Targeting Services to Individuals Most Likely to Enter Shelter: Evaluating the Efficiency of Homelessness Prevention

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ABSTRACT Successful strategies for homelessness prevention must efficiently target people at greatest risk for experiencing homelessness. We developed a model to target homelessness prevention services to individuals and evaluate its results compared to a similar model we developed for families. We tracked 10,220 individuals who applied for community-based homelessness prevention in New York City from 2004 to 2010 using Cox regression to predict shelter entry over the next 2–8 years. Both the comprehensive model and a brief screening model based on seven variables are at least as efficient as worker judgments, increasing correct predictions by 77 percent and reducing unidentified cases of subsequent homelessness by 85 percent. Risk factors for homeless individuals were mostly a subset of risk factors for families. The evidence suggests that, despite limitations, empirical models increase the efficiency of prevention services for individuals. Investigators in other cities may improve the efficiency of local prevention programs with empirical targeting models.

INTRODUCTION

Nationwide in 2014, more than 1.48 million people stayed in a homeless shelter for at least one night, and almost two-thirds of them were individuals who were not part of family units (HUD 2015*a*). Shelter stays are expensive for cities (Spellman et al. 2010; Culhane, Park, and Metraux 2011), and homelessness is associated with a variety of adverse outcomes for people who are

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experiencing it (e.g., increased criminal activity, higher rates of drug and sexual-risk behaviors; Aidala et al. 2005; Burt and Spellman 2007; Fischer et al. 2008; Fazel, Geddes, and Kushel 2014). Accurately targeted and effective community-based prevention programs can be cheaper for cities than expensive shelter stays (Culhane, Metraux, and Byrne 2011). Although studies show reductions in homelessness rates resulting from increased investment in deep subsidies such as permanent supportive housing (e.g., Byrne et al. 2014) or vouchers (Gubits et al. 2015), there is limited research that investigates the effectiveness and efficiency of targeted homelessness prevention, or prevention programs that direct services to people at highest risk for shelter entry. Previous studies acknowledge the difficulties (and importance) of identifying which recipients would benefit most from social services as well as political challenges that arise when seeking to target services narrowly (O'Flaherty 2009; Theodos et al. 2012). Our study develops a model to predict shelter entry for adult applicants for the HomeBase homelessness prevention program in New York City.

The goal of this study is to help service providers target prevention services to the individual applicants who can benefit most. Here individuals are defined as adults without children. In New York City, couples without children can be sheltered together and are considered part of the individual adult system, so they are included as individuals here. In order to improve targeting of prevention services, this article addresses the following questions: Which risk factors contribute to shelter entry for individual applicants for prevention services? How do risk factors for shelter use vary between families and individual applicants? Are some individual applicants at such high risk that prevention services make little difference? How does the efficiency for an empirical model predicting shelter entry for individuals compare with decisions made by service providers in the absence of such a model?

BACKGROUND

THE HOMEBASE HOMELESSNESS PREVENTION PROGRAM

HomeBase offers customized services, including case management, eviction prevention, landlord mediation, short-term emergency funding, and assistance in obtaining employment and public benefits, to families and individuals who are at risk for homelessness. People find HomeBase through public awareness campaigns, street outreach, and word of mouth (Taylor 2015), and they apply for services at offices operated by nonprofit service agencies located in their communities. Applicants are required to have incomes below 200 percent of the poverty line. Prior to the development of our model for determining eligibility, the HomeBase program determined eligibility for services based on one or more of the following additional criteria: significant overcrowding or household discord, residency threatened by legal eviction action, unworkable landlord relationship, unsafe living conditions, desire to reintegrate into community district, or shelter application within the past 3 months. However, the program is flexibly designed to allow all HomeBase offices discretion when determining eligibility. The number of households served continues to grow over time, with 20,000 served in 2015 (more than double the number of households served in 2014). Services are modest; only 25 percent of clients receive financial assistance, and the average cost per household is $2,000 (internal Department of Homeless Services analysis by coauthor Jonathan Kwon).

The HomeBase program is unique in its flexible program design and its use of community-based services. Additionally, HomeBase administrators hold service providers accountable for both low rates of shelter entry for those who receive services and lower rates of homelessness in communities served by HomeBase, compared to others. The program has been shown to be modestly effective, at least for families, in experimental and quasi-experimental studies (Messeri, O'Flaherty, and Goodman 2012; Rolston, Geyer, and Locke 2013), but it serves many families who are at such low risk for shelter entry that they derive little benefit. After our team developed an empirical model that was adopted by New York City to target services to families who could benefit most (Shinn et al. 2013), officials asked us to develop a parallel model for individuals.

HOMELESSNESS IN NEW YORK CITY

There are several differences between homelessness in New York City and in the United States as a whole. The trends in homelessness rates for individuals in shelter appear to be headed in opposite directions. From 2007 to 2015, the numbers of homeless individuals in shelter fell by 3 percent nationally, compared to a 50 percent increase in New York City (HUD 2015*b*). Although the rates are based on point-in-time (PIT) estimates for a single night, the opposite trends are noteworthy. Individuals form the largest group of people experiencing homelessness nationwide, but not in New York City (HUD 2015*b*). Of all homeless people staying in shelter or transitional housing in New York City on a single night in January 2015 (HUD 2015*b*), less than 37 percent were individuals. This is lower than the national proportion of individuals in shelter both because of the high cost of housing in New York City (which is particularly problematic for families) and because the city's legal right to shelter means that families who might put up with extremely poor housing conditions in other jurisdictions are more likely to enter shelter in New York City. The landmark case *Callahan vs. Carey* in 1981 ruled that New York City is legally required to accommodate every person who needs shelter (Department of Homeless Services 2016).

