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Do Shallow Rental Subsidies Promote Housing Stability? Evidence on Costs and Effects from DC's Flexible Program

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Abstract

Residents of cities face housing instability due to high housing costs. We conduct a randomized experiment evaluating the impacts of a flexible "shallow subsidy" among 668 qualified renters with recent housing instability. This local subsidy provides $7,200 a year directly to families earning less than 30 percent of the median family income, who choose how much assistance to use each month. Using administrative data, we track outcomes for the first year of program administration. After one year, the program has no statistically significant effect on homelessness, cash benefit receipt, or emergency rental assistance utilization, demonstrating no harm when compared to alternatives. However, the program leads to a 29 percentage point decrease in participants' use of other types of local government housing services, which they must weigh against the shallow subsidy. We show that the program can be administratively cost-saving, but is not always beneficial for a very low-income subset of applicants.

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Introduction

One in five households in the United States experiences housing insecurity. Housing insecurity takes several forms, from "doubling up" with another household to falling behind on rent, moving often, living in inadequate spaces, or being unsheltered (Cox et al. 2017). According to the American Community Survey, in 29 majority-renter cities, more than 40 percent of renters are considered burdened, spending more than the US Department of Housing and Urban Development's (HUD) recommended maximum of 30 percent of gross income on rent. Washington, DC exemplifies these challenges, as a majority-renter city with 60 percent of its approximately 280,000 households renting as of 2018, and 70 percent of them being rent-burdened by HUD's definition (Schuetz, LaRose and Schuetz 2020). About 0.8 percent of the DC population is in emergency shelters, transitional housing facilities, or is unsheltered (The Community Partnership 2020).

In late 2017, the District of Columbia Department of Human Services (DHS) aimed to identify and test a model that would allow the District to serve more families than it previously could by targeting services to a segment of the population experiencing housing instability, but not homelessness ("D.C. Law 22–65. Homeless Services Reform Amendment Act of 2017. D.C. Law Library" 2017). To this end, DHS began piloting the Flexible Rent Subsidy Program (DC Flex). The program's eligibility requirements attempt to prioritize families in need of assistance while screening out families that might need deep subsidies with more intensive support services and that therefore would be better served by a different program. This program is an attempt to move upstream and provide assistance to households with children who are users of DHS's homelessness-avoidance services though who are not currently homeless or at imminent risk of homelessness. This study evaluates the causal effects of a housing support tool that operates at the nexus of more traditional rental assistance programs and savings, credit, and basic income support. DC Flex is a "shallow subsidy" offering a middle ground between a permanent rental subsidy program (which might pay a larger share of housing costs, often indefinitely) and emergency rental assistance (which might provide relatively small amounts of short-term rent assistance).

This flat-rate, time-limited shallow subsidy is innovative on several levels. For governments, it provides administrative simplicity. Recipients receive a fixed subsidy that does not vary with differences in income, family size, or housing costs. For governments, the model reduces burdens from administrative error, complex benefit calculation, and improper reporting. For tenants facing income volatility, it provides flexibility and control of the subsidy instead of handing decisions over to their landlords. The DC Flex program provides $7,200 a year (equivalent to a $600 monthly rental subsidy) to families earning less than 30 percent of the District's median family income for up to 4 years. Unlike other programs, including Housing Choice Vouchers (HCVs) or Rapid Re-Housing, that pay the rental assistance to landlords, DC Flex assistance goes directly to participants and can be used like a savings account or line of credit. The $7,200 is deposited into a dedicated account, and participants are responsible for choosing how much of the subsidy to use each month. Participants cannot withdraw more than their full month's rent each month and can monitor the balance in their accounts. At the end of each year, participants are required to recertify that they met the program's requirements. Importantly, their income is allowed to rise above the initial 30 percent of median family income limit, addressing possible concerns that the program might reduce incentives to work. If they remain eligible, any unspent funds at the end of the year carry over to the next year's balance for up to 4 years.

DC Flex is primarily a financial support program. It does not offer case management, housing search assistance, employment services, or help with access to other benefits; the program does not employ social workers. Participants are required to attend a mandatory program orientation, a one-on-one financial coaching session, and a group financial coaching session within their first year. Beyond these two sessions, however, there is no requirement for participants to contact program staff other than to show proof that they paid their rent, which then allows money to be transferred from their escrow to their checking accounts each month. The program administrator may provide ad hoc guidance to participants, particularly if they rapidly exhaust their DC Flex funds.

Cities (and institutions) continuously search for ways to optimize their scarce housing assistance resources to meet resident needs through lower-cost and time-limited options. At the end of 2020, The United States Department of Veterans Affairs also started a new shallow subsidy initiative (US Dept of Veterans Affairs 2020) that provides a flat-rate subsidy based on 35 percent of the fair market rent. The program is a shallow subsidy, like DC Flex, but differs in that it does not provide the flexibility for recipients to adjust payments month-to-month. If proven effective, shallow subsidies, like DC Flex, represent an opportunity for policymakers to serve more people within their existing funding constraints. Because enrolling in the program requires participants to give up existing housing assistance and forgo most types of housing assistance while in the program, it is also important to quantify the net benefits from participating in the program both for the government and for different types of participants.

This study is the first known randomized evaluation of a shallow, flexible rent subsidy and evaluates the effectiveness of the first year of the program (October 2018–September 2019). The next sections of this paper provide the experimental design and implementation; report the effects and costs of DC Flex against usual care on rates of homelessness, use of local government housing services in the homelessness Continuum of Care ("CoC services"), Emergency Rental Assistance Program (ERAP), and Temporary Assistance for Needy Families (TANF) cash benefits. We find that shallow subsidies have no economically or statistically significant effect on homelessness, the rate of cash benefit receipt, or the amount of emergency rental and cash assistance. These results demonstrate that the program does no harm, relative to other services that government could offer. However, the program leads to a 28.6 percentage point decrease in participants' use of CoC services, which they must forgo in order to participate in DC Flex. The program, on average, increases the overall monetary benefits to participants, but it can decrease benefits for a subset of lower socio-economic status participants. The program is also one of the less-costly rent support programs to the government. Finally, we discuss how the results can inform initial discussions in other jurisdictions on the utility of shallow, flexible rent subsidies. The decisions about which programs to offer rarely hinge solely on program effectiveness and involve tradeoffs between the funding available and the dramatic numbers of people who could benefit from housing assistance.

Urban Rental Assistance and the Promise of Shallow Subsidies

Housing research describes several models of rental assistance and documents their effects. Below, we situate DC Flex's shallow subsidy in the context of models including vouchers, rapid re-housing, emergency rental assistance, and broader financial support.

HUD's landmark Family Options Study demonstrates that adults and children experiencing homelessness benefit significantly more from Housing Choice Vouchers (HCVs, also known as "Section 8" vouchers) than from other forms of temporary housing and services, and that these benefits accrue across several dimensions beyond housing stability, including physical and emotional wellbeing (Gubits et al. 2016). HCVs, however, are expensive for governments, and not available to all who need them. Despite the evidence and high demand for affordable housing, less than 20 percent of the qualifying population receive federal assistance (CBPP 2019). In Washington, DC, for example, the waiting list for vouchers closed to new applicants in 2013, with approximately 70,000 applicants on the waiting list at the time (DeBonis 2013).

While falling short of the HCVs' permanent rent subsidies, temporary rental assistance has long been a tool for promoting housing stability and preventing homelessness. For example, Rapid Re-Housing is a model of rental assistance used extensively by state and local governments that provides a time-limited option for averting homelessness while not providing the sustained benefits—nor incurring the costs—of permanent subsidies (Gubits et al. 2016). Rapid Re-Housing participants generally receive a fixed monthly subsidy for 12 months (with an extension of up to six months) with the expectation that families would be able to pay rent independently after the Rapid Re-Housing assistance ends. Studies have shown that Rapid Re-Housing has low barriers to entry, low rates of return to the homeless system, and no impact on employment (Cunningham, Gillespie and Anderson 2015).

Emergency rental assistance is another standard model of temporary assistance. Individuals who are behind on rent or facing eviction can receive one-time assistance to avert homelessness or other negative consequences of housing instability. Emergency rental assistance has been found to reduce rates of homelessness, leading to as much as a 76 percent reduction in entering homeless shelters (Evans, Sullivan and Wallskog 2016). In addition to federally funded HCV and locally funded equivalents, Washington, DC relies on both Rapid Re-Housing (known locally as the Family Rehousing Stabilization Program, FRSP) and emergency rental assistance (DC's Emergency Rental Assistance Program, ERAP) (DHS 2018). Between 2017 and 2019, in DC, there were approximately 4,000 ERAP applications per year, of which less than 50 percent were approved. In 2018, 2,400 families enrolled in Rapid Re-Housing. While both Rapid Re-Housing and ERAP are widely used nationally and supported by evidence, they are both reactive—a person cannot access either program unless they are at serious risk of eviction (ERAP) or are already experiencing homelessness (Rapid Re-Housing). Beyond these two programs, Washington, DC's other primary tools to reduce homelessness also tend to be reactive or to focus on broad approaches to housing affordability, like inclusionary zoning or the Housing Production Trust Fund, which seek to lower the equilibrium price of housing city-wide (DHCD 2020a, 2020b).

