Using Near-Repeat Analysis To Measure the Concentration of Housing Choice Voucher Program Participants

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Abstract

Public housing authorities (PHAs) are often concerned about housing voucher recipients' reconcentrating after entering the Section 8 voucher program. I use a near-repeat analysis method in this analysis for Dallas, Texas, to test whether new voucher recipients concentrate and, if so, how quickly. The results reveal that new recipients do locate in close proximity to each other at a steady pace over time. PHAs can use this method and subsequent results to measure the progress of deconcentration plans and to help new housing voucher recipients make more informed choices about where to locate.

Housing Choice Vouchers, Deconcentration Plans, and Monitoring Mobility

The Housing Choice Voucher Program (HCVP) provides low-income families the opportunity to move out of impoverished neighborhoods and relocate to better neighborhoods with greater economic opportunity.[1] A common concern for local PHAs about the freedom HCVP offers, though,

[1] In 2010 alone, approximately 2.1 million families received assistance through HCVP. (Public & Indian Housing Tenant-based Rental Assistance: 2012 Summary Statement and Initiatives, 2010) http://portal.hud.gov/hudportal/documents/huddoc?id=Tenant_BR_Assis_2012.pdf.

is that participants will reassemble in the same neighborhoods and potentially undo efforts to deconcentrate poverty, which could lead to the emergence of a range of social and economic problems (Ellen, Lens, and O'Regan, 2012; Freeman and Botien, 2002; Mast and Wilson, 2013; Pendall, 2000; Popkin, et. al., 2012; Wilson and Mast, 2013). In addition, PHAs are concerned that voucher holders will reconcentrate in neighborhoods and be exploited by landlords. For example, landlords could set higher rents than average because rents for nearby properties become uniform. Landlords might not maintain properties to maximize profits because residents are unlikely to organize and demand better conditions. Further, lack of property upkeep can lead to neighborhood blight and deter additional investment, which ultimately leaves voucher recipients with diminished economic opportunities.

Many PHAs develop plans to measure and monitor poverty deconcentration, but these plans are primarily aimed at public housing developments.[2] Rules set forth by Title 24, Part 903 of the Code of Federal Regulations[3] list a number of factors PHAs must measure in their plans to ascertain whether public housing developments are achieving poverty deconcentration; several of the factors require identifying geographic areas to evaluate change. Many plans include the use of vouchers as a mechanism to facilitate poverty deconcentration because participants relocate out of public housing developments altogether (Huartung and Henig, 1997) and into other neighborhoods with mixed income levels. Given the geographic nature of mobility, spatial analysis tools can be used to assess if HCVP participants are reconcentrating or dispersing. By using an approach that incorporates time into the spatial analysis, PHAs can determine not only if voucher holders are reconcentrating, but also how fast they are co-locating with other HCVP participants. Results may also be used to examine the neighborhoods where new voucher recipients are co-locating to gain an understanding of their mobility choices or garner an idea of how likely other voucher holders are to move into areas where other participants have relocated.

I demonstrate in this article how to perform a near-repeat analysis to geographically measure the speed at which new HCVP participants concentrated when they entered the HCVP between 2007 and 2010 in the Dallas-Arlington-Fort Worth, TX metropolitan area. I used 13,788 new HCVP participant admission locations from the Public and Indian Housing (PIH) Inventory Management System (IMS)/PIH Information Center (PIC) databases.[4] The results depict the likelihood that new HCVP recipients will co-locate in proximity to each other and the speed with which they co-locate. I extend the analysis by identifying relocation density clusters that reveal the least and greatest relocation concentration.

The Near-Repeat Concept

A near-repeat analysis is an approach used in measuring the spatial and temporal relationships of crime. Research indicates that crime incidents can occur at the same location (repeat) or nearby

[2] An Internet search with terms similar to "public housing deconcentration plans" yields a number of web addresses that link to existing plans established all over the United States.

[3] 24 CFR 903, "Public Housing Agency Plans." Available at http://www.gpo.gov/fdsys/granule/CFR-2011-title24-vol4/CFR-2011-title24-vol4-part903/content-detail.html.

[4] http://portal.hud.gov/hudportal/HUD?src=/program_offices/public_indian_housing/systems/pic.

