Rational Choice and the Process of Becoming Homeless for Survivors of Domestic Violence

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Chapter 1

Introduction

Becoming homeless is not usually considered to be a choice. Rather, public opinion is more inclined to perceive homelessness either as the negative product of a society that does not allocate its resources efficiently, or as the result of individual pathologies that bring about instability. By most measures, homelessness is an unfortunate phenomenon, and nowhere is that more clear than in the case of families with children, the fastest-growing subgroup of the homeless population. But what if we imagine homelessness not as the interaction of a number of unfortunate circumstances, but as the product of rational decision-making under extreme conditions? What if we imagine homeless individuals – and particularly those with children – to be active agents in their lives, choosing homelessness when it is indeed their best available option?

In the emerging field of behavioral economics, human behavior is reconsidered under the assumption that humans exhibit utility-maximizing behavior. In the coming paper, we hold individuals with violence in the household to the same standard; specifically, we predict that victims of domestic violence choose housing quality and safety level in order to maximize utility. We examine the relationship between domestic violence and homelessness within the framework of rational choice theory,

with the hypothesis that domestic violence is a significant cause of homelessness for women and families with children.

We find that individuals who become homeless because of domestic violence differ from individuals who become homeless for other reasons. Predictably, they are more likely to be female and have children. They are also more likely to have mental health problems and less likely to have drug or alcohol problems. Using data on the New York City shelter population over time, we find that in certain specifications, the ease of proximity of domestic violence support services – as measured by domestic violence hotline calls – has a positive relationship with homeless family counts.

The body of this paper precedes as follows: Chapter 2 gives background information on the study of homelessness from an economics perspective, providing several explanations for the causes of homelessness for individuals and within cities. This section also sets the stage to examine the intersection between homelessness and domestic violence and to consider both survivors of domestic violence and homeless individuals as rational actors. Chapter 3 offers a theoretical framework to explain why some individuals with violence in the household choose homelessness, while others choose to remain in housing. We look at homelessness as a series of choices in which individuals select housing quality and safety level in order to maximize utility.

Chapter 4 is divided into two subsections that each test the theoretical model using data on homelessness and domestic violence. In the first subsection, we use data from the National Survey of Homeless Assistance Providers and Clients to examine the differences between individuals who become homeless primarily because of domestic violence, and those who become homeless primarily for other reasons. The second subsection attempts to explain changes in the size of the New York City shelter population at the turn of the millennium, using data on the availability of support services offered to survivors of domestic violence. Shelter counts exhibit a large degree of correlation between time periods, and so we attempt a number of different measures

to correct for autocorrelation in regression analysis. Chapter 5 concludes, and offers suggestions for further research.

Chapter 2

Background Information

2.1 Perspectives on Domestic Violence and Homelessness

The homeless population increased greatly in the early 1980s, pushing homelessness as an issue to the forefront of American consciousness and inspiring a wealth of research on the subject. The increase has been credited to the deinstitutionalization of the mentally ill, the crack epidemic, the increase in long-term joblessness, and the destruction of skid row (Jencks, 1994). According to a 2005 estimate by the National Coalition for the Homeless, the United States homeless population ranges from 444,000 people in October (346,000 households) to 842,000 people in February (637,000 households). Because at any point in time the number of homeless people varies greatly, estimates for an annual projection of the homeless population range from 2.3 million to 3.5 million, including 0.87 million to 1.35 million children.

As scholarship continues to tackle the issue of homelessness, researchers have learned that the homeless population is far from homogeneous. Currently, women with children are the fastest-growing subgroup of the homeless population (Burt and Cohen, 1989). Families are a distinct subgroup of the homeless population: while 77%

of single homeless assistance program clients are male, only 16% of adult clients in homeless families are male. Furthermore, 69% of single homeless clients had problems with alcohol, drugs, or mental illness within one month of being surveyed, compared to 49% of clients in homeless families.[1] The most important issues for the single homeless population are not the most important issues for families; hence, because these families represent a large portion of the homeless population, it is necessary to consider them separately from the population as a whole.

Research that focuses exclusively on homeless women reveals that many have the common experience of abuse in their lives (Wesely and Wright, 2005). These women can be considered *survivors* rather than *victims* of domestic violence. The semantic distinction is important when we consider the power that the term "survivor" affords to its subject: "The image of women as rational ('logical' rather than mentally 'deficient'), active (making 'efforts' rather than 'giving up and giving in'), and altruistic ('heroically assertive and persistent' in defense of their children as well as themselves) . . . explicitly counters previous framings" (Dunn, 2005, p. 20). Survivors of domestic violence are rational actors.