While the majority of housing stability programs target housing directly, another set of programs seeks to improve housing stability as well as other outcomes by improving a person's overall financial security. These efforts are based on the theory that, while many individuals are rent-burdened, one of the fundamental determinants of housing stability is access to savings or credit. The Federal Reserve's 2018 survey found that almost 40 percent of American adults would not be able to cover a $400 emergency with cash, savings, or a credit card (SHED 2019). When incomes or expenses fluctuate wildly from month to month, families risk not being able to pay rent or mortgage without access to savings or credit. Since the 1960s, jurisdictions have experimented with various financial stability programs, including basic income in the form of negative income tax. Basic income efforts have seen renewed interest in recent years (MGI 2020). Early results from Stockton, CA show positive effects on employment and self-reported financial, emotional, and physical wellbeing (West et al. 2021). A shallow subsidy like DC Flex is akin to basic income, as the tenant's contribution to rent is not pegged to their income and therefore should not impact their incentive to work. In this respect, there have been a number of conditional shallow subsidies with varying parameters—from eligibility to duration—but none to the best of our knowledge that focused on housing stability (Marinescu 2019).

While there are theoretical reasons that suggest a shallow subsidy might be an effective tool for increasing housing stability, a housing subsidy level below some threshold might be insufficient to help low-income families because high housing costs combined with local housing codes and HUD quality standards sharply limit the pool of decent, lower-rent units. As a result, shallow subsidies might not improve low-income families' well-being because families would still be paying unsustainable shares of their rents or living in poor-quality housing (Moffitt 2016).

Study Design and Implementation

DC Flex is designed to test how participation in a shallow, flexible subsidy program affects:

- the rate at which applicants experience homelessness,
- the rate at which applicants seek housing assistance beyond the shallow subsidy,
- the rate at which applicants use additional one-time rent assistance through ERAP and cash benefits through TANF, and
- the costs and benefits, compared to other local housing assistance programs.

Below we describe the outcomes for the initial DC Flex cohort of 229 participants through their first year in the program relative to the 439 participants who were not offered DC Flex. To promote scientific research integrity by reducing researcher discretion after experimental outcomes have been realized, we registered this study on the Open Science Framework.[1]

Sample

To recruit applicants that would likely have been eligible to be in the pilot, DHS used administrative records to identify roughly 9,000 households that had participated in government-funded housing programs—Rapid Re-Housing, the Homelessness Prevention Program, or had submitted multiple applications to ERAP—within the previous 48 months. The agency then sent families letters and text messages including information about the DC Flex program and instructions on how to apply. In total, DHS received 3,692 applications to the DC Flex program. Applications were screened for duplicates and incomplete responses, and then the self-reported application information was compared against program eligibility criteria. Families applied for DC Flex from December 2017 through July 2018. When the application closed in July 2018, there were 719 eligible applicants with fully completed applications.

To be eligible for DC Flex, applicants must be 21 years or older and have physical custody of at least one minor child. Applicants must be considered at risk of homelessness, meaning they have incomes up to 30 percent of the local area median family income and have applied for or received emergency or temporary assistance from a government-funded housing program administered by the District in the 48 months prior to their application. Applicants also had to have a lease on a legal rental unit and be employed or have a history of recent employment, defined as having worked in the six months before submitting their program application. The program's eligibility requirements (e.g., having a recent work history and living in a home with their names on the lease), relatively small subsidy, flexibility, and absence of case management had the goal of attracting families with low service needs and some financial stability. Unlike typical federal voucher programs, DC Flex does not require standards for the apartments in which participants live beyond the rule that they be legal rental units registered with the District. The subsidy cannot be used outside the District.

Starting in January 2018, the first of five cohorts of eligible participants were randomized to receive DC Flex and had to subsequently provide documentation to DHS to verify their eligibility. The eligibility verification process began in February 2018, and families who enrolled in the program then began receiving funds in May 2018. By September 2018, 102 families had started using DC Flex (out of 229 families offered the program).

Methods

Randomization

Seven hundred nineteen applicants entered a blocked, random lottery with a roughly 1 : 2 allocation ratio over the period of this study (Figure 1). In the

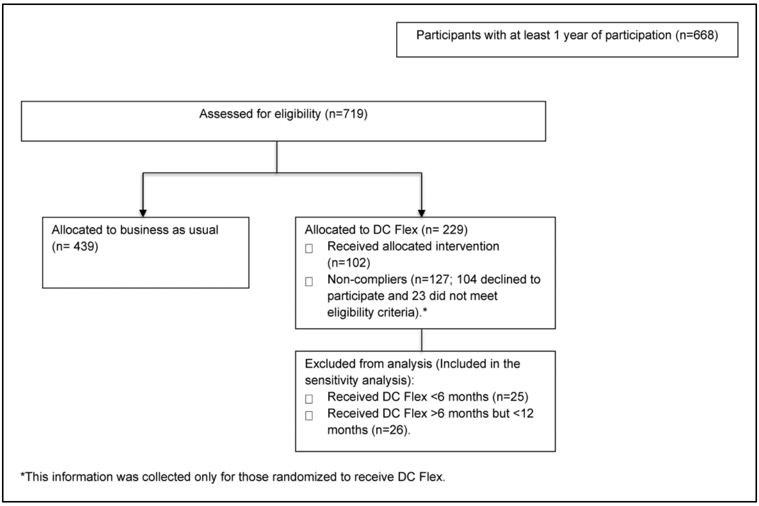

Figure 1. CONSORT diagram.

first program year, 668 individuals took part in the study, of which 229 participants were selected for treatment in five program lotteries, 102 of whom successfully enrolled in DC Flex by October 1, 2018—our cut-off date for the evaluation of the first program year. Five lotteries were run between January 2018 and July 2018. Because of rolling enrollment, applicants were eligible for different lotteries, depending on when they applied (Appendix A2 shows the date and number of the first lottery in which a participant was included). If a person was not picked for the program during a lottery, they were included in the lotteries that followed. This means that households that applied earlier have a higher probability of being offered DC Flex. This method of short, ranked lists was designed to promote compliance with experimental design, to allow those who applied after the first lottery date to be eligible to be selected, to ensure that program staff could perform eligibility verifications efficiently, and to encourage DHS to do persistent outreach to those selected by limiting the number of participants the agency needed to contact at any one time.

To ensure balance across the treatment and control groups, we used a non-bipartite matching procedure that allowed us to incorporate several variables at the same time, creating many small blocks within each of which we assigned applicants to treatment conditions. This procedure groups applicants with similar characteristics and then randomizes treatment assignment within these groups. While unblocked randomization balances potential outcomes in expectation, a blocked randomization method ensures that the characteristics of households are similar between the applicants offered treatment in the lottery and those who were not. This balance helps us attribute any differences in post-treatment outcomes to the program itself. We conduct the block randomization using the blockTools v0.6-3 package (Moore and Schnakenberg 2016) in R (R Core team 2017). We measure similarity between households with the Mahalanobis distance[2] calculated from nine pre-treatment variables.[3] We use two metrics to determine whether the groups are different from one another across all the applications' variables at baseline: p-values and standardized mean differences (Table 1).

Data Sources

This study relies on six data sources: (1) DC Flex applications. These contain self-reported information from questions geared to certify program eligibility. For example, applicants were asked to report their age, lease information, employment status, past applications for housing services, the number of dependents in their household and their weekly, monthly, and annual income. Asking individuals to self-report this information may not be as accurate as using administrative data, but the implementing agencies determined that using administrative data would not be feasible before administering the lottery as DHS did not have enough staff available to pre-screen hundreds of applications for the pilot. (2) Homeless Management Information System (HMIS). HMIS provides information about study families' use of DHS's services, like Rapid Re-Housing, transitional housing, and other programs. Because our data is from services rendered in DC, we do not know if a participant received assistance from nearby jurisdictions or from non-governmental providers like community-based or faith-based organizations. (3) Temporary Assistance for Needy Families records. TANF is a federal program that provides cash assistance to working families in need for a total of 60 months in a lifetime, along with access to supportive services like coaching towards education, employment and parenting goals, childcare, and behavioral, mental health, and substance abuse support. A family's qualification and the amount received under TANF depend on the household's monthly income and family size. Our data is limited to the monetary benefit amount received. (4) Emergency Rental Assistance Program (ERAP) application records. ERAP helps low-income residents pay overdue rent, late costs, court fees, and security deposits when facing a housing emergency, defined as a situation where immediate action is needed to avoid homelessness and re-establish a home or to prevent eviction. (5) Bank ledgers from the program administrator for those randomized to treatment and who accepted the offer. For each

Table 1. Mean Values, *t*-Test *p*-Values and Standardized Differences of Baseline Variables.