There is reason to believe that the risk model we developed previously for families might not apply to individuals because they have different characteristics in national data. For example, single homeless people in shelters have higher rates of disabilities than sheltered families, and African Americans are overrepresented in both groups but especially among families (HUD 2015*a*). Other studies find that baby boomers have maintained high risk for individual homelessness, leading to an increase in average age for individuals over the last three decades, whereas a similar aging trend is not evident for families (Culhane et al. 2013). Further, among individuals, longer durations of homelessness are associated with older age and arrest history (Caton et al. 2005). Several authors have developed risk models for families (Shinn et al. 1998, 2013; Barnett et al. 2011), for undifferentiated groups of individuals and families (Hudson and Vissing 2010), or for veterans (Greenberg et al. 2006). Given the differences between individuals and families, it is important to develop a separate risk model for individuals.

WHY DO FAMILIES AND INDIVIDUALS DIFFER?

Structural forces that shape homelessness, such as economic and social policy, account for the differing rates of homelessness for families and individuals. During the second half of the twentieth century, contemporary homelessness emerged first for individuals and then for families in step with shifts in political, social, and economic forces. In the 1950s and 1960s, older single men living in urban skid rows exemplified homelessness. Increases in coverage and amounts of social security in the 1960s and 1970s reduced homelessness (Rossi 1994). At the same time, cities began demolishing flophouses, single-room-occupancy hotels, and other cheap housing, which led to homelessness among new groups of younger single men and then women. In the early 1980s, greater unemployment, an economic recession, and less financial assistance from the state led to the emergence of family homelessness. In spite of an economic boom in the late 1980s, the wealthiest Americans' financial gains failed to trickle down to the poorest families and rates of family homelessness increased (Rossi 1994). In the 1990s, many states restructured welfare programs to require employment, which posed a challenge for single mothers and contributed to increases in the overall number of homeless families (Shinn 2010). Discrimination across domains such as housing, employment, and imprisonment likely leads to greater rates of homelessness for minorities for both families and individuals (Shinn 2010).

The financial costs of housing further differentiate families and individuals. Families require larger units than individuals, and families with infants and young children are at particular risk for homelessness because costs of childbirth and care for young children can require the use of funds that might otherwise have been used for housing. Individuals may have lower financial burdens, but disabilities and more restrictions on assistance impede their ability to afford housing. Across at-risk groups, but especially for families with children, a lack of affordable housing pushes financially constrained households into homelessness (Shinn and Weitzman 1994).

Disabilities such as mental illness and substance abuse often factor into discussions of homelessness, particularly for individuals. In 2011, rates of mental illness for sheltered persons (severe mental illness, 26.2 percent; chronic substance abuse, 34.7 percent) were much higher than national rates of mental illness (16.2 percent), substance abuse (6.3 percent), or both (2.9 percent; Paquette 2011; SAMHSA 2014). For individuals with long or recurrent episodes of homelessness, the rates are even higher: 30 percent experienced mental health problems, and approximately 50 percent exhibited co-occurring substance abuse (Paquette 2011). Further, individuals with mental illness might alternate repeatedly between shelters, jails, and substance or mental health facilities, a phenomenon that is sometimes called the "institutional circuit" (Hopper et al. 1997, 659). Additionally, the exclusion of substance abuse as a disability to qualify for Supplemental Security Income (SSI) likely exacerbated already constrained financial situations, especially for individuals (Burt 2001; Baumohl et al. 2003; Norris et al. 2003).

In sum, the characteristics of families and individuals who experience homelessness tend to differ in response to economic, social, and political structures. Ending homelessness requires making housing more affordable, and structural change that would accomplish this occurs slowly. In the meantime, people lose homes. Provision of rapid, effective, targeted homelessness prevention to those at risk can reduce the immediate financial and emotional costs of shelter entry. Accordingly, a model predicting shelter entry for individuals, distinct from those developed previously for families, can guide service providers and programs to target services to people who are most in need.

RISK FACTORS AND MODEL EFFICIENCY

Many studies of homelessness describe risk factors, but for purposes of prevention, investigations should assess how efficiently a collection of risks organized into a targeting model can select people at risk for homelessness (Burt, Pearson, and Montgomery 2007; Shinn and Greer 2011). To test the efficiency of a model, evaluations should examine hit rates and false-alarm rates at various levels of assessed risk (Swets 1996; Shinn et al. 1998, 2013). The hit rate is defined as the proportion correctly predicted to enter shelter among all shelter entrants. The false-alarm rate is defined as the proportion of people incorrectly predicted to enter shelter among all people who avoid shelter entry. In the case of a continuous risk model, agencies can provide services to all those who exceed some cutoff of risk, with that cutoff suggesting a particular trade-off between hit rates and false-alarm rates (Shinn et al. 2013).

Models predicting homelessness tend to have low hit rates unless researchers and policy makers are willing to tolerate high false-alarm rates. For example, in a nationally representative sample, Christopher Hudson and Yvonne Vissing (2010) correctly predict 2.6 percent of the people who self-reported an experience of homelessness, at a false-alarm rate of 0.1 percent. The authors chose such a low cutoff for risk because the false-alarm rate applied to the entire population of the nation. This study used demographic, socioeconomic, and mental illness predictors, but it did not differentiate between families and individuals.