This essay attempts to address an individual's choices in the process of becoming homeless, using a rational choice approach unique to the field of economics. Gary Becker defines the economic approach to research as "the combined assumptions of maximizing behavior, market equilibrium, and stable preferences, used relentlessly and unflinchingly" (Becker in Febrero and Schwartz, 1995, p.5). It is with this definition in mind that the coming essay will consider the process of becoming homeless for rational individuals in abusive relationships. Economic literature about homeless women in general – and on survivors of domestic violence specifically – is hard to come by, and so the proposed model is based on models of homelessness.

[1]Demographic estimates come from the 1996 National Survey of Homeless Assistance Providers and Clients. Details about the survey can be found in the text of this essay.

2.2 Causes of Homelessness

Researchers have struggled to define and identify the single causes of homelessness, and generally agree that the causes of homelessness vary greatly between individuals. Previous economic scholarship has approached the topic of homelessness in two distinct ways: 1) By focusing on the causes of homelessness for the individual, researchers have been able to identify personal characteristics that put individuals at risk of homelessness, and 2) By focusing on changing rates of homelessness across cities, researchers have isolated market characteristics associated with homelessness.

Three studies use survey data of the homeless and housed populations to examine individual-level causes of homelessness. Wasson and Hill (1998) compare the population of female-headed households arriving at homeless shelters that spent the previous night in their primary residence, to the population that spent the previous night doubled up. The authors find that homeless spells of those arriving from primary residency are more likely to be explained by variables associated with rent or income, while homeless spells of those arriving from a doubled-up residency are more likely to be explained by variables related to sharing difficulties.[2] The implication is that living either on one's own or with others represent two distinct housing outcomes.

Early (2004) finds that households headed by women and people over 50 are less likely to be homeless. Early (2005) looks at homelessness as the probability of three possible outcomes (in housing, homeless and in a shelter, homeless and living on the street). He finds that the most important individual factors associated with an increased probability of homelessness are presence of children, young heads-of-household, and head-of-household history of drug or alcohol problems. Households with children were more likely to become homeless, but, if homeless, households with children and female-headed households were less likely to be living on the street.

[2] "Doubled up" is defined as a single household containing more than one nuclear family (US Census Bureau).

A second set of studies uses national or city-wide homeless population counts to explore intercity variation in homelessness rates. Honig and Filer (1993) find that the proportion of households below the poverty line positively predicts crowding,[3] while higher maximum Aid to Families with Dependent Children (AFDC) benefits were associated with lower rates of homelessness. Labor market measures show that growth in private-sector employment has a negative relationship to homelessness. Finally, housing market characteristics show that average rent at the tenth-percentile level is positively correlated with homelessness. In general, tighter housing markets are positively associated with higher levels of homelessness (Quigley et al., 2000), and the size of the homeless population is sensitive to changes in income distribution and simultaneous changes in housing costs (Mansur et al., 1998).

An alternative economic approach to the study of homelessness considers the interaction between individual and market characteristics. In previously-described research, pooling the at-risk population with the population not-at-risk of homelessness reduces the average effect of the housing market and increases the effect of personal characteristics on incidence of homelessness. To explain contrasting findings of homelessness studies that use individual-level and city-level data, it is possible to limit observation to people who are at risk of becoming homeless, and to assume that there is a fixed number of housing units available in any given city (O'Flaherty, 2002).

A final model of homelessness explains the phenomenon as an interaction between the housing market and income distribution (O'Flaherty, 1996). The model imagines that homelessness is only an option for people at the lowest end of the income distribution, who choose between low-quality housing and homelessness. As housing depreciates in quality over time, housing market conditions only affect homelessness rates for the population at-risk of homelessness. The rational at-risk individual is simply indifferent between paying for low-quality housing and homelessness at zero

[3] "Crowding" is defined as living in a housing unit with more than one person per room (US Census Bureau).

rent. In the text of this essay, we will expand this assumption of rationality to the at-risk population living in violent households.

