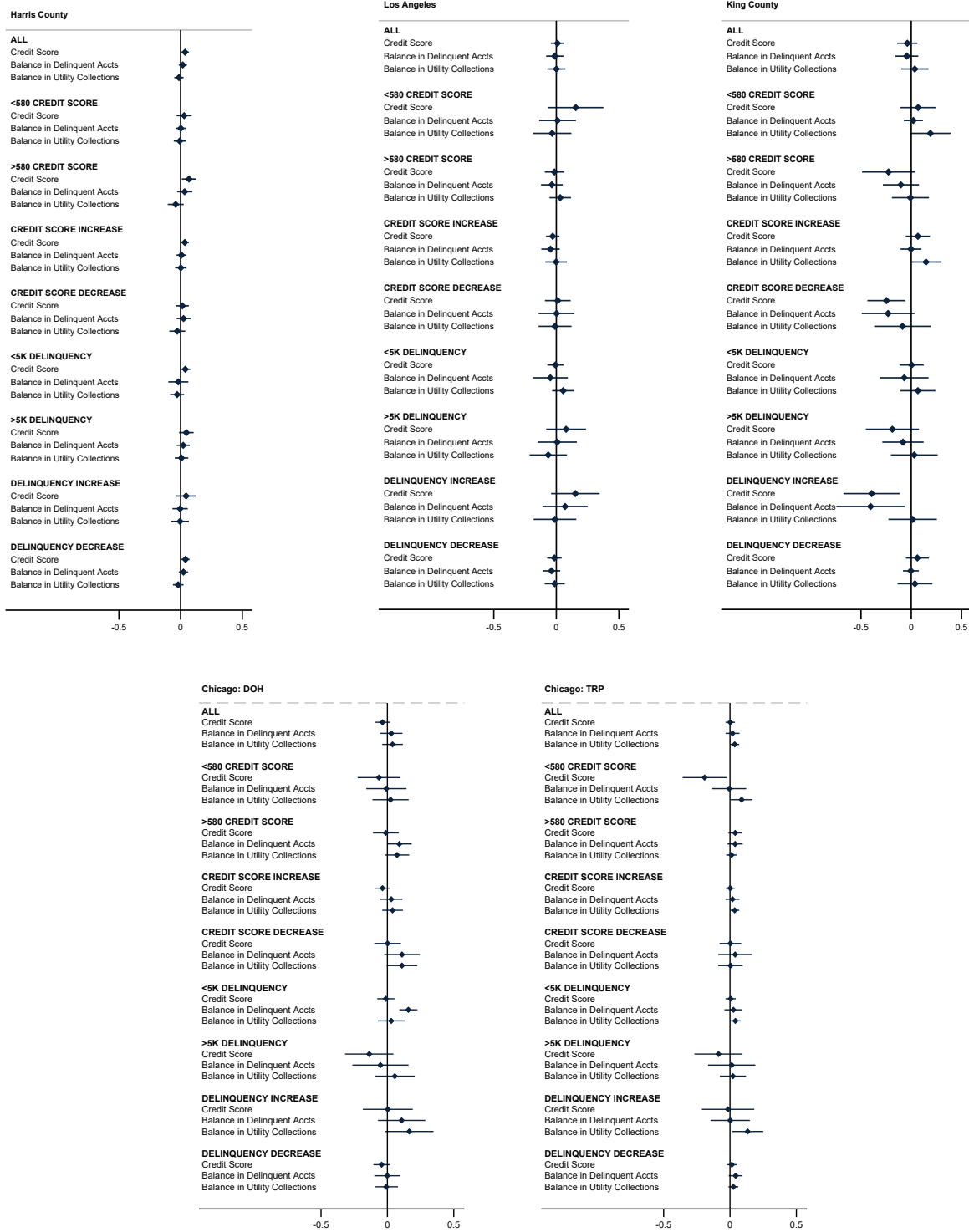
Notes: This figure plots the IV estimates of the effects on credit outcomes for different subgroups. The subgroups are in bold and followed by the three credit outcomes: credit score, balance in delinquent accounts, balance in utility collections. Point estimates are standardized by dividing the IV estimate by the standard deviation of the outcome in the control group. The leftmost forest plot is for Harris County and is followed by the plots of Los Angeles and King County. The sample includes applicants linked to the Experian credit data.

