Housing Policy Debate

ISSN: 1051-1482 (Print) 2152-050X (Online) Journal homepage: http://www.tandfonline.com/loi/rhpd20

The Impact of Homeless Prevention on Residential Instability: Evidence From the Homelessness Prevention and Rapid Re-Housing Program

Gabriel Piña & Maureen Pirog

HOUSING POLICY DEBATE
https://doi.org/10.1080/10511482.2018.1532448

The Impact of Homeless Prevention on Residential Instability: Evidence From the Homelessness Prevention and Rapid Re-Housing Program

Gabriel Piña and Maureen Pirog

School of Public and Environmental Affairs, Indiana University, Bloomington, USA

ABSTRACT
Millions of individuals and families in the United States do not have access to stable housing. Recent policies in the United States and the rest of the developed world emphasize programs intended to prevent homelessness through temporary financial assistance. This article explores the impact of the largest homelessness prevention program in U.S. history, the Homelessness Prevention and Rapid Re-housing Program (HPRP), on residential instability, using a national sample of families with children enrolled in school. The identification strategy exploits variations on the location of HPRP providers. Using data on the ratio of K–12 students experiencing homelessness in school districts, we find that HPRP is associated with reductions in the percentage of homeless students for districts closer to an HPRP provider. However, the impacts of HPRP fade out when program benefits end, bringing into question whether homeless prevention can help families achieve self-sufficiency in the long run.

ARTICLE HISTORY
Received 7 March 2018
Accepted 2 October 2018

KEYWORDS
Homeless prevention; rapid rehousing; homelessness; residential instability

Millions of individuals and families in the United States do not have access to stable housing. This includes approximately 1.5 million people who experience homelessness (U.S. Department of Housing and Urban Development, 2015), and around 7 million people in poor households who are doubled up with family and friends—the most common situation before becoming homeless (National Alliance to End Homelessness, 2016). Although the number of people experiencing homelessness in a given year has decreased by 6% since 2007, U.S. families still struggle to meet their basic needs. More than 1.3 million students enrolled in public schools are homeless or doubled up for financial reasons, an increase of 3.5% in the last 3 years (National Center for Homeless Education, 2016). This situation is not unique to the United States; in recent years almost every country in Europe has seen a significant increase in the number of homeless as well as in the cost of housing (Serme-Morin & Coupechoux, 2018).

As rising numbers of low-income families struggle to pay rent and make ends meet, there has been a recent redirection in homelessness assistance policies worldwide (Culhane, Metraux, & Byrne, 2011). Homeless assistance policies in the U.S. and other countries have shifted from providing housing services to those who are already homeless (through emergency shelters or transitional housing) toward an emphasis on programs intended to prevent homelessness among households at imminent risk of housing loss. Prevention programs vary from universally available solutions, such as affordable housing, to programs targeted to those facing longer term homelessness problems and needs, such as Housing First (Culhane et al., 2011; Mackie, 2015). In the middle of this spectrum are programs, commonly called secondary prevention programs, that seek

CONTACT Gabriel Piña gpinabla@indiana.edu

to identify and end an episode of homelessness very quickly. These programs' services include emergency rental assistance, family or tenant/landlord mediation, and moving individuals to a transitional place as quickly as possible (Apicello, 2010; Berg, 2013; Culhane et al., 2011).

One important example of homelessness prevention is the U.S. Department of Housing and Urban Development (HUD)'s Homelessness Prevention and Rapid Re-housing Program (HPRP), the largest allocation of federal funds in the United States to prevent long-term homelessness to date (U.S. Department of Housing and Urban Development, 2011). The program allocated $1.5 billion between 2009 and 2012 with the goal of reducing the negative social and health outcomes associated with homelessness, mainly by providing short-term financial resources to individuals and families at risk of homelessness and to those who were recently homeless. Some of the lessons learned through this program have been incorporated into the redesigned Emergency Solutions Grants (ESG) program, the Continuum of Care grants (CoC), and state and local efforts to prevent homelessness (U.S. Department of Housing and Urban Development, 2016).

Despite the influence of HPRP on national policies, the empirical evidence of housing outcomes from HPRP and other prevention and rehousing programs is limited. This study contributes to the scarce literature on the impact of secondary homeless prevention programs by being the first to evaluate the impact of HPRP on residential instability outcomes. If doubling up with other families is generally a precondition to homelessness, we can expect that families will reduce or, at the very least, delay their entry to shelters as they are provided with temporary financial assistance. This study also contributes to this literature by providing an externally valid test of homeless prevention programs by using a national sample, as previous studies have focused on New York and Chicago, Illinois, which have their unique contexts and programs.

Our research question is: Did HPRP reduce or prevent an increase in residential instability for school-age children and their families in communities where the program was implemented? We exploit variations on the location of HPRP providers using data on the ratio of K–12 students experiencing homelessness in school districts, and we find that HPRP is associated with reductions in the percentage of homeless students in districts closer to an HPRP provider.

Prior Research on Homeless Prevention Programs

Historically, policies oriented to homeless individuals and families worldwide have focused on providing housing services to those who are already homeless through emergency shelters or transitional housing, but in more recent years, the policy focus has moved away from treating those who are already homeless toward homelessness prevention initiatives (Apicello, 2010; Berg, 2013; Busch-Geertsema et al., 2008; Culhane et al., 2011; Mackie, 2015). Almost every country in the developed world has implemented programs that focus on preventing homelessness (Mackie, 2015), as have other, developing countries (Ross & Pelletiere, 2014). Today, in Europe and Australia prevention is a central part of national strategies to address homelessness (Gaetz & Dej, 2017). Across Europe there is widespread use of prevention services such as emergency rent, security deposits, moving assistance, mortgage and utility assistance, tenant/landlord mediation, education, and job training (Mackie, 2015; Szeintuch, 2017). However, despite the increased importance of these policies, homeless programs in Europe and the United States have still not been reoriented toward homelessness prevention, with most spending still focused on temporary accommodation such as shelters (MacKie, Thomas, & Bibbings, 2017).

There is some consensus around a three-level categorization of homelessness prevention: primary, secondary, and tertiary (Culhane et al., 2011; Mackie, 2015; Parsell & Marston, 2013; Shinn, Baumohl, & Hopper, 2001). Primary prevention tries to prevent new entrants into homelessness with universally available programs such as affordable housing. Secondary programs, such as rapid rehousing or emergency rent, seek to identify and end an episode of homelessness very quickly. Tertiary programs, such as Housing First, target long-term homelessness or housing problems, aiming to reduce the impacts of longer term housing needs (Culhane et al., 2011; Mackie, 2015). Long-term commitment to homelessness prevention has been evident in the United Kindom, Germany, and Finland, where primary prevention is approached as expanded access to housing and a serious response to family homelessness (Fitzpatrick, Johnsen, & Watts, 2012; Szeintuch, 2017).

In her review of the homelessness prevention literature, Apicello (2010) argues that homelessness prevention policies are still in their infancy and there is little scientific knowledge to guide their implementation. Although some early evidence suggested potential benefits of homeless prevention programs in England and Germany (Busch-Geertsema & Fitzpatrick, 2008; Pleace & Culhane, 2016), most improvement occurred before the dramatic declines in homelessness between 2003 and 2007, making it hard to test whether these policies can really prevent homelessness (Shinn & Greer, 2011). Basic questions about the effectiveness of shelters and homeless prevention programs remain unanswered (Ellen & O'Flaherty, 2010). Despite the recognized shift in policy in the United States toward homelessness prevention, few methodologically rigorous evaluations of homelessness prevention programs have been conducted (Byrne, Treglia, Culhane, Kuhn, & Kane, 2016; Evans, Sullivan, & Wallskog, 2016).

Current support for U.S. prevention policies comes from evaluations of New York City's Homebase, a New York Department of Homeless Services program that included a wide variety of services beyond short-term financial assistance, such as landlord mediation, legal assistance, short-term mental health and substance abuse services, childcare, and job search assistance (Goodman, Messeri, & O'Flaherty, 2016). Studies evaluating Homebase have found evidence that the intervention prevented 5–11% of participating households from entering into shelters (Goodman et al., 2016; Locke, Gan, Fiore, Unlu, & Rolston, 2011; Messeri, O'Flaherty, & Goodman, 2011). Similarly, Evans, Sullivan, and Walskog (2016) exploited the volatile nature of funding availability for rent assistance in Chicago, finding that individuals requesting assistance when funding is available are 76% less likely to enter into a homeless shelter. Another relatively large-scale study of homelessness prevention programs comes from Byrne et al. (2016) who study the Supportive Services for Veteran Families program. These authors found that the majority of veterans who received assistance were able to avoid homelessness even after the assistance ceased.