Other investigations model homelessness risk for families (Shinn et al. 1998, 2013; Barnett et al. 2011). With a targeting model, Marybeth Shinn and colleagues (1998) correctly identify 66 percent of shelter entrants (i.e., the hit rate) with a false-alarm rate of 10 percent of families receiving public assistance in New York City. Families receiving public assistance are a more select group than the national population, but offering services to 10 percent of the public assistance caseload at the time of the study would have meant that over 80 percent of services would have gone to people who would have avoided shelter without them (Shinn, Baumohl, and Hopper 2001). In a sample of 2,602 homeless families, half of whom participated in the rapid exit program in Hennepin County, Jamie Barnett and colleagues (2011) attempted to predict shelter reentry and found a hit rate of 48 percent of reentrants with a false-alarm rate (or those who were predicted to reenter shelter but who did not) of 23 percent.

In a recent investigation (Shinn et al. 2013), we examined the efficiency of targeting models for families who applied to the HomeBase prevention program in New York City. We used Cox proportional hazards modeling to identify risk factors for shelter entry over 3 years among 11,105 families who applied for HomeBase services. We calculated that if HomeBase continued to serve the same percentage of applicants (66.5 percent) but selected them according to the targeting model rather than worker judgments, they would improve the hit rate to 90.4 percent from 71.6 percent among applicants who entered shelter, at the expense of a false-alarm rate of 65.7 percent among applicants who remained housed. However, targeting remains difficult: even in the highest decile of risk, only 44 percent of families who failed to receive services entered shelter.

We found only one peer-reviewed study that considered the efficiency of predictive models for any population subgroups other than families. Greg Greenberg and colleagues (2006) created a model that predicts rates of subsequent homelessness for previously homeless veterans in a Veterans Health Administration medical center. They find that, for the lowest-risk group, 2.9 percent of veterans experienced subsequent homelessness, whereas 27.6 percent of the highest-risk group experienced homelessness again. Housing statuses included literal homelessness, doubled-up living situations, being transferred to another institution, and living independently. The authors find that better housing status at discharge originated from entering the program without a status of homeless, receiving treatment in a substance abuse or psychiatric program rather than a medical program, and having greater income or access to financial assistance. The authors do not report false-alarm rates.

This study adds to the literature by developing a risk model for subsequent shelter entry for individuals who applied for homelessness prevention services in New York City. Following this model, we compare the risk factors and the efficiency of the resulting targeting models for individuals with findings from our study of targeting among families (Shinn et al. 2013). The investigation permits targeting of prevention services to individuals who will benefit most.

METHOD

Participants are 10,220 individuals who applied for New York's HomeBase prevention services from September 28, 2004, to December 29, 2010. The sample contains mostly females (61 percent), African Americans (56 percent), and high school graduates (59 percent). Further, the majority were middle-aged (median age = 46), currently employed (66 percent), without a veteran status (97 percent), unmarried (88 percent), and without a self-reported history of a mental health diagnosis (79 percent) or substance abuse (82 percent).

VARIABLES

At the time of application, intake workers surveyed participants about the following domains: demographics, human capital, housing conditions, disability, interpersonal discord, childhood experiences, and shelter history. (Variables used in analysis are described in table 1. Appendices A and B, which are available online, include the full screening survey and a correlation matrix of all independent variables, respectively.) Measures relied on respondents' self-reports and interpretations of questions, as is typical in the coordinated entry systems being developed by many communities. The New York City Department of Homeless Services (DHS) merged these survey results with administrative records of applicants' previous interactions with the DHS shelter system (administrative records used in this investigation started in the 1990s) and the date of any subsequent shelter entry through June 2013.

ANALYSES

We developed a risk model predicting subsequent shelter entry for individuals. Then we compared results using that risk model for individuals to those found in our previous investigation of families (Shinn et al. 2013). Comparisons included risk factors and rates of shelter entry among applicants who were judged eligible for services (and presumably received them) and

TABLE 1. Descriptive Data, Adjusted Hazard Ratios, and Confidence Intervals for Predictors of Shelter Entry in Cox Regression for Individuals

Predictor	No Shelter; % or Mean (n = 9,663)	Shelter; % or Mean (n = 557)	Hazard Ratio	95% Confidence Interval
Demographics:				
Male	38.1	45.5	.979	.735–1.303
African American	55.1	69.8	.859	.544–1.356
Hispanic	37.5	22.5	.684	.418–1.117
English speaker	71.6	95.0	1.506	.865–2.623
Age	*44.6*	*41.6*	*.977******	*.967–.987*
Married/partner	11.5	21.1	1.013	.726–1.413
Veteran	2.8	4.3	1.077	.529–2.192
Human capital:				
High school /GED	59.0	57.7	.889	.690–1.145
Currently employed	55.1	71.7	1.075	.715–1.618
Currently receiving public assistance	56.8	62.0	1.630	.969–2.742
Lost benefits in past year	10.4	17.5	1.075	.636–1.814
Housing conditions:				
Name on lease	45.7	65.3	.627	.343–1.146
Overcrowding or discord	19.1	14.3	.866	.586–1.280
Arrears ($)	*1,600*	*3,429*	*1.018******	*1.008–1.027*
Doubled up	26.8	19.8	1.459	.944–2.255
Verbal eviction threat	13.2	29.6	2.085***	1.353–3.212
Legal eviction action	32.5	28.4	.648*	.456–.921
Rent > 50% income	38.0	47.6	1.211	.809–1.811
Unsafe conditions	6.4	10.1	1.072	.721–1.593
Level of disrepair	*4.2*	*3.2*	*.613*	*.260–1.442*
Moves in past year	*.7*	*.6*	*.797*	*.629–1.010*
Currently receiving subsidy	4.9	5.5	1.194	.629–2.264