(near repeat) in short periods of time from each other (Bowers and Johnson, 2004; Johnson, Bowers, and Hirshfield, 1997; Ratcliffe and Rengert, 2008; Short et al., 2009). These repeats occur because the areas in which the incidents occur share location commonalities that offer opportunities for crime. The near-repeat concept is rooted in the First Law of Geography (Miller, 2004) that everything is related, but things close in proximity share a stronger relationship because they share common characteristics; *that is,* the events are spatially dependent based on proximity. The near-repeat approach capitalizes on this law by incorporating the temporal sequencing of event locations that occur within a series of increasing distances between events. Housing and urban problems readily lend themselves to this type of analysis because many problems exhibit spatial dependence between events and the urban landscapes.

Identifying Distance and Time Intervals To Set Near-Repeat Parameters

I first identified meaningful distance and temporal intervals in which new voucher admissions are expected to concentrate. Too large or small an interval can introduce measurement error from including or excluding too many locations within an interval. For the distance intervals I conducted a nearest neighbor (NN) analysis on all new admission locations to determine if vouchers were clustering. The NN analysis indicated that new voucher admissions were highly clustered with an index of 0.1417 (z = -189.27).[5] The average distance between new admission locations was 318.49 feet with a standard deviation of 1,760.21 feet. These results indicate that new HCVP participants co-locate very close to each other. I used approximately 0.33 miles (one standard deviation above the mean distance between locations) up to 4.00 miles to account for an HCVP participant to select a rental property across an area containing several neighborhoods.

Temporal intervals also need to be based on a meaningful timeframe. As with distance intervals, too large or small of a time interval will also introduce more measurement error. I used 30-day time intervals of up to 180 total, because the voucher admission process follows a series of monthly administrative stages to obtain a voucher and the relocation notification laws typically require 30 days' notice to move between residences.

Near-Repeat Calculations of New HCVP Admission Locations in the Dallas, Fort Worth, and Arlington, Texas Metropolitan Area

I used the near-repeat calculator (NRC)[6] to simultaneously measure the distance and time characteristics between new voucher locations. The NRC expands the original concept by George Knox (1964) who derived a statistical test that categorizes a pair of event locations in a 2 x 2 contingency

[5] A nearest neighbor analysis produces an index, which is a ratio of the observed and expected average distances. The index ranges in value from 0 to 2.149, with a balance point of 1.0. Values closer to 0 indicate clustering. Values around 1.0 indicate a random distribution. Values closer to 2.149 indicate dispersion.

[6] http://www.temple.edu/cj/misc/nr/.

table[7] in which two events occur in close proximity by (1) distance only (d_1, t_0), (2) time only (d_0, t_1), (3) both distance and time (d_1, t_1), or (4) not proximal in either (d_0, t_0). The NRC extends the Knox contingency table by creating an *N* x *N* contingency table with multiple distance and time intervals—from d_1 to d_n and t_1 to t_n—instead of just two intervals for each dimension (exhibit 1).

In addition, the NRC tests for repeat events at the same location, which distance is denoted d_0, and time t_0. The NRC measures and records the distances between all observed pairs of event locations and their date stamps for each specified distance and time interval. A Monte Carlo permutation approach is then employed to randomize only the event dates. The permutation process is carried out for each distance and time interval separately, up to 999 randomization trials.[8] For each trial, the event pairs' distances are remeasured with the reassigned dates and combined with the other trial results to create an expected (null) distribution. Locations remain fixed during the permutation process because the date randomization redefines the spatial relationship between locations, such that two locations may or may not be in proximity to each other within a time interval. The observed event pair-count is then compared with the mean of the expected distribution to determine if the actual number of nearby event locations is different than the expected in a time interval (exhibit 2).

Statistical significance for each distance and time interval is determined by calculating the number of times the observed event pair-count exceeds the mean of the expected distribution. If the observed count is outside the expected distribution, then the distance-time relationship between a pair of observations is likely due to some underlying process and not by chance.