Household Information	Offered DC Flex N = 229	Control N = 439	*p*-Value*	Standardized Differences **
Age	32.3 (7.9)	31.4 (7.8)	0.16	0.114
Number in household	3.3 (1.3)	3.3 (1.3)	0.91	0.01
Number of children	2.1 (1.1)	2.1 (1.2)	0.98	0.00
Currently working	79.0% (0.4%)	78.4% (0.4%)	0.84	0.02
Days since last reported date of employment (If not currently working) ***	87.3 (101.6)	97.9 (71.9)	0.46	0.12
Annual Income	$17,195 ($9,413)	$17,782 ($9,723)	0.45	0.06
Rent Amount	$863 ($442)	$932 ($450)	0.06	0.16
Split rent for housing unit with someone not in their household	8.3% (0.3%)	8.0% (0.3%)	0.88	0.01
Sought Services at Virginia Williams Family Resource Center in 48 Months prior to application	40.6% (0.5%)	40.8% (0.5)	0.97	0.00
Applied for Emergency Rental Assistance Program (ERAP) in Past 48 Months	48.5% (0.5%)	44.0% (0.5%)	0.27	0.09
Applied for Homelessness Prevention Program in Past 48 Months	13.5% (0.3%)	15.0% (0.4%)	0.60	0.04
Applied for Rapid Re-Housing in Past 48 Months	44.1% (0.5%)	49.9% (0.5%)	0.16	0.12
Applied for Transitional Housing in Past 48 Months	5.2% (0.2%)	4.6% (0.2%)	0.695	0.03
Currently Receiving Rapid Re-Housing	31.4% (0.5%)	36.7% (0.5%)	0.18	0.11
Currently Receiving Transitional Housing	0.9% (0.1%)	1.6% (0.1%)	0.44	0.07
Currently Receiving Housing Choice Voucher Program	6.1% (0.2%)	4.3% (0.2%)	0.31	0.08
Currently Receiving Project-based Section 8 Housing	2.2% (0.2%)	2.1% (0.1%)	0.91	0.01

Standard deviations are reported in parentheses. *Difference in means (< 0.05 is statistically significant). ** standardized differences > 0.25. *** There were 51 (21 percent) unemployed individuals in the treatment group and 100 (22 percent) individuals unemployed in the control group at the time of the application.

DC Flex participant, files contain information on the dates when the $7,200 was deposited, and the date and amount of each monthly withdrawal. (6) Program costs, including administrative, case management, and rent support costs for DC Flex and DHS's other housing assistance programs (Rapid Re-Housing, Permanent Supportive Housing, Targeted Affordable Housing, Emergency Shelter, Transitional Housing and the Homelessness Prevention Program).

HMIS, TANF and ERAP data were available from January 2017 (i.e., the calendar year prior to the enrollment year) to October 1, 2019. Bank ledgers cover transactions from May 2018 to October 2019. Program costs represent DHS average for the 2019 fiscal year.

Outcome Measures

Although many measures can illustrate a family's housing stability, the primary outcome of interest was the rate of homelessness, which we define as the rate at which participants entered Emergency Shelter or Transitional Housing.

We also looked at the rate with which families use related services—both housing assistance and homelessness/eviction prevention assistance, which we refer to as the homelessness Continuum of Care (CoC)—at any time during the first program year, as well as the rate of ERAP application and overall TANF benefit amount received. For primary and secondary outcomes, we expected DC Flex to reduce the need for each of the services measured. In Washington, DC, the Virginia Williams Family Resource Center (VWFRC) is the central intake for families with children experiencing homelessness (individuals have a separate intake system). Appendix A2 illustrates the process of allocating families to services which is based on the Westat assessment tool and the case manager's review (FSA 2015). The majority (90 percent) of families at the VWFRC are diverted to the Homelessness Prevention Program, which provides counseling and services to prevent eviction and homelessness. Based on their housing needs, the remaining families are assigned to other housing options in the CoC, including Emergency Shelter, Transitional Housing, Rapid Re-Housing, and Permanent Supportive Housing. ERAP can be accessed outside of the Continuum of Care, but is also a component of other services.

In general, the rental assistance DC Flex provides should reduce the need for participants to access ERAP and other housing-related services. First, if DC Flex is effective at increasing housing stability, these services should be less necessary. Second, program rules require DC Flex participants to forfeit their DC Flex funds if they access most other government housing programs to prevent the government "double paying" for the same person. This rule was eventually relaxed to allow participants to use ERAP once while in the program, but the change took effect so late that the majority of DC Flex participants spent most or all of the period of observation under the rule where ERAP receipt was prohibited. A small number of participants had used ERAP before the rule change, but they were not exited from DC Flex and allowed to retain their funds.

We conduct analyses on changes in TANF receipt and benefit amount. These analyses are exploratory because we did not have *a priori* expectations on the direction of effects on TANF. If DC Flex contributes to a household's overall financial stability, participants may have more time and less mental burden, making them more likely to go through the administrative steps to recertify for TANF on time (Moore et al. forthcoming). If, however, that same stability also contributes to increased income for families, participating households would no longer be eligible for TANF.

We are also interested in the relative cost (to DHS and to the beneficiary) of DC Flex compared to other housing programs, specifically because both the treatment and control groups may receive other housing services in addition to or in place of DC Flex throughout the course of the pilot. While we do not have data to measure all types of housing assistance, we have measured the cost to DHS of the six most used services–Rapid Re-Housing, Permanent Supportive Housing, Targeted Affordable Housing, Emergency Shelter, Transitional Housing and the Homelessness Prevention Program. There are two other large programs not administered by DHS, and therefore not included in the analyses: public housing and the federal HCV. Public housing units (approximately 8,000 with an occupancy rate of approximately 97 percent) are managed by the DC Housing Authority (DCHA), as are HCV vouchers.

To align with the fact that funding is provided on an annual basis, all outcomes are measured for a 1-year window. Because participants who enrolled in DC Flex (treatment compliers) began to receive funds at different times, the window in which outcomes are measured is participant-specific and held constant at one year long. To capture a 1-year window for all applicants, we randomly allocate measurement start dates for non-compliers and participants in the control group, and record outcomes of interest for that one-year window. We draw these start dates from the empirical distribution of treatment compliers' start dates (dates between May and September 2018 when participants first received funds). We repeat this process 100 times for each non-complier and control group participant to reduce idiosyncratic variation due to chance, and we record the average outcome for each participant across all 100 measurement start dates. For all analyses, we use the actual 1-year outcome for compliers, and the averaged 1-year outcome for non-compliers and control group participants.

Estimation

We estimate the impacts of DC Flex at one year for each of our eight outcomes (four binary and four continuous), denoted Y, for a given applicant i heading a household, using a bivariate linear model estimated via ordinary least squares:

$$Y_i = \alpha \ + \beta_{ITT} T_i + \epsilon_i \tag{1}$$

Where T_i represents an indicator variable equal to 1 if household i was offered the intervention and zero otherwise. Each participant's year starts on the day the DC Flex funds were first made available to them. As discussed above, controls and non-compliers are assigned random measurement start dates drawn from the empirical distribution of compilers' actual start dates, and we take the average of their outcomes from those 100 measurement periods.

We calculate both the intent-to-treat (ITT) and the Complier Average Causal Effect (CACE) for all eight outcomes of interest (Eq. 2) by dividing the ITT estimate (β_{ITT} in Eq. 1) by the probability of compliance (p_c).

$$\beta_{CACE} = \beta_{ITT} / p_c \tag{2}$$

The ITT analyses may underestimate the impact of the program when successfully delivered, because they combine individuals who do and do not receive the treatment. The CACE, on the other hand, reflects the effect for people who are interested, eligible, and would enroll in DC Flex if it were permanently available.

We adjust the alpha-level for multiple comparisons using the sequential Holm–Bonferroni method across all 8 outcomes (Holm 1979). We also conduct sensitivity analysis whereby we include the remaining 51 people who were selected in the lottery and offered DC Flex with less than six months left in the program year.

Our analyses adjust for the different probabilities of being assigned to treatment throughout the five lottery dates. Because offers of enrollment in DC Flex were assigned by rolling lotteries, each participant's outcome is weighted by the inverse of their probability of being selected for the treatment condition for which they were actually selected. This inverse probability weighting accounts for the chance that people who apply later or are selected in later lotteries are different from those selected early (additional details and computations are available in Appendix A3). Weighting helps adjust for treatment effect bias caused by unobserved confounders correlated with the applicant's randomization cohort.