2.3 The Question of "Perverse Incentives"

Some research has challenged government policies targeting homeless prevention and support, suggesting that such policies have the potential to create perverse incentives for the poor that thereby increase homeless shelter populations.[4] Perverse incentives can be created by government policy on the supply side – by federal housing programs displacing private housing – or on the demand side – by decreasing the net benefit of being among the privately-housed poor, or increasing the net benefit of being homeless (Troutman, Jackson, and Ekelund, 1999). In fact, the number of families receiving emergency shelter varies over place and time, with shifts corresponding closely to changes in family aid programs. Evidence from the 1988 New York University Study of New York City shelter entrants indicates that families arriving at homeless shelters often come directly from housing, and not from the street. Ellickson (1990) uses this information to conclude that one cause of the increase in homelessness in the 1980s may be the increase in the number of available shelter beds.

A second study questions the effect of New York City's policy to prioritize the placement of sheltered people into subsidized housing. Though the policy caused an increase in flows into the shelter system, the effect was not large enough to offset flows out of the shelter system as families were placed into housing (Cragg and O'Flaherty, 1998). Local programs that aim to indirectly treat homelessness have opposing effects: rent controls are associated with an increase in homelessness, while increases in

[4]Homeless counts that rely on shelter availability to estimate the size of the homeless population exacerbate this debate. Such estimates become a measure of the public or community response to homelessness, rather than a measure of homelessness itself. Other factors – besides the severity of a city's homeless problem – may have an independent effect on shelter capacity and thus bias studies that use cross-sectional homeless counts from different cities. A wealthier city, for example, may have more resources available to aid its homeless population, even if the actual number of homeless is lower than in a comparable-sized city.

funding for alcohol, drug, and mental health rehabilitation programs decrease homelessness (Troutman, Jackson, and Ekelund, 1999). Still, such evidence only gives half of the story: while we can see the effect of housing and social service programs on the level of homelessness, the overall effect on social welfare remains unclear. If the benefits of shelters exceed their cost, then the expansion of high-quality shelters may be a Pareto improvement (Cragg and O'Flaherty, 1998).

2.4 Domestic Abuse

Nowhere is the potential for Pareto improvement more clearly a consideration than in the case of shelters for battered women: "The whole point of these shelters is to lure women out of conventional housing and into a shelter. If this effort succeeds, the number of people counted as homeless will rise. The women in question are better off, and so is society" (Jencks, 1994, p. 105).

Women entering domestic violence shelters are unofficially described as having higher incomes and educational attainments than their counterparts entering homeless shelters, suggesting that the homeless survivors of domestic violence represent a different population from the general homeless.[5] Research shows that approximately one-third of homeless women have been the victims of partner violence, and two-thirds have histories of childhood physical or sexual abuse (Bassuk, Perloff, and Dawson, 2001). If the head of a family experienced "dislocation" as a child, then that family is at increased risk of homelessness regardless of whether the family lives in their own residence or lives doubled-up[6](Wasson and Hill, 1998).

While childhood trauma has repeatedly been shown to affect homeless out-

[5]Personal correspondence with Tracey Thorne, Director of Program and Policy Analysis, New York City Human Resources Administration, Office of Domestic Violence and Emergency Intervention Services.

[6]"Childhood dislocation" is a measure of trauma defined as having lived in a foster home, lived in an institution or group home, ran away from home for a week or more, or lived on the streets before the age of 18.

comes, researchers have come to different conclusions about the effect of adult abuse on homelessness. One study reports that adult abuse does not have a significant effect on the risk of entering shelter (Wasson and Hill, 1998). Another study of families with multiple homeless spells found that first-time homeless mothers who experienced partner violence after being re-housed were more than three times as likely to experience a second homeless spell (Bassuk, Perloff, and Dawson, 2001). While adult abuse cannot be viewed as the exclusive cause of homelessness, abuse plays a definite role in the creation of circumstances that make poor women more susceptible to homelessness (Williams, 2003).

Still, no previous economic research on homelessness has considered the impact of domestic violence on the choice to enter homeless shelters. One theoretical understanding of domestic violence is guided by "progression theory," which is the idea that, in a relationship, abusive acts start small and escalate over time. Women may not recognize that they are in an abusive relationship until the problem has progressed past a certain threshold point of violence (Bufkin and Bray, 1998).[7] Research on domestic violence attempts to understand the behavior of women in these situations. It is possible to combine the idea of a threshold point with rational choice theory and "survivor" discourse to consider the choice to become homeless. If improvements in shelter quality or homeless support services have the effect of increasing shelter populations, then it is important to look at this increase in the context of the potential benefits offered by the improved services, with an emphasis on those services targeting survivors of partner violence. This paper will therefore examine the relationship between the presence of domestic violence and the population of individuals considering homelessness.