I used a .01-significance level for the Monte Carlo tests to ensure my results were robust and to distinguish levels of statistical strength for each distance-time interval.[9] I measured new admission

Exhibit 1

N x *N* Knox Contingency Table To Test Distance and Time Relationships

0 → Time intervals → t

Distance intervals (0 → d)						
	D1 & T1	D1 & T2	D1 & T3	…	D1 & T*N*	~T for D1
	D2 & T1	D2 & T2	D2 & T3	…	D2 & T*N*	~T for D2
	D3 & T1	D3 & T2	D3 & T3	…	D3 & T*N*	~T for D3
	…	…	…	…	…	…
	D*N* & T1	D*N* & T2	D*N* & T3	…	D*N* & T*N*	~T for D*N*
	~D for T1	~D for T2	~D for T3	…	~D for T*N*	~T & ~D

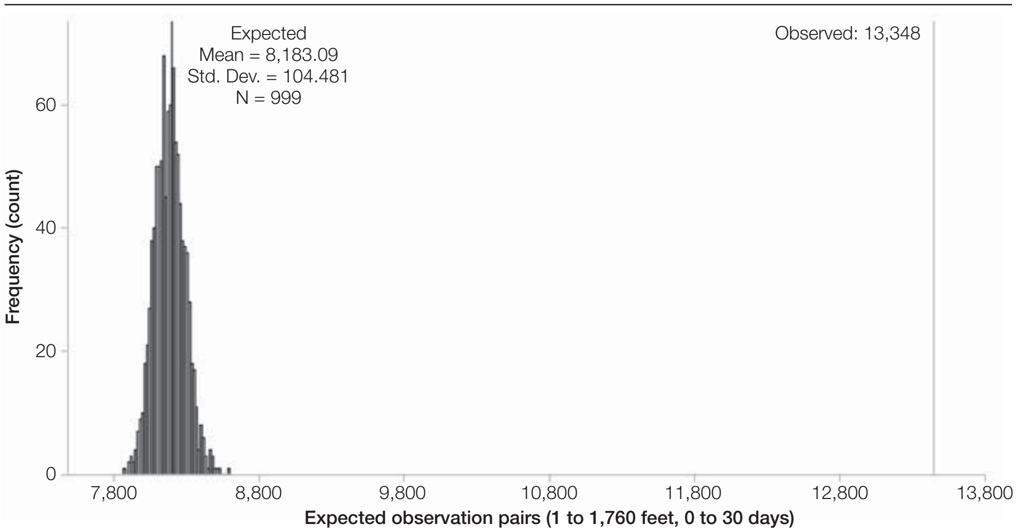
7 A contingency table in this context is a matrix of two or more categories that depict the relationship between each factor across all rows and columns.

8 The number of randomization trials is based on a selected level of significance to be achieved: $p \leq .5$: 19 randomizations; $p \leq .01$: 99 randomizations; $p \leq .001$: 999 randomizations.

9 Running a near-repeat analysis with significance levels at $p \geq .01$ or $p \geq .01$ with the NRC produces results that show which observed distance and time interval observed and expected ratios are the strongest and weakest based on which significance level was selected.

Exhibit 2

Distribution of Expected Pairs Within Second Distance and First Time Intervals



N = number. Std. Dev. = standard deviation.

locations with direct distances (Euclidean), because concentrations of new voucher admissions are about the direct proximity of one family to another in an area and do not have to follow a gridded street pattern (Manhattan) to be in proximity.

The NRC produces two contingency tables. The first table reports the likelihood ratios (Knox ratios)[10] of events repeating at the same location or repeating nearby within a certain proximity (exhibit 3).

Ratios of less than 1 indicate new voucher admissions are less likely to occur. Ratios greater than 1 indicate foreclosures are more likely to occur. For example, from exhibit 2, 8,183 new voucher admission counts are expected to occur within 1 to 1,760 feet of each other and within 0 to 30 days of each other, with the observed pair-count being 13,348 new admissions.[11] Dividing the observed pair-count by the expected number of new admissions creates a Knox ratio of 1.63 and indicates a 63 percent (Knox ratio minus 1) chance that another new voucher recipient will relocate within approximately 0.33 miles (1,760 feet), within 0 to 30 days, from an initial new admission location. Knox ratios in bold, black numbers are significant at .01 and bold, light-gray numbers are significant at .05—all small, unbold, light-gray numbers are not significant.

