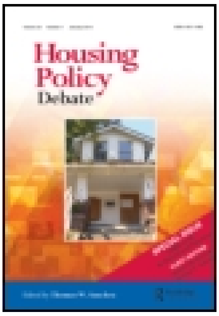


Housing Policy Debate
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/rhpd20

Assessing the Allocation of CDBG to Community Development Need

Robert A. Collinson[a]

[a] U.S. Department of Housing & Urban Development, Office of Policy Development & Research, Washington, DC, USA

Published online: 28 Jan 2014.

Housing Policy Debate, 2014
Vol. 24, No. 1, 91–118, http://dx.doi.org/10.1080/10511482.2013.854945

Assessing the Allocation of CDBG to Community Development Need

Robert A. Collinson*

U.S. Department of Housing & Urban Development, Office of Policy Development & Research, Washington, DC, USA

(*Received May 27, 2013; accepted October 3, 2013*)

This article evaluates how well the current allocation formula for the Community Development Block Grant (CDBG) program allocates funds with respect to community development need. We assemble an index of community development need from a variety of demographic and economic indicators which capture the components of need that can be addressed directly by the CDBG program based on its statutory objectives. We use this index to estimate the relation between funding levels and community development need and how this relation has changed over time. In particular, we assess the effectiveness of targeting by examining the horizontal and vertical equity of the formula. Results suggest that the relation between the formula data inputs and community development need has deteriorated over the past two decades. The present formula is shown to underfund Formula A grantees conditional on need and to overfund a select number of high-income, slow-growth, older communities. Finally, we consider several alternative formula specifications, which we evaluate against the community development needs index.

Keywords: community development block grant; CDBG; community development; HUD; department of housing and urban development

Created through the Housing and Community Development Act of 1974, the Community Development Block Grant (CDBG) program is the largest formula block grant from the U.S. Department of Housing and Urban Development (HUD) to state and local governments. In a typical year, CDBG allocates, via a formula, more than $2 billion to over 1,000 cities and urban counties. This article assess how well the current CDBG formula allocates funds with respect to community development need and how this allocation has changed over time. With real appropriations falling over the past two decades, it is critical that the formula allocate scarce resources effectively and accurately with respect to community development need.

This article makes two contributions. First, it assesses the CDBG allocation formula in three separate decades against a consistently measured community development needs index. Second, it provides an updated picture of the performance of the CDBG formula in allocating to need in 2010 using new 2010 census and American Community Survey five-year estimates. Finally, it proposes possible formula alternatives to enhance the equity of the present formula.

*Corresponding author. Email: collinson.rob@gmail.com

In Section 2, I review relevant literature. Section 3 describes the data used to develop the community development needs index and the formula allocations. Section 4 describes the factor analysis used to distinguish distinct components of community development need. Section 5 describes how a composite community development needs index is created. Section 6 assesses how well the formula has allocated funds with respect to need over time. Sections 7 and 8 describe flaws in the current formula, and alternative formula options, respectively; and Section 9 summarizes the findings.

1. Literature

This study builds on a number of important previous studies on the efficacy and equity of the CDBG formula. Similar to this study, many previous works have been descriptive analyses by HUD researchers familiar with the program. Most recently, Richardson (2005) assessed the effectiveness of CDBG in allocating resources to community development need. Richardson (2005) and an early study by Neary and Richardson (1995) followed the methodological approach of a seminal study by Bunce (1976). Bunce (and subsequent studies: Bunce et al., 1983; Neary & Richardson, 1995; Richardson, 2005) used principal component analysis to reduce a range of socio-economic and demographic characteristics to a manageable set of underlying factors characterizing urban distress. In a follow-up to his initial study, Bunce et al. distilled 18 input variables into three principal component factors (age and decline, poverty, and density), which the authors combined into a single composite needs index designed to capture community development need as described in the statutory objectives of CDBG. Bunce et al. weighted their poverty factor (which included the poverty rate, percentage of female-headed households, unemployment rate, educational attainment, and minority population) most heavily. Richardson found that a single factor absorbed many of the features of the three factors (decline, age, and poverty) identified by Bunce et al. In addition to this poverty/economic distress factor, Richardson identified two new factors: one associated with overcrowding and stresses from immigration and another reflecting poverty concentration in low-density communities. He then used ordinary least-squares (OLS) models to assess the fit between the needs index and the CDBG allocation amounts. He concluded that the formula still allocates to need but has some systemic flaws, including the overfunding of wealthy, slow-growth older suburbs; the chronic underfunding of Formula A grantees relative to comparably needy Formula B grantees; and a relatively flat relation between funding and need for Formula A grantees.

In addition to these HUD studies, a few outside studies have investigated the effectiveness of allocations in directing funds to needy communities. Dommel and Rich (1987) evaluated the effectiveness of allocation targeting with respect to community development need. As in the HUD studies, they constructed an index measure of need. They assembled a simple measure of "urban distress" by combining a community's poverty rate, percentage of housing built before 1940, and change in population between 1970 and 1982, each variable normalized by the mean value. They found this measure to be highly correlated with the analogous measures of community development need given by Bunce et al. (1983). A study by Burchell et al. (1981) reviewed measures of urban distress and concluded that a range of techniques used to measure urban distress produce similar practical rankings. Dommel and Rich (1987) compared changes in funding across need quintiles to assess the change in allocation quality. They found that while the 1980 formula still allocated funds effectively with respect to need, targeting of high-need communities weakened between 1970 and 1980.

I adopt an approach similar to that of previous HUD studies (Bunce et al., 1983; Neary & Richardson, 1995; Richardson, 2005) in conducting principal component analysis to identify latent structures characterizing community development need. I depart from previous works in applying this approach across longitudinal data, which allows for a consistent measurement of community development need across three time periods. Similar to Richardson, I use OLS regression analysis to assess the effectiveness of the CDBG allocation with respect to need.

2. Data

In order to assess the quality of the CDBG formula in addressing community development needs over time, I need a consistent measure of community development need. Community development need is typically thought of as a multivariate concept, incorporating elements such as economic prosperity, quality of infrastructure, caliber of public services, and poverty and deprivation. To account for this multidimensionality, I follow the approach taken in previous HUD studies (Bunce, 1983; Richardson, 2005; Richardson & Neary, 1995) and construct a composite community development needs index. Constructing a consistent measure across three separate periods imposes inevitable data-availability limits due to changing community sizes and variable definitions over time. Still, I construct an index incorporating 14 variables and capturing community development need across more than 900 grantees.

Consistent with previous research assessing the CDBG formula allocation, I use the statutory objectives of the CDBG program (Appendix 1) as a guide in selecting community development variables. The features of CDBG eligibility require that the formula allocate funds to three types of communities:

1. Principal cities in metropolitan areas
2. Counties with more than 200,000 in population after excluding metropolitan cities[1]
3. Other cities above 50,000 in population[2]

Therefore, data must be available for the balance of counties after removing metropolitan cities, as well as small cities which historically contained more than 50,000 in population but have experienced large population declines since the introduction of the program. I combined three sources of data to capture key elements of community development need. These elements are listed in Table 1, along with the corresponding year or source. For each data source, I attempted to assemble data from the years 1990, 2000, and 2010 for the universe of FY2012 grantees. For 2000 census geographies (and data), HUD had already created a digital cross reference of Federal Information Processing Standards (FIPS) codes to CDBG geographies to run formula allocations with the 2000 census data. HUD's internal CDBG-ID (an internal key uniquely identifying grantees) allowed fairly easy mapping of 2000 data to the FY2012 grantee universe. Assembling 1990 data for the FY2012 grantees was slightly more challenging. Using GIS, I assembled a county census summary level 070 which divides the country into units with the following hierarchy: county-subdivision-place/remainder shapefile, which could be cleanly linked to 1990 census data using the summary level-070. I then spatially joined this shapefile to the FY2012 CDBG grantee boundaries to link 1990 FIPS codes to current grantee boundaries. In most instances the desired census tabulation could be created across all three census periods (1990, 2000, 2005/10), but a few variables were interpolated through similar tabulations (details given in Appendix 2). Local crime data were from the FBI's Uniform Crime Report, via HUD's State of the Cities Data System, and Interuniversity Consortium for Political and Social Research (ICPSR)'s county-level crime tabulations. Due to data availability, I used 1992's reported offenses in place of 1990 values. I used Bureau of Labor

Table 1. Needs index variables (1990–2010).

Statutory objective	Measures	Source
Decent housing	Percentage of pre-1960 housing units occupied by a poor renter	Census SF3 1990, 2000, ACS 06/10
	Percent overcrowded	Census SF1 1990, 2000, 2010
Economic opportunity	Employment-to-population ratio	BLS LAUS 1990, 2000, 2010
	Unemployment rate	BLS LAUS 1990, 2000, 2010
	Percentage age 25 or older with a BA or higher	Census SF1 1990, 2000, 2010
	Drop-out rate (age 18–24)	Census SF3 1990, 2000, ACS 06/10
Low- and moderate-income persons	Poverty rate (excluding enrolled college students)	Census SF3 1990, 2000, ACS 06/10
	Percent of households with a single parent	Census SF1 1990, 2000, 2010
	Ratio of Metro Mean Household Income to Municipal Mean Household income	Census SF3 1990, 2000, ACS 06/10
	Percentage in high-poverty census tracts	Census SF3 1990, 2000, ACS 06/10
Suitable living environment	Minority segregation	Census SF1 1990, 2000, 2010
	Poor persons in high-vacancy census tracts	Census SF3 1990, 2000, ACS 06/10
	Violent crime rate	UCR 1992, 2000, 2010
	Murder rate	UCR 1992, 2000, 2010

Note. ACS = American Community Survey. LAUS = Local Area Unemployment Statistics. SF = Summary File. UCR = Uniform Crime Reports.

Statistics Local Area Unemployment Statistics (BLS LAUS) data for local unemployment rates and employment-to-population ratios.

3. Factor Analysis of Community Development Need

Community development need is a multidimensional concept, which makes it difficult to measure objectively. A purely quantitative approach is likely to miss unobservable factors such as strength of local institutions or quality of public services, while a purely qualitative approach will introduce bias from the data collector and is difficult or costly to execute at scale. A mixed-methods approach is probably desirable in measuring community development need but is beyond the scope of this article. This article requires a broad assessment of community development need across hundreds of jurisdictions, so I take an entirely quantitative approach. As in previous studies of the HUD formula (Bunce, 1983; Neary & Richardson, 1995; Richardson, 2005), I used factor analysis to distill a large number of variables into a few uncorrelated factors which capture the latent structure of community development need.[3] The set of k community need variables $X_1, X_2 \ldots X_k$ can be thought of as a linear combination of m factors $F_1, F_2 \ldots F_m$, where $m < k$. Then the ith variable is equivalent to

$$X_i = \alpha_{i1}F_1 + \alpha_{i2}F_2 \ldots \alpha_{\mathrm{im}}F_m + \varepsilon_i$$

where each α_{is} is the factor loading for variable i and factor s, and ε_i is the unexplained variation in variable i. I performed principal component analysis, which limits the number of factors to those with eigenvalues above 1, and I performed an orthogonal rotation to generate uncorrelated factors. Factor analysis can be sensitive to the variable inputs, but the basic aim is to describe a large proportion of the variance in the data while keeping the number of factors small.