Credit Outcomes by Month Relative to Application – Program Applicants vs Local Renter Population

Notes: This figure plots the average credit characteristics for the treatment and control groups and for renters against the number of months since application. Data on local renters come from a 10 percent sample of individuals from Equifax and include individuals outside of the applicant pool. Control and treatment samples include only applicants linked to the Experian credit data. Applications were submitted at different times across sites. Each column corresponds to a different credit characteristic: credit score, balance in delinquent accounts, and balance in utility collections. Each row corresponds to a different location: Harris County, King County, Los Angeles, Chicago DOH, and Chicago TRP. The dashed vertical line indicates the month of application, and the red vertical line indicates March 2020.

Emergency Shelter Entry Rate by Random Assignment and Take-up of Treatment
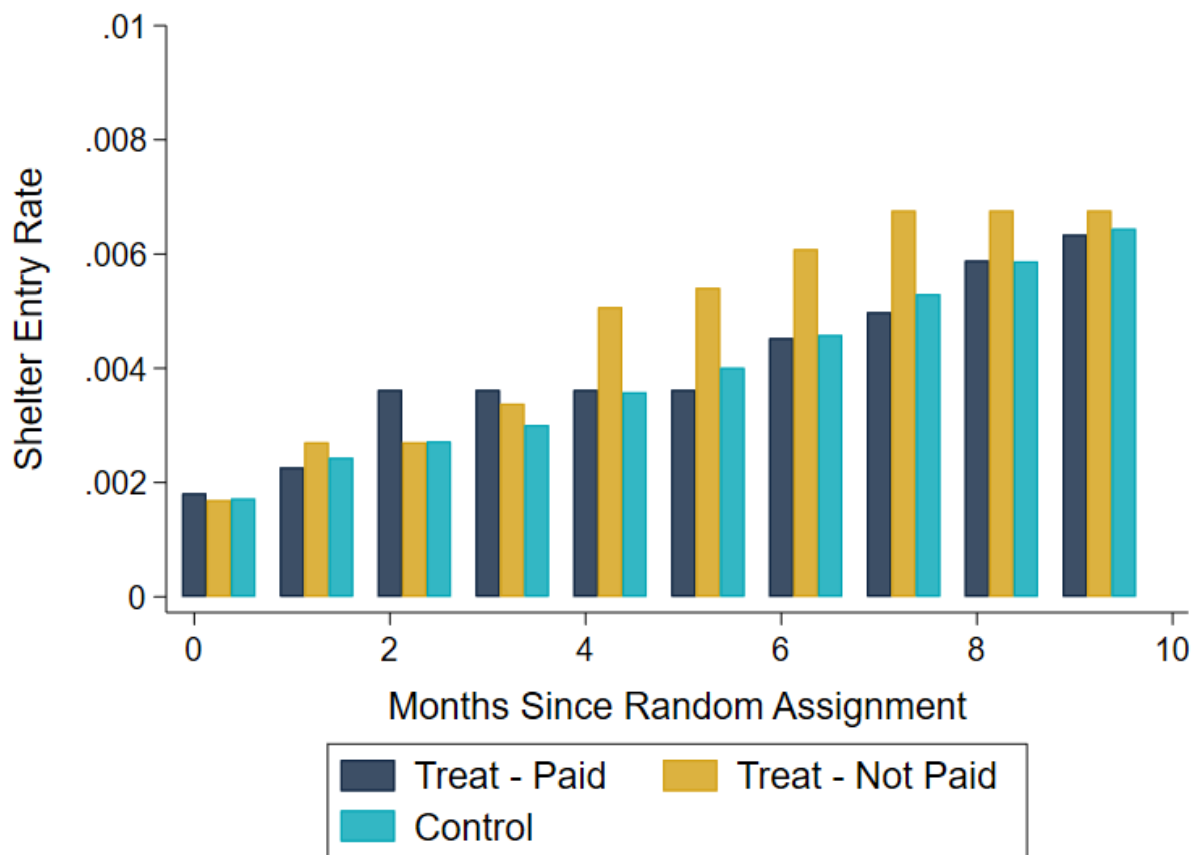
Notes: This figure plots the rate at which assistance applicants enroll in emergency shelters as tracked by HMIS data. The sample includes all lottery applicants in King County. Treatment and control groups are split by random assignment; the treatment group is further split by whether the assistance was successfully paid.