The second table reports significance levels for each corresponding Knox ratio (exhibit 4). Statistical significance is determined by calculating *p*-values from the observed and expected pair-count comparison. *p*-values are calculated for each distance and time interval with $p = 1 - n_e / (n_s + 1)$, where n_e is the Knox ratio and n_s is the number of randomization trials. For example, with new voucher admission locations that occur within 1 to 1,760 feet, within 0 to 30 days, the *p*-value for

[10] For a more detailed discussion of Knox ratios, see Grubesic and Mac (2008).

[11] The observed and expected counts are reported in another table produced by the NRC, which is titled "Verbose."

Exhibit 3

Observed Over Mean Expected Values for Near-Repeat HCVP Voucher Admission Locations, 2010

	0 to 30 Days	31 to 60 Days	61 to 90 Days	91 to 120 Days	121 to 150 Days	151 to 180 Days	More Than 180 Days
Same location	**6.04**	**3.61**	**2.51**	**1.84**	**1.19**	0.99	0.43
1 to 1,760 feet	**1.63**	**1.41**	**1.54**	**1.48**	**1.48**	**1.37**	0.85
1,761 to 3,520 feet	**1.21**	**1.17**	**1.11**	1.00	0.99	0.96	0.97
3,521 to 5,280 feet	**1.36**	**1.26**	**1.15**	**1.06**	0.98	0.90	0.96
5,281 to 7,040 feet	**1.24**	**1.17**	**1.13**	**1.05**	1.02	0.96	0.97
7,041 to 8,800 feet	**1.28**	**1.25**	**1.13**	**1.07**	1.01	0.95	0.96
8,801 to 10,560 feet	**1.29**	**1.22**	**1.10**	**1.04**	**1.04**	0.95	0.96
10,561 to 12,320 feet	**1.21**	**1.14**	**1.09**	**1.04**	1.01	0.99	0.97
12,321 to 14,080 feet	**1.25**	**1.17**	**1.14**	**1.07**	**1.03**	**1.04**	0.96
14,081 to 15,840 feet	**1.23**	**1.14**	**1.08**	**1.02**	0.99	0.98	0.97
15,841 to 17,600 feet	**1.20**	**1.14**	**1.08**	**1.03**	0.99	1.01	0.97
17,601 to 19,360 feet	**1.17**	**1.11**	**1.07**	**1.04**	1.01	**1.02**	0.98
19,361 to 21,120 feet	**1.29**	**1.18**	**1.12**	**1.10**	**1.04**	**1.04**	0.96
More than 21,120 feet	0.98	0.99	0.99	1.00	1.00	1.00	**1.00**

HCVP = Housing Choice Voucher Program.

Notes: Bold, black values are statistically significant at p ≤ .01. Bold, light-gray values are statistically significant at p ≤ .05. Small, unbold, light-gray values are not statistically significant.

Exhibit 4

Significance Values for Near-Repeat HCVP Voucher Admission Locations, 2007 to 2010

	0 to 30 Days	31 to 60 Days	61 to 90 Days	91 to 120 Days	121 to 150 Days	151 to 180 Days	More Than 180 Days
Same location	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	0.70	1.00
1 to 1,760 feet	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	1.00
1,761 to 3,520 feet	**0.01**	**0.01**	**0.01**	0.45	0.74	1.00	1.00
3,521 to 5,280 feet	**0.01**	**0.01**	**0.01**	**0.01**	0.94	1.00	1.00
5,281 to 7,040 feet	**0.01**	**0.01**	**0.01**	**0.01**	0.07	1.00	1.00
7,041 to 8,800 feet	**0.01**	**0.01**	**0.01**	**0.01**	0.12	1.00	1.00
8,801 to 10,560 feet	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	1.00	1.00
10,561 to 12,320 feet	**0.01**	**0.01**	**0.01**	**0.01**	0.15	0.77	1.00
12,321 to 14,080 feet	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	1.00
14,081 to 15,840 feet	**0.01**	**0.01**	**0.01**	**0.05**	0.95	0.97	1.00
15,841 to 17,600 feet	**0.01**	**0.01**	**0.01**	**0.05**	0.84	0.18	1.00
17,601 to 19,360 feet	**0.01**	**0.01**	**0.01**	**0.01**	0.05	**0.05**	1.00
19,361 to 21,120 feet	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	1.00
More than 21,120 feet	1.00	1.00	1.00	1.00	1.00	1.00	**0.01**

HCVP = Housing Choice Voucher Program.