In previous analyses of community development need, the authors have conducted factor analysis of need within a single time period. This is sufficient for cross-sectional analysis but does not allow the authors to assess how the quality of allocations have changed over time. Each of the previous studies has used slightly different variables and significantly different factor loadings, making it impossible to evaluate how the quality of allocations has evolved. To get around this issue, I developed a constant measure of community development need by pooling the three time periods of data and conducting a factor analysis where each unit is a grantee-year observation. Because I was interested in how effectively CDBG allocates funds with respect to need within a given year, each variable was standardized within one year. These standardized variables were pooled together for the longitudinal factor analysis. This ensured that the same set of variables and, importantly, the same factor loadings were used to construct each factor.

The regression weights used to construct the factors are reported in Table 2, panel A, and eigenvalues in panel B. (The orthogonal rotated factor loadings appear in Appendix 2.) Similarly to previous research (Bunce 1983; Richardson, 2005), the input variables produced three distinct factors. Factor 1 explains approximately 46% of the total variance across all 16 variables; it is driven by minority segregation, violent crime, homicides per capita, and the percentage of persons that are poor and residing in neighborhoods (census tracts) with a preponderance of vacant homes. Other variables capturing the depth of poverty deprivation (the percentage of persons in concentrated poverty, poor renters living in old housing, and the percentage of single-parent households) are positively correlated with Factor 1. Table 3 highlights communities that rank very high on Factor 1 in each of the three decades. Chronically distressed communities such as Gary, Indiana; Camden,

Table 2. A: Factor scores (regression weights). B: Eigenvalues.

A	Factor 1	Factor 2	Factor 3
Minority segregation	0.255	−0.214	0.164
Population-to-employment ratio	−0.132	0.401	−0.220
Unemployment rate	−0.057	0.258	0.046
Poverty rate (excluding enrolled college students)	0.100	0.129	−0.114
Percentage in high-poverty census tracts	0.098	0.132	−0.235
Poor persons in high-vacancy census tracts	0.079	0.130	−0.389
Percentage age 25 or older without a BA or higher	−0.130	0.338	0.088
Percentage of households with a single parent	0.128	0.017	0.159
Percentage of pre-1960 housing units occupied by a poor renter	0.159	0.020	−0.216
Percentage overcrowded	0.027	−0.063	0.538
Drop-out rate (ages 18–24)	−0.159	0.251	0.241
Violent crime rate	0.260	−0.211	0.129
Murder rate	0.248	−0.166	0.035
Ratio of municipal mean household income of metro household income to municipal income	0.095	−0.008	0.206

B	Eigenvalue	Proportion of explained variance
Factor 1	4.80789	0.52
Factor 2	3.01287	0.33
Factor 3	1.42552	0.15
Sum	9.24628	1.00

Table 3. Factor 1 (poverty/crime/deprivation/distress): Top communities 1990–2010.

Rank	1990	Score	2000	Score	2010	Score
1	Camden, NJ	5.56	Camden, NJ	5.05	Chester, PA	5.85
2	St. Louis, MO	4.81	St. Louis, MO	4.67	Detroit, MI	5.55
3	Detroit, MI	4.58	Chester, PA	4.61	Flint, MI	5.35
4	Atlanta, GA	4.31	Detroit, MI	4.23	Camden, NJ	5.14
5	New Orleans, LA	4.27	Gary, IN	4.15	Gary, IN	4.70
6	Gary, IN	4.24	Baltimore, MD	4.06	St. Louis, MO	4.63
7	Washington, DC	4.16	Atlanta, GA	3.57	Harrisburg, PA	4.15
8	Compton, CA	4.12	Hartford, CT	3.52	Newburgh, NY	3.85
9	Miami, FL	4.04	New Orleans, LA	3.46	Wilmington, DE	3.60
10	Newark, NJ	3.82	Washington, DC	3.44	Hartford, CT	3.59

New Jersey; Detroit, Michigan; and New Orleans, Louisiana, are among the top 10 communities for Factor 1 across each of the three decades. A number of communities, such as Miami, Florida, and Washington, DC, rank extremely high in 1990 but leave the top 10 by 2010 as city conditions improve. Factor 1 clearly captures an important suite of characteristics related to social disorganization, as identified by Sampson et al. (1997).

Factor 2 accounts for similar proportion of the variance as Factor 1, among the principal component factors. Mechanically, it describes a distinctly different element of community development. Factor 2 captures community development need associated with low levels of educational attainment, weak labor markets, and high rates of young people failing to finish high school. In particular, the percentage of the population (25 and older) without a bachelor's degree, the population to employment ratio, the unemployment rate, and the estimated drop-out rate among 18–24-year-olds are positively correlated with Factor 2. Table 4 displays high-need communities with respect to Factor 2 in 1990, 2000, and 2010. These tend to be smaller Southwestern and Western cities with large immigrant and low-skilled worker populations, such as Delano city, Madera, and Hidalgo County—all in California. Also among the high-need communities are several distressed industrial communities in the East and Midwest.

Finally, Factor 3 makes up the residual variance of the principal component factors. Factor 3 is driven almost entirely by overcrowding. It is also positively correlated with minority segregation, the ratio of metropolitan to community income. Communities high

Table 4. Factor 2 (weak labor market/low-skill workforce/low education): Top communities 1990–2010.

Rank	1990	Score	2000	Score	2010	Score
1	Pharr, TX	5.41	Delano City, CA	4.81	Delano City, CA	4.67
2	Mission, TX	5.15	Hidalgo County, TX	4.09	East Cleveland, OH	4.31
3	Hidalgo County, TX	4.84	Camden, NJ	3.64	Madera, CA	3.26
4	El Centro, CA	3.02	East Cleveland, OH	3.59	Hidalgo County, TX	2.79
5	Brownsville, TX	2.99	El Centro, CA	3.46	Yuba City, CA	2.75
6	Chino, CA	2.65	Madera, CA	3.30	Elkhart, IN	2.70
7	Mckeesport, PA	2.62	Port Arthur, TX	3.21	Perris City, CA	2.69
8	Delano City, CA	2.61	Pharr, TX	3.18	Muskegon, MI	2.69
9	Johnstown, PA	2.57	Johnstown, PA	3.09	Johnstown, PA	2.68
10	Yuma, AZ	2.55	Brownsville, TX	3.05	Saginaw, MI	2.63

Table 5. Factor 3 (over-crowding/low-fiscal capacity): Top communities 1990–2010.

Rank	1990	Score	2000	Score	2010	Score
1	Huntington Park, CA	5.58	Huntington Park, CA	4.93	Huntington Park, CA	6.00
2	Lynwood, CA	5.33	Lynwood, CA	4.86	Santa Ana, CA	5.23
3	El Monte, CA	4.81	South Gate, CA	4.51	Lynwood, CA	4.75
4	South Gate, CA	4.72	Paramount City, CA	4.47	South Gate, CA	4.46
5	Santa Ana, CA	4.39	Santa Ana, CA	4.33	Compton, CA	4.35
6	Baldwin Park, CA	4.22	Baldwin Park, CA	4.09	El Monte, CA	3.99
7	Paramount City, CA	4.12	Compton, CA	3.92	Elizabeth, NJ	3.96
8	Compton, CA	3.83	El Monte, CA	3.78	Passaic, NJ	3.90
9	Rosemead, CA	3.68	Watsonville, CA	3.55	Paramount City, CA	3.67
10	Pico Rivera, CA	3.51	Oxnard, CA	3.33	Santa Maria, CA	3.67

on factor 3 have higher segregation, more single parent households, and higher ratios of metropolitan to community level income (a proxy of municipal fiscal capacity suggested by Richardson [2005]), and the percentage of single-parent households. Table 5 list communities that rank highly for Factor 3. They are concentrated heavily in California.

4. A Composite Community Development Need Index

In order to develop a tractable framework to assess CDBG formula efficacy, it is useful to construct a single composite community development need measure. The community development need index is useful to summarize aggregate need for activities which could be addressed through CDBG-supported programming or investments. Given CDBG's emphasis on upgrading physical capital (housing and infrastructure) and eliminating blight, it is important to target communities with significant levels of physical decay—this is captured in Factor 1 through the percentage of the population that is poor and living in high-vacancy census tracts. CDBG is also a resource for community services targeted to low- and moderate-income persons. Thus, an important dimension of the composite needs index should be the presence of the population groups that might benefit most from such programming (such as ex-offenders, recent immigrants, and young people). Recent evidence suggests that youth programming in particular may be highly effective in reducing violent crime among teens in communities of concentrated poverty (Ludwig et al., 2013). Because it is both an outcome that CDBG might be able to influence and an important variable in the quality of life of a community, crime appears to be another major input to community development need. With a rapid increase in the skills–wage premium over the past three decades, documented by Autor et al. (2003) and many others, the skills of a community's workforce have become important in determining its economic fate. Given the increased importance of human capital in determining city-level outcomes, Factor 2 should be sufficiently weighted in the composite needs index.