We use randomization inference (RI) to test whether observed outcomes are likely to have been observed by chance even if the treatment had no effect. To implement the RI for the ITT, we repeated the lottery that selected applications to DC Flex 5,000 times. In each of these "pseudo-lotteries," people who received DC Flex could end up in the pseudo-control group and vice versa. Assuming a sharp null treatment effect, we compare all of the results under the pseudo-lotteries to what occurred in the actual experiment to measure the probability that we would have found similar effects of the program due to chance alone.

Analysis of Costs to DHS and Benefits to Participants

While cost saving was not the primary goal of the DC Flex program at the onset, if subsidies prevent the need for more costly housing services, cost-savings would provide an additional reason for policymakers to pursue these subsidies as an additional housing support program. The fact that funds are conditional on participants keeping up rent payments and that the program's rules limit the use of other types of housing support might have broader implications on household behavior. It becomes, therefore, important to understand how assignment to the program might interact with observed and unobserved participant characteristics that also influence outcomes. For example, if DC Flex is cost saving from the government's point of view, is that only for some segment or type of participants? To what extent do subsidies impact benefits participants would be eligible to receive in the absence of the program?

We begin by comparing the costs of DC Flex to seven programs administered by the local government: Rapid Re-Housing, Emergency Shelter, Transitional Housing, Permanent Supportive Housing, Targeted Affordable Housing, the Homeless Prevention Program, and ERAP (the eligibility requirements, benefits, and durations of these programs are described in Appendix A4). To generate a cost for each of the programs, we obtain administrative data on the number of days each of these seven programs were used by people in the treatment and control groups between October 2018 and October 2019. To align with agency unit cost data, we then convert days into months; e.g., 37 days in emergency shelter is equivalent to 1.2 months. We use unit cost information provided by DHS on the total average monthly cost per person of providing these services. If a household spent 1.2 months in emergency shelter (resource use) and the cost per month of emergency shelter was $5,417 (unit cost), the cost would be 1.2 months times $5,417 per month = $6,500. For ERAP and Homeless Prevention Program costs, we use the actual dollar amounts provided to beneficiaries during the study period and add a fixed administrative cost per person based on DHS's estimations. For the other five housing services, we use average unit prices provided by DHS based on their total cost incurred per family during the fiscal year 2018 and 2019. This was a practical approach as the dollar amount per family would vary based on need and the administrative records do not include information on administrative or case management costs.

We describe cost analyses on the program's impact as possible exploratory analyses in our pre-analysis plan, but we do not pre-specify a method. We pursue two approaches to better understand the impact of treatment assignment on costs to DHS and net benefits to participants. First, we compute both ITT and CACE estimates for both types of costs. Second, we explore *essential heterogeneity* (Ravallion 2011) with respect to the costs. This second analytical approach attempts to model the choice of taking up DC Flex based on a combination of observable characteristics that make a participant more or less likely to accept their randomly assigned offer. We think that this is particularly applicable to cost outcomes, since the value of the benefit—compared to other programs—is relatively transparent to potential enrollees. That is, a participant can much more easily use administratively-unobserved factors to determine the cash value of DC Flex to their household than to determine the value in reducing their probability of homelessness, for example.

Since participation in DC Flex is voluntary, a participant assigned to DC Flex must choose between DC Flex or other housing services they currently use or could access in the future. That status quo may include a range of existing housing supports like Rapid Re-Housing or HCV, or they may have no current support. Based on their past experiences with housing instability, they will have the knowledge that ERAP and CoC services are available in an emergency (program eligibility required that participants had applied for or received emergency or temporary assistance from a government-funded housing program administered by the agency in the 48 months prior to their application). These choices may result in savings to DHS if DC Flex attracts people away from other more costly programs or prevents them from entering those programs after enrolling in DC Flex. Conversely, these choices end up being more costly to DHS if DC Flex attracts people who are not currently receiving assistance or fails to prevent them from enrolling in those programs after enrolling in DC Flex. This selective take-up is a well-known source of bias that random assignment can correct under the assumption that assignment to treatment only affects outcomes via uptake. When analysing costs to the government and the net benefits to participants of a program, the CACE estimates assume that the marginal cost of each DC Flex offer is zero. Because of those who choose DC Flex over their status quo, the selective take-up may mean that the marginal cost of extending the program is not necessarily zero for the government (there could be savings or losses) or the participants (net benefits would increase or decrease). When thinking about the cost of providing a new service to residents, CACE estimates may not be informative enough because participants will adopt programs based on eligibility criteria and preferences, which are both observed and unobserved characteristics that are correlated with costs to DHS.

We use the setup described in Heckman, Urzua and Vytlacil (2006) to estimate essential heterogeneity. In the first stage, we regress the probability of DC Flex uptake on baseline covariates using a linear probability model. The predicted values from this first stage, $\widehat{p_i}$, are then used as predictors of the household-specific cost to DHS, C_i:

$$C_i = \alpha \ + \gamma_0 T + \gamma_1 \ \widehat{p_i} T_i + \beta_1 \ \widehat{p_i} \ + \epsilon_i \tag{3}$$

Equation (3) modifies the CACE estimation by allowing the effect on cost to vary by predicted probability of program uptake. In addition to the perspective of agency costs, we also explore essential heterogeneity from the participants' point of view, measured by the benefits received from different services they are eligible for. While in practice, 10 percent of selected individuals (23/229) are ineligible at the verification stage, for those who are eligible, impact heterogeneity could be important because people make choices about whether to participate based on their status quo.

Our estimate of the treatment effect on cost to DHS is:

$$C_i\left(\widehat{p_i}\right) = E\left[C_i \middle| T_i = 1, \widehat{p_i}\right] - E\left[C_i \middle| T_i = 0, \widehat{p_i}\right] \tag{4}$$

To estimate the impacts on costs as a function of the probability of uptake in Eq. 4, we test for linear and higher order polynomials (quadratic and cubic) to allow for the possibility of non-linear relationship between the probability of uptake and the treatment effect on costs. We then plot the marginal average treatment effect, which is referred to in the literature as essential heterogeneity, to understand for which segments of the participating population DC Flex represents a cost savings to the government and for what segments the offer of DC Flex would not be a cost-saving intervention. In addition, to understand how the probability of uptake varies across population characteristics, we also use non-parametric, locally weighted scatterplot smoothing curves (LOWESS) to visualize the relationships between uptake and participants' characteristics at baseline.

Results

Baseline Characteristics of Participants

Table 1 displays self-reported information for participants offered spots in DC Flex and in the control group. On average, participants were single mothers in their late 20s and early 30s, with two dependent minors. The majority were employed, had an average self-reported income of approximately \$17,500

(SD: $9,500)[4] annually and spent approximately 60 percent of their income on rent (the average rent was $863 a month, SD: $442). As a reference point, the median household income in DC for a family of four in 2019 was $121,300 (DMPED, 2019). By design, all participants had applied to at least one housing service in the 48 months prior to application, but less than 40 percent were receiving housing support services or subsidies at the time of DC Flex's launch. Among individuals receiving housing support services or subsidies at launch, the overwhelming majority received Rapid Re-Housing.

While there are minor differences in some variables between the DC Flex and control groups at baseline, the randomization process effectively produced two groups with similar baseline characteristics, as expected. None of the *t*-tests found statistically significant differences between the treatment and control groups at the 0.05 level. Still, the rent amount is close ($p = 0.06$), suggesting that families in the control group reported higher rents on average at application. We also computed standardized differences because these are not affected by sample size (unlike *t*-test *p*-values) and are more reliable indicators of whether the random assignment is balanced at any sample size. There were standardized differences above 0.10 (but no differences are above 0.25)[5] between those offered DC Flex and the control group for the following variables: age, rent amount, days since the applicant had been employed (for those unemployed at the time of application), percent that had applied for Rapid Re-Housing in the past 48 months, and the percent receiving Rapid Re-Housing at the time of application. Not all these differences are meaningful or economically important. For example, a difference in age of one year, a difference in self-reported rent of $69 a month, or a difference in 10 days since the applicant had last been employed is unlikely to meaningfully affect any of our outcomes of interest.

Utilization

In the first year, 45 percent (102 of 229) of applicants selected in the lottery successfully enrolled and completed one year of participation in the program. It is important to note that program uptake is not solely driven by selection but also by eligibility verification.[6] While we do not have complete data on reasons why participants did not take the program, we know that 23 out of the 229 households assigned to treatment were ineligible at the verification stage. Some prospective participants had multiple reasons for ineligibility (e.g., lack of dependents, employment and leaseholder status). The main reason for ineligibility in virtually all cases however was having an annual income above 30 percent of the area median family income.

After one year in the program, DC Flex participants had an average of $543 (SD: $1,683) of unused funds in their DC Flex accounts (Table 2).

Table 2. Amount of Money Left in Participants' Escrow Accounts at end of First Year.