[7] An alternative – though by no means exclusive – approach understands domestic abuse to occur within a "cycle of violence," in which abuse is part of a three-phase cycle. First tension builds, then there is a violent incident, followed by a period of calm and then the repetition of the cycle (Walker, 1980).

Chapter 3

Theoretical Model of Domestic Violence and Homelessness

In the housing market, households choose housing quality in an attempt to maximize utility given the options available for their income. Households at risk of homelessness – those households at the lowest end of the income distribution – must make this decision under extreme income constraints. Still, many of these at-risk households behave rationally to maximize their utility given available housing options.[1] While the average household may not think about homelessness or very-low-quality housing as a utility-maximizing option, households at the lowest end of the income distribution may choose between paying for low-quality housing and homelessness at zero rent. What is more, such decisions are not limited to consumption of housing alone: households take into account the total combination of goods and services they demand – including housing, food, clothing, etc. – when making housing-related decisions.

[1] Certain characteristics common in the homeless population – including mental illness or substance abuse – make the assumption of rational choice difficult to extend to the whole homeless population. However, it is possible to consider those factors within the context of heterogeneous preferences. In the case of homelessness, it is reasonable to assume that tastes are not homogeneous across individuals. Personal characteristics like mental illness or drug use are ways of talking about differing preferences.

The costs of homelessness are not monetary – individuals may pay for their experience with homelessness in pride, sense of stability, or friendship. Similarly, the costs of housing can be non-monetary, particularly when living in available housing means living with someone who puts one's own safety, or the safety of one's children, at risk, as is the case for individuals living with abusive partners. The goal of this model is to take into account the non-monetary costs and benefits of homelessness using a rational choice theoretical model of homelessness, where the outcome of homelessness depends on a gamble between homelessness on the street and homelessness in a shelter. By considering the interplay of housing quality and safety level in the decision to become homeless, the model provides a framework through which it is possible to consider the connection between domestic violence and homelessness.

If the process of becoming homeless can be described as decision-making under extreme income conditions, then this theoretical model expands on the idea of "extreme conditions" to include the non-monetary condition of safety. In this model, individuals considering homelessness are making decisions under extreme conditions where safety level is low. Therefore, these individuals must explicitly take into account the role of safety when considering homelessness. Simply put, this model imagines that housing choice is a function of safety level as well as housing quality. Housing quality, as already stated, is related to income. Safety level, on the other hand – defined as the security of a place of residence or as the absence of a direct threat of domestic violence – is independent of income and housing quality.

The individual will choose both housing quality and safety level in order to maximize utility:

$$U = U(H, S, Z|X),$$

subject to the budget constraint

$$P_H H + P_S S + P_Z Z = Y,$$

where H is a continuous measure of housing quality, S is safety level measured on a continuous scale from 0 to 1, Z is a composite basket of other consumption goods, and X represents individual characteristics held constant. P_H is the price of H, P_S is the price of S, and P_Z is the price of Z. Y represents total household income for the living unit – that is, when the individual is living with a partner or family member, Y represents combined income, but when the individual is living alone, Y represents only the individual's income. For the majority of this paper, Z is held constant across preferences for housing and safety, and so we can consider the budget constraint as

$$P_H H + P_S S = Y - P_Z Z, \tag{3.1}$$

so that $Y - P_Z Z$ represents real income.

To isolate the role of domestic violence in the process of becoming homeless, the model proposes that each individual has a maximum level of safety available if living in conventional housing with a given partner. The quality of housing is already determined by the combined income of the individual and his or her partner, and so the individual may choose safety level given housing quality until he or she reaches the maximum safety available. For low levels of safety, improvements in safety have no cost, and so current housing provides a certain level of H and S where S is maximized given income and housing quality. If the individual wants to increase safety past the maximum safety level, he or she must implicitly pay for further improvements in safety with decreasing housing quality. For example, being housed with one's parents would be an improvement in safety level at the cost of housing quality, where the lack of independence that comes from living with one's parents is measured as lower-quality housing. Likewise, moving in with friends can improve safety but decrease housing quality because of crowding or the loss of personal space. Thus, the maximum safety level in housing with a partner represents the safety threshold point after which

increasing safety is paid for by decreasing housing quality.