APPENDIX TABLE D.6

AVERAGE CREDIT CHARACTERISTICS – PROGRAM APPLICANTS VS LOCAL POPULATION

	Harris County			King County			Los Angeles			Chicago			
												DOH	TRP
	All	Renters	Assisted	All	Renters	Assisted	All	Renters	Assisted	All	Renters	Assisted	Assisted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Credit Characteristics:													
Credit Score	707	684	566	748	725	584	727	710	649	712	691	613	658
	(94)	(94)	(78)	(75)	(80)	(85)	(84)	(85)	(1)	(95)	(97)	(93)	(89)
Balance Across All Trades ($1000s)	68.8	19.1	27.9	118.8	15.4	21.4	103.2	16.7	22.1	71.9	19.5	30.7	23.6
	(155.2)	(30.6)	(47.4)	(263.1)	(32.2)	(60.8)	(345.8)	(37.6)	(0.7)	(161.3)	(36.4)	(60.7)	(54.3)
Balance in Collections ($1000s)	0.591	0.721	3.320	0.168	0.219	1.651	0.229	0.292	0.918	0.281	0.327	1.226	0.419
	(2.637)	(2.285)	(4.299)	(1.220)	(1.166)	(3.451)	(2.033)	(2.356)	(0.038)	(1.794)	(1.575)	(2.346)	(1.311)
Balance In Delinquent Accounts ($1000s)	1.514	1.661	9.426	0.549	0.709	7.428	1.025	1.167	4.671	1.126	1.126	6.626	1.821
	(6.898)	(6.966)	(12.816)	(5.776)	(6.549)	(20.045)	(8.040)	(8.407)	(0.168)	(8.397)	(7.045)	(15.320)	(6.099)
Any Auto Loan or Lease	0.398	0.355	0.326	0.282	0.261	0.349	0.346	0.322	0.279	0.274	0.250	0.305	0.214
	(0.490)	(0.479)	(0.459)	(0.450)	(0.439)	(0.477)	(0.476)	(0.467)	(0.007)	(0.446)	(0.433)	(0.461)	(0.410)
Any Personal Banckruptcy	0.012	0.012	0.019	0.019	0.026	0.100	0.026	0.031	0.046	0.050	0.061	0.140	0.031
	(0.108)	(0.108)	(0.137)	(0.135)	(0.158)	(0.300)	(0.161)	(0.173)	(0.003)	(0.217)	(0.239)	(0.348)	(0.174)
Any Open Revolving Line of Credit	0.847	0.807	0.384	0.929	0.906	0.505	0.887	0.870	0.703	0.874	0.848	0.599	0.583
	(0.360)	(0.395)	(0.469)	(0.256)	(0.291)	(0.500)	(0.316)	(0.336)	(0.007)	(0.332)	(0.359)	(0.491)	(0.493)
Observations:	26,086	14,803	6,169	14,408	7,358	491	24,579	16,603	8,702	14,399	9,200	357	640

Notes: This table reports the average credit characteristics for program applicants and a sample of local residents from outside the applicant pool for each site. Data on local residents come from a 10 percent sample of individuals from Equifax. "All" includes both renters and homeowners, and "Renters" is limited to individuals who rent. "Assisted" are the treated individuals who are linked to the Experian credit data at the time = 0. All monetary values are expressed in 2020 U.S. dollars divided by 1000. Standard deviations are reported in parentheses.