The above considerations suggest that each factor should be included in the composite needs index. However, Factors 1 and 2 appear to capture a wider set of programmatic objectives than does Factor 3. Factor 1 is similar to the poverty/infrastructure/economic distress factor identified by Richardson (2005) and to the poverty, age and decline factor identified by Bunce et al. (1983). Given that Factor 1 captures the most elements described in the statutory objectives and also explains the greatest proportion of total variance, it is reasonable to weight it most heavily. Factor 2 explains a similarly large proportion of variance, and is closely connected to economic prosperity. Similar to the immigration stress/overcrowding factor identified by Richardson, Factor 3 captures a more narrow subset of community development need. I began by constructing a composite measure based on the proportion of the total variance captured by the three factors. This was done by weighting each factor by the ratio of its eigenvalue to sum of all eigenvalues such that the composite factor F_c is equivalent to

$$F_c = \frac{\lambda_1}{\lambda_1 + \lambda_2 + \lambda_3} F_1 + \frac{\lambda_2}{\lambda_1 + \lambda_2 + \lambda_3} F_2 + \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3} F_3$$

This approach produced weights of 0.52 for Factor 1, 0.33 for Factor 2, and 0.15 for Factor 3. These factor weights seem appropriate on normative grounds. Factor 1 is weighted most heavily, as with similar factors in previous studies (Bunce 1983; Richardson, 2005). Factor 2 emerges as an important component, which is consistent with the increasing importance of an educated labor force as a determinant of economic prosperity and quality of life. Factor 3 receives a similar weight to the analogous factor in previous works (Bunce 1983; Richardson, 2005). I constructed the composite needs score as using the following weighting:

Factor 1 (poverty/crime/deprivation/distress)	0.50
Factor 2 (weak labor market/low-skill workforce/low education)	0.35
Factor 3 (overcrowding/low fiscal capacity)	0.15

This weighting scheme departs slightly from recent studies of community development need (Richardson, 2005) in that it gives greater weight to variables associated with labor-market weakness. Still, the list of high-need community development grantees remains similar to previous work. Table 6 lists the highest-need communities along the composite index. One striking feature is the durability of high need. Four communities remain in the 10 highest-need communities across all three decades. Table 7 summarizes the input variables for the 10 highest-need and the 10 lowest-need communities. It confirms that the composite index effectively differentiates between high- and low-need communities. The highest-need communities exhibit unemployment rates between 2 and 3 times those of low-need communities, poverty rates 10 times as high, substantially lower educational attainment, more violent crime, a greater preponderance of crowding, and lower labor-force participation. Table 8 shows the 50 highest-need large grantees (200,000 or greater population). The list of high-ranking communities in 2000 is similar to those from previous HUD studies (Richardson, 2005), providing additional support for this measure of community development need. The next section measures this index against the CDBG allocation formula in three separate allocation periods: 1990, 2000, and 2010.

Table 6. Composite community development needs index: Top communities 1990–2010.

Rank	1990	Score	2000	Score	2010	Score
1	Camden, NJ	3.14	Camden, NJ	3.34	Camden, NJ	3.00
2	Compton, CA	2.47	Compton, CA	2.44	Detroit, MI	2.94
3	Detroit, MI	2.46	Detroit, MI	2.25	Flint, MI	2.84
4	Miami, FL	2.20	Gary, IN	2.20	Chester, PA	2.79
5	Gary, IN	2.18	Chester, PA	2.19	Gary, IN	2.62
6	Newark, NJ	2.09	East Cleveland, OH	2.14	East Chicago, IN	2.18
7	St. Louis, MO	1.96	Newark, NJ	2.04	Huntington Park, CA	2.12
8	Pharr, TX	1.95	Hartford, CT	2.04	Hartford, CT	2.11
9	Hidalgo County, TX	1.93	Delano City, CA	2.04	East Cleveland, OH	2.08
10	Lynwood, CA	1.92	St. Louis, MO	1.92	Compton, CA	2.01

Table 7. Summary statistics, highest- and lowest-need community development grantees (2010).

	Poverty rate	% in high-poverty tracts	% poor in high-vacancy tracts	% single-parent households	% overcrowding	% poor renters in pre-1960 housing	% with BA+	% of 18–24 w/o HS diploma	Violent crimes per 100k	Murder per 100k	Mean household income/metro mean household income	Isolation index	Unemployment rate	Employment/population (age 25+)
Highest need														
Camden, NJ	0.35	0.53	0.06	0.48	0.06	0.19	0.07	0.32	1,350	48	0.49	0.60	0.19	0.52
Chester, PA	0.34	0.77	0.09	0.40	0.03	0.18	0.09	0.22	1,077	71	0.49	0.52	0.13	0.60
Compton, CA	0.22	0.14	0.00	0.37	0.24	0.13	0.07	0.29	792	26	0.63	0.31	0.21	0.59
Detroit, MI	0.33	0.58	0.24	0.37	0.03	0.24	0.12	0.29	1,352	43	0.57	0.59	0.23	0.60
East Chicago, IN	0.31	0.35	0.13	0.35	0.06	0.18	0.09	0.33	515	37	0.45	0.46	0.15	0.49
East Cleveland, OH	0.36	0.77	0.32	0.33	0.02	0.27	0.11	0.30	9	0	0.54	0.62	0.12	0.49
Flint, MI	0.34	0.60	0.20	0.33	0.02	0.19	0.12	0.30	1,499	52	0.68	0.50	0.23	0.58
Gary, IN	0.33	0.66	0.17	0.35	0.03	0.18	0.12	0.34	644	65	0.48	0.48	0.14	0.46
Hartford, CT	0.31	0.53	0.05	0.36	0.05	0.20	0.13	0.22	643	21	0.46	0.66	0.17	0.59
Huntington Park, CA	0.23	0.31	0.00	0.35	0.39	0.13	0.07	0.30	752	10	0.56	0.30	0.19	0.67
Lowest need														
Douglas County, CO	0.03	0.00	0.00	0.10	0.00	0.00	0.54	0.14	52	0	1.48	0.01	0.07	0.85
Fairfield, CT	0.03	0.00	0.00	0.10	0.00	0.03	0.59	0.01	25	0	1.44	0.04	0.08	0.75
Flower Mound Town, TX	0.03	0.00	0.00	0.11	0.01	0.00	0.55	0.15	12	0	1.74	0.02	0.07	0.84
Frisco, TX	0.04	0.00	0.00	0.10	0.01	0.00	0.58	0.11	30	0	1.50	0.03	0.07	0.91
Greenwich, CT	0.03	0.00	0.00	0.12	0.01	0.02	0.65	0.13	15	0	2.22	0.05	0.07	0.67
Naperville, IL	0.03	0.00	0.00	0.09	0.01	0.01	0.65	0.11	9	0	1.58	0.05	0.08	0.79
Newport Beach, CA	0.04	0.00	0.00	0.09	0.01	0.01	0.63	0.05	53	0	2.07	0.02	0.06	0.66
Newton, MA	0.05	0.00	0.00	0.10	0.01	0.04	0.73	0.04	25	0	1.70	0.02	0.06	0.85
Palo Alto, CA	0.05	0.00	0.00	0.09	0.03	0.03	0.79	0.05	61	0	1.46	0.02	0.06	0.66
Yorba Linda, CA	0.02	0.00	0.00	0.12	0.02	0.00	0.46	0.07	22	0	1.71	0.01	0.06	0.78

Table 8. Community development needs index: Large grantees (pop. > 200,000).

Rank	1990	Score	2000	Score	2010	Score
1	Detroit, MI	2.46	Detroit, MI	2.25	Detroit, MI	2.94
2	Miami, FL	2.20	Newark, NJ	2.04	Cleveland, OH	1.89
3	Newark, NJ	2.09	St. Louis, MO	1.92	Newark, NJ	1.85
4	St. Louis, MO	1.96	Baltimore, MD	1.81	St. Louis, MO	1.85
5	Cleveland, OH	1.77	Miami, FL	1.80	Buffalo, NY	1.48
6	New Orleans, LA	1.75	Cleveland, OH	1.64	San Bernardino, CA	1.43
7	Baltimore, MD	1.61	Hidalgo County, TX	1.54	Rochester, NY	1.35
8	Atlanta, GA	1.61	Buffalo, NY	1.53	Baltimore, MD	1.33
9	Chicago, IL	1.39	New Orleans, LA	1.53	Birmingham, AL	1.29
10	Washington, DC	1.30	Philadelphia, PA	1.42	Miami, FL	1.26
11	Buffalo, NY	1.29	Birmingham, AL	1.40	Milwaukee, WI	1.25
12	Birmingham, AL	1.29	Rochester, NY	1.35	Philadelphia, PA	1.24
13	Philadelphia, PA	1.14	Atlanta, GA	1.33	New Orleans, LA	1.23
14	Oakland, CA	1.08	Chicago, IL	1.33	Cincinnati, OH	1.19
15	New York, NY	1.07	Washington, DC	1.18	Hidalgo County, TX	1.18
16	Rochester, NY	1.01	Milwaukee, WI	1.13	Santa Ana, CA	1.14
17	Richmond, VA	0.99	Memphis, TN	1.04	Memphis, TN	1.12
18	Milwaukee, WI	0.97	Stockton, CA	1.03	Chicago, IL	1.05
19	Jersey City, NJ	0.94	Santa Ana, CA	1.03	Stockton, CA	1.05
20	Stockton, CA	0.94	Shreveport, LA	0.96	Oakland, CA	1.02
21	Los Angeles, CA	0.90	Oakland, CA	0.95	Kern County, CA	0.79
22	Santa Ana, CA	0.90	Hialeah, FL	0.95	Kansas City, MO	0.78
23	Shreveport, LA	0.90	New York, NY	0.92	Fresno, CA	0.76
24	Kansas City, MO	0.87	Los Angeles, CA	0.89	Atlanta, GA	0.73
25	Fresno, CA	0.85	Fresno, CA	0.87	Laredo, TX	0.70
26	Cincinnati, OH	0.83	Cincinnati, OH	0.85	Toledo, OH	0.70
27	Memphis, TN	0.83	Long Beach, CA	0.82	Hialeah, FL	0.69
28	Dallas, TX	0.80	Dallas, TX	0.80	Richmond, VA	0.68
29	Pittsburgh, PA	0.75	Jersey City, NJ	0.79	Clayton County, GA	0.68
30	Fort Worth, TX	0.73	Kern County, CA	0.77	Dallas, TX	0.66
31	Tampa, FL	0.71	Kansas City, MO	0.75	Augusta-Richmond County, GA	0.65
32	Houston, TX	0.70	Pittsburgh, PA	0.71	Indianapolis, IN	0.64
33	Boston, MA	0.66	Houston, TX	0.65	Houston, TX	0.61
34	Akron, OH	0.64	Tampa, FL	0.65	Los Angeles, CA	0.61
35	Norfolk, VA	0.63	Fresno County, CA	0.63	New York, NY	0.55
36	El Paso, TX	0.61	Sacramento, CA	0.58	Washington, DC	0.55
37	Long Beach, CA	0.58	Norfolk, VA	0.58	Jersey City, NJ	0.55
38	San Antonio, TX	0.57	Boston, MA	0.52	Long Beach, CA	0.53
39	Kern County, CA	0.54	Akron, OH	0.47	Pittsburgh, PA	0.53
40	Toledo, OH	0.54	Prince Georges County, MD	0.46	Stanislaus County, CA	0.52
41	St. Petersburg, FL	0.44	Fort Worth, TX	0.45	Fresno County, CA	0.51
42	Fresno County, CA	0.38	Phoenix, AZ	0.43	Sacramento, CA	0.47
43	Sacramento, CA	0.38	EL Paso, TX	0.43	Boston, MA	0.45
44	Minneapolis, MN	0.37	Nashville-Davidson, TN	0.42	Phoenix, AZ	0.44
45	Denver, CO	0.36	Montgomery, AL	0.39	DeKalb County, GA	0.40
46	Corpus Christi, TX	0.35	Toledo, OH	0.38	Prince Georges County, MD	0.39
47	Nashville-Davidson, TN	0.30	Clayton County, GA	0.36	Columbus, OH	0.38
48	Oklahoma City, OK	0.30	Tucson, AZ	0.34	Tampa, FL	0.38
49	Jacksonville-Duval County, FL	0.28	Minneapolis, MN	0.33	Tulsa, OK	0.37
50	Louisville, KY	0.26	Jefferson Parish, LA	0.32	St. Paul, MN	0.36