To date, the Family Options Study is the largest experimental study of housing interventions of varying intensity for families with children in the United States, including rental assistance and rapid rehousing, usual care (shelters), and permanent housing subsidies (Gubits et al., 2016). The study followed families in 12 urban communities who were already living in shelters, finding that 3 years after being randomly assigned to an intervention, families receiving rental assistance showed no difference in subsequent housing stability when compared with families receiving traditional care (shelters). Instead of focusing on programs like Homebase or Chicago's rental assistance program, the Family Options Study focused on long-term outcomes measured after rental assistance and rapid rehousing programs were not available anymore for families, because of their temporary nature. Second, all treated and control families were already in shelters at the time of the intervention.

In contrast, we conduct a study with both national-level data and data from 26 states, covering a broad array of communities, cities, and rural areas. Second, we focus largely on families with children in school and who are at risk of becoming homeless, as they comprise the larger share of our sample. This latter contribution is important given the shift at the federal level toward homelessness prevention through programs such as the CoC. The majority of the families receiving HPRP assistance were not homeless (U.S. Department of Housing and Urban Development, 2016), and so we provide a test of the impact of short-term financial assistance on actually preventing homelessness during the time of the intervention. Finally, the emphasis is on residential instability and not just homelessness, as families that end up in shelters are just a subset of the homeless and a smaller subset of families experiencing residential instability.

The Homeless Prevention and Rapid Re-Housing Program

In 2009, the U.S. Congress included $1.5 billion in the American Recovery and Reinvestment Act (ARRA) for HPRP for 535 grantees across the nation, the first ever large-scale homelessness prevention program in U.S. history. A large goal of HPRP was homelessness prevention by targeting individuals who were not necessarily homeless or living in a shelter, but at risk of becoming homeless. HPRP established four types of assistance: financial assistance (such as rental assistance, paying security deposits, paying utilities, legal assistance, housing search rental assistance, and assistance with moving costs), housing relocation and stabilization services (such as case management, outreach, legal services, and housing search), data collection and evaluation, and administrative costs (capped at 5% of the grants). Almost 80% of the funds were directed toward financial assistance (U.S. Department of Housing and Urban Development, 2016).

The funds under this program were intended to target two populations facing housing instability: (a) individuals and families who were in housing but at risk of becoming homeless and needed temporary assistance to maintain housing (homeless prevention); and (b) individuals and families who were experiencing recent homelessness (rapid rehousing). With HPRP, communities had some flexibility to design their own prevention assistance packages, including limiting the duration of financial assistance, setting the share of rent to be paid and maximum expenditure levels, and making financial assistance contingent on progress toward goals (Cunningham & Burt, 2015). HUD established several eligibility requirements while granting some flexibility in the use of the funds. The income maximum for program participant eligibility was set at 50% of the area median income (higher than the Emergency Shelter Grant), "to reach a wider net of individuals and families—still considered 'very low-income' by HUD's standards—who were affected by the economic downturn, about to become homeless, and needed urgent, short- or medium-term help" (U.S. Department of Housing and Urban Development, 2016). At the same time, HUD communicated that funds should be aimed at those most likely to actually become homeless without assistance. The HPRP Notice of Funds Availability outlined an approach to eligibility determination that came to be known as the *but for* test. Providers were encouraged to ask: would a program participant be homeless but for the HPRP assistance? As a consequence, the majority of the individuals served were individuals at risk of becoming homeless (75%), rather than actual homeless (25%), and most of them were families with children (73%; U.S. Department of Housing and Urban Development, 2016).

HPRP shifted the U.S. policy focus from short- to long-term solutions, including permanent supportive housing, rapid rehousing, and homelessness prevention services (Culhane et al., 2011; Priester et al., 2016). HPRP helped communities build homelessness prevention capacity and fostered partnerships among providers of homeless services and other agencies (Cunningham & Burt, 2015). For example, the Emergency Shelter Grant was renamed the Emergency Solutions Grant, and eligible services included more prevention and rehousing activities. Previously, only up to 30% of the allocated funds could be used on homelessness prevention (Culhane et al., 2011), and they were rarely used for this activity (Cunningham & Burt, 2015). Similarly, lessons from HPRP continue to inform the implementation of the CoC programs (U.S. Department of Housing and Urban Development, 2016). After the HPRP funds were exhausted, most of the communities involved in this program declared their desire to continue homelessness prevention activities, usually through local efforts and with help from HUD's ESGs (Cunningham & Burt, 2015). Given its size and the influence that HPRP had in changing homelessness policies in the United States, it is surprising that little empirical research has examined housing outcomes associated with this program (for an exception see Brown, Vaclavik, Watson, & Wilka, 2017).

Our identification strategy relies on the fact that the funds had to be subgranted to local organizations using the Community Development Block Grant (CDBG) formula. HPRP used a variation of the CDBG allocation formula, which bases funding largely on community population and does not necessarily respond to community need (Collinson, 2014). This formula ranks cities, urban counties, and states according to five variables: population, population under the poverty line, number of rooms occupied by one or more individuals, population growth, and number of housing units built before 1940 (for details see Joice, Winter, & Johnson, 2011). HUD then selected a threshold of minimum amount funded to determine the number of communities that will receive resources. As a consequence of this allocation process, larger communities received funds directly, whereas smaller communities did not receive any funding directly from HUD. Moreover, HUD set aside 42% of the funds to go directly to the states, so that the states could allocate the funds to other communities not receiving funds directly from HUD. However, the states redirected a large share of the funds to communities already entitled to receive funds directly from HUD; 41% of entitled communities received additional HPRP funds from their states.

As the states directed funds largely to entitled communities and places with nonprofit organizations with the capacity to implement the program, many communities ended up far away from an HPRP provider. Previous research shows that the spatial accessibility of service providers is an important determinant of service utilization among welfare recipients (Allard, Tolman, & Rosen, 2003) and that low-income families face limitations of public transportation systems and low car ownership rates (Herbst & Tekin, 2016). Spatial accessibility is especially relevant for housing policies and programs that are usually implemented by local nonprofit organizations (Russell, Moulton, & Greenbaum, 2014).

As a result, some families lived very close to an organization administering the funds, whereas other equally eligible individuals and families did not. Provided they lived within a jurisdiction where HPRP was administered, families living far from the agency administering the program would have to travel to request the funds and start the application process and screening. Others may not have even heard about this program; a qualitative study by HUD (U.S. Department of Housing and Urban Development, 2016) shows that in many cases, media outreach was not accessible to the target population, potential program participants were not aware of the program, and even supporting agencies and staff were unaware of HPRP and did not refer potential program participants.[1]

Homelessness and Residential Instability

One of the main reasons for the lack of evidence of homeless prevention program success is that the homeless population is typically not included in the sampling for large national surveys, and administrative data from Homeless Management Information Systems (HMIS) are difficult to acquire and restrict the analysis to one jurisdiction (e.g., a county's HMIS). This is why some researchers studying services for the homeless have focused instead on families in shelters, as these families are more easily found and counted. However, families that end up in shelters are a subset of the homeless and a smaller subset of families experiencing residential instability. Further, the very focus of HPRP and other homeless prevention programs is intervention before families are in shelters or in the streets. For these reasons, we choose to examine the impact of HPRP on residential instability.

Although there is no common definition for the concept of residential instability (Cotton & Schwartz-Barcott, 2016; Priester, Foster, & Shaw, 2016), most authors would agree that housing instability is at least an antecedent to homelessness (Cunningham, Harwood, & Hall, 2010; Priester et al., 2016). Previous research has recognized different forms of housing instability, such as moving frequently, foreclosure, doubling up, episodic homelessness, or moving because of housing costs (Gilman, Kawachi, Fitzmaurice, & Buka, 2003; Priester et al., 2016).

The definition of homeless used today by HUD overlaps with residential instability. Historically, different agencies within the U.S. federal government have defined homelessness differently. Whereas in the past HUD's definition of homeless did not include doubled-up families, other federal agencies such as the Department of Education (ED) and the Department of Health and Human Services have included doubled-up families in the definition of homeless. In 2011, HUD expanded the definition of homeless by including "families with children or unaccompanied youth who are defined as homeless by other federal laws and who have moved constantly in the last 60 days."[2] In other words, since 2011, if a child and their family are doubled up in another household, and this has been acknowledged by the local education agency, then this family would fit HUD's definition of homeless. However, HUD's point-in-time estimates of homelessness only include people in shelters and places not meant for human habitation.

Overall, research shows that residential instability is a disruptive experience for children and families. Unpredictable and undesired moves from one's home (e.g., foreclosures and evictions) negatively influence the family support system and children's development and well-being (Buckner, 2008; Grant, Gracy, Goldsmith, Shapiro, & Redlener, 2013). Children experiencing residential instability show lower vocabulary skills, more behavioral problems, increased high school dropout rates, and lower adult educational attainment compared with children living in stable households (Sandstrom & Huerta, 2013). Additional negative impacts can occur during economic downturns as child poverty increases significantly, particularly for lower income families (Hanratty, 2016, 2017). Homelessness can be considered a severe form of residential instability, disproportionately occurring among young children from low-income families (Fantuzzo, LeBoeuf, Chen, Rouse, & Culhane, 2012).