APPENDIX FIGURE D.9
EVICTION FILING BY MONTH: HARRIS COUNTY
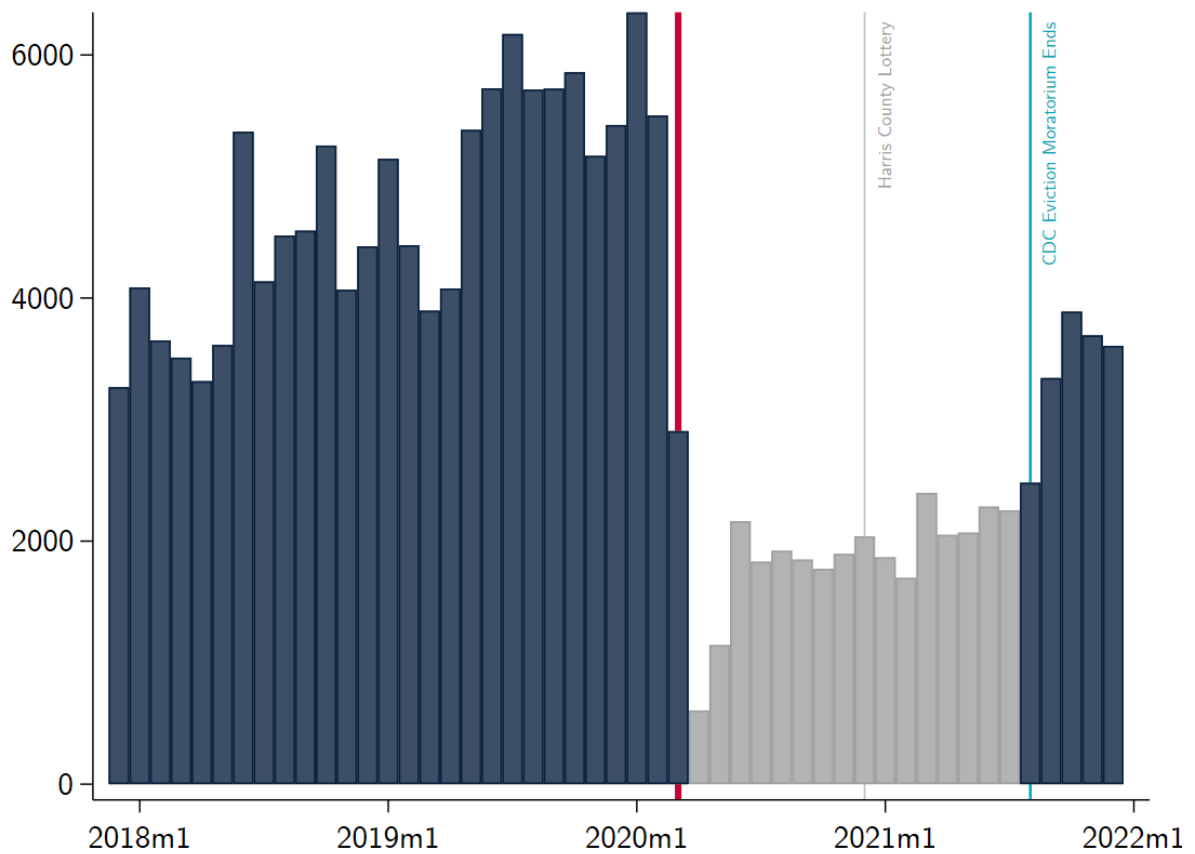
Notes: This figure plots monthly eviction filing volumes in Harris County. Months with no eviction moratorium are in blue, months with an active moratorium are in gray. The red line denotes the start of the CARES Act mortorium, the gray line denotes the time of the Harris County lottery that we study. The teal line denotes the end of the CDC Eviction mortatorium. Data is the authors calculations based on administrative data from the Harris County Justice of the Peace.