Given these conditions, homelessness can be viewed as a two-stage process. In the first stage, the individual chooses between housing and homelessness. In the second stage, if homeless, the individual enters a gamble for which the specific outcome – either homeless on the street or homeless in a shelter – is unknown with certainty, but has a certain probability. When people choose to become homeless, they do not know if they will be able to find a space in a shelter or if they will be homeless on the street. Thus, when the individual chooses to enter the gamble, he or she is accepting an outcome of either of the two possibilities.

Depending on the relative probabilities of either homeless outcome, the expected payoff of the gamble changes in value. However, because the exact probability of either outcome is unknown, the individual must rely on his or her expectation of the relative probabilities of the homeless outcomes when making the decision to enter the gamble:

$$E(B_{st-sh}) = p * E(A_{street}) + (1-p) * E(A_{shelter}).$$

A_{street} represents street homelessness, in which housing quality and safety level are both at their lowest values, h_{street} and s_{street}. $A_{shelter}$ represents homelessness at a shelter, where housing quality and safety level are both slightly greater, at $h_{shelter}$ and $s_{shelter}$. Point B_{st-sh} represents the expected payoff of homelessness. The expected payoff of the gamble also depends on the housing quality and safety level of both street homelessness and shelter homelessness. The expected housing quality depends on a combination of the housing quality of street homelessness and the housing quality of shelter homelessness. The expected safety level depends on a combination of either outcome's safety level, so that

$$\begin{aligned} E(B_{st-sh}) &= p * E(A_{street}) + (1-p) * E(A_{shelter}) \\ &= p * E(h_{street}, s_{street}) + (1+p) * E(h_{shelter}, s_{shelter}). \end{aligned}$$

The model can be explained graphically as follows. Utility for households at risk of homelessness is a function of safety level and housing quality, where housing quality conditions only affect the decision to become homeless for the at-risk population with violence in the household. Utility is represented as a Cobb-Douglas utility function of the form:

$$U = U(H, S, Z|X) = H^{\alpha} S^{1-\alpha} Z^{\beta} | X, \tag{3.2}$$

where α is a positive constant, the size of which indicates the relative importance of housing quality to level of safety. β is a constant.

Maximizing the utility function 3.2 subject to the budget constraint 3.1, holding P_H and P_S fixed, yields,

$$\begin{aligned} MU_H &= \lambda * P_H = \alpha(\frac{S}{H})^{1-\alpha} Z^{\beta} \\ MU_S &= \lambda * P_S = (1-\alpha)(\frac{H}{S})^{\alpha} Z^{\beta}, \end{aligned}$$

where λ is the marginal utility of real income. [2] The shadow prices of housing quality and safety level are P_H and P_S, respectively. For values of α greater than 0.5, the individual has a stronger preference for housing quality over safety. When $\alpha < 0.5$, the individual has a stronger preference for safety over housing quality.

Figure 3.1 graphically depicts the budget constraint for housing and homelessness for an individual with maximum safety level s^*. Z is still held constant across preferences for housing and safety so that the graphical model can be represented in two dimensions. For all values of s^*, the budget constraint for housing alone is:

$$\begin{aligned} H &= \underline{h} \; if \; S < s^*, \; and \\ H &= \underline{h} - P_S S \; if \; S > s^*, \end{aligned}$$

[2] Recall from (2.1) that real income equals $Y - P_Z Z$.

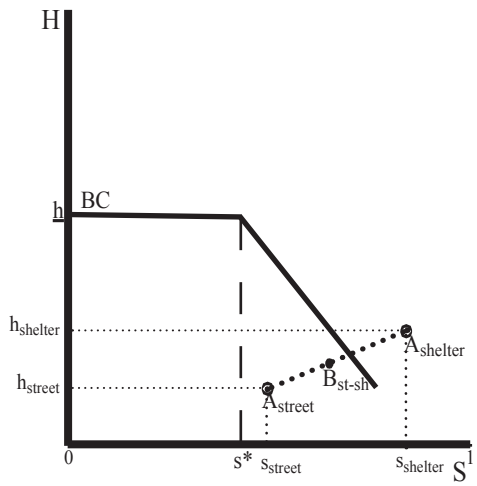

Figure 3.1: Budget Constraint for Housing and Homelessness

where $\underline{h}$ represents the maximum housing quality available for a given income. s^* is defined as the threshold point at which there is a tradeoff between safety and housing quality. P_S represents the implicit price of safety that must be paid for by decreasing housing quality. P_S is positive because after s^*, there is a tradeoff between housing quality and safety. Housing of lower quality than the housing quality level of street homelessness does not exist.