5. Assessing the Formula Allocation Over Time

With a consistent measure of community development need constructed for each time period, it was possible to assess the quality of the CDBG allocation formula. I created three mock allocations for a constant-grantee universe using the 1990, 2000, and 2010 censuses with the American Community Survey (ACS) 2005–2010 five-year estimates and the needs index developed in Section 5. As in the actual allocations, I calculated a grant size under Formula A and Formula B for each grantee. Formula A relies on population, persons in poverty, and overcrowded households (one or more persons per room) to construct an allocation share. Formula B uses persons in poverty, population growth lag,[4] and housing units built before 1940 to calculate a share of the overall grant amount. In detail, the formulas are:

Formula A for entitlement communities

$$A = \left[\left(0.25 \times \frac{\mathrm{Pop}_i}{\mathrm{Pop}_{\mathrm{MA}}}\right) + \left(0.5 \times \frac{\mathrm{Pov}_i}{\mathrm{Pov}_{\mathrm{MA}}}\right) + \left(0.25 \times \frac{\mathrm{Crowd}_i}{\mathrm{Crowd}_{\mathrm{MA}}}\right)\right] \times \mathrm{Appropriation}$$

Formula B for cities

$$B = \left[\left(0.2 \times \frac{\mathrm{Glag}_i}{\mathrm{Glag}_{\mathrm{MC}}}\right) + \left(0.3 \times \frac{\mathrm{Pov}_i}{\mathrm{Pov}_{\mathrm{MA}}}\right) + \left(0.5 \times \frac{\mathrm{Pre40}_i}{\mathrm{Pre40}_{\mathrm{MA}}}\right)\right] \times \mathrm{Appropriation}$$

Formula B for urban counties

$$B = \left[\left(0.2 \times \frac{\mathrm{Glag}_i}{\mathrm{Glag}_{\mathrm{ENT}}}\right) + \left(0.3 \times \frac{\mathrm{Pov}_i}{\mathrm{Pov}_{\mathrm{MA}}}\right) + \left(0.5 \times \frac{\mathrm{Pre40}_i}{\mathrm{Pre40}_{\mathrm{MA}}}\right)\right] \times \mathrm{Appropriation}$$

where i subscripts the value for a given grantee, MA is the value for all metropolitan communities, MC is the value for all metropolitan cities, and ENT is the value for all entitlement communities. For a discussion of the history of the formula and details on eligibility, see Richardson (2005). I set the appropriation amount at \$3 billion for each year. The formula was applied to 70% of this value (excluding 30% that would be allocated to nonentitled portion of states). After calculating grants under both Formula A and Formula B, I took the maximum of both grants. Summing these maximum grants exceeded the total appropriation amount, so a pro-rata reduction was applied so that the grants summed to the total appropriation amount.

With estimated grants for each year (1990, 2000, and 2010), it was possible to analyze how effectively the formula allocates funds with respect to community development need. I estimated a simple OLS model of per capita grant (g) on the community development needs index:

$$g_i = \alpha + \beta \mathrm{cdneed}_i + \varepsilon_\iota \qquad (1)$$

where α is the regression intercept, β is the OLS estimate of the relationship between community development need, and ε is the regression residual, i indexes grantees. I estimated this model separately for each of the three time periods. There are two important concepts when evaluating formula performance. The first is *horizontal equity*, meaning grantees of comparable need receive similar grant amounts per capita. A horizontally equitable allocation exhibits a tight fit between per capita allocation and the needs

Table 9. Relation between per capita funding and community development need, 1990–2010.

	(1) 1990	(2) 2000	(3) 2010
Needs index	7.773*** (0.256)	6.605*** (0.256)	6.481*** (0.248)
R^2	0.491	0.409	0.417
N	959	959	959
F	923.4	663.3	684.7
rss	21,816	24,468	23,881
ll	− 2,859	− 2,914	− 2,902

Note. ll = lower limit of the confidence interval. rss = residual sum of squares. Standard errors are in parentheses.
***$p < .01$.

Table 10. Relation between per capita funding and community development need (weighted), 1990–2010.

	(1) 1990	(2) 2000	(3) 2010
Needs index	8.155*** (0.363)	7.479*** (0.297)	7.615*** (0.433)
R^2	0.672	0.626	0.583
N	959	959	959
F	503.6	634.1	309.3
rss	14,820	14,668	15,320
ll	− 2,674	− 2,669	− 2,689

Note. ll = lower limit of the confidence interval. rss = residual sum of squares. Standard errors are in parentheses.
***$p < .01$.

Table 11. Allocation to need: A versus B, 2010.

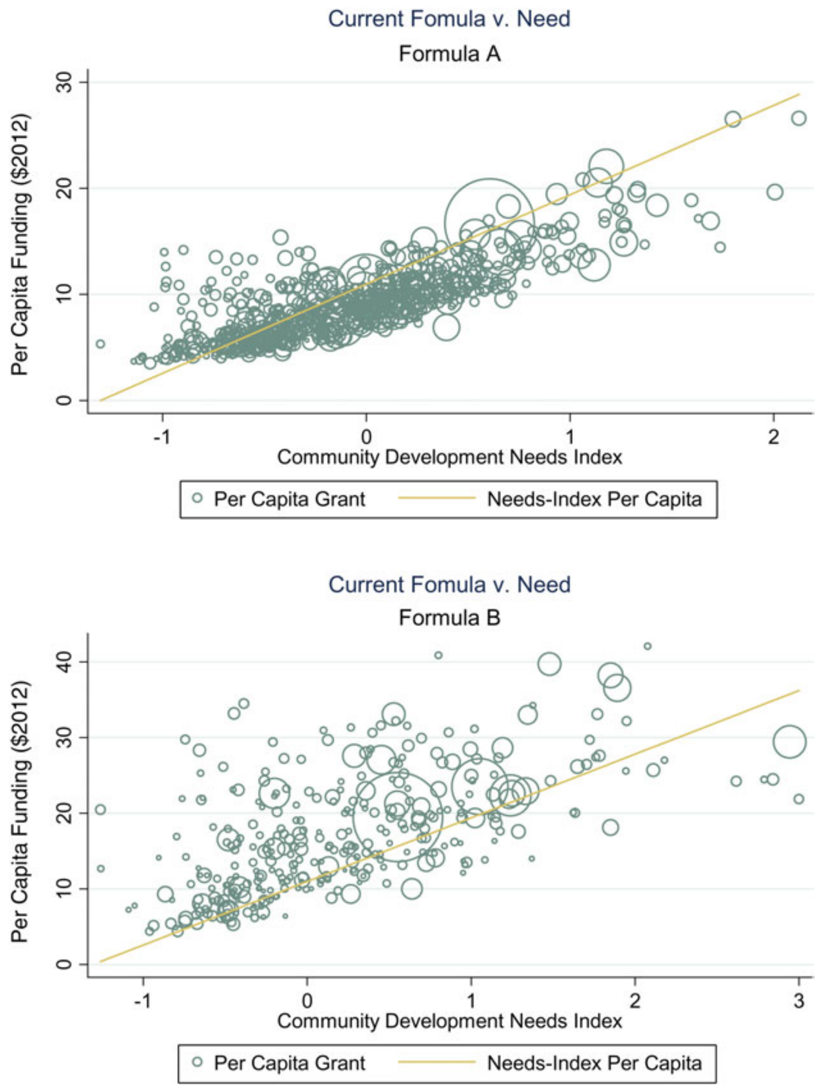
	(1) A	(2) B	(3) A (weighted)	(4) B (weighted)
Needs index	4.943*** (0.149)	5.955*** (0.456)	5.771*** (0.366)	7.379*** (0.587)
R^2	0.635	0.345	0.701	0.559
N	633	326	633	326
F	1,097	170.5	248.7	158.0
rss	2,760	12,781	2,220	8,534
ll	− 1,364	− 1,061	− 1,295	− 994.8

Note. ll = lower limit of the confidence interval. rss = residual sum of squares. Standard errors are in parentheses.
***$p < .01$.

index—this can be measured by the R^2 from the model estimated above. The second is *vertical equity*, which captures the extent to which needier grantees get more funding per capita than less needy grantees. This can be captured by the coefficient β on the needs index from the model estimated above. The central results of this article appear in Table 9, which reports these parameters estimated for each time period: 1990, 2000, and 2010.

These results suggest that the current allocation formula is only modestly successful in targeting community development need. In the unweighted model, the R^2 drops from 0.49 to 0.41 from 1990 to 2010. The levels and trend are troubling. Similarly, the coefficient of need shrinks in each year, a standard deviation increase in the needs index increased per capita funding by $7.7 per capita in 1990, but only $6.48 per capita in 2010. I estimate a population-weighted Equation (1) in Table 10. Overall fit improves, but the slope and the trend of declining goodness of fit persist. Table 11 re-estimates Equation (1) separately

Figure 1. Formula allocation and need.



Note. Dots are sized by estimated grant size.

for Formula A and Formula B grantees. Formula B exhibits a particularly poor fit ($R^2 = 0.34$), while Formula A has a comparatively flat slope. These differences are visualized in Figure 1, which plots actual allocations against a line approximating a needs-based allocation. The next section attempts to diagnose the problems with the current formula.