Disability/criminal justice:				
Chronic health/hospitalization	53.6	44.7	.969	.605–1.553
Mental illness/hospitalization	21.6	18.4	.615*	.386–.981
Substance problem/treatment	17.2	25.0	1.195	.464–3.077
Criminal justice involvement	21.1	31.0	.885	.581–1.348
Interpersonal discord				
Domestic violence	15.9	13.8	1.003	.602–1.672
Protective services involvement	4.3	6.7	.890	.386–2.052
Discord rating	*2.1*	*1.6*	*.962*	*.819–1.130*
Childhood experiences:				
Adversity index	*.5*	*.6*	*1.058*	*.870–1.286*
Shelter history (self-reported):				
Shelter history as adult	23.4	75.0	1.400	.872–2.250
Shelter application last 3 months	3.3	17.1	2.517***	1.758–3.604
Reintegrating into community	10.4	27.5	1.372*	1.058–1.780
From administrative data:				
Previous shelter stay	7.2	70.6	18.561***	12.620–27.297

Note.—N = 10,220. Continuous predictors are in italics. To create a robust model, we estimated it initially in two independent random subsamples of 50 percent of the data. (For each, we imputed 50 data sets based only on the information in the subsample.) The resulting models were substantially similar to the complete model with the exception that mental illness failed to be a reliable predictor in either subsample. Accordingly, mental illness is omitted from the screening survey. We report the model for the full sample here. Omitted race/ethnicity category is all other races. Overcrowding and discord were combined in the original data set. Arrears are truncated at $15,000—HR and CI are in units of $100. Criminal justice involvement includes any family member ever incarcerated or whether the respondent is on probation or parole. Protective services involvement is any ACS investigation in the past year, open case, child ever in foster care, or currently in protective care. Discord rating is a 9-point scale and includes averaged values of discord with landlord, leaseholder, or household members. The childhood adversity index is a count of five experiences in childhood: family receipt of public assistance, abuse, shelter, foster care, and four or more residential moves.

* = $p \leq .05$.

** = $p \leq .01$.

*** = $p \leq .001$.

those judged ineligible by level of risk. Next we developed a short screening model to streamline the assessment process. Finally, we examined the efficiency of the model.

We use survival analysis (Cox proportional hazards) to model the hazard of entering shelter on any given day after applying for prevention services among individuals who had not already entered shelter following their application for services. Use of survival analysis rather than logistic regression is important because individuals had different follow-up periods. Additionally, survival analysis models time to shelter entry and not simply whether shelter entry occurred. Hazard ratios represent the amount by which the predicted rate of shelter entry is multiplied for people who exhibit the characteristic (or for continuous variables the multiple for each additional increment such as year of age), adjusted for other variables (Cox 1972). The hazard ratio and 95 percent confidence interval for each predictor are adjusted for all other variables in the model. To account for missing data, we imputed 50 complete data sets with Stata, including auxiliary variables according to the literature (Sinharay, Stern, and Russell 2001; Graham, Olchowski, and Gilreath 2007).

Following the creation of the full model, we created a short screening model by eliminating nonsignificant variables via backwards regression and then verifying that each remained nonsignificant when added back to the final model. In line with the body of forecasting literature (Dawes and Corrigan 1974; Dana and Dawes 2004) and our previous study of homeless families (Shinn et al. 2013), we assigned weights based on the comparative magnitudes of coefficients for dichotomous predictors and shelter entry rates at each value of continuous predictors. A model with integer weights capitalizes less on chance than a model based on precise weights from a particular sample. The brevity of the screening model saves time and leads to higher quality data because workers are less likely to skip questions, which led to large amounts of missing data on the original intake survey for applicants.

Next we examined the efficiency of these models by considering their hit rates (proportion of individuals correctly predicted to enter shelter) relative to their false-alarm rates (proportion of individuals incorrectly predicted to enter shelter among all people who avoided it). Any model with continuous risk scores will generate multiple hit rates and false-alarm rates depending on what cutoff is used for risk. When individuals with few risk factors are predicted to experience the outcome, the hit rate will be high but so will the false-alarm rate. When only individuals with many risk factors are predicted to experience the outcome, both hit rates and false-alarm rates will be lower. Policy makers decide how many false alarms they can tolerate to obtain as many correct hits as possible.

A receiver-operating characteristic (ROC) curve is a graph of hit rates against corresponding false-alarm rates for all possible cutoffs. In the present study, ROC curves were generated using logistic regression. Predicted scores from a logistic regression were averaged across the 50 imputed data sets to create an average risk score for shelter entry. ROC curves can be used to compare competing models with the goal of selecting the model with the highest hit rates as compared to the lowest false-alarm rates at any level of risk (Swets 1996). The area under the curve (AUC) provides a global measure of model efficiency.

RESULTS

Table 1 contains descriptive statistics, hazard ratios, and confidence intervals for the model predicting shelter entry for individuals. Only 5.4 percent of those who applied for services entered shelter subsequently (over the next 2–8 years), and the majority of people who entered shelter did so within 1 year of applying for services.

Among demographic variables, only age made a reliable contribution to the model. Controlling for the other variables in the model, younger applicants were more likely to enter shelter. None of the human capital variables contributed to the full model. For housing conditions, rent arrears and threats of eviction contributed to the model. Increasing arrears were associated with a significantly higher risk of shelter entry. Findings for threats of eviction were mixed. Those who were verbally threatened with eviction had a risk of entering shelter that was more than two times the risk of those who were not. On the other hand, those who faced a legal eviction action had slightly less than two-thirds the risk of entering shelter of those who did not indicate a legal eviction threat.