Notes: Bold, black values are statistically significant at p ≤ .01. Bold, light-gray values are statistically significant at p ≤ .05. Small, unbold, light-gray values are not statistically significant.

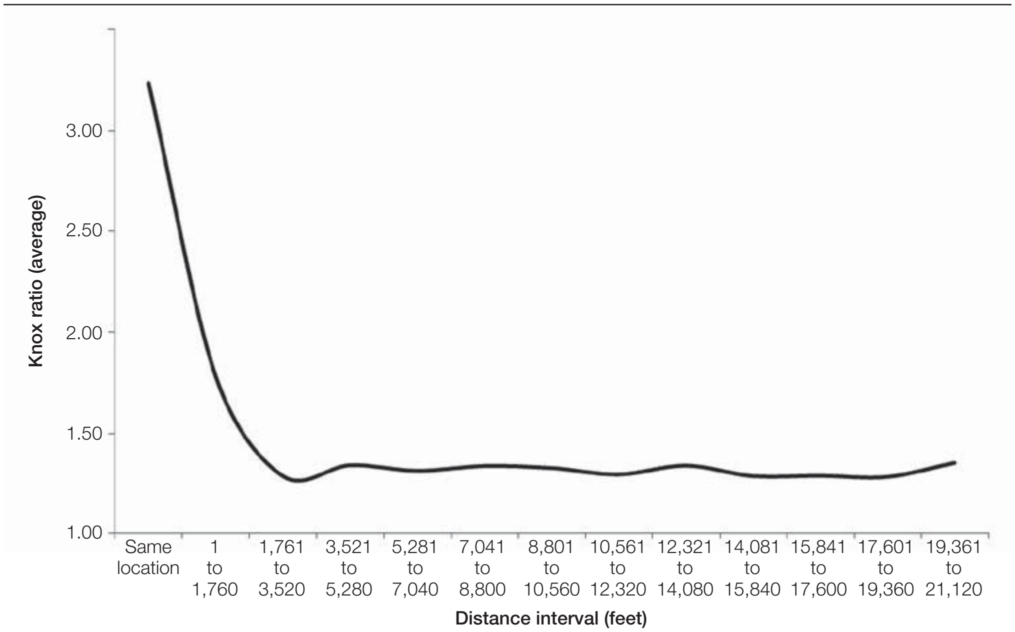
the 1.63 Knox ratio is $p = 1 - 1.63 / (99 + 1)$, evaluating to $p = 0.0063$. This p-value is statistically significant at the .01-level and the likelihood of the 2,856 new admissions being in the closest proximity to each other within the first 0 to 30 days is not due to chance.

Exhibit 3 shows an extensive and ongoing clustering of vouchers across time. The Knox ratios indicate a general pattern of time and distance decay[12] for new HCVP admissions after an originating new admission. Exhibits 5 and 6 summarize exhibit 3.

New admissions appear to have the greatest propensity to move to the same location, which is likely to be a low-income apartment or other multifamily complex. Distance decreases much more rapidly than time for near-repeat admissions, indicating new HCVP participants primarily co-locate in neighborhoods where other vouchers holders already live on a steady basis for about 3 months. In other words, the greatest chances of new participants co-locating are within 5,280 feet (1 mile) and within 90 days of the originator.