Treatment Effects on Homelessness System Use (King County and Chicago)

	King County Full Sample	King County Survey Respondents	Chicago DOH Full Sample	Chicago TRP Full Sample
Any Homelessness Services	0.020**	0.027*	-0.00213	-0.00346**
	(0.0083)	(0.016)	(0.00546)	(0.00172)
	[0.027]	[0.027]	[0.0092]	[0.00555]
	{0.048}	{0.047}	{0.0109}	{0.00449}
Emergency Shelter	0.0028	-0.000065	-0.00028	-0.00026
	(0.0039)	(0.0077)	(0.00153)	(0.00041)
	[0.0064]	[0.0081]	[0.000779]	[0.00853]
	{0.018}	{0.022}	{0.00242}	{0.00155}
Street Outreach	0.0067*	0.015**	0.00157	-0.0007*
	(0.0036)	(0.0068)	(0.00215)	(0.00041)
	[0.0037]	[0.0023]	[0.000602]	[0.00064]
	{0.0091}	{0.0098}	{0.00208}	{0.00139}
Diversion	0.0081*	0.0020	-0.0019	-0.00225
	(0.0045)	(0.0095)	(0.00502)	(0.00148)
	[0.0070]	[0.010]	[0.00782]	[0.00384]
	{0.019}	{0.017}	{0.00702}	{0.0017}
Any Longer-Term Subsidies	0.0012	0.010	-0.00097***	-0.00065*
	(0.0059)	(0.011)	(0.00018)	(0.00039)
	[0.015]	[0.013]	[0.000424]	[0.00064]
	{0.021}	{0.019}	{0.000656}	{0.00062}
Coordinated Entry	0.00100	0.0013		
	(0.0024)	(0.0038)		
	[0.0024]	[0.0023]		
	{0.0078}	{0.0070}		
N	12148	3152	74663	6453

Notes: This table reports the effects of assistance receipt on homelessness services use among King County and Chicago program applicants. Outcomes were measured 9 months after application based on administrative homelessness management information system (HMIS) data. Columns (1) and (2) report the IV estimates of the effects of assistance on the measure listed in the row for the full King County sample and the sample of King County survey respondents, respectively. Columns (3) and (4) report the IV estimates of the effects of assistance for the Chicago DOH and TRP samples, respectively. Robust standard errors are reported in parentheses, and the control group means are reported in brackets. The pre-COVID means for March 2019 to February 2020 are reported in braces. Statistical significance is denoted by: * $p \leq 0.1$; ** $p \leq 0.05$; *** $p \leq 0.01$.

APPENDIX TABLE D.8
ADDITIONAL SURVEY CHARACTERISTICS

	Harris County (1)	King County (2)	Los Angeles (3)	Chicago DOH (4)	Chicago TRP (5)
Financial Characteristics:					
Monthly Rent	1.021	1.472	1.571	1.122	1.026
Months of Rent Owed	1.090	3.259	1.745	–	0.839
Monthly Income (Feb 2020)	1.498	1.722	–	1.374	1.150
Any Paid Work (Feb 2020)	0.891	0.837	–	0.762	0.759
Demographics:					
Age	–	37.287	41.576	38.409	39.289
Female	0.783	0.620	0.564	0.637	0.613
Household Size	3.520	2.867	2.629	3.314	3.988
White	0.083	0.343	0.239	0.120	0.021
Black	0.613	0.364	0.114	0.373	0.117
Hispanic	0.271	0.186	0.531	0.430	0.807
N	1422	2621	24374	14681	1352

Notes: This table reports the mean of each characteristic for all who filled out the survey in each site (includes treatment and control). We report reweighted means to adjust for survey nonresponse. All monetary values ("Monthly Rent" and "Monthly Income (Feb 2020)") are divided by 1,000. We report the maximum sample size for each site. Monthly income is household income in February 2020. Note that, for King County, the variable "Months of Rent Owed" comes from administrative payment data, not the survey.

Fraction of Participants Receiving Assistance in Future Rounds

	King County		Chicago: DOH	
	Assigned:		Assigned:	
	Control (1)	Treatment (2)	Control (3)	Treatment (4)
Received Assistance in Future Round	0.28	0.31	0.07	0.13
N	6,982	5,166	73,126	1,537

Notes: This table reports the fraction of lottery participants who received assistance in a future round. The definition of the treatment and control groups is from the round one assignments. For Chicago DOH, these numbers include those who received assistance from round 2 of DOH or from TRP.