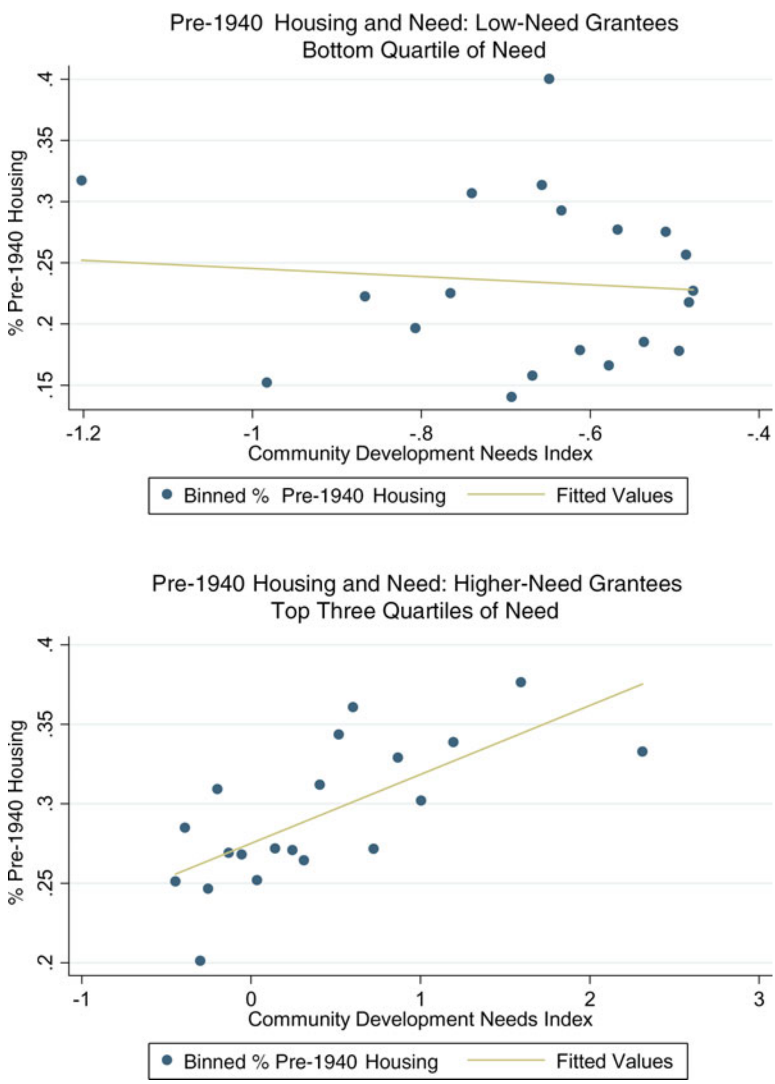
6. Flaws in the Current Formula

There are several flaws that contribute to the weakness of fit identified in Section 5. Many of the problems identified by Richardson (2005) persist in 2010. I highlight the key problems below, and then provide support for each:

- Overfunding of low-need, slow-growth older communities due to Pre-1940 Housing and Growth Lag variables
- Overfunding of college towns due to off-campus college students living in poverty
- Underfunding of Formula A grantees, conditional on need
- Vertical inequity among Formula A grantees

Prodding at the poor fit among Formula B grantees, it is apparent that there are three sources of the weak fit. The first is the variable for housing built before 1940. Figure 2 plots a regression of pre-1940 housing on the needs index for the bottom quartile of the needs index. For the bottom quarter of communities, a higher level of pre-1940 housing

Figure 2. Pre-1940 housing and need.

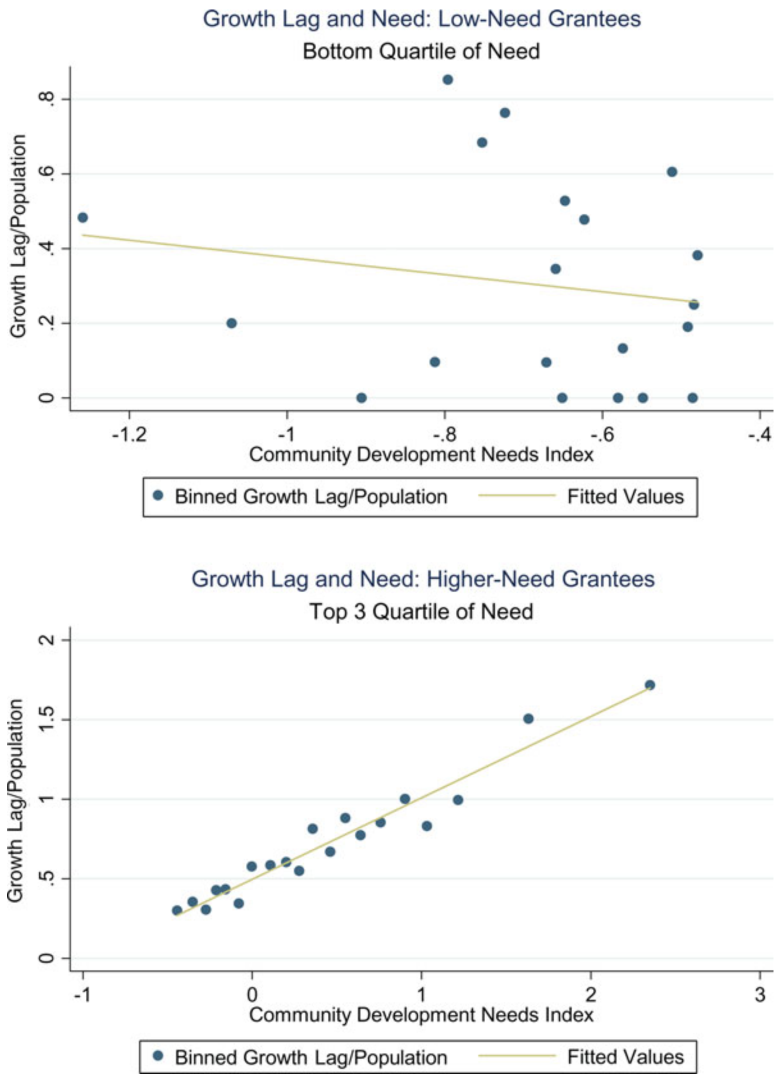


Note. Scatter plot is conditional means of % Pre-1940 housing for 20 quantiles of the needs index.

has no discernible relation to community development need. Pre-1940 housing is positively related to need for the top three-quarters of grantees, but the absence of a meaningful correlation for lower-need communities contributes to weak targeting. A similar phenomenon exists with the population growth lag measure. The relation between growth lag and need for the top three-quarters of communities is strikingly positive (*t*-stat over 13; see Figure 3). However, for the bottom quarter of communities, there is no meaningful relation. This means that equivalent low-need communities receive drastically different funding levels per capita.

The third contributor to horizontal inequity among the Formula B grantees (and poor fit among Formula A grantees) is the use of conventional poverty measures, which capture

Figure 3. Growth lag and need.

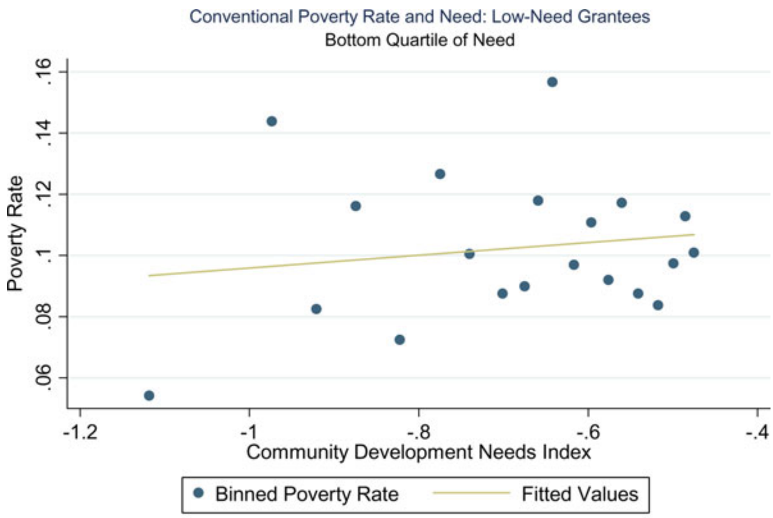


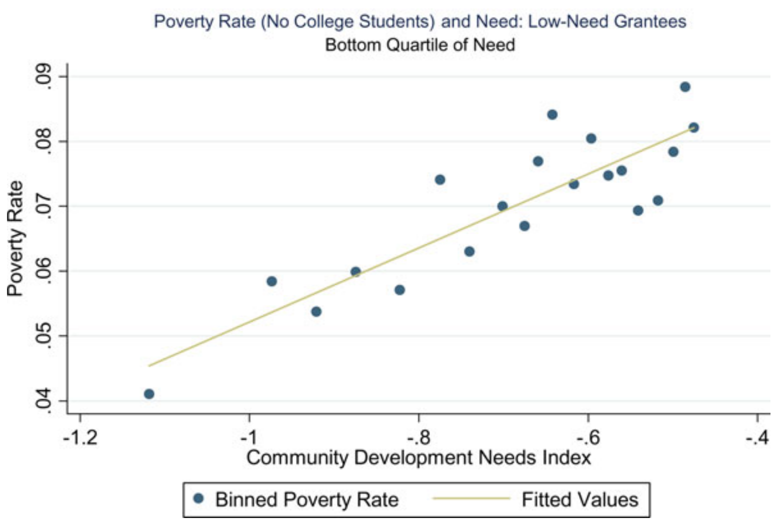
Note. Scatter plot is conditional means of Growth lag\Population for 20 quantiles of the needs index.

a large number of off-campus college students in communities with large university populations. Figure 4 plots the relation between conventional poverty rates and community development need for the bottom quartile of communities. Conventional poverty rates have little bearing on community development need for the bottom quarter of communities along the needs index. The bottom of Figure 4 plots how this relation changes for the same bottom quarter of communities when the poverty rate excludes enrolled college students in poverty. This subtle change leads to a much more visible positive relation between the poverty rate and overall community development need.

Formula B's flaws are more numerous, but Formula A also has weaknesses. Like Formula B, Formula A uses the conventional poverty rate, which leads to relative

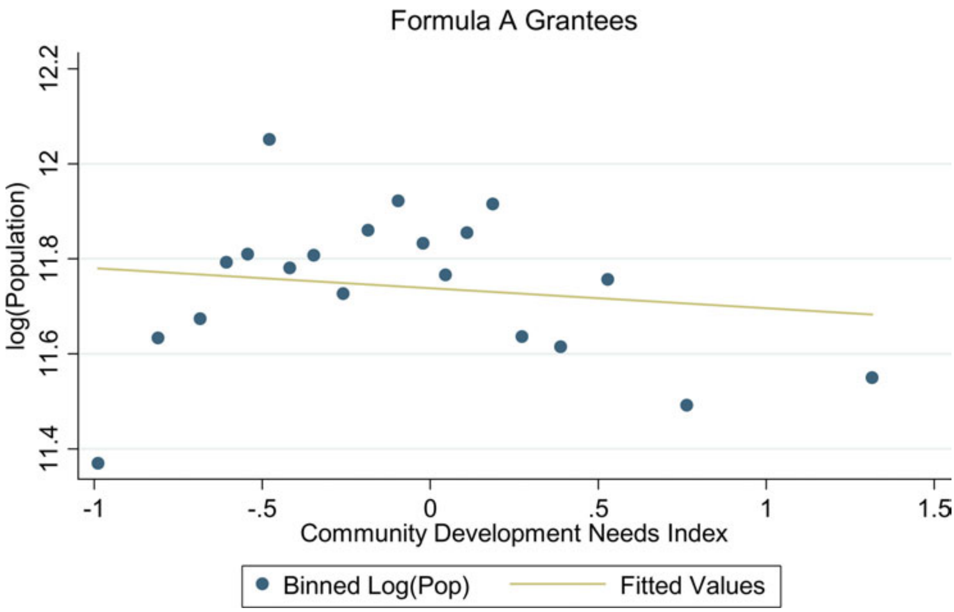
Figure 4. Poverty rate and need.