Methods

Data Sources

We estimate the impact of HPRP on the proportion of students experiencing homelessness as defined by ED at the district school level. We favor these data over HUD's point-in-time counts not only because our main interest is to measure residential instability, but also because HUD data are available mostly for large cities and urban counties where all HPRP grantees receive funds allocated based on a population-driven formula. Using the point-in-time counts would force us to leave out most of the variation in HPRP implementation, as explained in the upcoming Empirical Strategy section.

School districts collect homeless information during each school year and report it to the states. The ED's definition of homelessness includes individuals who are living in emergency or transitional shelters, or in cars, parks, public spaces, or abandoned buildings, or in other places not ordinarily used as a regular sleeping accommodation for human beings (Cunningham et al., 2010). However, the ED definition also includes children living in households that are temporarily doubled up because of hardship or loss of housing, and children who are temporarily living in motels or hotels. Unfortunately, these counts do not capture school-age children and youth who experience homelessness during the summer only, those who dropped out of school, or young children who are not enrolled (National Center for Homelessness Education, 2016).

We requested information on homeless student counts from all states, receiving responses from 38 of them. Some states that answered the request explained that they did not store data about the number of homeless students before 2009, the year HPRP started. To retain the pre and post variation, we only use states that started reporting homeless student counts before HPRP started. The final sample comprises 26 states and 6,679 school districts. Table 1 shows the responses we received from each state. Only six states sent the information disaggregated by housing situation

Table 1. States' responses to requests for information.

States that sent the information	Arizona, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Idaho, Indiana, Iowa, Kansas, Louisiana, Maryland, Massachusetts, Minnesota, Missouri, Nevada, New Mexico, New York, Ohio, Oregon, Utah, Virginia, West Virginia, Washington, Wisconsin*
States that did not respond or did not send the information	Alabama, Alaska, Delaware, Maine, Montana, Nebraska, North Carolina, Rhode Island, South Carolina, Wyoming, New Jersey, Oklahoma, South Dakota
States that did not have data for years before HPRP	Hawaii, Illinois, Kentucky, Michigan, New Hampshire, Pennsylvania, Tennessee, Texas, Vermont
States that denied the request	Mississippi, North Dakota

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program.
*All states were included in the models except for Georgia.

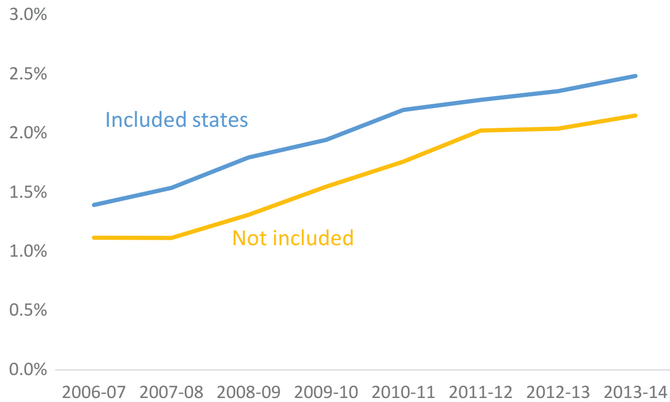

Figure 1. Homeless students per 100 students in states with and without data available for the period. School years 2006–2007 to 2013–2014.
Federal Data Summary Years 2006–2007 to 2013–2014. National Center for Homeless Education. 2017.

(doubled up, in motel/hotel, in shelter, and unsheltered), so we use the aggregated total number of students considered homeless. From the disaggregated data for these six states, we can see that most students were doubled up (69%), 21% were living in shelters, 8% were living temporarily in a hotel or motel, and 2% were unsheltered. This is consistent with previous data collected at the state level (Cunningham et al., 2010). Using homeless student count data from the National Center for Homeless Education at the state level, we can see that the states included in our sample represent an important share of the homeless student population, accounting for approximately 850,000 homeless students, or 67% of the homeless student population. Moreover, these 26 states include some states with relatively higher incidences of homelessness, but their trend is not different from that of states with no data available at the school district level (see Figure 1).

Dependent Variable

We computed the number of homeless students per 100 students in district. To calculate this ratio, we divided the homeless student counts (provided by the states) by the number of students in each district (provided by the National Center for Education Statistics [NCES] for each school year). These data sets do not measure the same populations. NCES removes duplicate students, only counting a student in the district where s/he spent most of the academic school year. The total number of homeless students includes duplicates. For example, if a student moved to a shelter and then moved to a doubled-up household, s/he would be counted twice. Measures of residential instability include moving frequently, so the ratio captures the concept of being unstable. However, this ratio should not be considered an exact percentage.

Empirical Strategy

The proposed model on the district-level proportion of homeless students is:

$$Y_{it} = \beta_1 HPRP_{it} + \beta_2 C_{it} + \propto_i + \vartheta_t + \varepsilon_{dt} \tag{1}$$

for district *i* and school year *t*. Data availability for the number of homeless students constrains the sample to school years 2005–2006 to 2013–2014. Y_{it} is the outcome of interest: the number of homeless students per 100 students in district *i*. The model includes district fixed effects (α_i) and school year fixed effects (ϑ_t). The inclusion of fixed effects for each district rules out the possibility that the estimated effects of the HPRP are the result of other activities or investments that differ systematically across districts in time-invariant ways that are correlated with HPRP investments. Time-fixed effects at the year level control for the overall secular change in homelessness rates, as well as macroeconomic outcomes influencing Y. C_{it} is a vector of time-variant district-level controls that could affect the outcome.

$HPRP_{it}$ is the main policy variable of interest. It is an indicator variable equaling 1 if HPRP funds were available in district *i*, during the school year HPRP was available (school years 2009–2010 to 2011–12).[3] HUD required that 60% of funds had to be expended within 2 years of the date HUD signed the grant agreement, and 100% had to be expended within 3 years of the agreement date, or unused funds would be returned to the Treasury (U.S. Department of Housing and Urban Development, 2016). We cannot distinguish how much the community spent on homeless prevention or rapid rehousing, but most of the assistance was directed to homeless prevention (75%; U.S. Department of Housing and Urban Development, 2016). To measure whether a district received funds, we define an HPRP district, or *treated*, in three different ways: if the district is in a county where an organization administered HPRP funds, if the district is within 10 miles of an HPRP organization, or if the district is within 20 miles of an HPRP provider. We do this for several reasons. First, this provides a more flexible approach, as school districts do not necessarily overlap perfectly with counties or cities. Second, as states had to make their funds available through all their territory, citizens in any community within the state were entitled to apply for assistance from the closest HPRP provider.

We measure $HPRP_{it}$ using data on HPRP provider organizations' geographical locations and expenditures, originally published on the recovery.gov website. We first measure $HPRP_{it}$ considering whether district *i* is in a county where an organization with funding is providing HPRP services, in which case $HPRP_{it}$ takes the value of 1 in a particular school district *i*. We also measure $HPRP_{it}$ as a dummy taking a value of 1 if the school district address is within 10 miles of the closest HPRP organization in the state. Similarly, in a third model we also measure $HPRP_{it}$ as 1 if the school district is within 20 miles of an HPRP organization having funds for a given year. District location information is provided by NCES based on the address where the local education agency is located. We matched homeless student data with school district information from NCES.

All models include county and district characteristics as control variables. Following previous research on the impact of economic conditions on homelessness (Hanratty, 2017), we include the unemployment level in the county where the district is located, the percentage of minority (nonwhite) students in the district, the percentage of students who are in the reduced price and free lunch program (as a measure of school district poverty), a ratio of the cost of renting a two-bedroom apartment relative to the median income in the county as a measure of rental housing costs, and the percentage of rental units that are vacant. Some variables such as unemployment level and rental housing costs do not match the school year perfectly, since they are measured for calendar years. We use these variables for the first half of the school year (e.g., for school year 2008–2009 we use the unemployment rate of calendar year 2008).[4]

We also control for spending on other programs that might be correlated with the allocation of HPRP funds.[5] Since HPRP allocation follows a similar structure to CDBG, we include a dummy controlling for CDBG projects that were finalized in each school district zip code and school year. Similarly, we control for programs that expanded during some of the years of HPRP and that could influence residential mobility. One of these programs is the Neighborhood Stabilization Program (NSP). NSP provided \$2 billion in assistance for the redevelopment of abandoned and foreclosed homes and residential properties to return these properties to productive use. We include a measure of the NSP per-capita expenditures in the county. Similarly, in 2008 ARRA provided \$5 billion for the Temporary Assistance for Needy Families (TANF) Emergency Fund. This fund was used by some states to provide utilities assistance, housing assistance, job support and readiness, and other services. We include a dummy variable for states using the TANF emergency funds for utilities assistance, housing assistance, and emergency assistance.