Exhibit 5

Distance Decay of New HCVP Participants, 2007 to 2010

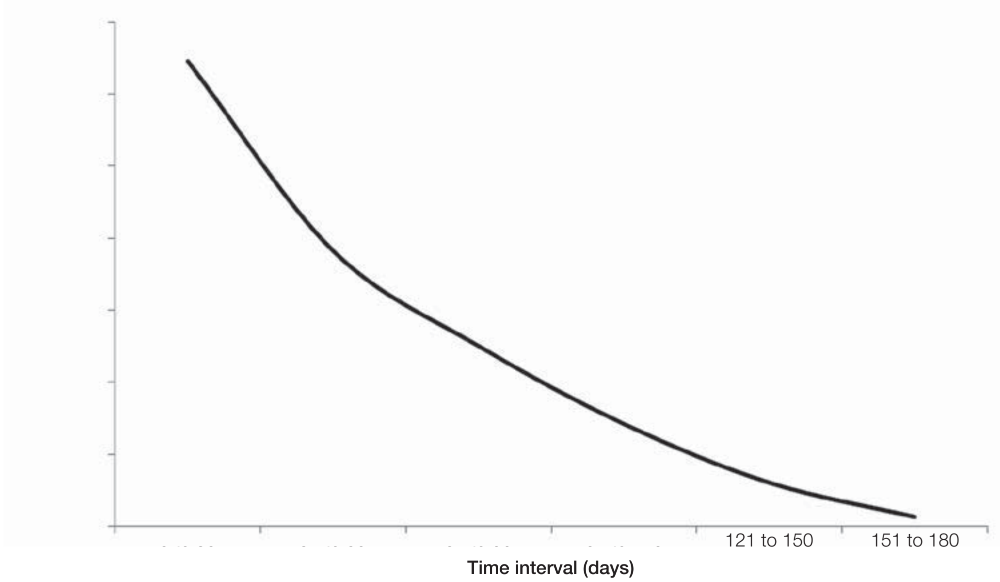


HCVP = Housing Choice Voucher Program.

[12] If spatial analysis is to be conducted later, the plotting of values in a spreadsheet graph will show the distance decay curve that could be used to visualize the appropriate mathematical function to use for distance parameter specification. The shape of the distance decay curve from the results can help in selecting the mathematical function that produces a similar curve to weight distance.

Exhibit 6

Temporal Decay of New HCVP Participants, 2007 to 2010



HCVP = Housing Choice Voucher Program.

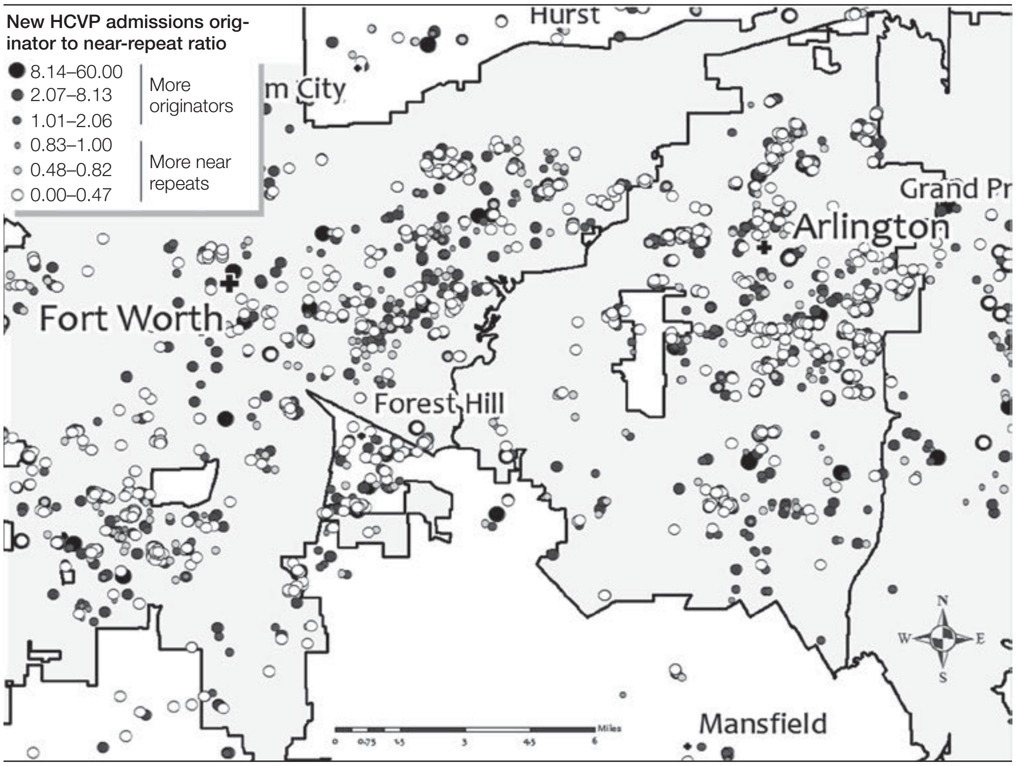
Visualizing the Near-Repeat Calculator Results