In addition to the budget constraint for housing, the available options of homelessness exist as a line determined by the two homeless outcomes: homelessness on the street, or in a shelter. Homeless outcomes are independent of income and safety level s^*. The homelessness outcome points are labeled A. Line $A_{street} - A_{shelter}$ represents mixes of street and shelter homelessness dependent on the probability of finding a place in a shelter. The coordinates of point B_{st-sh} are determined by calculating the weighted expected values of h_{street} and $h_{shelter}$, and s_{street} and $s_{shelter}$:

$$\begin{aligned} h_{st-sh} &= p * (h_{street}) + (1-p) * (h_{shelter}), \ and \\ s_{st-sh} &= p * (s_{street}) + (1-p) * (s_{shelter}), \end{aligned}$$

where p represents the probability of street homelessness, and $(1-p)$ represents the probability of shelter homelessness.

The budget constraint for housing and homelessness can shift for six reasons. The first three shocks affect the budget constraint for housing alone, and the final three shocks affect the budget constraint for homelessness, and thus the expected payoff of the homelessness gamble.

1. When individuals experience a negative shock to safety, the budget constraint for housing contracts. For example, when abuse in the home increases in severity, s^* falls to s^{**}, as in Figure 3.2. As a result, the length of the line segment $H = \underline{h}$ shrinks, and the $H = \underline{h} - P_S S$ line segment shifts inwards.

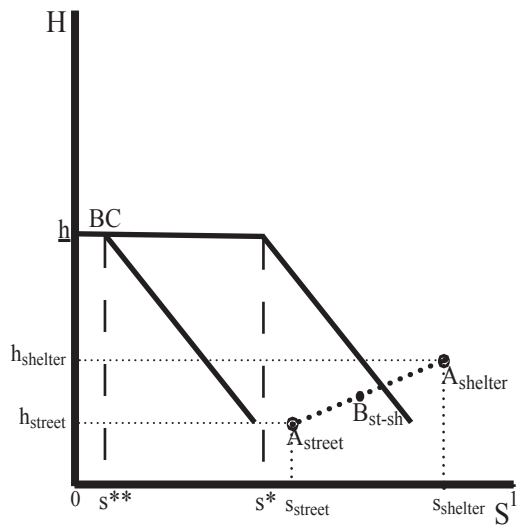

Figure 3.2: Safety Shock

2. A change in household income shifts the budget constraint for housing alone. In Figure 3.3, an increase in income causes an increase in $\underline{h}$, or the maximum housing quality available, so that the entire budget constraint for housing shifts upwards.

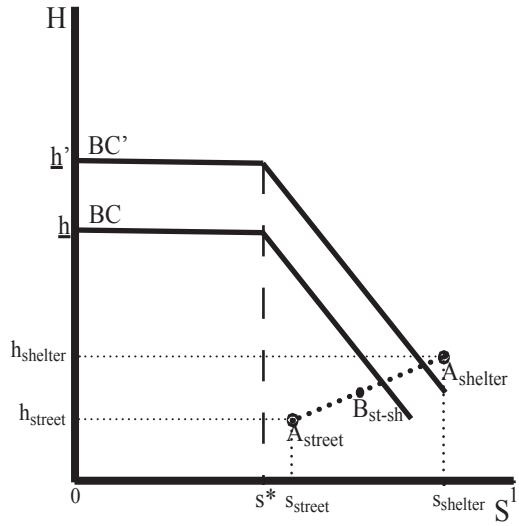

Figure 3.3: Income Shock

3. The price of the basket of consumption goods Z can fall, thus causing an increase in real income, and increasing the value of $\underline{h}$ as in Figure 3.3.