Main Results

Implicit in our identification strategy is the assumption that the introduction of HPRP in a particular district-year is uncorrelated with other district-year determinants of outcomes. One valid concern about the identification strategy in Equation (1) is that there might have been shocks to outcomes in districts close to HPRP providers but not in comparison districts, which could create bias. For example, one might be concerned that communities experiencing higher increases in homelessness rates were more likely to receive funds while also experiencing weak economic conditions, and might have expanded or created other social programs that could provide low-income individuals with additional sources of income, which would cause upward bias in estimates of the effect of HPRP.

Table 2 compares school district information on several variables in the year before HPRP started. Each column compares districts with an HPRP provider with a comparison group, districts within 10 miles of an HPRP provider with a comparison group, and districts within 20 miles of a provider with a comparison group. As a consequence of the CDBG formula and states' reliance on large nonprofit organizations, school districts close to an HPRP provider are larger and more urban. The unemployment, poverty, and homeless student rates are higher for districts in counties with an HPRP provider, but the difference vanishes as the treated group is defined as districts within 10 miles and 20 miles of a provider. Moreover, the identifying assumption of a two-way fixed-effect model does not concern equal means, but parallel trends. The key assumption is that the trends for districts with and without access to the program would be the same if HPRP never existed. This can only be tested in the period before HPRP starts. As Table 2 shows, the average change in homeless per 100 students in districts near an HPRP provider and in the comparison districts was almost the same before HPRP started.

To formally assess the validity of the parallel trend assumption, we estimate regressions that interact the treatment group indicator with year indicator variables for all years before school year 2008–2009, which was the year HPRP began. The models are the same as model 1 but limited to the pretreatment period and a complete set of interactions between the indicators of treatment status and indicators of years (see Table 3). The results show that none of the coefficients in any of the models is significant, suggesting that preimplementation trends in districts with HPRP and all other districts did not differ significantly, which lends credibility to the identification strategy.

Given the importance of school district location, we excluded some observations from the analysis. School districts that are charter schools are excluded. Charter schools usually do not require students to live within school district boundaries and this could generate substantial error in several of the location-based measures. Additionally, the state of Georgia is excluded because we could not obtain exact location data for its HPRP providers. Unlike any other state, Georgia allocated the funds to one unique organization (The Salvation Army of Georgia). This organization distributed the funds among several of its geographical units, and this information was not reported. Hence, for the final models we use 5,136 school districts and 26,400 observations.

Table 4 shows the descriptive statistics for the sample of school districts. The ratio of homeless students is obviously low, with an average of 2.2 homeless students per 100 students per district. The variable *HPRP in the county* shows the percentage of districts in a county having an HPRP provider for the school years when the program operated (this variable takes a value of 0 for all school years before September 2009 and after September 2012). Approximately 54% of all school districts had an organization working in the same county at some point in time, so around half of the sample can be considered treated.

Table 5 presents the results from three models. All models include year fixed effects, fixed effects at the district level, and robust standard errors clustered at the district level to account for heteroscedasticity and serial correlation. The first model in column 1 includes a variable measuring whether there is an HPRP provider in the district's county. The second and third models, in columns 2 and 3, respectively, include a dummy taking a value of 1 if the school district is located within 10 and 20 miles from an HPRP provider.

Table 2. Descriptive statistics for districts with and without the Homelessness Prevention and Rapid Re-housing Program in 2008.

	HPRP in the county	Comparison group	*t*-test	HPRP within 10 miles	Comparison group	*t*-test	HPRP within 20 miles	Comparison group	*t*-test
Homeless per 100 students	2.118	1.746	0.37*** (0.12)	2.033	1.904	0.13 (0.12)	1.902	2.052	− 0.15 (0.13)
Change in homeless per 100 students	0.366	0.307	0.06 (0.07)	0.410	0.293	0.12* (0.07)	0.383	0.262	0.12* (0.07)
Unemployment rate	6.220	5.990	0.23*** (0.06)	5.952	6.232	− 0.28*** (0.06)	6.042	6.257	− 0.21*** (0.07)
Relative rent costs	15.32	13.94	1.38*** (0.12)	15.65	14.09	1.56*** (0.13)	15.04	14.14	0.90*** (0.11)
Nonwhite students (%)	33.92	15.08	18.84*** (0.87)	38.03	17.40	20.63*** (0.98)	30.30	17.46	12.84*** (0.91)
Students with free lunch (%)	32.02	33.97	− 1.94*** (0.68)	33.01	32.79	0.21 (0.72)	31.22	35.85	− 4.63*** (0.70)
Renter share (%)	32.67	26.93	5.74*** (0.29)	33.52	27.91	5.62*** (0.32)	31.77	27.29	4.48*** (0.29)
Vacancy rate (%)	6.598	7.886	− 1.29*** (0.13)	6.580	7.550	− 0.97*** (0.12)	6.772	7.853	− 1.08*** (0.15)
Students in the district	9,235.0	2899.7	6335.36*** (602.95)	12,103.7	2688.3	9415.38*** (807.85)	8,962.0	2031.3	6930.68*** (531.38)
No. school districts in each group	1,710	2,226		2,465	1,511		1,505	2,457	

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program. Control variables include Community Development Block Grant project, unemployment rate, relative rent costs, nonwhite students (%), students with free lunch (%), renter share (%), and vacancy rate (%). Clustered standard errors are given in parentheses.

*$p < .1$. **$p < .05$. ***$p < .01$.

Table 3. Test result for pre-Homelessness Prevention and Rapid Re-housing Program parallel trends. Dependent variable: homeless students per 100 students in a school district. School years 2005–2006 to 2008–2009.

Variables	(1) HPRP in the county	(2) HPRP within 10 miles	(3) HPRP within 20 miles
HPRP*2006–2007	0.2035	0.1383	0.0767
	(0.1336)	(0.1335)	(0.1677)
HPRP*2007–2008	0.2018	0.1173	0.0015
	(0.1370)	(0.1409)	(0.1759)
HPRP*2008–2009	0.0032	0.1150	− 0.0344
	(0.1628)	(0.1509)	(0.1879)
School district fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
No. observations	6,740	6,740	6,740
R^2	0.0338	0.0312	0.0314
No. school districts	3,615	3,615	3,615

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program.

Table 4. Descriptive statistics. School years 2005–2006 to 2012–2013.

Variables	(1) *N*	(2) Mean	(3) *SD*	(4) Min.	(5) Max.
Homeless per 100 students	28,692	2.226	3.533	0	68.39
HPRP in the county	28,692	0.237	0.425	0	1
HPRP within 10 miles	28,692	0.157	0.364	0	1
HPRP within 20 miles	28,692	0.257	0.437	0	1
CDBG project	28,692	0.0719	0.258	0	1
Neighborhood stabilization program ($ per capita)	28,692	3.196	9.796	0	250.3
Emergency TANF state	28,692	0.0811	0.273	0	1
Unemployment rate	28,687	7.777	2.878	1.900	28.90
Relative rent costs	28,692	15.95	4.363	7.132	58.01
Nonwhite students (%)	28,596	24.70	26.95	0	100
Students with free lunch (%)	27,489	35.82	19.78	0	100
Renter share (%)	28,691	30.36	8.937	6.186	80.89
Vacancy rate (%)	27,473	6.927	3.534	0	66.96
Distance (miles)	28,654	21.94	27.81	0.000214	324.2
Students in the district	28,692	5,952	17,892	1	687,534
No. school districts	5,136	5,136	5,136	5,136	5,136

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program. CDBG = Community Development Block Grant. TANF = Temporary Assistance for Needy Families.

Results show a small but significant difference in districts more likely to receive HPRP funds, and the coefficients are similar across models. By providing prevention services to families, HPRP may have avoided homelessness or doubling-up episodes for 10 students and their families per school district. Having HPRP in the county or closer to the school district reduces the rate of homeless students by 0.13 percentage points. This may look like a relatively small number, but it is due to the lower value of the dependent variable. On average, in the pre-HPRP period, 1.6 per 100 students were identified as homeless, so a 0.13 percentage points reduction is equivalent to an 8% decrease in the rate of homeless students. This is equivalent to an average of 10 students per district who did not end up in a shelter or living with another family during the recession.[6] Moreover, the approach identifies the lower bound *intent to treat*. The comparison is between groups that are more and less likely to receive help from HPRP organizations (because of their locations); we can only expect that the percentage of families with children in school receiving some services from HPRP would be higher for those living closer to an HPRP organization.

Other control variables are worth mentioning. The unemployment rate has a positive impact on the homelessness rate, as expected. A 1% increase in the unemployment rate in the county where the

Table 5. Homelessness Prevention and Rapid Re-housing Program impact on student homelessness. Dependent variable: homeless students per 100 students. School years 2005–2006 to 2012–2013.