Note. Scatter plot is conditional means of Poverty Rate for 20 quantiles of the needs index.

Figure 5. Population and need.



Note. Scatter plot is conditional means of log (Population) for 20 quantiles of the needs index.

overfunding of university towns with large off-campus student populations. Also, Formula A applies a 25% weight to population—and Figure 5 suggests that there is no meaningful relation between population and community development need, as measured by the needs index, among Formula A grantees. The inclusion of population contributes to a less vertically equitable formula. A Formula A grantee in the 40th percentile of need gets approximately \$8 per capita in CDBG funding, while a grantee in the 80th percentile gets just \$11 per capita (Table 12).

Perhaps the most glaring problem with the present CDBG formula is an inequity in relative funding between Formula A and Formula B grantees. Adding an indicator for formula type (1 = Formula type A, 0 = otherwise) to Equation (1) gives:

$$g_i = \alpha + \beta \mathrm{cdneed}_i + \gamma A_i + \varepsilon_\iota \tag{2}$$

Table 12. A–B funding inequity by need decile, 2010.

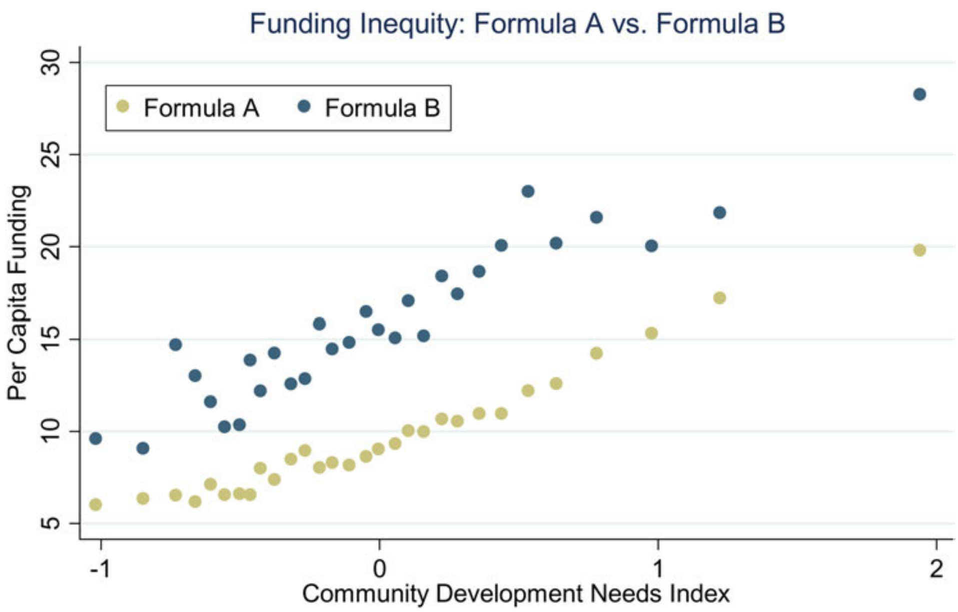
Need decile	Mean need	Per capita A	Per capita B	Difference (B − A)
1	−0.87	6.30	11.02	4.72
2	−0.61	6.65	11.93	5.28
3	−0.47	7.02	12.14	5.13
4	−0.32	8.16	12.98	4.82
5	−0.17	8.17	15.05	6.88
6	0.00	9.02	15.89	6.87
7	0.16	10.23	16.87	6.64
8	0.36	10.84	18.60	7.76
9	0.65	12.89	21.59	8.70
10	1.38	17.07	23.94	6.88

Table 13. Funding inequity, 2010.

	(1)	(2) Weighted
Needs index	5.440*** (0.206)	6.611*** (0.328)
AB (B = 0)	−6.352*** (0.283)	−5.162*** (0.464)
R^2	0.618	0.721
N	959	959
F	774.0	336.4
rss	15,640	10,256
ll	−2,699	−2,497

Note. ll = lower limit of the confidence interval. rss = residual sum of squares. Standard errors are in parentheses.
***$p < .01$.

Figure 6. Formula A and B inequities.



The coefficient γ on the formula type variable expresses the bias in the present formula results. Conditional on need, Formula A grantees receive about $6.6 less per capita than equivalently needy Formula B grantees (Table 13). This inequity is easily conveyed visually. Figure 6 plots conditional means of the needs index and per capita allocation for 30 quantiles of the needs index. At each level of need, formula B grantees received more funding per capita than equivalently needy formula A grantees.

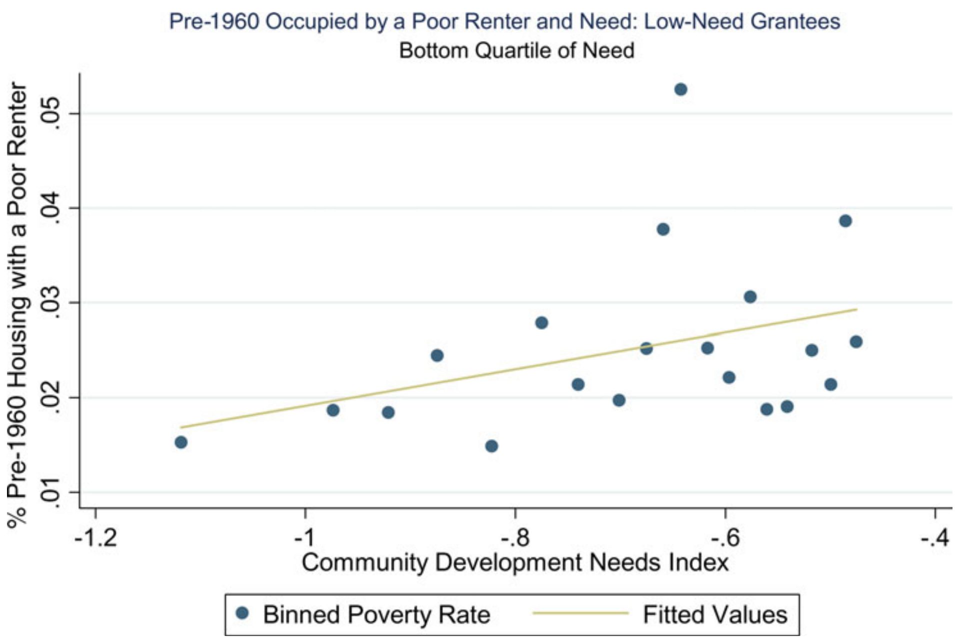
7. Alternatives

Given the problems with the current formulas, highlighted in the previous section, it is worth considering some possible alternatives that would mitigate these weaknesses. Using the community development needs index, each of the input variables, and a set of regression weights, it is possible to construct a formula that allocates precisely according to the needs index. However, this would be exceedingly complex to administer and would assume that the needs index is infallible. For practical purposes, this section considers formula alternatives which rely entirely on Census Bureau data and contain a limited number of input variables (the dual formula currently features five variables, so I limit us to five here). The first alternative considered retains much of the current structure of the formula but tweaks several variables to improve the fit. The second alternative is designed to fit the needs index as closely as possible with a limited set of variables. Finally, a third alternative explores a more concentrated formula that focuses allocations in the highest-need communities.

7.1. Alternative 1 ("Tweaked Formula")

As demonstrated in the previous section, the inclusion of enrolled off-campus college students in the poverty numbers, the use of pre-1940 housing in Formula B as a measure of housing stock quality, and the population growth lag in slow-growth suburbs contribute to poor targeting and to excess relative funding of wealthier, older, slow-growth communities. Fortunately, there are census tabulations which allow us to remove enrolled college students from the poverty counts. We can replace pre-1940 housing with pre-1960 housing occupied by a poor renter to get a slightly better fit among low-need communities (Figure 7). And we can deflate growth lag for wealthy communities[5] by the ratio of the community poverty rate to the national mean poverty rate. These somewhat minor tweaks substantially improve the allocation fit. Table 16 compares current formula performance (Column 1) to the tweaked formula described here (Column 3). The horizontal equity of

Figure 7. Pre-1960 housing occupied by a poor renter versus need (low-need grantees).



Note. Scatter plot is conditional means of Poverty Rate for 20 quantiles of the needs index.

the formula, as measured by the R^2, improves considerably, from 0.39 to 0.56. The vertical equity also increases, with the slope moving from 7.9 to 9.8.

While Alternative 1 delivers improved allocations with respect to need with fairly minor adjustments, retaining the current formula's structure, it does not resolve some of the structural problems of the current formula—including the funding inequity between Formula A and Formula B grantees.

7.2. *Alternative 2 ("Fit Formula")*

I now turn to a single-formula allocation option that involves more dramatic changes to the formula but resolves some of the flaws created by the dual-formula structure. To select the input variables I regress the needs index on the subset of standardized census variables used in the factor analysis.[6] From this regression I focus on the five variables with the largest positive coefficients (Table 14). These are the poverty rate (excluding college students), the percentage of the population that is poor in high-vacancy neighborhoods, the percentage of single-parent households, the percentage of the population that are poor renters occupying pre-1960 housing, and the percentage of households that are overcrowded. I then create a needs variable equal to the needs index (adjusted to have a minimum of zero) multiplied by the population. I sum this quantity and create a variable that is the share of this total need.[7] This share of composite need is then regressed on the shares of each formula variable:

$$\text{shareneed}_i = \alpha + \beta_1 \frac{\text{pop}_i}{\text{pop}_{\text{ent}}} + \beta_2 \frac{\text{singleHH}_i}{\text{singleHH}_{\text{ent}}} + \beta_3 \frac{\text{poorhivac}_i}{\text{poorhivac}_{\text{ent}}} + \beta_4 \frac{\text{crowd}_i}{\text{crowd}_{\text{ent}}} + \beta_5 \frac{\text{poorOldh}_i}{\text{poorOldh}_{\text{ent}}} \quad (3)$$

The β coefficients approximate the weights of each input in the formula. The results can be found in Table 15. Mechanically, nearly all of the variation in the need share can be explained by the five input variables ($R^2 = 0.99$). Table 15 presents estimates with weighted and unweighted variables. I create the new formula weights according to the

Table 14. Community development need and census data inputs, 2010.