Amount Left at Month 12	Cumulative Percentage of Participants	Range of Amount Left at Month 12	Percentage of Participants
Less than $1	46%	$0–$0.99	46%
Less than $100	59%	$1–$99	13%
Less than $500	63%	$100–$499	4%
Less than $1,000	70%	$500–$999	7%
Less than $2,000	90%	$1,000–$,1999	21%
Less than $3,000	92%	$2,000–$2,999	2%
Less than $4,000	95%	$3,000–$3,999	3%
Less than $5,000	97%	$4,000–$4,999	2%
Less than $5,761	100%	$5,000–$5,761	3%

For context, the average monthly rent based on account data was $1,147, indicating that, on average, participants had less than a month's rent left at the end of the year. There is, however, also considerable heterogeneity on how quickly participants used funds. Twelve percent of the 102 enrolled families exhausted their full $7,200 six months into the program and one third of participants spent down their accounts by the eighth month. We suspect that these rapid use patterns result from participants who may have entered the program with an immediate need for assistance for current or past due rent, or may have relied on the program to pay rent while using other income, which would ordinarily have gone to rent. Table 2 shows the amount of DC Flex funds remaining for each of the 102 participants after 12 months and the percentage of participants with less than a specified amount remaining in the account. Appendix A5 summarizes graphically how participants spent down their accounts over time. For example, by the end of their first program year, 59 percent of participants had $100 or less in their DC Flex accounts, indicating that they used the full $7,200 during the year. Eighty-six percent of households had less than $2,000 remaining in their accounts after 12 months. A meaningful number of participants (21 percent) had between $1,000 and $1,999 in their accounts at the end of the year. Since DC Flex funds can be carried over to the next year if the household remains eligible for DC Flex, this result suggests that some families may elect to keep roughly one month's rent available as an additional buffer for the next program year. It is also possible that some participants were unaware of their balance. Other reasons for not fully using funds available are termination and exit from the program. Thirteen participants (out of 102) received DC Flex funds but exited the program voluntarily, were terminated from the program for misuse of funds (e.g., intentionally making withdrawals exceeding the monthly rent amount), or moved out of the jurisdiction. Five of these 13 participants were able to use the full \$7,200 amount before exit, and the remaining 8 participants used between \$1,670 and \$6,922 before exit. At the time of analysis, 12 participants had failed to recertify for year two of the program. These families used, on average, \$5,963 (SD: \$1,971) during year one. Families that did not recertify for year two of the DC Flex program may have become ineligible or were "opting out" of the program (e.g., moving out of the District, or opting for another type of housing assistance with a higher dollar value, like a voucher) and were not using the funds.

Primary Outcomes

Homelessness. Participants in both DC Flex and the control group were unlikely to experience homelessness in their first program year. During this time, 1.8 percent of DC Flex participants entered an emergency shelter; no participant used transitional housing. Without the shallow, flexible rent subsidy, we estimate that 2 percent of participants would have used these supports. This small difference is not statistically significant (Table 3). Randomization inference shows that 91.7 percent of feasible randomizations would produce a difference as large or larger than the 0.1 percentage point difference observed for the ITT. This high percentage demonstrates that the differences observed could easily have arisen by chance. The confidence interval around the estimates for homelessness range from a nine-percentage point decrease in homelessness to a seven-percentage point increase. Overall, these results suggest that eligibility and selection criteria for DC Flex identified a population that had a relatively low risk of homelessness within a one-year window (4.7

Table 3. DC Flex Impact on Homelessness and Service Utilization.

Year 1 results:	Entered Emergency Shelter or Transitional Housing	Continuum of Care
Complier Outcome (n = 102)	1.8%	21.7%
Counterfactual Complier Outcome	2.0%	50.3%
CACE coefficient (SE)	−0.2pp (3.7pp)	−28.6pp (9.9pp)
Treatment Group Outcome (n = 229)	4.6%	32.2%
Control Group Outcome	4.7%	44.9%
ITT coefficient (SE)	−0.1pp (1.7pp)	−12.7 pp (4.2pp)
RI *p*-value	0.917	<0.001

SE = standard error. pp = percentage points. RI = Randomization Inference.

percent across treatment compliers, treatment non-compliers, and control). This finding is consistent with the program's intent not to serve families who are in immediate need of assistance. The baseline rate of homelessness among participants was, however, much lower than expected. Finding a statistically significant impact of DC Flex on the rate of homelessness will be impossible in future program years unless the overall rate of homelessness for the DC Flex group and control group were to increase or the program was expanded dramatically to increase the sample size.

Secondary Outcomes

Continuum of Care. As a secondary outcome, we estimate the program's effects on the rate at which people seek services in the homelessness continuum of care at least once during the program year. The results for the use of support services show meaningful and statistically significant results. For participants selected in the DC Flex lottery—regardless of whether they ever received DC Flex funds—the rate of using support services is 12.7 percentage points lower than in the control group (the ITT estimate). The effect of actually using the DC Flex funds on using support services is a 28.6 percentage point decrease compared to the control group (the CACE estimate). The randomization inference p-value suggests that there is less than a 0.1 percent chance that we would observe a difference of at least 12.7 percentage points from chance alone.

While the impact of DC Flex on service utilization is striking, much of the effect is driven by the fact that many DC Flex participants were receiving some form of assistance at the time they applied. For example, 31.5 percent of participants offered DC Flex reported that they were enrolled in Rapid Re-Housing at the time of application (Table 1). For those participants, they had to agree to exit other housing support services, like Rapid Re-Housing, before enrolling in the DC Flex program. Table 4 shows the percentage of DC Flex participants, non-compliers, and control group participants who received housing support between October 2018 and October 2019. Appendix A6 shows the average number of days each of these services were used. Examining the control group's experience illustrates what would have happened to participants offered DC Flex, if the program did not exist —what "business-as-usual" looks like. The unweighted values represent crude averages, and the weighted averages adjust for the different probabilities of being selected across lotteries. Columns exceed the program utilization reported in Table 4 because some individuals access multiple programs in a year. The rate of service utilization of non-compliers is very similar to those of controls and exceeds that of controls in the case of entering an emergency shelter. This difference may result from the eligibility verification step that

Table 4. Breakdown of Service Utilization Between October 2018 and October 2019.

	Unweighted Average Rates			Weighted Average Rates		
Programs and services	Compliers (N = 102)	Non-Compliers (N = 127)	Controls (N = 439)	Compliers (N = 102)	Non-Compliers (N = 127)	Controls (N = 439)
PSH	0%	0%	0.9%	0%	0%	0.9%
TAH	0%	0.8%	2.7%	0%	1.4%	2.8%
RRH	7.8%	27.8%	30.3%	9.13%	27.7%	29.8%
ES	2%	7.3%	4.6%	1.8%	6.1%	4.7%
HPP	7.8%	14.3%	13.3%	11.7%	13.3%	13.4%
ERAP	11.8%	7.4%	11.2%	10.7%	7.4%	11.2%

Note: No DC Flex participants used transitional housing. ERAP utilization is not part of the "service utilization" outcome definition but it is one program offered by DHS and included in our benefit receipt and cost estimates. Permanent Supportive Housing (PSH), Targeted Affordable Housing (TAH), Rapid Re-Housing (RRH), Emergency Shelter (ES), the Homeless Prevention Program (HPP).

occurs after randomization as a participant who entered emergency shelter after applying for DC Flex but before verification would not be allowed to enroll in DC Flex based on the program rules. Therefore, they could only be a non-complier due to ineligibility, mechanically increasing the rate among non-compliers relative to the control, which contains both compliers and non-compliers in expectation. The notable exception is Rapid Re-Housing, where less than 10 percent of treatment compliers accessed Rapid Re-Housing, compared to nearly 30 percent of non-compliers and controls. These differences are the primary driver of DC Flex's impact on service utilization.

For all outcomes, Appendix A7 shows the sensitivity analyses conducted whereby we include the 51 households that had not completed one year in the study. The same number of individuals in the control group are present in both sets of analyses. The inclusion results in no meaningful change in the point estimates or *p*-values.

ERAP and TANF Receipt. As secondary outcomes, we also assess whether DC Flex had any effect on the rate of ERAP and TANF utilization and the amount of benefits received by participants in these two programs (Tables 5 and 6). Though point estimates suggest less utilization and benefit receipt for DC Flex participants, there was no statistically significant effect of DC Flex on the rate or amount of ERAP utilization in the first program year. Applicants randomized to be offered DC Flex received, on average, $87 less per month in ERAP benefits than the control group members. For compliers, the difference was $197 less for those receiving DC Flex. When we test this difference using randomization inference, we find a larger difference in roughly 16 percent of pseudo-lotteries. Participants enrolled in DC Flex were 5.3 percentage points less likely to receive ERAP assistance during the first program year than

Table 5. DC Flex Impact on ERAP Amount Received and Likelihood of ERAP Receipt in one Year.