Variables	(1) HPRP in the county	(2) HPRP within 10 miles	(3) HPRP within 20 miles
HPRP	− 0.1342***	− 0.0897**	− 0.0995**
	(0.0447)	(0.0451)	(0.0475)
CDBG project	− 0.0057	− 0.0068	− 0.0052
	(0.0613)	(0.0613)	(0.0612)
Neighborhood stabilization program	0.0039	0.0037	0.0036
	(0.0024)	(0.0024)	(0.0024)
Emergency TANF state	0.1804***	0.1774***	0.1781***
	(0.0581)	(0.0579)	(0.0578)
Unemployment rate	0.0741***	0.0731***	0.0739***
	(0.0187)	(0.0187)	(0.0187)
Relative rent costs	0.0494***	0.0498***	0.0497***
	(0.0130)	(0.0130)	(0.0130)
Nonwhite students (%)	0.0023	0.0023	0.0023
	(0.0082)	(0.0082)	(0.0082)
Students with free lunch (%)	0.0178***	0.0179***	0.0180***
	(0.0043)	(0.0043)	(0.0043)
Renter share (%)	0.0158	0.0155	0.0154
	(0.0157)	(0.0157)	(0.0157)
Vacancy rate (%)	− 0.0132	− 0.0134	− 0.0135
	(0.0108)	(0.0108)	(0.0108)
Constant	− 0.8751	− 0.8793	− 0.8799
	(0.6125)	(0.6123)	(0.6114)
School district fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Mean dependent variable pre-HPRP	1.6	1.6	1.6
No. observations	26,400	26,400	26,400
R^2	0.0717	0.0715	0.0715
No. school districts	5,136	5,136	5,136

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program. CDBG = Community Development Block Grant. TANF = Temporary Assistance for Needy Families. Clustered robust standard errors are given in parentheses.
*$p < .1$. **$p < .05$. ***$p < .01$.

district is located increases the homelessness rate by 0.07 percentage points, equivalent to a 4.3% increase. Poverty has a similar effect: an increase of 1% in the number of students receiving free or reduced-price lunches is associated with an increase of 1.7 percentage points in the homelessness rate. Finally, the relative cost of rent is also associated with increases in homelessness rates.

Robustness Checks

Whether identifying students or adults, methods for counting homeless individuals are not without limitations. Changes in counting methods and reporting errors are commonly reported by researchers and government officials (Hanratty, 2017; U.S. Department of Housing and Urban Development, 2015). For school districts, homeless liaisons work with other school personnel, community, and state agencies to ensure students who lack fixed, regular, and adequate nighttime residence are identified and receive education and services. However, recent increases in the number of homeless students might be due to improved reporting methodology, and an increasing number of districts counting homeless students. We interviewed states' staff in charge of gathering these data from school districts, and they told us that whereas the recent trend may be explained by improved counting, it may also be explained by actual increases in numbers of homeless students. There is good reason to believe that at least some of the increase reflects real

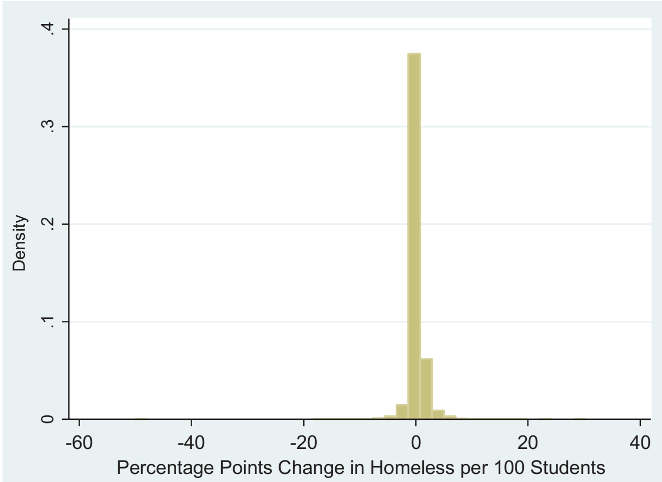

Figure 2. Distribution of percentage-point change in homeless students per 100 students.

growth in this population; in school year 2009–2010 an estimated 87% of school districts were counting homeless students (Child Trends, 2015).

To correct for large changes in homeless counts caused by changes in counting methodology or reporting errors, we run the same models but exclude school districts that had a year-to-year increase or decrease of more than 10 percentage points. As Figure 2 shows, the majority of the changes are concentrated within this range, so we exclude outliers that could potentially drive the results. Table 6 shows that excluding school districts having large annual changes in homelessness produces very little change in the estimated impacts of HPRP.

Similarly, previous studies used population weights to estimate models of the impacts of community characteristics and homeless programs on homeless rates to address measurement concerns (Corinth, 2017; Hanratty, 2017). Researchers have argued that the use of population weights would give more weight to observations with more precise estimates of homelessness. Also, because there are more homeless people in large communities, population-weighted models would be more likely to reflect the experience of an average homeless person. Table 7 shows the results of the same models but using the number of students in each district as a weight. Results do not change significantly; the coefficients remain significant in all models and are fairly similar in model 1, and even larger for models 2 and 3. For instance, model 3 shows that HPRP can reduce the homeless rate by up to 12%.

Finally, we expect that the effects of HPRP on student homelessness rates would dissipate as the distance increases. We expect that the previous results would dissipate as the treated and comparison groups are equally likely to receive (or not) services from HPRP. We estimate the same models but measure HPRP as those school districts at 30, 40, and 50 miles from an HPRP provider (see Table 8). When we measure HPRP with 30 miles the coefficient gets closer to zero, and is no longer significant. Moreover, using 40 and 50 miles shows a coefficient almost equal to zero, and no longer significant. As the majority of the treated and comparison groups are unlikely to receive HPRP, we see no effect. These findings lend credibility to the identification strategy.

Table 6. Homelessness Prevention and Rapid Re-housing Program impact on student homelessness excluding school districts with changes over +10 and − 10 percentage points. Dependent variable: homeless students per 100 students. School years 2005–2006 to 2012–2013.

Variables	(1) HPRP in the county	(2) HPRP within 10 miles	(3) HPRP within 20 miles
HPRP	− 0.1400***	− 0.0755**	− 0.1339***
	(0.0361)	(0.0374)	(0.0391)
CDBG project	0.0142	0.0135	0.0142
	(0.0514)	(0.0514)	(0.0514)
Neighborhood stabilization program	0.0040*	0.0037	0.0037
	(0.0023)	(0.0024)	(0.0023)
Emergency TANF state	0.1407***	0.1374***	0.1387***
	(0.0451)	(0.0451)	(0.0451)
Unemployment rate	0.0631***	0.0623***	0.0631***
	(0.0152)	(0.0152)	(0.0152)
Relative rent costs	0.0425***	0.0428***	0.0430***
	(0.0116)	(0.0116)	(0.0116)
Nonwhite students (%)	− 0.0001	− 0.0000	− 0.0001
	(0.0073)	(0.0073)	(0.0073)
Students with free lunch (%)	0.0183***	0.0184***	0.0184***
	(0.0030)	(0.0030)	(0.0030)
Renter share (%)	0.0253**	0.0249*	0.0250*
	(0.0129)	(0.0129)	(0.0128)
Vacancy rate (%)	− 0.0096	− 0.0099	− 0.0098
	(0.0093)	(0.0093)	(0.0093)
Constant	− 1.0513**	− 1.0519**	− 1.0594**
	(0.4695)	(0.4700)	(0.4699)
School district fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Mean dependent variable pre-HPRP	1.5	1.5	1.5
No. observations	26,041	26,041	26,041
R^2	0.1028	0.1023	0.1027
No. school districts	5,090	5,090	5,090

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program. CDBG = Community Development Block Grant. TANF = Temporary Assistance for Needy Families. Clustered robust standard errors are given in parentheses.
$*p < .1$. $**p < .05$. $***p < .01$.

Exploring Long-Term Impacts of Preventative Assistance

A remaining question pertains to the difference between our results and those of Gubits et al. (2016), who found no effect of short-term financial assistance programs on different outcomes. In the Family Options Study, families in shelters were randomly assigned to different housing interventions, including short-term financial assistance after entering into a shelter. These families were tracked for 3 years and were extensively interviewed at baseline, 20 months after random assignment, and again at 37 months after random assignment to assess outcomes related to housing stability, family preservation, adult well-being, child well-being, and self-sufficiency. As a consequence, the Family Options Study collected information about outcomes months and years after the longest possible short-term financial assistance had already ended, so the effects of the program may have faded away. We test to what extent districts receiving HPRP show lower homelessness rates in the year after HPRP ends. If HPRP is able to stabilize families so they can have a more permanent location to live, then we would expect to see a significant difference in the homelessness rate in districts receiving HPRP services versus those that did not receive services in the year after the program ends, when compared with the years before HPRP existed. We test this hypothesis by estimating the same models but adding a dummy for the year post HPRP (2012–2013). Table 9 shows that districts that had HPRP do not show a significantly different homelessness rate than those without access to this program in the year following the end of HPRP (the coefficient of the variable HPRP*2012–2013 is not significantly different from zero). The coefficients

Table 7. Homelessness Prevention and Rapid Re-housing Program impact on student homelessness weighted by total number of students. Dependent variable: homeless students per 100 students. School years 2005–2006 to 2012–2013.