Comparison of Lotteries to Other Emergency Relief Assistance Programs by Site

	Chicago DOH (1)	Chicago TRP (2)	Houston (3)	LA (4)	Seattle (5)	CARES Act ERAP (6)	Treasury ERAP[†] (7)
Monthly Amount of Assistance	$1,000	$1,000	$1,200	$1,000-$2,000	min(80% of rent or HUD FMR)	Median: $1,200 Mean: $1,700 Range: $300 – $3,300 (94%)	Max: $17,000
Duration of Assistance	1 Month	1 Month	1 Month	1 Month	1-6 Months (Median:3)	≤3 Months (60%) 6–12 Months (30%)	Max: 15 Months
Recipient	Tenant	Tenant	Tenant	Tenant or Landlord	Landlord	Landlord (94%) Tenant (6%)	Tenant (71%)
Application Dates	Apr-20	Jul-21	Nov-20	Jul-20	Sept–Nov-20	Mar/Apr-20 (15%) May/Jun-20 (39%) Jul/Aug-20 (41%)[‡]	Jan/Mar-21 (ERA1) Mar-21/Jun-22 (ERA2)[*]
Dates of Assistance	Apr–Jun-20	Jul–Aug-20	Nov–Dec-20	Aug–Dec-20	Oct–Dec-20	First-come, first-served (45%) Lottery (16%)	First-come, first-served (56%) Lottery (3%)

Notes: The data for CARES Act ERAP come from Reina et al. (2021) and Yae et al. (2023) from the National Low Income Housing Coalition and the Housing Initiative at Penn. The sample of programs in this study includes 220 programs spanning 40 states (including Washington, DC). The percentages in parentheses represent the number of sites in the sample with the listed characteristics.

[†] The sample for Treasury ERAP consists of 389 programs across the US. For *Monthly Amount of Assistance*, we report the median of the maximum amount of assistance programs reported giving. Data for average monthly assistance across programs are currently unavailable. For *Duration of Assistance*, we also report the median of the maximum number of months programs reported providing assistance.

[‡] These dates show the months when the programs first began accepting applications. These percentages are based on 179 of the 220 total programs. Only 1% of programs began in January of 2020, and 4% in September of 2020.

[*] The December 2020 Consolidated Appropriations Act of 2021 created the Treasury ERA Program, establishing ERA1. In March of 2021, Congress provided additional funds to the Treasury ERA Program through the American Rescue Plan Act, establishing ERA2. June 2022 was the last month for which states with ERA programs were required to provide monthly reporting to the treasury. ERA spending rapidly increased in the months leading up to the end of the federal eviction moratorium in August of 2021.

RENTAL AGREEMENTS WITH LANDLORDS

|	Harris County (1)	King County (2)	Chicago: DOH (3)	Chicago: TRP (4)
$P(\textbf{Missed Payment} \bigcap \textbf{Had an Agreement})$	0.304	0.487	0.316	0.286
$P(\textbf{Had an Agreement}\|\textbf{Missed Payment})$	0.721	0.724	0.735	0.880
Agreement with:				
Written agreement	0.273	0.277	0.223	0.133
Some rent forgiven	0.073	0.035	0.061	0.040
Had more time	0.741	0.331	0.556	0.715
Had payment plan	0.306	0.161	0.174	0.195
Had more time- late fee	0.306	0.045	0.116	0.074
Late fees waived	0.177	0.146	0.221	0.118
Other	0.086	0.061	0.069	0.059
N	1,675	2,626	14,681	1,352

Notes: This table describes the types of agreements that tenants who missed rent payments reached with their landlords. These numbers are taken from the answers to Q38–Q40 in the Harris County and King County surveys. The first row is the fraction of respondents in each site who missed a payment and had an agreement with their landlord. The second row is the fraction among those respondents who missed a payment who had an agreement with their landlord. The rows that follow describe the content of these agreements. The categories listed are not mutually exclusive: respondents were instructed to select all features included in their agreement. These numbers should be interpreted as the fraction of respondents whose agreement included *at least* this feature.