No disability/criminal justice variables, interpersonal discord variables, or childhood experience variables contributed reliably to the full model. For shelter history variables, a self-reported shelter application in the last 3 months increased the hazard for shelter entry by over 2.5 times. Individuals who were reintegrating into the community from an institution had more than 1.3 times the risk of shelter entry compared to those who were not reintegrating. Individuals who had a previous shelter stay had more than 18.5 times the risk of entering shelter compared to those without a previous shelter stay.

Some of these results were unexpected, so we explore them further. We start with the seemingly protective effect of legal eviction threats. If service providers are likely to target and counteract a factor that increases risk in the absence of services such as legal eviction, the net effect of the factor might be zero or even protective. In other words, the HomeBase program might reduce some risk factors more effectively than others. Under these circumstances, the factor might appear to confer risk for those who did not receive services and protection for those who received services. In statistical terms, one would say that services interacted with the factor in predicting shelter entry.

To determine whether this was the case for eviction or any other variables, we looked systematically for statistical interactions showing differential associations of variables with shelter entry for individuals who service providers deemed eligible or ineligible for services. (Eligibility is a proxy for service receipt.) We created separate predictive models for individuals who were deemed eligible for services and for those who were deemed ineligible. The two models differed minimally across risk factors, and in post hoc tests of interactions involving the variables with largest differences in coefficients in the two models, only one interaction was significant: doubled-up living (sharing a housing unit with another household) had a modest, nonsignificant association with shelter entry in applicants who were eligible for HomeBase services and a stronger association (HR = 1.74) in applicants who were deemed ineligible, leading to a significant interaction effect. It is possible that HomeBase was differentially effective for applicants who were living doubled up; however, given the post hoc nature of the test, the result could also be due to chance. We also investigated the relationship between legal eviction and subsequent shelter entry for all ineligible individuals. The association, while still protective, approached zero (HR = .92), and the interaction was not significant.

The strongest support for the idea that legal eviction might appear protective only because of an association with services comes from the subset of individuals who were judged ineligible for services because they lived outside of the community district served by the HomeBase office (n = 907). For these applicants, who could not receive services, legal eviction was a modest but significant risk factor for subsequent shelter entry (HR = 1.34).

For this reason, we exclude legal eviction as a protective factor for homelessness in the screening model, even though it serves to reduce the predictive power of the model in a combined sample of those who did and did not receive services.

Having a previous shelter stay was by far the most potent predictor of entering shelter after applying for preventive services. To better understand the implications of this finding for primary prevention among individuals without prior stays, we repeated the full analysis including only those individuals who did not have a prior stay in shelter (n = 9,131). Results were similar with the exception of two variables: public assistance and doubled-up living. The receipt of public assistance did not contribute reliably to the model. Living doubled up, on the other hand, increased the hazard of shelter entry by over 1.8 times. Similar to the results from the full sample, we find that the hazard of shelter entry increased for individuals who were younger, had increasing arrears, received a verbal eviction threat, applied for shelter within the last 3 months, and sought to reintegrate into the community from an institution. This analysis provides further evidence that living doubled up should be investigated further in future studies of homelessness prevention, although overall risk was quite low: the rate of shelter entry after applying for prevention services is much lower for individuals without a previous record of shelter entry compared to those with a record (1.8 percent vs. 5.4 percent).

SCREENING MODEL

As described in the method section, we created a screening model by eliminating nonsignificant variables via backwards regression and then verifying that each remained nonsignificant when added back to the final model. We added public assistance to the model at this stage because it became significant after correlated variables were removed. We assigned each variable 1–6 points based on the comparative magnitudes of coefficients for dichotomous predictors and shelter entry rates at each level for continuous predictors.

Table 2 introduces the screening model. Individuals could score from 0 to 16 points across seven variables, with increasing scores associated with increased risk for shelter entry. Actual scores (averaged across 50 imputed data sets) ranged from 0 to 14.1 points, with the median score of 1.4. Receiving a score of 3 or more placed individuals in the ninth decile of risk, and

TABLE 2. Screening Model Predicting Individuals Who Should Receive HomeBase Services

Variable	Points
Reintegrating into community from shelter, jail, or treatment program	1
Currently receiving public assistance	1
Reports being asked to leave by landlord or leaseholder	2
Reports applying for shelter in the last 3 months	2
Has administrative record of previous shelter stay	6
Age (years):	
29–32	1
28 or younger	2
Rental arrears ($):	
5,000–8,000	1
8,000 or greater	2

a score of 7 or more placed individuals in the highest decile of risk. Thus, almost all applicants with a previous shelter stay (6 points) were in the top decile of risk, and few applicants without such a stay reached the top decile.

COMPARISON TO FAMILIES

We compared the model developed here for individuals with a model we developed previously for families who applied for HomeBase services from October 2004 to June 2008 (Shinn et al. 2013). Although the dates of applications were different for individuals and families (individuals applied between September 2004 and December 2010), comparisons between the two groups are useful to assess how the targeting of services may differ across groups. Individuals entered shelter at half the rate of families over a 3-year period (6.4 percent vs. 12.8 percent), considering only applicants with 3 years of data. Overall, individuals received services at lower rates (39.1 percent) than did families (66.5 percent). Further, risk factors for individuals differed from those for families. Families had many more significant predictors than did individuals and, for the most part, risk factors for individuals were a subset of those for families. The only new risk factor for single individuals was the amount of rent arrears. With the exception of legal eviction, variables that contributed to shelter entry for both groups did so in the same direction. Note that for families, self-reports of previous shelter were more predictive than administrative records, perhaps because families were more likely to include domestic violence shelters that would not be part of DHS records. For individuals, the administrative records were stronger predictors. In each case, these variables were correlated so that only one entered the final model and, in each case, prior shelter was the strongest predictor in the models.