4. As illustrated in Figure 3.4, independent changes in the positions of points A_{street} and $A_{shelter}$ – holding the relative probabilities of street and shelter homelessness constant – affect the position of line A_{street} - $A_{shelter}$, and hence affect the coordinates of B_{st-sh}. When shelters improve in terms of housing quality, hshelter shifts to $h'_{shelter}$ and point $A_{shelter}$ shifts upwards. Point B'_{st-sh} has a new coordinate for housing quality,

$$h'_{st-sh} = p * (h_{street}) + (1 + p) * (h'_{shelter}).$$

The expected payoff of B'_{st-sh} with shelter housing quality $h'_{shelter}$ is greater than the expected payoff of B_{st-sh}. This situation would occur if shelters throughout a city improve in housing quality by offering more support services to residents, such as counseling or job placement assistance. A policy that puts homeless people living in shelters onto the top of the waiting list for subsidized housing

would have a similar effect. The anticipation of placement into housing would increase the expected value of the housing quality of homeless shelters.

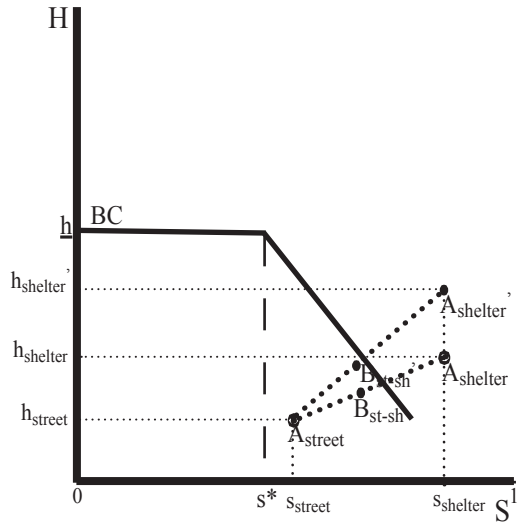

Figure 3.4: Improvement in Shelter Quality

5. When city streets improve in terms of housing quality – for example, if crime in a city falls, or if temperatures rise – the expected payoff of the homelessness gamble increases (Not pictured).

6. Finally, the relative probabilities of street and shelter homelessness can change. Graphically, the placement of B_{st-sh} on line A_{street} - $A_{shelter}$ would shift. When a city opens a new shelter – holding constant the size of the homeless population and homeless shelters' quality and safety level – the expected payoff of the homelessness gamble becomes more favorable towards shelter (Not pictured).

Equilibrium occurs when utility is maximized given the budget constraint for housing and homelessness combined. When the utility-maximizing point lies on the budget constraint for housing, then the individual remains in housing and does not choose homelessness. For a given low level of safety s^*, it is welfare-enhancing for the individual to leave home if there is a homeless shelter $A_{shelter}$ available with

certainty, or if the expected payoff of homelessness B_{st-sh} lies above the indifference curve representing the utility-maximizing housing choice. Households for whom the expected payoff of the homelessness gamble B_{st-sh} lies within the budget constraint for housing will choose to maximize safety given the maximum housing quality available for the household's income. Those households will cluster at point O, where safety level equals s^*.

Figure 3.5 graphically depicts two individuals with different sets of preferences. Individual 1 has a preference for safety over housing quality, so $\alpha_1 < 0.5$. Individual 2 has a preference for housing quality over safety, so $\alpha_2 > 0.5$. Individual 2 is more risk averse than Individual 1, because Individual 2 prefers to remain in housing rather than enter the homelessness gamble.

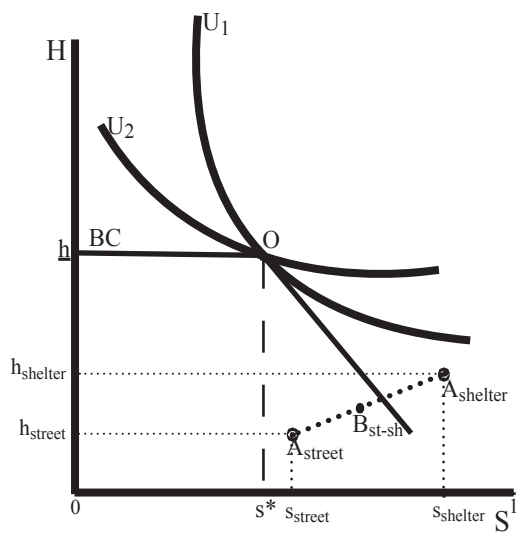

Figure 3.5: Budget Constraint for Housing and Homelessness with Indifference Curves

For each shift in the budget constraint for housing and homelessness, individuals must reevaluate their consumption of housing quality and safety in order to maximize utility given the new available options.