Rates of Government Assistance

	King County (1)	Chicago: DOH (2)	Chicago: TRP (3)
Pre-Pandemic			
UI	0.117	0.041	0.014
Disability	0.030	0.018	0.013
Medicaid	0.168	0.196	0.137
Medicare	0.090	0.074	0.070
SNAP	0.293	0.348	0.339
WIC	0.091	0.062	0.057
TANF	0.059	0.013	0.005
Social Security	0.091	0.059	0.050
Community	0.035	–	–
Food Bank	0.166	0.048	0.078
Housing	–	0.043	0.016
Union	–	0.009	0.015
Post-Lottery			
UI	0.166	0.140	0.022
Disability	0.013	0.017	0.014
Medicaid	0.101	0.210	0.137
Medicare	0.047	0.080	0.078
SNAP	0.188	0.411	0.367
WIC	0.039	0.062	0.058
TANF	0.032	0.014	0.006
Social Security	0.045	0.059	0.054
Community	0.029	–	–
Food Bank	0.086	0.059	0.086
Housing	0.056	0.042	0.017
Union	–	0.015	0.015
N	2,626	14,681	1,352

Notes: This table reports the pooled estimates for the treatment and control groups of the rates of government assistance pre-pandemic and post-lottery for the different sites (based on survey responses). For King County, the data from the pre-pandemic period are from February 2020 and from August 2020 for the post-lottery period. For Chicago DOH, the pre-pandemic period is February 2020, and the post-lottery period is April 2020. For Chicago TRP, the pre-pandemic period is February 2020 and the post-lottery period is February 2021.

APPENDIX FIGURE D.10
UNEMPLOYMENT RATE BY TENURE
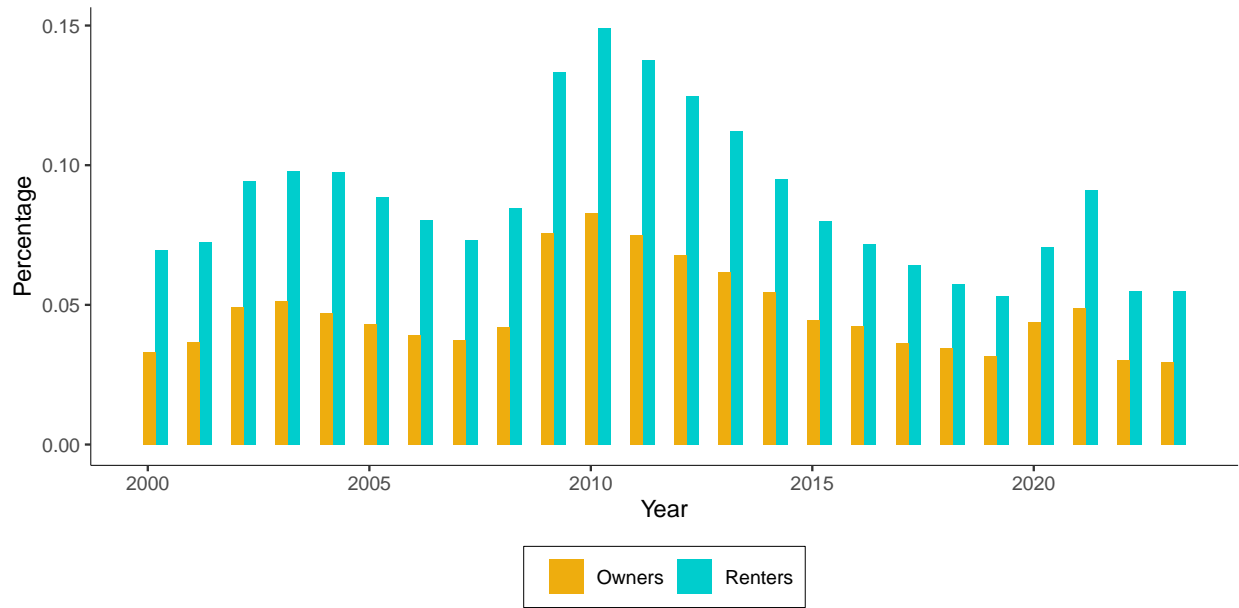
Notes: This figure shows unemployment rates for renters and homeowners. Source: Current Population Survey Data Annual Social and Economic Supplements (CPS ASEC).