Variables	(1) HPRP in the county	(2) HPRP within 10 miles	(3) HPRP within 20 miles
HPRP	− 0.1378**	− 0.1180**	− 0.1980**
	(0.0598)	(0.0581)	(0.0812)
CDBG project	0.0828	0.0832	0.0844
	(0.0848)	(0.0847)	(0.0848)
Neighborhood stabilization program	0.0032	0.0031	0.0031
	(0.0020)	(0.0020)	(0.0019)
Emergency TANF state	0.1509**	0.1456**	0.1479**
	(0.0738)	(0.0734)	(0.0736)
Unemployment rate	0.0882***	0.0857***	0.0863***
	(0.0241)	(0.0241)	(0.0241)
Relative rent costs	0.0472*	0.0474*	0.0475*
	(0.0265)	(0.0266)	(0.0266)
Nonwhite students (%)	− 0.0182	− 0.0184	− 0.0184
	(0.0127)	(0.0128)	(0.0127)
Students with free lunch (%)	0.0129**	0.0129**	0.0128**
	(0.0054)	(0.0054)	(0.0054)
Renter share (%)	0.0399	0.0410	0.0405
	(0.0263)	(0.0264)	(0.0263)
Vacancy rate (%)	− 0.0001	0.0004	− 0.0001
	(0.0167)	(0.0168)	(0.0167)
Constant	− 0.6689	− 0.6979	− 0.6811
	(1.1998)	(1.2049)	(1.2016)
School district fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Mean dependent variable pre-HPRP	1.7	1.7	1.7
No. observations	26,346	26,346	26,346
R^2	0.1483	0.1483	0.1485
No. school districts	5,110	5,110	5,110

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program. Clustered robust standard errors are given in parentheses.
$^*p < .1$. $^{**}p < .05$. $^{***}p < .01$.

are closer to zero and not significant in each of the models. This may explain the difference between the Family Options Study and previous studies that found that homeless assistance programs can work. Homeless prevention programs can prevent homelessness during the time of the intervention, but the programs might not be able to move a family from a precarious situation to a more stable one.

Exploring Impacts in Districts With Many Families Renting

Finally, since the majority of HPRP focused on helping individuals and families to pay rent, paying utilities bills, mediating with landlords, and providing other services oriented exclusively to help renters, we expect a stronger effect when limiting the analysis to districts with a large number of families renting properties. Table 10 shows the same models for school districts, but this time restricted to districts in counties with more than 30% of households renting (this is approximately the average percentage of households renting in the sample). The results remain similar, but the size of the coefficient is almost two times the size of models with the entire sample. This is explained in part by the higher rate of homeless students in this subsample (1.98%). However, the effect is equivalent to a 12% reduction in the number of homeless students and families. In other words, when limiting the sample to districts with a high percentage of renters and close proximity to an HPRP provider, an average of 13 students did not end up in a shelter or living with another family during the recession. These findings give more confidence about the main results.

Table 8. Homelessness Prevention and Rapid Re-housing Program (HPRP) models increasing the distance to HPRP location. Dependent variable: homeless students per 100 students. School years 2005–2006 to 2012–2013.

Variables	(1) HPRP within 30 miles	(2) HPRP within 40 miles	(3) HPRP within 50 miles
HPRP	− 0.0698	0.0052	− 0.0135
	(0.0592)	(0.0737)	(0.0822)
CDBG project	− 0.0049	− 0.0037	− 0.0039
	(0.0613)	(0.0613)	(0.0613)
Neighborhood stabilization program	0.0035	0.0033	0.0034
	(0.0024)	(0.0024)	(0.0024)
Emergency TANF state	0.1770***	0.1766***	0.1766***
	(0.0579)	(0.0579)	(0.0579)
Unemployment rate	0.0744***	0.0735***	0.0738***
	(0.0186)	(0.0185)	(0.0187)
Relative rent costs	0.0495***	0.0493***	0.0493***
	(0.0130)	(0.0129)	(0.0130)
Nonwhite students (%)	0.0023	0.0024	0.0024
	(0.0082)	(0.0082)	(0.0082)
Students with free lunch (%)	0.0180***	0.0180***	0.0180***
	(0.0043)	(0.0043)	(0.0043)
Renter share (%)	0.0153	0.0151	0.0151
	(0.0157)	(0.0157)	(0.0157)
Vacancy rate (%)	− 0.0134	− 0.0136	− 0.0136
	(0.0108)	(0.0108)	(0.0108)
Constant	− 0.8782	− 0.8625	− 0.8660
	(0.6104)	(0.6101)	(0.6130)
School district fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Mean dependent variable pre-HPRP	1.6	1.6	1.6
No. observations	26,400	26,400	26,400
R^2	0.0714	0.0713	0.0713
No. school districts	5,136	5,136	5,136

Note. HPRP = Homeless Prevention and Rapid-Rehousing Program. CDBG = Community Development Block Grant. TANF = Temporary Assistance for Needy Families. Clustered robust standard errors are given in parentheses.
**p* < .1. ***p* < .05. ****p* < .01.

Conclusions and Policy Implications

Short-term financial assistance programs are the cheapest policy interventions for preventing homelessness, when compared with vouchers, transitional housing, and shelters (Gubits et al., 2016). Today, a large number of countries have implemented programs that focus on preventing homelessness, as homelessness prevention can provide a cost-effective option to reduce the negative impacts of residential instability, even if only temporarily. Studies have only recently begun to examine the potential impacts of secondary prevention programs as a means of preventing homelessness and residential instability. HPRP was the largest homelessness prevention program in U.S. history and it exerted substantial influence on current national policies regarding housing and homelessness. Despite its size and influence, empirical evidence regarding the efficacy of this program is exceptionally limited. With this study, we begin to fill this gap and contribute to the scarce international literature studying homeless prevention programs.

We find a significant decrease in the probability of being homeless in school districts that were more likely to have received HPRP funds. Having HPRP in the county, or closer to the school district where families with children in school live, on average reduces the number of homeless students by 8–12%. This is equivalent to 8–13 children and their families in an average school district who were prevented from moving away from their homes and ending up in shelters, temporarily doubling up, moving to motels, or even having to stay on the street.

This study contributes to the international literature on homeless prevention by being the first to evaluate the impact of secondary prevention programs on residential instability outcomes, as

Table 9. Homelessness Prevention and Rapid Re-housing Program impact on student homelessness including a postprogram dummy. Dependent variable: homeless students per 100 students. School years 2005–2006 to 2012–2013.

Variables	(1) HPRP in the county	(2) HPRP within 10 miles	(3) HPRP within 20 miles
HPRP	− 0.1401***	− 0.0927*	− 0.1132**
	(0.0488)	(0.0481)	(0.0522)
HPRP*2012–2013	− 0.0224	− 0.0102	− 0.0466
	(0.0606)	(0.0609)	(0.0631)
CDBG project	− 0.0058	− 0.0068	− 0.0053
	(0.0613)	(0.0613)	(0.0612)
Neighborhood stabilization program	0.0040*	0.0038	0.0037
	(0.0024)	(0.0024)	(0.0024)
Emergency TANF state	0.1800***	0.1774***	0.1781***
	(0.0583)	(0.0579)	(0.0578)
Unemployment rate	0.0743***	0.0731***	0.0738***
	(0.0187)	(0.0187)	(0.0187)
Relative rent costs	0.0492***	0.0497***	0.0495***
	(0.0130)	(0.0130)	(0.0130)
Nonwhite students (%)	0.0023	0.0023	0.0023
	(0.0082)	(0.0082)	(0.0082)
Students with free lunch (%)	0.0178***	0.0179***	0.0180***
	(0.0043)	(0.0043)	(0.0043)
Renter share (%)	0.0160	0.0156	0.0158
	(0.0157)	(0.0157)	(0.0157)
Vacancy rate (%)	− 0.0131	− 0.0134	− 0.0134
	(0.0108)	(0.0108)	(0.0108)
Constant	− 0.8802	− 0.8807	− 0.8850
	(0.6124)	(0.6127)	(0.6119)
School district fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Mean dependent variable pre-HPRP	1.6	1.6	1.6
No. observations	26,400	26,400	26,400
R^2	0.0717	0.0715	0.0715
No. school districts	5,136	5,136	5,136

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program. CDBG = Community Development Block Grant. TANF = Temporary Assistance for Needy Families. Clustered robust standard errors are given in parentheses.
**p* < .1. ***p* < .05. ****p* < .01.

the evidence supporting the effectiveness of these programs is extremely limited. If doubling up with other families is generally a precondition to homelessness, then by providing temporary financial assistance we can expect that families will reduce or, at the very least, delay their entry into shelters. Additionally, this study contributes to this literature by providing an externally valid test of homeless prevention programs in the United States. Previous studies have focused on New York and Chicago, which have their unique contexts and programs. As we mentioned, New York's Homebase was innovative in providing services beyond homeless prevention by agencies that were experienced providers of case management and comprehensive social welfare services. Despite these differences, the results are consistent with the Goodman et al. (2016) study in terms of impact sizes.