RISK MODELS FOR INDIVIDUALS AND FAMILIES

Next we investigated whether some individuals were at such high risk for entering shelter that prevention services would make little difference in subsequent rates of shelter entry. This does not appear to be the case. Figure 1 shows the proportion of individuals who entered shelter by decile of risk (calculated by averaging predicted scores across imputed data sets) and the parallel model for families from our previous investigation (Shinn et al. 2013), in each case dividing the group into those workers judged eligible and ineligible for services. Ignoring eligibility, the probability of shelter entry was similar for families and individuals at the lowest decile of risk (families = 1 percent and individuals = 0 percent) and at the highest (families = 39 percent and individuals = 36 percent). The proportion of individuals who entered shelter stayed low for the first 8 deciles and then rose rapidly. For families, risk increased more gradually. Services seemed most helpful for individuals

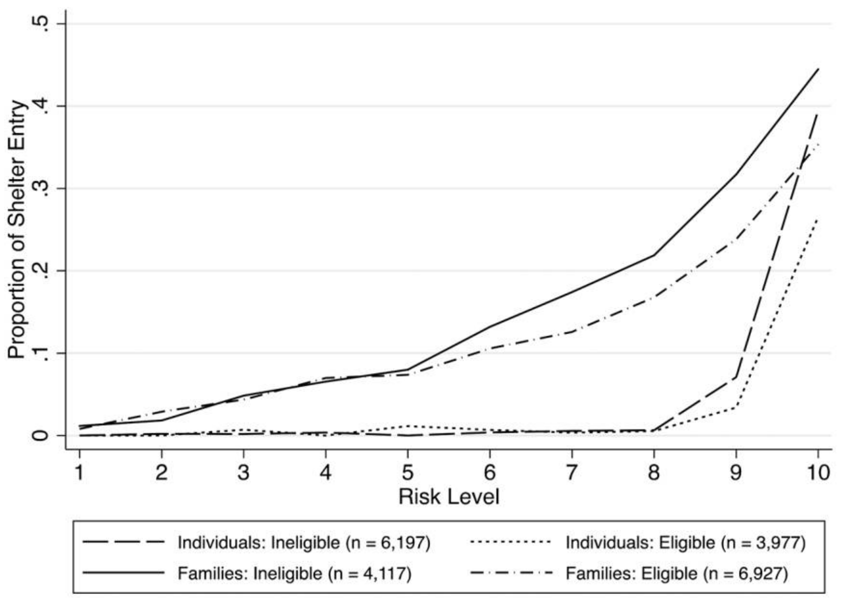

FIGURE 1. Rate of shelter entry for deciles of risk by eligibility status. Family data are from our previous study of families who applied for HomeBase services (Shinn et al. 2013).

in the tenth decile, although they also appeared to make some difference for those in the ninth decile, as judged by the vertical separation in shelter entry rates for individuals who were and were not eligible for services. Services did not appear to matter for individuals or families in risk deciles whose members rarely entered shelter, most likely because there was little risk to avert. Similar to families, the majority of individuals avoided shelter entry, even in the highest risk decile, and even without receiving services.

A parallel model for individuals who had not been in shelter prior to their application for prevention services still showed potential benefits for individuals at the highest risk for homelessness. Shelter entry after application for services was harder to predict, but there was evidence that services reduced rates of shelter entry for the highest-risk group: for individuals scoring 4 or more points (12 percent of the sample with no previous shelter entry), 6.5 percent of those deemed ineligible and 3.9 percent of those deemed eligible entered shelter.

MODEL EFFICIENCY

Figure 2 shows the efficiency of the resulting models for individuals and families. The ROC curves plot hit rates against false-alarm rates for the full and screening model at all levels of predicted risk. Considering only the models for individuals, the full model is only slightly more efficient than the screening model at high levels of risk, but it departs at lower levels. A one-variable model based on whether the applicant had experienced previous shelter exhibited a high hit rate (70.6 percent) compared to a low false-alarm rate (7.2 percent) and was far more efficient than worker decisions during the period under study (hit rate = 50.7 percent and false-alarm rate = 43.4 percent). This comparison excluded those who were ineligible because they were outside of the service area or refused services (n = 1,137). If service providers targeted only applicants who had been in shelter previously, they would serve fewer applicants (10.7 percent compared with 39.1 percent currently) but attain a higher hit rate. Holding the proportion of applicants served constant at 39.1 percent, the screening model would increase the current hit rate to over 90 percent and misses would fall by over 85 percent.

A comparison of the models for individuals and families shows that the individual model was far more efficient. For individuals, the full model had an AUC of .92 (CI .91 – .94), and the screening model had an AUC of .90 (CI .88 – .91). For families, the full model had an AUC of .76 (CI .74 – .77), and