Year 1 results	ERAP amount received (per month)	% ERAP Receipt
Complier Outcome (n = 102)	$353	10.7%
Counterfactual Complier Outcome	$550	16.0%
CACE coefficient (SE)	−$197 ($185)	−5.3pp (5.1pp)
Treatment Group Outcome (n = 229)	$292	8.9%
Control Group Outcome	$379	11.2%
ITT coefficient (SE)	−$87 ($81)	−2.3pp (2.3 pp)
RI *p*-value	0.166	0.333

SE = standard error. pp = percentage points. RI = Randomization Inference.

Table 6. DC Flex Impact on TANF Amount Received and Likelihood of TANF Receipt.

Year 1 results	TANF amount received (per month)	% TANF Receipt
Complier Outcome (N = 102)	$185	38.9%
Counterfactual Complier Outcome	$169	39.2%
CACE coefficient (SE)	$17 ($56)	−0.3pp (9.7pp)
Treatment Group Outcome (N = 229)	$207	42.3%
Control Group Outcome	$200	42.4%
ITT coefficient (SE)	$7 ($25)	−0.1pp (4.3pp)
RI *p*-value	0.832	0.999

SE = standard error. pp = percentage points. RI = Randomization Inference.

participants in the control group. The confidence interval around the estimate of the effect on the rate of ERAP benefit receipt ranges from an 18 percentage point decrease to a 7.5 percentage point increase in the use of ERAP benefits.

There was no statistical or economically meaningful effect of DC Flex on the rate at which participants received TANF cash benefits, nor on the monthly benefit amount in their first program year. Applicants randomized to be offered DC Flex received, on average, $7 more per month in cash benefits than the control group members during the first program year. When measuring the CACE—the effect of actually receiving DC Flex funds—the difference was roughly $17 more for those receiving DC Flex. The estimate of the effect on the monthly amount received ranges from a $118 decrease to a $151 increase. When we test this difference using randomization inference, we find a larger difference in roughly 83 percent of pseudo-lotteries. Participants enrolled in DC Flex were almost equally likely to receive TANF assistance as participants in the control group. The 0.1 percentage point difference is neither meaningful nor statistically significant as a larger difference was found in roughly 99 percent of pseudo-lotteries. The estimate of the effect on the rate of TANF benefit receipt ranges from a 19 percentage point decrease to a 19 percentage point increase in the use of TANF benefits.

Costs and Benefits

This section explores two types of financial impacts of the program: cost incurred by the agency and direct benefits to participants. This analysis was not pre-specified. Housing programs and services vary in availability, eligibility criteria, and benefits. These factors are likely to impact both program uptake and the rate at which DC Flex is used as a substitute for other programs. DHS provided us with a total average monthly cost per family for all the housing services offered based on the 2019 fiscal year (Table 7). For all programs, except for transitional housing, the agency provided a breakdown of costs into amounts that families received for rent support and amounts families receive indirectly via case management. Most programs seek to keep administrative expenses below 10 percent of the total budget allocated to a program. Emergency shelters and the Homeless Prevention Program have higher administrative costs due to high levels of in and out-flows from these services. Total average unit costs were multiplied by actual utilization using administrative (HMIS) data.

DC Flex is the lowest-cost housing program, on average, aside from ERAP and HPP, which are predominantly one-time payments for overdue rent. Shallow, flexible subsidies such as this can be cost saving if they serve as a substitute or as prevention for more costly programs. During the first year of the program, the cost of serving individuals in the treatment group was on average \$234 (SD = \$993) more than control group expenditures. Both the ITT and CACE estimates (\$529) are considerably less than the cost of providing the program per person per annum, \$7,200 (Table 8). This highlights that programs do not happen in a vacuum; and that they are influenced by and viewed in comparison to other programs and outcomes. This is especially true for a case like DC Flex, where the alternative to the program is a complex set of housing support services.

We also look at the impact of the program on the expected amount of benefits received across all local services. As we discuss above, receipt of DC Flex impacts other housing benefits participants might receive. Therefore, it is important to understand the net impact of the program on the total monetary aid a person might receive. To compute benefits, we use the same approach as with total costs, but use as unit costs the dollar amount participants received directly through rent support shown in the third column of Table 7 (i.e., removing administrative costs and case management costs). We exclude emergency shelter from the computation because the high cost of shelter is not entirely transferred to the participants and the benefit is not as fungible as other direct or indirect subsidies. The average net annual benefit to individuals in the treatment group during the first year of the program was \$993 (SE = \$620) higher than the control group, but the difference is not statistically significant. Even after accounting for compliance (CACE estimate = \$2,239), this is substantially lower than the face value benefit of the program, \$7,200 per household/family per annum.

To test for the presence of essential heterogeneity, we first estimate the probability of uptake. While the first stage of the essential heterogeneity model is not particularly robust (AUROC = 0.68 and a *p*-value of 0.45 of

Table 7. Unit Costs of DHS Services per Household.

Program Type	Total Average Monthly Cost	Average Monthly monetary Benefit or Rent Support	Average Monthly Cost for Case Management, Personnel	Average Monthly Cost for Admin/Other Expenses
DC Flex	$611	$544*	Not applicable	$67
Rapid Re-Housing	$2,818	$1,713	$987	$118
Permanent Supportive Housing	$3,395	$2,355	$997	$43
Targeted Affordable Housing	Not Available	$2,355	Not Available	Not Available
Emergency Shelter	$5,795.50	$3,600	$978.50	$1,218
Homeless Prevention Program	$2,783	$433	$880	$1,470
ERAP	$400	350	Not applicable	$50

Note: The total average monthly cost for Transitional Housing is $5,417. No DC Flex participants used Transitional Housing.
(*) $544 represents the average monthly utilization of DC Flex in the sample. Due to premature exit from the sample or under-utilization of funds, the average is less than $7,200 per annum.

Table 8. Impact of DC Flex on Costs to DHS and Benefits to Participants During the First Year.

Year 1 results	Total cost per household per year	Total benefit per household per year
Complier Outcome (n = 102)	\$9,558	\$8,521
Counterfactual Complier Outcome	\$9,038	\$6,383
CACE coefficient (SE)	\$529 (\$2,419)	\$2,239 (\$1,370)
Treatment Group Outcome (n = 229)	\$9,989	\$6,493
Control Group Outcome	\$9,755	\$5,500
ITT coefficient (SE)	\$234 (\$1,073)	\$993 (\$620)
RI *p*-value	0.668	0.167

SE = standard error. RI = Randomization Inference.

the F-test for joint significance of the coefficients in the model), the probability of uptake, $\hat{p}$, has good support (ranging from 0 to 0.8) and the predicted probability of uptake has an impact on treatment effects (Figure 2, bottom graph). We use a likelihood-ratio to test for different model specifications and compared a quadratic and cubic model to the linear-only nested model, finding that the cubic polynomial model fits significantly better than the model containing only the linear term ($\chi^2 = 16.06$, $p = 0.003$), meaning that the relationship between the probability of uptake and the treatment effect on costs is non-linear:

$$C_i = \alpha + \gamma_0 T_i + \gamma_1 \widehat{p_i} T_i + \gamma_2 \widehat{p_i}^2 T_i + \gamma_3 \widehat{p_i}^3 T_i + \beta_1 \widehat{p_i} + \beta_2 \widehat{p_i}^2 + \beta_3 \widehat{p_i}^3 + \epsilon_i \tag{5}$$

Where T_i represents treatment assignment and $\widehat{p_i}$ the estimated probability of uptake based on observed characteristics. The estimated treatment effect on cost to DHS is:

$$\begin{aligned} C_i(\widehat{p_i}) &= E[C_i | T_i = 1, \widehat{p_i}] - E[C_i | T_i = 0, \widehat{p_i}] \\ &= \gamma_0 + \gamma_1 \widehat{p_i} + \gamma_2 \widehat{p_i}^2 + \gamma_3 \widehat{p_i}^3. \end{aligned} \tag{6}$$

Appendix A7 shows the results of the first and second stage of the heterogeneity model. Figure 2 shows that the probability of uptake was lowest when participants had existing housing assistance and among individuals with high costs to the agency. While on average the ITT estimate shows that the program costs \$234 dollars more per person per year, for the representative participant, the program is actually cost saving. This is because heterogeneity and selective uptake reveal variation in net costs of the program—there is a set of households for whom participation provides a cost-savings to DHS. When the probability of uptake is 0.45 (in Equation 6), the marginal impact of DC Flex is savings equal to $305 to DHS in a year. For probabilities of uptake between 0.31 and 0.52, DC Flex is cost saving to the agency. As the probability of program uptake increases above 0.52, DC Flex costs the agency more because participants with higher probabilities of program uptake previously received little or no assistance. These individuals had relatively lower financial burdens (e.g., with higher self-reported annual incomes, lower number of dependents, or more likely to be employed) and therefore were less likely to be enrolled in or access other DHS housing services. For them, DC Flex represented an entirely new benefit (and cost to DHS). Interestingly, when $\widehat{p_i}$ is less than 0.31, DC Flex might *also be more* costly to DHS (though this effect is not statistically significant). Participants with a low probability of uptake typically have higher costs to DHS. If they enroll in DC Flex, DHS incurs the costs of DC Flex and the costs of additional allowable support beyond what DC Flex provides. In Table 4, we see that some treatment compliers still access other housing support programs. These experiences represent additional costs to DHS, likely because the monetary and case management support offered by DC Flex is not enough to help families with acute needs. These families would likely have been better served by a deeper subsidy and case management services. It is important to note that the interaction terms in Equation 5 are not jointly significant in the case of total annual costs (see Appendix A8.2 for additional details). This means that heterogeneity or selective uptake does not appear to play a moderation role with treatment assignment in determining costs to DHS. The lack of power is also the result of overdispersion in costs, as we show in Appendix A8.