A remaining question pertains to the different results found by us as well as Goodman et al. (2016), compared with the Gubits et al. (2016) study, which found no effect of rapid rehousing programs on different outcomes. As we show in our results, districts that had HPRP do not show a significantly different homelessness rate than those without access to this program in the year following the end of HPRP. Since the Family Options Study collected information about outcomes months and years after the longest possible short-term financial assistance had already ended, the effects of the program may have faded away. Second, and perhaps more importantly, this study mostly measures residential instability for families with children in school who were not necessarily homeless (about 75% of those served by HPRP), whereas Gubits et al. (2016) followed families who were already in shelters and received financial assistance (i.e. rapid rehousing). As a consequence,

Table 10. Homelessness Prevention and Rapid Re-housing Program impact on student homelessness in counties with more than 30% of households renting. Dependent variable: homeless students per 100 students. School years 2005–2006 to 2012–2013.

Variables	(1) HPRP in the county	(2) HPRP within 10 miles	(3) HPRP within 20 miles
HPRP	− 0.2105***	− 0.1428*	− 0.2216**
	(0.0813)	(0.0742)	(0.0914)
CDBG project	0.0136	0.0117	0.0131
	(0.0825)	(0.0824)	(0.0824)
Neighborhood Stabilization Program	0.0004	0.0001	0.0002
	(0.0031)	(0.0030)	(0.0030)
Emergency TANF state	0.2827***	0.2824***	0.2814***
	(0.1018)	(0.1018)	(0.1018)
Unemployment rate	0.1001***	0.0950***	0.0980***
	(0.0351)	(0.0350)	(0.0349)
Relative rent costs	0.0542**	0.0551***	0.0556***
	(0.0210)	(0.0211)	(0.0211)
Nonwhite students (%)	− 0.0144	− 0.0144	− 0.0144
	(0.0097)	(0.0097)	(0.0098)
Students with free lunch (%)	0.0197***	0.0197***	0.0196***
	(0.0068)	(0.0068)	(0.0068)
Renter share (%)	− 0.0033	− 0.0032	− 0.0031
	(0.0303)	(0.0303)	(0.0303)
Vacancy rate (%)	− 0.0166	− 0.0171	− 0.0169
	(0.0236)	(0.0236)	(0.0236)
Constant	0.3275	0.3157	0.2923
	(1.2115)	(1.2135)	(1.2101)
School district fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Mean dependent variable pre-HPRP	1.98	1.98	1.98
No. observations	12,400	12,400	12,400
R^2	0.0781	0.0779	0.0782
No. school districts	2,748	2,748	2,748

Note. HPRP = Homelessness Prevention and Rapid Re-housing Program. CDBG = Community Development Block Grant. TANF = Temporary Assistance for Needy Families. Clustered robust standard errors are given in parentheses.
$^*p < .1$. $^{**}p < .05$. $^{***}p < .01$.

when thinking about temporary financial assistance, the Family Options Study provides evidence about the capacity of homeless prevention programs to lift families out of shelters, whereas this study provides evidence about the impact of homeless prevention programs on actually preventing homelessness and residential instability.

This study is not without limitations. In neither of the models can we neatly identify treated and untreated individuals or families. The research design only allows us to say that one child is more likely to have received HPRP than another, by virtue of their location. As such, the treatment and comparison groups should differ in the percentage of individuals receiving HPRP assistance, with the treated districts having a higher percentage of units that are receiving HPRP services. Obtaining precise estimates of the impact of HPRP is not feasible given the structure, outreach, and lack of experimental design of the program. In this context, the estimates of this study can be interpreted as lower bound effects; the actual effects might be larger. However, most policies are evaluated with intent-to-treat effects, including the only randomized study of different housing interventions to date (Gubits et al., 2016), and the few local evaluations of the impact of short-term financial assistance programs.

A second limitation pertains to the measures used in this study. Our measure of homelessness has limitations, as does any other measure of homelessness and residential instability. We may be missing families moving during the summer, as well as families with children not enrolled in school. Consequently, all impacts of HPRP are constrained to families with children in schools and limited to the school year. However, we do not think that our way of measuring homelessness influences the results. Since we are using fixed effects, we would expect bias in the impact of HPRP if the formula (and hence population size) is correlated with the change in measurement error. In other words, for the measurement error to influence the results, larger communities would have to get better (or worse) at measuring homelessness at the same time HPRP was introduced. Additionally, this study does not provide any information about the effectiveness of different types of implementation, such as rapid rehousing and homeless prevention, either about the duration of the financial help, or about decisions regarding what type of organization will implement the program. From this study we can only learn that on average there was a statistically significant difference in residential instability between communities with more access to the funds and others that might not have received as much funding and help during the years of the program. Given that in HPRP homeless prevention was significantly more common as an intervention than was rapid rehousing, we argue that our results provide evidence of the effectiveness of homeless prevention programs, but we cannot distinguish whether rapid rehousing and homeless prevention have distinctive effects.

Despite these limitations, this article provides much-needed information about the effects of homeless prevention policies on residential outcomes. Homelessness continues to persist in countries with varying degrees of assistance from welfare systems, as some groups of people fall through all safety nets (European Commission, 2013). Despite the increased policy priority, housing policies in Europe and the United States are still focused on temporary solutions such as shelters, a more expensive answer to temporary homelessness. This study contributes to the scarce literature on the impact of secondary homeless prevention programs by showing that these programs can be an effective method to reduce temporary residential instability when compared with traditional homeless policies such as shelters. Future research could explore what characteristics of homeless prevention programs (e.g. duration of assistance, rapid rehousing or tenant assistance) drive this effectiveness.

Notes

1. One state HPRP administrator interviewed by the authors explained that the population eligible for HPRP was not the typical population served through housing programs, and hence it was hard to reach them through announcements in shelters or social security administration offices.
2. See U.S. Department of Housing and Urban Development, "Homeless Emergency Assistance and Rapid Transition to Housing: Defining Homeless," RIN 2506–AC26.
3. A continuous measure of the amount of funding may also be relevant. Unfortunately, the quality of the data does not allow us to compute an accurate estimate of the amount of money spent in each community.
4. Results are not sensitive to changing the calendar year used for these two variables.
5. One program allocated using the CDBG formula is the CoC program. Unfortunately, for this program data are aggregated by CoC, which could include many counties or the whole balance of state. Despite this, we do not think we are missing a relevant omitted variable: CoC program expenditures were mostly renewals during HPRP years; about 88% of the expenditures were renewals of previous programs in 2009 according to HUD's grant reporting system. Hence, the county fixed effects should capture most of the influence of these two programs. Similarly, the ESG grant follows a similar formula to that for HPRP, but since it is a formula grant, the allocation barely changed during HPRP years, according to HUD's grant-reporting system.
6. The average school district in the sample has around 6,000 students, with approximately 120 of them being homeless.

Acknowledgments

We appreciate the help from many government officials in helping us to obtain the data from each state. Special thanks to Susan Ziff and Elizabeth Rudd from HUD for providing guidance about the program and sources of data for this study.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Notes on Contributors

Gabriel Piña is a Research Scientist at Child Trends. His research agenda focuses on Social Policy, with an emphasis on impact evaluations of housing policies and early childhood programs. He received a PhD in Public Affairs from Indiana University.

Maureen Pirog is the Rudy Professor of Policy Analysis Emeritus at the School of Public and Environmental Affairs at Indiana University, Bloomington. She was the Editor-in-Chief of the *Journal of Policy Analysis and Management* for ten years. Professor Pirog holds honorary appointments in Russia, South Africa and China and is a fellow of the National Academy of Public Administration. Her research focuses on the effectiveness of social welfare programs for low-income families and households.

References

Allard, S. W., Tolman, R. M., & Rosen, D. (2003). Proximity to service providers and service utilization among welfare recipients: The interaction of place and race. *Journal of Policy Analysis and Management*, *22*(4), 599–613.

Apicello, J. (2010). A paradigm shift in housing and homeless services: Applying the population and high-risk framework to preventing homelessness. *Open Health Services and Policy Journal*, *3*, 41–52.

Berg, S. (2013). The HEARTH Act. *Journal of Policy Development and Research*, *15*, 317–323.

Brown, M., Vaclavik, D., Watson, D. P., & Wilka, E. (2017). Predictors of homeless services re-entry within a sample of adults receiving Homelessness Prevention and Rapid Re-Housing Program (HPRP) assistance. *Psychological Services*, *14*(2), 129.