	(1) Need index
Poverty rate	0.154*** (0.00796)
Percentage poor in high-poverty areas	0.0409*** (0.00610)
Percentage poor in high-vacancy areas	0.0694*** (0.00339)
Percentage with a BA +	0.0739*** (0.00412)
Percentage single-parent households	0.251*** (0.00525)
Percent poor in pre-1960 housing	0.0806*** (0.00455)
Percent overcrowded	0.0861*** (0.00350)
Drop-out rate	0.0540*** (0.00345)
R^2	0.941
N	2,892
F	5,788
rss	67.09
ll	1,339

Note. ll = lower limit of the confidence interval. rss = residual sum of squares. Standard errors are in parentheses.
$^{***}p < .01$.

Table 15. Alternative 2 variable weights, 2010.

	(1) Unweighted	(2) Weighted	(3) Re-weighted, omitting Poor Renters in Pre-1960 Housing variable
Share of poor	0.443*** (0.0187)	0.430*** (0.120)	0.457*** (0.122)
Share of single-parent	0.443*** (0.0164)	0.398*** (0.0953)	0.434*** (0.0938)
Share of poor in high-vacancy area	0.0429*** (0.00195)	0.0625*** (0.0180)	0.0602*** (0.0171)
Share of poor renters in pre-1960 housing	0.0212*** (0.00485)	0.0262 (0.0230)	n/a
Share of overcrowding	0.0657*** (0.00521)	0.0826*** (0.0282)	0.0737*** (0.0280)
R^2	0.994	0.999	0.999
N	964	964	964
F	30,547	7,534	13,696
rss	4.34e-05	0.000223	0.000230
ll	6,786	5,997	5,982

Note. ll = lower limit of the confidence interval. rss = residual sum of squares. Standard errors are in parentheses.
$^{***}p < .01$.

weighted model, but the results do not differ dramatically. Because the poor renter in pre-1960 housing variable has an implied regression weight of less than 2.5% and is not statistically significant in this specification, I drop it and re-estimate Equation (3) excluding it. This model implies the following weights after rounding values to multiples of 5:

Persons in poverty	0.45
Single-parent households	0.4
Poor persons in high-vacancy areas	0.05
Overcrowding	0.1

I calculate a single allocation using these weights, where each variable is expressed as a share of the entitlement total. I then re-estimate Equation (1) with the dependent variable as Alternative 2 grants per capita. The results are in Column 5 and Column 6 of Table 16. Alternative 2 greatly improves the fit. This is best visualized in Figure 8, where the top panel plots the current formula allocation per capita against the rank of the needs index. The vacillating blue line indicates the arbitrary horizontal inequities of the present formula. The bottom panel illustrates the same concept under Alternative 2 allocations. Alternative 2 greatly improves the horizontal equity of the formula; but it does so at the expense of vertical equity. The slope is about 12% lower, meaning that the highest-need grantees get relatively less under this allocation method. This arises because both poverty and single-parent households are fairly widespread problems and are heavily weighted in this alternative formula. Conversely, growth lag and overcrowding are fairly concentrated variables. The move to a single formula, along with the new formula weights, is sufficient to nearly close the funding gap between Formula A and Formula B grantees. This is visualized in Figure 9. Alternative 2 makes for a far more even, horizontally equitable allocation. However, it does further reduce the vertical equity of the formula.

7.3. *Alternative 3 (Concentration Formula)*

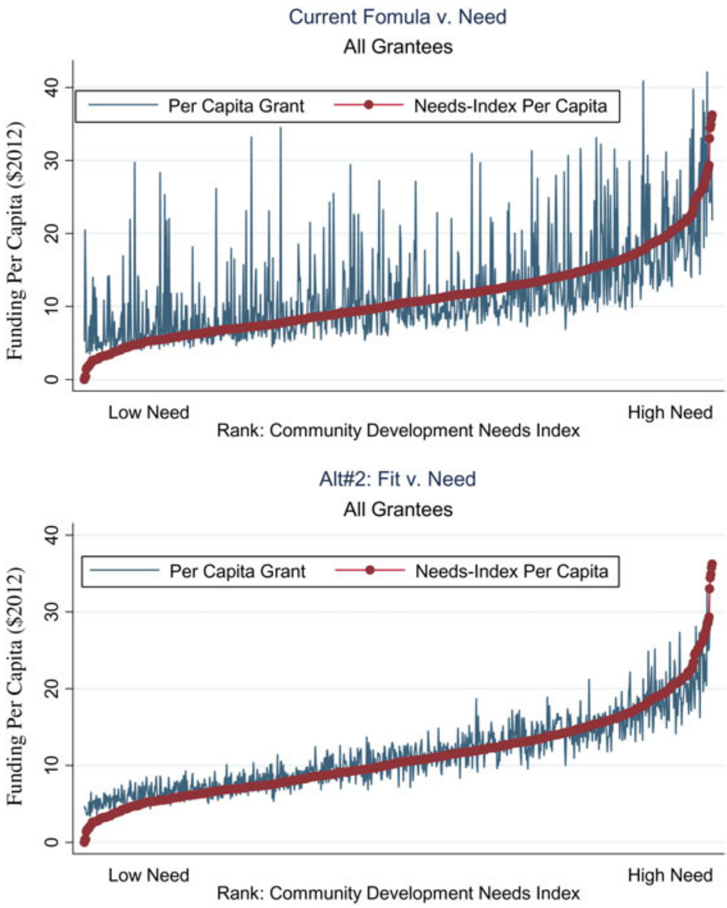
In addition to improving the horizontal equity of the current CDBG formula, policymakers may be interested in how to maintain or increase the vertical equity. There may be

Table 16. Formula alternatives comparison (2010).

	(1) Current	(2) Current (weighted)	(3) Alternative 1	(4) Alternative 1 (weighted)	(5) Alternative 2	(6) Alternative 2 (weighted)	(7) Alternative 3	(8) Alternative 3 (weighted)
cdneed	7.918*** (0.314)	9.257*** (0.565)	9.842*** (0.279)	10.64*** (0.587)	6.996*** (0.0852)	7.070*** (0.216)	12.01*** (0.248)	12.55*** (0.904)
R^2	0.399	0.565	0.566	0.699	0.875	0.881	0.708	0.782
N	959	959	959	959	964	964	964	964
F	636.1	268.8	1,246	328.7	6,744	1,067	2,337	192.5
rss	38,365	24,363	30,258	17,927	2,841	2,495	24,173	16,215
ll	−3,130	−2,912	−3,016	−2,765	−1,889	−1,826	−2,921	−2,728

Note. ll = lower limit of the confidence interval. rss = residual sum of squares. Standard errors are in parentheses.
$^{***}p < .01$.

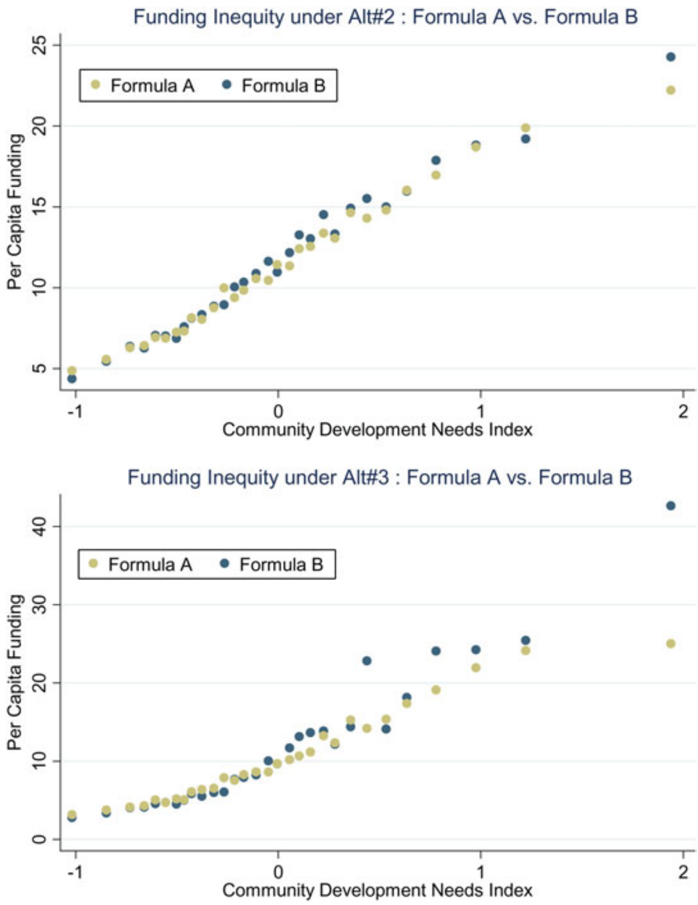
Figure 8. Current allocation versus Alternative 2.



additional economic reasons why a more concentrated formula is desirable. In a recent paper, Suarez and Winegender (2011) found that federal discretionary spending has greater multiplier effects in communities with greater labor-market slack. Additional recent empirical work finds evidence of greater government spending effects on income and job growth in periods when unemployment in high (Shoag, 2012). Alternative 3 uses largely the same variables from Alternative 2, but it increases the weights on the two more concentrated variables (overcrowding and poor in high-vacancy areas) and adds poor persons in tracts of concentrated poverty (poverty rates above 30%) to further concentrate funds in communities where there exist neighborhood concentrations of poverty. The formula uses the following weights:

Persons in poverty	0.3
Person in poverty in tracts with 30% + poverty	0.2
Single-parent households	0.2
Poor in high-vacancy tracts	0.15
Overcrowding	0.15

Figure 9. Narrow inequity.

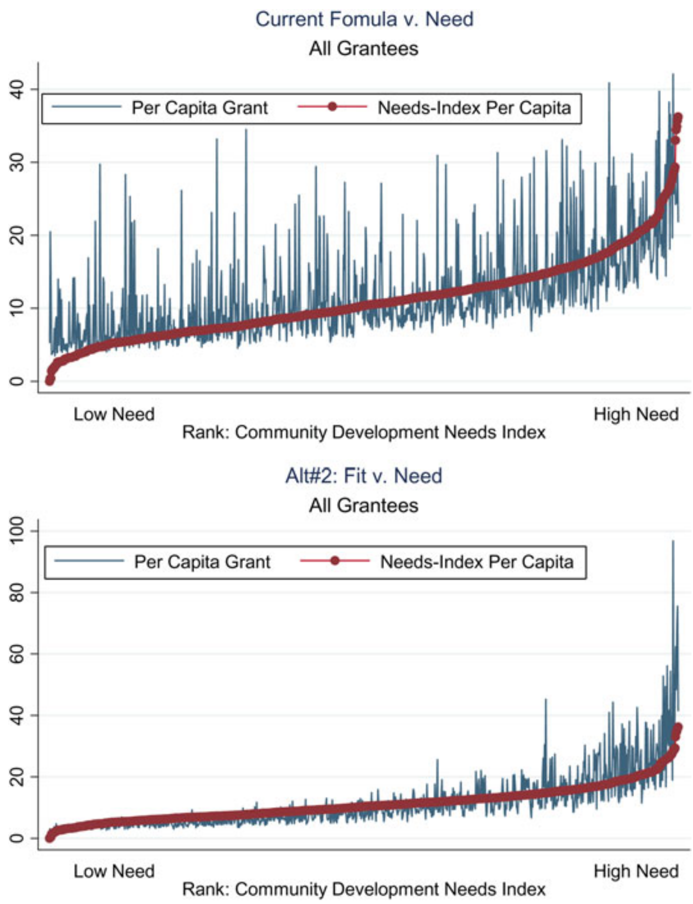


After allocating using the weights above, I re-estimate Equation (1) with Alternative 3 per capita allocation as the dependent variable. This appears in Table 16, Columns 7 and 8. Unsurprisingly, Alternative 3 does not fit as tightly as Alternative 2. Still, Alternative 3 is an improvement over the existing formula (by a large margin) and over the tweaked option. The reduction in fit is driven in part by a large increase in slope. The slope is nearly double that of Alternative 2. Alternative 3 also substantially narrows the inequities between Formula A and Formula B grantees, though not as successfully as Alternative 2 (Figure 10). Alternative 3 offers an option that increases both the horizontal and the vertical equity of the CDBG formula. Each formula alternative offers advantages over the current formula. Figure 11 offers a visual depiction of each alternative, along with the status quo.