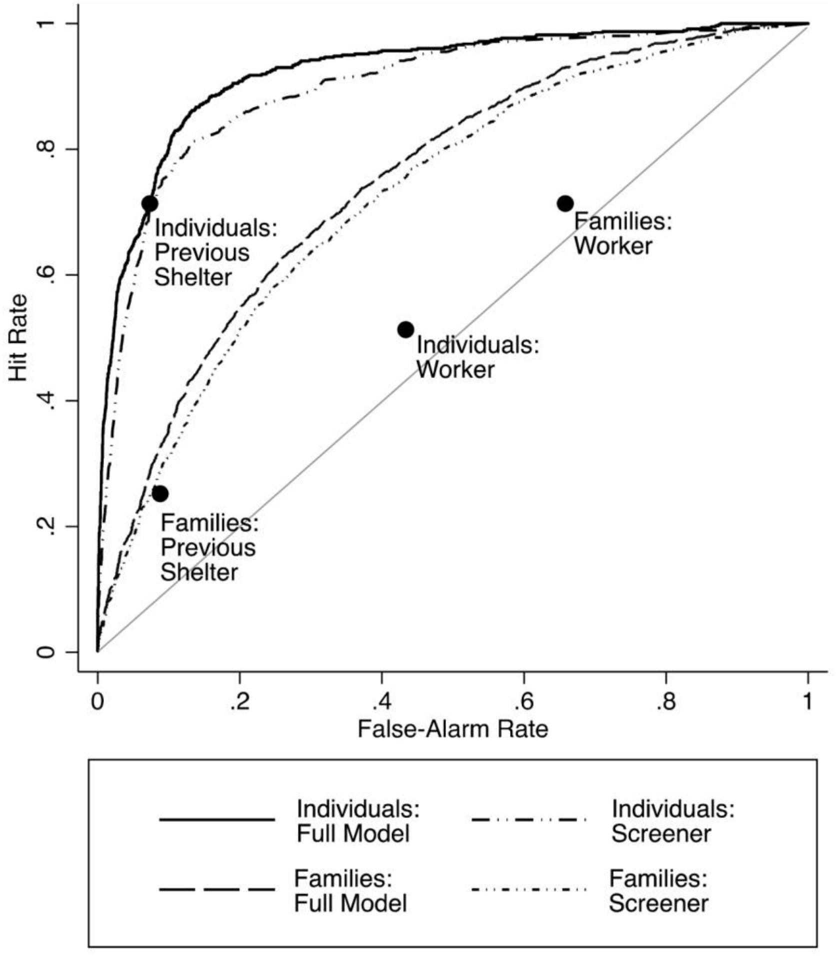

FIGURE 2. ROC curves for model efficiency. Figure shows point estimates for one-variable models based on whether administrative records showed that the respondent had been in shelter previously (*previous shelter*) and whether the intake worker deemed the respondent eligible for services (*worker*). Models include families (*n* = 10,410) and individuals (*n* = 9,083) living inside appropriate community districts and not refusing services. Family data are from our previous study of families who applied for HomeBase services (Shinn et al. 2013).

the screening model had an AUC of .74 (CI .73 – .75). A model for individuals with no prior shelter entries had an AUC of .73 (CI .70 – .77). The lower AUC value for individuals without a prior shelter entry suggests that targeting first-time shelter entrants for prevention services is more difficult than targeting those with a previous entry.

As a further test of the robustness of the screening model, we examined how well it predicted shelter entry for people who were deemed ineligible for services for different reasons. By targeting 39.1 percent of applicants (the same proportion who are offered services currently) with the screening model, we identified 89 percent of the 283 applicants who were deemed ineligible for services but who entered shelter subsequently. This includes 85 percent of 47 individuals thought to have insufficient housing risk, 89 percent of 161 individuals deemed eligible for a more appropriate program, 97 percent of 29 individuals who did not comply with the intake process, 89 percent of 19 individuals who refused services (DHS classified this group as ineligible), and 81 percent of 27 individuals who lived outside of the community district.

DISCUSSION

The study developed a model for shelter entry among individuals who applied for HomeBase prevention services that seems to be more efficient than the decisions of intake workers. One predictor stood out: the rate of shelter entry was much higher for individuals with a previous stay in homeless shelters. Few predictors other than previous shelter stays contributed reliably to the full model. Other significant risk indicators included lower age, higher rental arrears, verbal eviction threat, no legal eviction threat, an application for shelter within the past 3 months, reintegrating from an institution, and public assistance receipt. Subsequent analyses cast doubt on the robustness of legal eviction and mental health predictors; these variables were eliminated from the screening model.

In the full sample of individuals, only 5.4 percent of individuals subsequently entered shelter, and only 1.8 percent of individuals with no prior shelter stays did so. Our findings suggest that HomeBase is especially beneficial for individual applicants at the highest level of risk. Services did not seem to matter for applicants below the eighth decile of risk, most likely because there was little risk to avert. Services seemed more helpful for individuals in the ninth decile of risk and above.

INDIVIDUALS WITHOUT PRIOR SHELTER STAYS

For individuals without previous stays in homeless shelters, a targeting model was less efficient than the model that included the complete sample of individuals who applied for prevention services. On the other hand, the model for the limited sample was still more efficient than the decisions of intake workers. The model that excluded those with previous shelter stays differed from the full model in two ways. First, doubled-up living arrangements contributed reliably to the model that excluded individuals with previous shelter records, suggesting that a point may be added to the risk model in this case. Second, receiving public assistance failed to predict shelter entry reliably for this group of individuals, possibly suggesting dropping a point from the risk model under these circumstances. However, we acknowledge that the investigations are post hoc tests. Accordingly, we remain cautious about the reliability of our findings.

IMPLEMENTING THE SCREENING MODEL

In the full sample of individuals, a few variables might lead to adjustments to the screening model if they were supported by additional research. For example, the fact that legal eviction was associated with staying out of shelter might be taken as evidence for the effectiveness of eviction prevention services. Additionally, a significant interaction between doubled-up living and eligibility suggests that services may reduce shelter entry for individuals who are living in doubled-up households, so that one point could be added to the risk model for such applicants. As described above, we remain cautious about the findings from two of many post hoc tests. Doubled-up living and legal eviction might be useful variables to explore in future models in New York City and elsewhere.