Buckner, J. C. (2008). Impact of homelessness on children: An analytic review of the literature. In D. Rog, S. Holupka, & C. Patton (Eds.), *Characteristics and dynamics of homeless families with children: Final report*. (pp. A1–A36). Washington, DC: U.S. Department of Health and Human Services, Office of Human Services Policy, Office of the Assistant Secretary for Planning and Evaluation.

Busch-Geertsema, V., & Fitzpatrick, S. (2008). Effective homelessness prevention? Explaining reductions in homelessness in Germany and England. *European Journal of Homelessness*, *2*, 69–95.

Byrne, T., Treglia, D., Culhane, D. P., Kuhn, J., & Kane, V. (2016). Predictors of homelessness among families and single adults after exit from Homelessness Prevention and Rapid Re-housing Programs: Evidence from the department of veterans affairs supportive services for veteran families program. *Housing Policy Debate*, *26*(1), 252–275.

Child Trends. (2015). *Indicators of child and youth well-being*. Retrieved from https://www.childtrends.org/indicators/homeless-children-and-youth/

Collinson, R. A. (2014). Assessing the allocation of CDBG to community development need. *Housing Policy Debate*, *24*(1), 91–118.

Corinth, K. (2017). The impact of permanent supportive housing on homeless populations. *Journal of Housing Economics*, *35*, 69–84.

Cotton, B. P., & Schwartz-Barcott, D. (2016). Residential instability among low-income families: A concept analysis. *Archives of Psychiatric Nursing*, *30*(2), 257–261.

Culhane, D. P., Metraux, S., & Byrne, T. (2011). A prevention-centered approach to homelessness assistance: A paradigm shift? *Housing Policy Debate*, *21*(2), 295–315.

Cunningham, M., & Burt, M. (2015). *Homeless prevention study: Prevention programs funded by the homelessness prevention and rapid re-housing program*. Washington, DC: U.S. Department of Housing and Urban Development Office of Policy Development and Research.

Cunningham, M., Harwood, R., & Hall, S. (2010). *Residential instability and the McKinney-Vento homeless children and education program: What I know, plus gaps in research*. Urban Institute (NJ1). Retrieved from http://eric.ed.gov/?id=ED510555

Ellen, I. G., & O'Flaherty, B. (2010). *How to house the homeless*. New York, NY: Russell Sage Foundation.

European Commission. (2013). *Confronting homelessness in the European Union*. Brussels: Author.

Evans, W. N., Sullivan, J. X., & Wallskog, M. (2016). The impact of homelessness prevention programs on homelessness. *Science*, *353*(6300), 694–699.

Fantuzzo, J. W., LeBoeuf, W. A., Chen, -C.-C., Rouse, H. L., & Culhane, D. P. (2012). The unique and combined effects of homelessness and school mobility on the educational outcomes of young children. *Educational Researcher*, *41*(9), 393–402.

Fitzpatrick, S., Johnsen, S., & Watts, B. (2012). *International homelessness policy review: A report to inform the review of homelessness legislation in Wales*. Retrieved from http://orca.cf.ac.uk/47872/

Gaetz, S., & Dej, E. (2017). *A new direction: A framework for homelessness prevention*. Toronto, ON: Canadian Observatory on Homelessness Press.

Gilman, S. E., Kawachi, I., Fitzmaurice, G. M., & Buka, S. L. (2003). Socio-economic status, family disruption and residential stability in childhood: Relation to onset, recurrence and remission of major depression. *Psychological Medicine*, *33*(8), 1341–1355.

Goodman, S., Messeri, P., & O'Flaherty, B. (2016). Homelessness prevention in New York City: On average, it works. *Journal of Housing Economics*, *31*, 14–34.

Grant, R., Gracy, D., Goldsmith, G., Shapiro, A., & Redlener, I. E. (2013). Twenty-five years of child and family homelessness: where are I now? *American Journal of Public Health*, *103*(S2), e1–e10.

Gubits, D., Shinn, M., Bell, S., Wood, M., Dastrup, S., Solari, C. D., & Abt Associates, Inc. (2016). *Family options study: 3-year impacts of housing and services interventions for homeless families*. Washington, DC: U.S. Department of Housing and Urban Development. Retrieved from http://www.huduser.gov/portal/sites/default/files/pdf/FamilyOptionsStudy_final.pdf

Hanratty, M. (2016). Family shelter entry and re-entry during the recession in Hennepin County: The role of race, residential location, and family earnings. *Housing Policy Debate*, *26*(2), 334–345.

Hanratty, M. (2017). Do local economic conditions affect homelessness? Impact of area housing market factors, unemployment, and poverty on community homeless rates. *Housing Policy Debate*, *27*(4), 640–655.

Herbst, C. M., & Tekin, E. (2016). The impact of child-care subsidies on child development: Evidence from geographic variation in the distance to social service agencies: Impact of child-care subsidies on child development. *Journal of Policy Analysis and Management*, *35*(1), 94–116.

Joice, P. A., Winter, B., & Johnson, H. (2011). *Redistribution effect of introducing 2010 census and 2005–2009 ACS data into the CDBG formula*. Washington, DC: U.S. Department of Housing and Urban Development Office of Policy Development and Research.

Locke, G., Gan, K., Fiore, N., Unlu, F., & Rolston, H. (2011). *Evaluation of the homebase community prevention program: Year one summary report*. Cambridge, MA: Abt Associates Inc.

MacKie, P., Thomas, I., & Bibbings, J. (2017). Homelessness prevention: Reflecting on a year of pioneering Welsh legislation in practice. *European Journal of Homelessness*, *11*(1), 81–107.

Mackie, P. K. (2015). Homelessness prevention and the welsh legal duty: Lessons for international policies. *Housing Studies*, *30*(1), 40–59.

Messeri, P., O'Flaherty, B., & Goodman, S. (2011). *Can homelessness be prevented? Evidence from New York City's homebase program*. Retrieved from http://homelesshub.ca/resource/can-homelessness-be-prevented-evidence-new-york-city%E2%80%99s-homebase-program

National Alliance to End Homelessness. (2016). *The state of homelessness in America*. Retrieved from http://www.endhomelessness.org/library/entry/SOH2016

National Center for Homeless Education. (2016). *Federal data summary school years 2012–13 to 2014–15*. Retrieved from https://nche.ed.gov/downloads/data-comp-1213-1415.pdf

Parsell, C., Jones, A., & Head, B. (2013). Policies and programmes to end homelessness in Australia: Learning from international practice: Policies and programmes to end homelessness. *International Journal of Social Welfare*, *22*(2), 186–194.

Pleace, N., & Culhane, D. (2016). *Better than Cure? Testing the case for enhancing prevention of single homelessness in England*. Retrieved from http://eprints.whiterose.ac.uk/106641/

Priester, M. A., Foster, K. A., & Shaw, T. C. (2016). Are discrimination and social capital related to housing instability? *Housing Policy Debate*, *27*(1), 120–136.

Ross, L. M., & Pelletiere, D. (2014). Chile's new rental housing subsidy and its relevance to U.S. housing choice voucher program reform. *Cityscape*, *16*(2), 179–192.

Russell, B. D., Moulton, S., & Greenbaum, R. T. (2014). Take-up of mortgage assistance for distressed homeowners: The role of geographic accessibility. *Journal of Housing Economics*, *24*, 57–74.

Sandstrom, H., & Huerta, S. (2013). *The negative effects of instability on child development: A research synthesis*. Urban Institute. Retrieved from http://www.urban.org/sites/default/files/alfresco/publication-pdfs/412899-The-Negative-Effects-of-Instability-on-Child-Development-A-Research-Synthesis.PDF

Serme-Morin, C., & Coupechoux, S. (2018). *The third overview of housing exclusion in Europe 2018*. Retrieved from https://www.feantsa.org/en/report/2018/03/21/the-second-overview-of-housing-exclusion-in-europe-2017

Shinn, M., Baumohl, J., & Hopper, K. (2001). The prevention of homelessness revisited. *Analyses of Social Issues and Public Policy*, *1*(1), 95–127.

Shinn, M., & Greer, A. L. (2011). The European consensus conference on homelessness—Kudos, and some cautions, to Europe. *European Journal of Homelessness*, *5*(2).

Szeintuch, S. (2017). Homelessness prevention policy: A case study. *Social Policy & Administration*, *51*(7), 1135–1155.

U.S. Department of Housing and Urban Development. (2011). *Homelessness Prevention and Rapid Re-housing Program: Year 1 summary*. Retrieved from http://www.hudexchange.info/resources/documents/HPRP_Year1Summary.pdf

U.S. Department of Housing and Urban Development. (2015). *The 2014 Annual Homeless Assessment Report (AHAR) to congress*. Retrieved from https://www.hudexchange.info/resources/documents/2014-AHAR-Part1.pdf

U.S. Department of Housing and Urban Development. (2016). *Homelessness Prevention and Rapid Re-housing Program: Year 3 summary*. Retrieved from https://www.hudexchange.info/resources/documents/HPRP-Year-3-APR-Analysis.pdf