The near-repeat calculator can output the number of times an event is an originator location to other nearby locations, and it can output the count of near-repeat events to other locations. This output allows for visualizing the event space-time clusters in a geographic information system, or GIS. The originator and near-repeat quantities can be mapped by individual counts or by combining the number of times a location is an originator and a near repeat into a ratio to show a bivariate relationship. Exhibit 7 shows the ratio of originator voucher admissions for nearby admissions to the near-repeat admissions patterns across the Fort Worth and Arlington areas for up to 4 miles (21,192 feet) and 4 months (120 days), which matches the significance patterns in exhibit 4.

The size of the graduate symbol expresses how many times a new admission is an originator for other new admissions or is a near-repeat admission to other new admission locations. The larger and darker the circles, the more a new admission serves as a clustering source for other (near-repeat) admissions; that is, other new voucher recipients followed the original recipient to the same location or nearby. The larger and lighter the circles, the more times a new admission is a near repeat to other new admissions. The patterns reveal where the clustering trend started—dark circles being the most influential catalysts—and where the expansion occurred (lighter circles) around those original admissions. For example, in the area between Fort Worth and Arlington, several large, black circles with groupings of dark- and light-gray circles are in close proximity. Black circles indicate locations that were originators for a significant number of new voucher admissions within the proximity. The numerous light-gray and white circles indicate the extent of new voucher

Exhibit 7

Ratio of Originator to Near Repeats of New HCVP Admissions, 2007 to 2010



HCVP = Housing Choice Voucher Program.

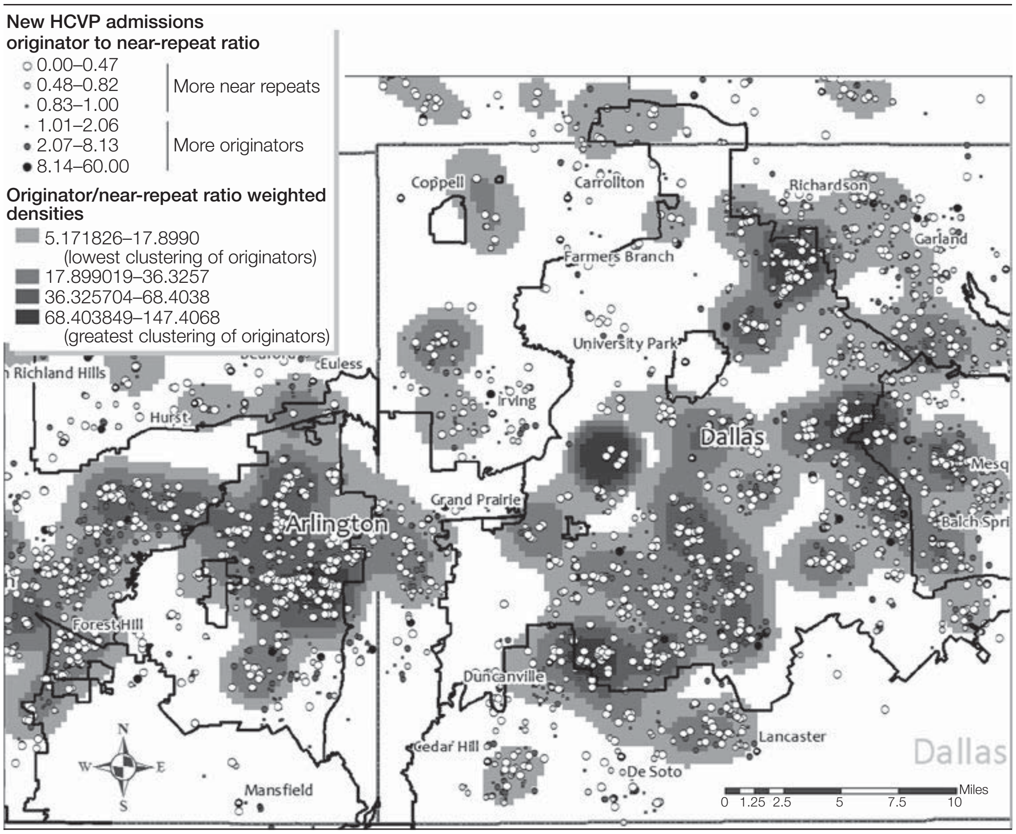
admissions that are located near originating or other near-repeat admission locations. This visualization is useful for identifying the originating new admission location, and it shows how many near repeats voucher recipients are around the originating admissions and the direction they extend. Clusters of dark circles can signal a gravity effect in which the likelihood of another new admission locating in the general vicinity is strong. Clusters of lighter circles can reveal the extent of near-repeat admissions around other new admissions.