8. Conclusion

I examined the CDBG formula to assess the formula's ability to effectively allocate funds with respect to need. To do this, I assembled a composite community development needs index, which consistently measures need across more than 900 communities over three

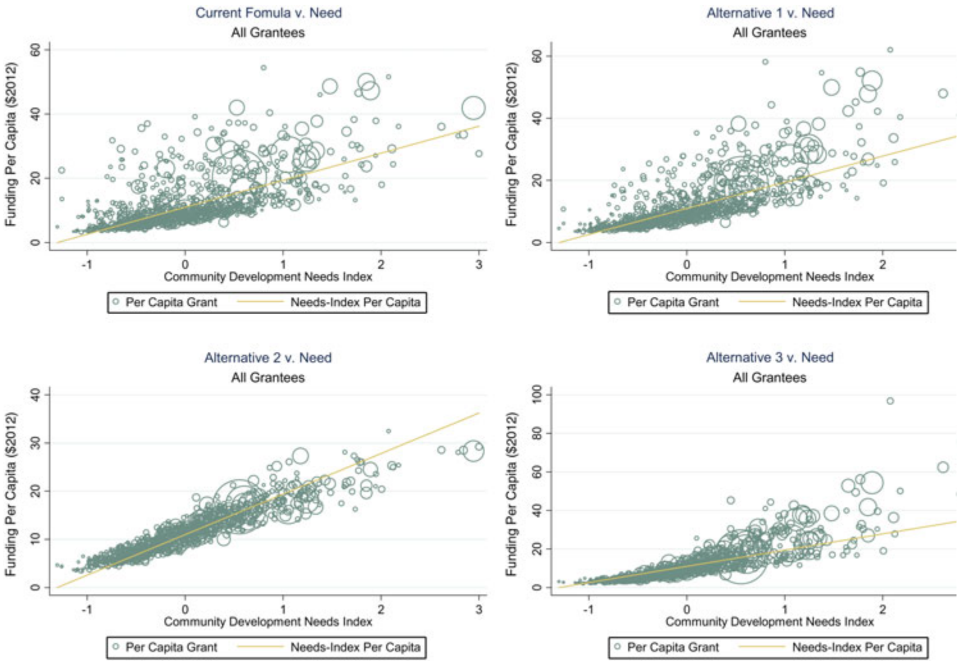
Figure 10. Current allocation versus Alternative 3.



decades. Constructing mock allocations for three time periods (1990, 2000, and 2010), the analysis suggests that the relation between the formula data inputs and community development need has degraded over the past two decades. I characterize allocation effectiveness through the lenses of horizontal equity and vertical equity. Horizontal equity is a positive objective of the formula: grantees of comparable need should receive similar allocations. While a flat allocation is likely to be considered undesirable by many, the degree of vertical equity is a policy choice open to debate. Increasingly, economic evidence suggests that fiscal stimulus is more effective in communities with labor-market slack, which lends support to providing more vertical equity in the formula. However, if high-need grantees are less effective at spending their funds, then a formula which directs relative increases in allocations toward high-need grantees may be problematic. The alternatives laid out in this article provide policymakers with options in pursuing their goals.

Future research should investigate the relative importance of community need and local capacity in determining outcomes for neighborhoods and communities. More generally, additional research is needed on the effectiveness of CDBG. Better

Figure 11. Alternatives comparison.



Note. Dots are sized by estimated grant size.

understanding whether and how CDBG has an impact on local communities, neighborhoods, and vulnerable populations will improve HUD's ability to construct an allocation formula that maximizes impact. To facilitate further research on programs such as CDBG, higher-frequency data at the neighborhood level is important. One example is the IRS's Statistics of Income ZIP Code Data. If smaller geography summary levels of the Statistics of Income data (i.e. by census tract or block group) could be produced at annual intervals (taking the necessary confidentiality protections), it would greatly expand researchers' ability to study neighborhood change. These data could be released retroactively, which would provide a novel panel data-set for studying neighborhood investments. Additionally, HUD should create a public-use neighborhood-level summary file of CDBG activity data using their improving CDBG reporting systems.

Notes

1. Or those previously grandfathered in.
2. Or those previously grandfathered in.
3. Factor analysis was performed using Stata's *factor* command.
4. Population growth lag is the difference between a community's population in period *t* and the population it would have had if it had grown at the average rate of all metropolitan cites since 1960.
5. Wealthy communities are defined as having per capita income of more than 125% of national per capita income *or* poverty rate lower than 75% of the national poverty rate.
6. I exclude the isolation index which is derived from census data.
7. That is: $\text{shareneed}_i = \frac{\text{cdneed}^* \text{pop}_i}{\text{cdneed}^* \text{pop}_j}$.

References

American Community Survey 2006–2010. Five-Year Estimates, U.S. Census Bureau.

Autor, D., Levy, F., & Murnane, R. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, *118*, 1279–1333.

Bunce, H. L. (1976). *An evaluation of the Community Development Block Grant formula*. Washington, DC: U.S. Department of Housing and Urban Development.

Bunce, H. L., Neal, S. G., & Gardner, J. L. (1983). *Effects of the 1980 census on community development funding*. Washington, DC: U.S. Department of Housing and Urban Development.

Burchell, R. W., Listokin, D., Sternlieb, G., Hughes, J. W., & Casey, S. C. (1981). Measuring urban distress: A summary of urban hardship indices and resource allocation systems. In R. W. Burchell & D. Listokins (Eds.), *Cities under stress*. New Brunswick, NJ: Rutgers University.

Dommel, P. R., & Rich, M. J. (1987). The rich get richer: The attenuation of targeting effects of the Community Development Block Grant program. *Urban Affairs Review*, *22*, 522–579.

Ludwig, J., Pollack, H. A., Heller, S., & Ander, R. (2013). *Preventing youth violence and dropout: A randomized field experiment*. NBER Working Paper 19014.

Neary, K., & Todd, R. (1995). *Effect of the 1990 census on CDBG program funding*. Washington, DC: U.S. Department of Housing and Urban Development.

Richardson, T. M. (2005). *CDBG targeting to community development need*. Washington, DC: U.S. Department of Housing and Urban Development.

Sampson, R., Raudenbush, S., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, *277*, 918–924.

Shoag, D. (2012). *The impact of government spending shocks*. HKS Working Paper. Retrieved from http://www.hks.harvard.edu/fs/dshoag/Documents/shoag_jmp.pdf.

Suarez, J. S., & Winegender, P. (in press). Estimating local fiscal multipliers. *Econometrica*.

Appendix 1

The objectives of the Housing and Community Development Act of 1974 are:

- The elimination of slums and blight and the prevention of blighting influences and the deterioration of property and neighborhood and community facilities of importance to the welfare of the community, principally persons of low and moderate income.
- The elimination of conditions which are detrimental to health, safety, and public welfare through code enforcement, demolition, interim rehabilitation assistance, and related activities.
- The conservation and expansion of the Nation's housing stock in order to provide a decent home and a suitable living environment for all persons, but principally for those of low and moderate income.
- The expansion and improvement of the quantity and quality of community services, principally for persons of low and moderate income, which are essential for sound community development and for the development of viable urban communities.
- A more rational utilization of land and other natural resources and the better arrangement of residential, commercial, industrial, recreational, and other needed activity centers.
- The reduction of the isolation of income groups within communities and geographical areas and the promotion of an increase in the diversity and vitality of neighborhoods through the spatial deconcentration of housing opportunities for persons of lower income and the revitalization of deteriorating or deteriorated neighborhoods.
- The restoration and preservation of properties of special value for historic, architectural, or esthetic reasons.
- The alleviation of physical and economic distress through the stimulation of private investment and community revitalization in areas with population out-migration or a stagnating or declining tax base.
- The conservation of the Nation's scarce energy resources, improvement of energy efficiency, and the provision of alternative and renewable energy sources of supply.

Appendix 2: Rotated Factor Loadings.

	Factor 1	Factor 2	Factor 3
Minority segregation	0.802	0.062	0.207
Population-to-employment ratio	0.204	0.752	−0.104
Unemployment rate	0.351	0.675	0.213
Poverty rate (excluding enrolled college students)	0.728	0.545	−0.029
Percentage in high-poverty census tracts	0.670	0.467	−0.202
Poor persons in high-vacancy census tracts	0.504	0.315	−0.431
Percentage age 25 or older without a BA or higher	0.205	0.773	0.293
Percentage of households with a single parent	0.730	0.458	0.297
Percentage pre-1960 housing units occupied by a poor renter	0.713	0.288	−0.221
Percentage overcrowded	0.232	0.236	0.738
Drop-out rate (age 18–24)	−0.066	0.548	0.440
Violent crime rate	0.818	0.060	0.162
Murder rate	0.820	0.104	0.053
Ratio of Metropolitan Mean Household Income to Municipal Mean Household Income	0.534	0.336	0.332

Appendix 3: Variable Interpolation.

Poverty Rate

To develop a consistent measure of the percentage of persons in poverty who are not enrolled in college, I needed to interpolate the 1990 and 2000 values of this variable. To do so, I adjusted the number of 18–24-year-olds who reported being in poverty in 1990 and 2000 by multiply it by the share of 18–24-year-olds who reported being in poverty and *not* enrolled in college according to the ACS 2006/2010.

Violent Crime Rate

Data on aggravated assaults are not available in every year for agencies that report through Uniform Crime Reports (UCR), FBI. To overcome this, I estimated a panel regression of assaults per capita on murders per capita and robberies per capita, and included year and grantee fixed effects.