Figure 3 shows the non-parametric LOWESS curves between uptake and participants' characteristics at baseline. While on the surface, the LOWESS plots tell a seemingly straightforward story—that those with lower financial pressures (i.e., with higher self-reported annual incomes, lower number of dependents, and more likely to be employed) are more likely to take up DC Flex, in reality, it is worth emphasizing that uptake is both supply-driven (in terms of the availability of other programs) and demand-driven. For example, the availability and generosity of other programs will create unique trade-offs for participants—those employed are better able to pay for market-rate housing and, therefore, less likely to be receiving a subsidy than those who are not. For them, DC Flex has few, if any, down sides. Similarly, for families with more children or higher rent, $7,200 buys less in a year since DC Flex is not scaled by family size.

Results from the perspective of participants in terms of net benefits from DC Flex are available in Appendix A8.3. Figure 4 shows that low uptake reduces the enrollment benefit in DC Flex to participants based on the

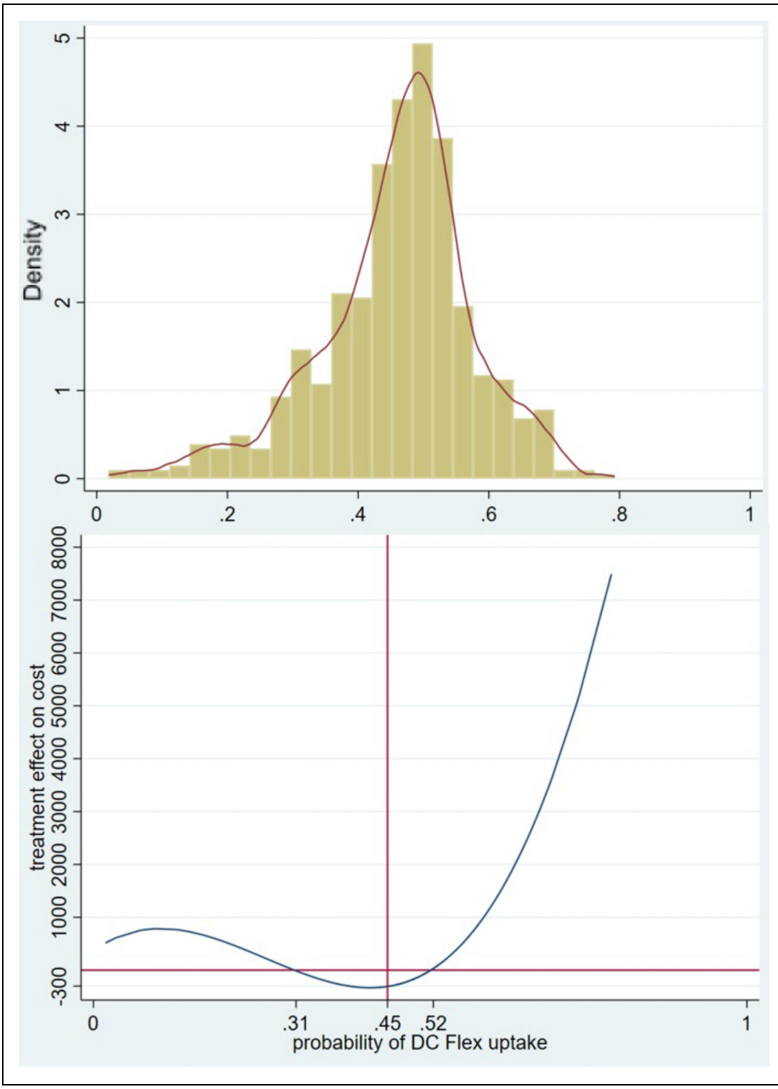

Figure 2. Probability of DC flex take-up and treatment effects on cost to DHS.

subset of programs for which we have data. On the contrary, for people who would have relatively lower financial burdens, DC Flex represents a net benefit as no trade-offs are being made for other programs. On average, in the first year, those assigned to treatment receive \$962 per family more than controls. For the representative participant, when $E(\widehat{p_i}) = .45$, the

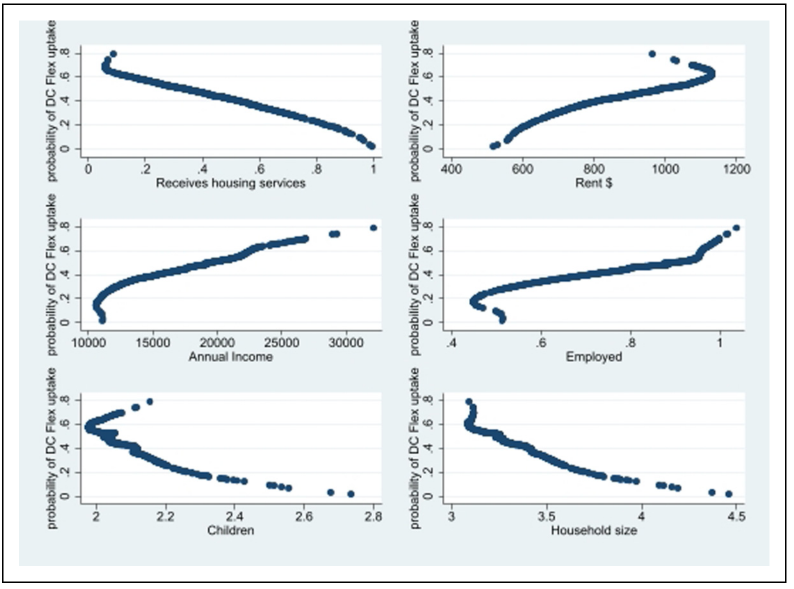

Figure 3. Determinants of DC flex uptake.

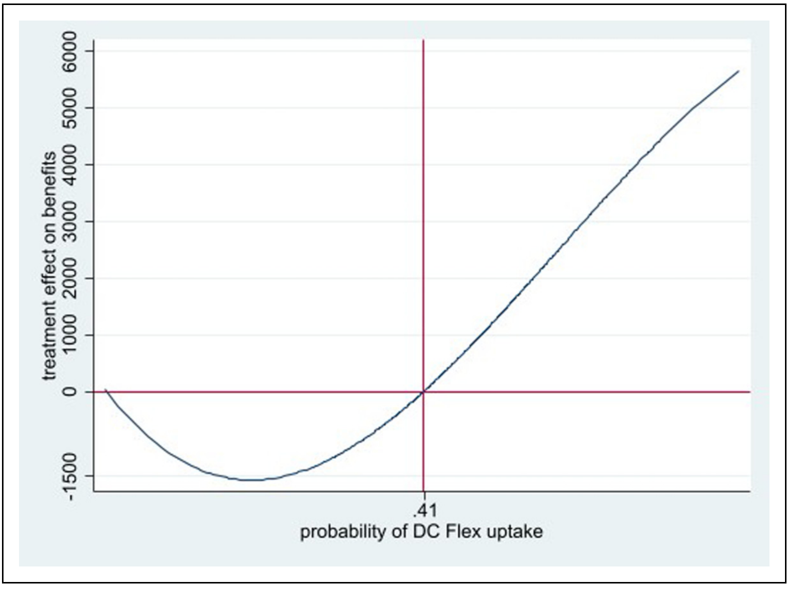

Figure 4. Treatment effects on benefits received by participants.

marginal impact of DC Flex generates a net benefit of $608. Individuals with a probability of uptake less than 0.41 receive less net benefits from enrolling into DC Flex than those in usual care. This decrease in benefits results from the amount of forgone aid from other programs exceeding the amount participants gain from the program. Unlike with costs to DHS, the coefficients on interaction terms between treatment assignment and probability of uptake are statistically significant at the 10 percent level, as shown in Appendix A7.3. Therefore, when looking at the benefits to participants, we find some evidence ($p = 0.1$) that participants with lower needs (and higher probability of uptake) gain more net rental benefits from the program than participants with higher needs (and lower probability of uptake). The effect of DC Flex on the dollar amount of benefits received is different at different values of $\widehat{p_i}$.