The graduated circles do not accurately depict cluster areas, however, and can be deceiving because their graphic display requires inflated sizes that make them appear closer than they really are. Therefore, density surfaces can enhance the visualization of the near-repeat results because the technique summarizes the proximity of the relationships with a smoothed surface based on the number and proximity of new admission locations. So, to extend the visualization of the near-repeat output, I conducted a kernel density estimation, or KDE, analysis to create a cluster surface of the repeat and near-repeat location output from the NRC. Using CrimeStat IV, I selected the quartic function for this analysis because it weights closer observations more uniformly in close proximity and gradually decreases the weighting subtly—similar to a bubble—the farther the observations are up to a specified distance.[13] The quartic function characterizes previous research findings that voucher holders tend to live in close proximity. I also weighted the new admissions' locations based on their originator to near-repeat ratio to emphasize the strength of a location's influence on, or draw to, other locations.[14] Finally, I used relative densities for the output to produce a density surface that represents the number of new voucher holders' relocations per square mile, accounting for an originator to draw other near repeats to the local area.

Exhibit 8 reveals multiple density clusters of varying levels of concentration of new HCVP admissions. The density surface extenuates the near-repeat locations to highlight areas where new HCVP participants are likely to live. These areas vary in densities with the gradients depicting areas with lowest (light gray) to highest (dark gray) densities of new HCVP participants per square mile.

Exhibit 8

Originator to Near-Repeat Ratio Densities (per square mile) of New HCVP Admissions, 2007 to 2010



HCVP = Housing Choice Voucher Program.

[13] The inclusion of only those observations within the specified distance is true for all the mathematical functions in CrimeStat 3.3 except for the normal function. The normal function includes all observations across the geography.

[14] Values closer to 0 indicated more near repeats to fewer originators, while values beyond 1 indicate the more times an originator is related to other near repeats.

One cluster to the west of downtown Dallas is an area with a number of near-repeat clusters at only a few locations. The cluster pattern indicates that it is a multifamily complex into which many new voucher holders are moving. Four other high-density, near-repeat clusters are present in the northeast, east, and southwest of Dallas, with one in south-central Arlington. Each cluster represents a significant number of near repeats, indicating that many voucher holders are locating to those areas, which may have a number of multifamily complexes and correspond with the higher Knox ratios for the same location in the tables in exhibits 3 and 4.

Monitoring and Planning Considerations

A near-repeat analysis offers a dynamic way to monitor the deconcentration of poverty, because the geographical analysis reveals where clusters of new admission relocations are emerging as time passes, including likelihoods where other voucher holders will relocate. After repeat and near-repeat locations are identified, a number of further visual or spatial analyses can be undertaken, such as comparing the results with income changes in the areas where they are relocating, determining if expansion is occurring into new areas; examining housing market and neighborhood conditions in the areas where new admissions are concentrating or expanding into; or using other spatial statistical techniques to measure mobility.

Specifically with the near-repeat calculator, numerous other ways to analyze data exist, because they can be partitioned along any number of criteria, such as certain areas versus other areas, such as poverty levels or housing submarkets. More specifically, the new voucher admission locations can be partitioned by time periods and analyzed sequentially to compare changes across time. In any analysis, the result of a near-repeat approach could help PHAs monitor deconcentration efforts and it could serve as a complement to analyzing mobility patterns, in general, with a more dynamic approach. This analysis approach can also help voucher holders, in general, make more informed decisions about the neighborhoods to which they may want to relocate.

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