As noted in our earlier study (Shinn et al. 2013), decisions about how to target services are not merely technical. Actuarial tools are useful, but moral and ethical considerations and costs to homeless people and to the public should be considered. Policy makers may be particularly concerned with reducing shelter entries, but services (whether offered under the rubric of homelessness prevention or in some other way) could also serve additional worthy goals such as reducing evictions or connecting applicants with employment or other services. The success of services in attaining their goals should be rigorously evaluated.

Program administrators can choose cutoff scores on the screening model that correspond to trade-offs of hit rates and false-alarm rates. The trade-off between narrow targeting (which might permit more intensive and possibly more effective services) and broader targeting, with more false alarms, is also a moral and political one. For example, it might make sense to offer services only to those individuals who had been in shelter previously, although

New York City has not chosen to do so. Policy makers must also decide what to do with applicants who are deemed ineligible for services. New York City gives them information about where to obtain various resources, but no help from caseworkers.

COMPARING INDIVIDUALS AND FAMILIES

Individuals differed from families in several ways. The lower rate of shelter entry for individuals among HomeBase applicants is consistent with the lower rate of shelter use by individuals than by families in New York City (HUD 2015*b*). This pattern might not generalize beyond New York City because nationally more shelter users are single adults (HUD 2015*a*). Risk rose more quickly for families, and services began to make a difference at lower deciles of risk compared to individuals. Additionally, we find that the risk model for individuals is more efficient than a comparable model for families, except in the case of individuals without a previous shelter stay. Further, predictors of shelter entry were fewer for individuals than for families. Finally, characteristics of individuals and families differed descriptively, in ways consistent with the literature. However, in the context of other variables, such as previous shelter stays, many of the variables that distinguished individuals and families failed to predict shelter entry. For example, rates of criminal justice involvement and substance abuse were higher for individuals than for families, but neither variable predicted higher levels of shelter entry. Although individual adults in shelter are getting older, as in the case of families, it was younger adults who were at greater risk. This was also true among individuals without a previous shelter stay.

Some limitations of this investigation were similar to limitations of our study of family homelessness. For example, most data were self-reports by individuals seeking services, and the validity of responses is not known. Service providers must often decide who among a large number of applicants to serve, or, in a coordinated entry system, what services to allocate to which individuals based on individuals' self-reports. It is possible that better measurement would yield better predictive power, at the expense of a more drawn-out assessment process. Further, to the extent that HomeBase services were effective, this fact weakens prediction. In the limit, if HomeBase worked perfectly, no one who received services would become homeless and prediction would be possible only for those workers deemed ineligible. Individuals who apply to HomeBase are not a random sample of all poor New Yorkers; the model is based on those who apply and might vary if, due to changes in advertising or for other reasons, the applicant population changed.

Additionally, the face of homelessness changes over time for both families and individuals. One primary challenge with targeting research includes a trade-off between timely models with current risk factors and the allowance of sufficient time for at-risk applicants to enter shelter so that models can be created and evaluated. Both studies of individuals and of families suggest that following applicants for at least a year is useful, as the majority of shelter entries happen within the first year.

Finally, we make a similar caution about model uptake in other locales as we did for the investigation of homeless families: the model may be a good starting point in the absence of local data, but the approach to better efficiency rather than the specific model is the transferrable tool from the current investigation. As discussed above, shelter entry rates for individuals in New York City are lower than for families, despite the right to shelter, which is not true nationally. Rents are higher in New York City than in most locales, and with the substantial tax base, services are relatively rich. Fortunately, other localities would not need tens of thousands of cases with outcomes recorded over years or complex statistical algorithms to create their own models. Simple models are likely to be nearly as good (Dawes 1979; Dana and Dawes 2004). Unfortunately, many communities currently rely on assessment instruments with no evidence of predictive validity in deciding how to allocate services.

Efficiency of targeting appears to increase for both individuals and families by means of an empirical model that directs services to those who can benefit most. Serving the same proportion of individuals with a screening model instead of current decision-making processes would have increased the hit rate to over 90 percent and reduced misses by over 85 percent. Even a one-variable model based on administrative records of prior shelter experiences is far more efficient than current decisions. However, targeting remains imperfect as evidenced by the fact that most individuals, like families, avoid shelter entry, even in the highest risk decile. Although empirical targeting is imperfect, a large body of research suggests that empirically based models tend to be more efficient than worker judgments (Dawes, Faust, and Meehl 1989; Grove et al. 2000; Ægisdóttir et al. 2006), as was the case here.

The New York City Department of Homeless Services (DHS) has adopted the empirical risk models for its HomeBase prevention services for both individuals and families. DHS allows workers to override model decisions in a limited number of cases, which is important to secure worker support for the process. Applicants who do not score high enough for full services receive an information packet. Separately, New York City has several programs, including free legal representation, to prevent eviction. By testing and employing similar empirical targeting models, other locations may improve the efficiency of their prevention programs and provide important information for further generalization. Accordingly, the limited resources that support homelessness prevention could be better targeted to help where they are most needed: for individuals and families who would otherwise enter shelter.

NOTE

Andrew L. Greer is a research associate on a program evaluation team at Westat, an employee-owned research firm in the Washington, DC, metro area. Recently, he completed his doctoral studies in Vanderbilt University's Community Research and Action program. Andrew's current work includes a range of international and domestic evaluations of community development programs in the areas of public health, housing, and homelessness.

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Jonathan Kwon is the lead teaching pastor at One Heart Baptist Church in Glen Cove, NY. He is a trusted community leader providing pastoral care and assistance to local community members in crisis and transition. Previously Jonathan worked for the Department of Homeless Services in New York City. Jonathan's research interests are in the field of technological systems integration and social transformation.

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