Discussion

The study finds statistically insignificant results on the impact of a shallow, flexible rent subsidy on homelessness, ERAP utilization, and TANF utilization in the first program year, but statistically significant reductions in the utilization of services in the homelessness Continuum of Care. These findings show two things: (1) There is evidence of no harm from the subsidy given that applicants are at almost an identical—but low—risk of homelessness after one year compared to business-as-usual. (2) The program represents an attractive and viable choice for some households relative to other mainstream programs, given that there is a 28.6 percentage point decrease in utilization of other housing-related services. This reduction is primarily driven by participants leaving Rapid Re-Housing for DC Flex or never entering Rapid Re-Housing during the period of observation. DC Flex participants cannot receive funds while also receiving assistance from other housing assistance programs. If DC Flex participants opt-out or are terminated from the program, all assistance programs remain available to them if they are eligible.

While we find low levels of homelessness among participants, the definition of homelessness used is based on administrative records and accounts for experiences of families who seek homeless services from the DC Government. This definition of homelessness does not capture a broader definition of housing instability, including needing to temporarily stay with family or friends or in other improvised doubled-up living arrangements.

In a high-cost city like Washington, DC, programs that provide cash assistance to low-income families, like TANF and ERAP, are essential. On average, the self-reported incomes for participants in this study were at 15 percent of the area median income for a family of four. Therefore, $7,200 a year might not be enough to support housing and other essential daily needs such as healthcare, food, and childcare. Although not statistically significant, participants have lower utilization of emergency cash assistance through ERAP (5.3 percentage points lower utilization). This reduction is economically relevant (equivalent to $197 per household per month). We also see a reduction, albeit smaller, in TANF benefits ($17 per household per month).

Since DC Flex shows no increased risk of homelessness and appears to be a viable alternative to other housing supports, cost will likely be a determining factor for jurisdictions considering similar subsidies. For example, the evidence supporting Rapid Re-Housing as a national model is not that it is more effective than the alternatives, but that it achieves similar results at a lower cost allowing jurisdictions to stretch scarce resources further (Gubits et al. 2016). In contrast, permanent subsidies like HCV, have been shown to reduce the proportion of families living in shelters and on the streets by three quarters (from 13 percent to 3 percent). The trade-off is that many more families could benefit from housing vouchers than jurisdictions have the resources to serve.

We examine cost from the perspective of the government and benefit from that of the participant, who, when faced with the offer of enrolling in an optional rent subsidy program, likely considers the dollar amount of rental assistance provided by that program compared to other housing services they receive or anticipate receiving in the future. For the District, we find that DC Flex costs $234-$529 more annually per participant, which is less than the programs' sticker price of $7,200, because it serves as an alternative to other existing housing subsidies. For a typical participant, it therefore also represents a lower benefit in expectation. For participants with higher predicted probabilities of enrollment and relatively lower financial pressures—e.g., higher earned income, employed, or with smaller families—DC Flex represents a substantial increase in benefits, and costs to DHS, because these families were, in most cases, not receiving housing assistance from DHS. Attracting applicants with lower needs may also be beneficial if the investment yields greater housing stability in the long run. The inverse scenario does not appear to be true. For participants with lower predicted probabilities of enrolling in DC Flex and higher financial pressures—e.g., less likely to be employed, lower earned income, and larger families—DC Flex provides a lower overall benefit and *higher* costs to DHS because participants often receive both the subsidy and additional services because the shallow subsidy is insufficient for their housing needs.

Uptake of the program was relatively low (45 percent), given that the program provides a completely new benefit to many and a longer-term benefit to those enrolled in time-limited programs, like RRH, indicating that the decision to enroll in the program is complex, reflecting personal preferences and incomplete information on the part of families. Consider the following examples: If a participant received no existing housing subsidies or was nearing their exit from Rapid Re-Housing when offered the subsidy, participating in this program represents a clear net benefit to them. If, however, someone is enrolled in Rapid Re-Housing, and does not anticipate exiting soon (i.e., if a participant has more than 4.2 months remaining), the $7,200 annual benefit of DC Flex may represent a net monetary loss since the average monthly rent benefit of Rapid Re-Housing is $1,713 ($20,556 annually). The calculus for participants receiving Rapid Re-Housing becomes more complicated over a longer time horizon because DC Flex is available for four years, as long as the participant remains eligible, while Rapid Re-Housing typically ends after 12–18 months. In the most extreme scenario, a participant offered DC Flex in their first month of receiving Rapid Re-Housing is deciding between two similar aggregate benefit amounts: $29,121 for a possible 17 subsequent months of Rapid Re-Housing versus $28,000 of DC Flex over four years if they remain eligible. Both expected benefits contain uncertainty. They may be exited from Rapid Re-Housing by DHS at 12 months rather than 18 months, or they may become ineligible for DC Flex any time before their fourth year. Moreover, they may not have sufficient income to cover their rent for the current year, so even if they prefer a benefit over four years, it may not be financially viable to accept it.

Policymakers will face similar trade-offs when considering adopting shallow, flexible subsidies. When they compare this new model to business-as-usual housing services, they may see a similarly effective program at preventing homelessness and one that appears to draw people away from more costly services, like Rapid Re-Housing. They may also see a program that, based on cost estimates, is insufficient for many eligible participants but yet represents a higher net benefit for others, at least in the short run. In particular, for families with a higher probability of program uptake (those with lower relative needs, empirically), the additional support from the subsidy may represent an upfront investment that will insulate families against future housing and financial shocks to come or it might mean excess funds that could be spent on other deserving families. Those that reject the subsidy or exit the program may still have access to other housing services, but in contexts where homeless services are far scarcer, these trade-offs are likely to have even more dramatic repercussions.

Over future years and with more data, we are likely to get clearer answers to these questions. If the risk of homelessness remains similar, then the relative costs of DC Flex compared to the other homelessness prevention and rental support services will become vital to understanding its usefulness as a model. There is also a lot more that future research can learn about shallow subsidies, such as (1) Why uptake is not higher (this will require tracking eligibility over time and reasons for opting out when eligibility is not a constraint)? (2)

What options do families find preferable for their housing situation (e.g., a short, deeper subsidy like Rapid Re-Housing or a longer, shallow subsidy like DC Flex), even if access to services is based on risk assessments and professional judgments? Are there some applications that are more onerous than others in terms of paperwork and administrative burden? (3) Do people move to better neighborhoods and housing? (4) Does money deposited directly into the recipients' accounts improve the power dynamic with landlords, especially as landlords are potentially unaware that tenants are program recipients? (5) Are there downstream labor market effects of shallow subsidies like this? (6) DC is a "right to shelter" jurisdiction, meaning that it will provide shelter for any individual or family in need and has made substantial investments to combat homelessness and housing instability; would the effects of a rent subsidy be different in less generous jurisdictions?

We show here that it would cost the agency less than the subsidy's sticker price to serve families at the margin. At the same time, the net benefit families receive because of the subsidy is equivalent to a cash transfer with a much lower monetary value than the one advertised by the program. Shallow subsidies appear to be a good use of resources if individuals retain the flexibility of choosing among housing options.

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Supplemental material

Supplemental material for this article is available online.

Notes

1. This registration occurred on January 3, 2020, prior to connecting treatment assignment to outcome data, and is available at https://osf.io/e3c2z/. Details of deviations and additions to the pre-registered analyses are available in Appendix A1.
2. The Mahalanobis distance is a commonly used metric describing how similar two observations are across multiple dimensions, while also taking into account how correlated the dimensions are with one another.
3. We block on days elapsed since application at time of the lottery, applicant's ZIP code, age of the head of the household, household size, number of dependent minors, annual income, an indicator variable denoting prior use of rental assistance services, rent amount, and whether the applicant splits rent with another adult.
4. Interquartile range (IQR): $650; $1186.
5. There is no scientific consensus on what standardized difference thresholds indicate good balance—some researchers believe that a value higher than 0.1 demonstrates a meaningful difference (Austin, 2009), while other researchers have proposed that only a standardized difference of 0.25 or more is cause for concern (Imbens & Rubin, 2015).
6. This take-up rate of 45 percent (ie., 102/229) is based on compliers who also had a full year of treatment and includes in the denominator the 23 households who were determined to be ineligible at the verification stage. While this rate is appropriate for calculating the CACE, different definitions and, therefore, rates of take-up could be used to understand the program operationally. For example, the full-participation rate among those selected is about 46 percent: (102 + 27)/(229 + 51); the full-participation rate among those selected and eligible is about 50 percent: (102 + 27)/(229 + 51–23). These calculations come from the 102 participants who were selected, eligible, and had a year of participation; the 51 participants who were selected, but did not complete a year of participation at the time the outcome data collection ended; the 27 out of those 51 who enrolled and therefore complied, the 229 participants who were assigned to the treatment arm and could have completed a year of participation at the time the outcome data collection ended; and, the 23 participants who were selected but ineligible.

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