1. At safety level s^{**}, some individuals will find it welfare-enhancing to leave home

for homelessness without the guarantee of shelter. For Individual 1 in Figure 3.6, the expected payoff of homelessness B_{st-sh} lies above the indifference curve representing the utility-maximizing housing choice. That is, curve U_1' is below curve U_1'' , and Individual 1's utility-maximizing point is O_1'', which is that same as point B_{st-sh}. Individual 1 will therefore choose to leave housing and enter the homelessness gamble. Individual 2, on the other hand, has a utility-maximizing point on the budget constraint for housing at O_2'.

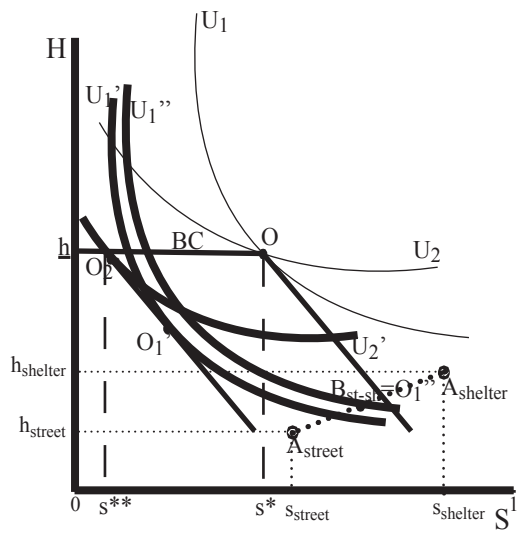

Figure 3.6: Safety Shock with Indifference Curves

2. In Figure 3.7, the income effect predicts that with the increase in income, the household's purchasing power increases, causing the individual to demand more housing quality and more safety. The substitution effect predicts that the increase in income will increase the relative price of housing quality compared to safety. Because the income effect and the substitution effect exert opposite forces, the end result of a change in income on housing choice is not the same for everyone. Individual 2 has a preference for housing quality over safety, and so the increase in income will cause Individual 2 to demand more housing quality,

and Individual 2 will maximize utility at point O_2'. Individual 1 has a preference for safety over housing quality, and so the increase in income will increase the relative price of housing quality, and Individual 1 will benefit by trading some housing quality for increased safety. Thus Individual 1 will maximize utility at point O_1', on the sloped portion of the budget constraint.

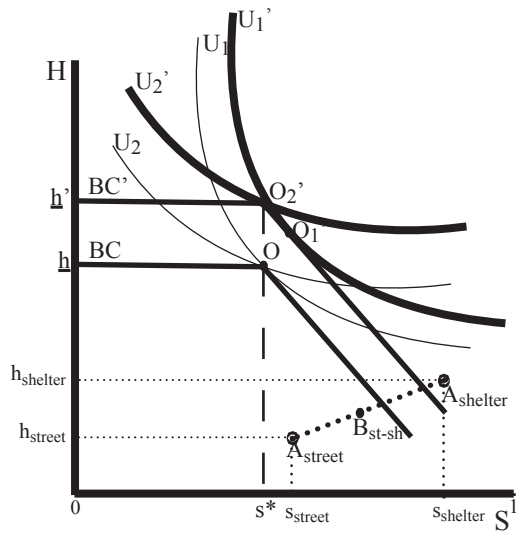

Figure 3.7: Income Shock with Indifference Curves

3. The effect of a change in the price of consumption goods on the budget constraint for housing will be similar to the effect of an increase in income, as shown in Figure 3.7. One distinction between the two, however, is that the decrease in P_Z will increase the price of housing quality relative to consumption goods Z and increase the price of safety relative to consumption goods. Individuals who have a preference for consumption goods over housing quality or safety will maximize utility by choosing to consume more consumption goods relative to housing quality and safety. (Not pictured)

4. When shelters improve in housing quality, the new expected payoff of the homelessness gamble B'_{st-sh} lies under the indifference curve representing the utility-

maximizing housing choice for both Individual 1 and Individual 2. Both individuals will maximize utility at point O in Figure 3.8. However, a larger improvement in shelter quality may cause Individual 1 or even Individual 2 to prefer the homelessness gamble.

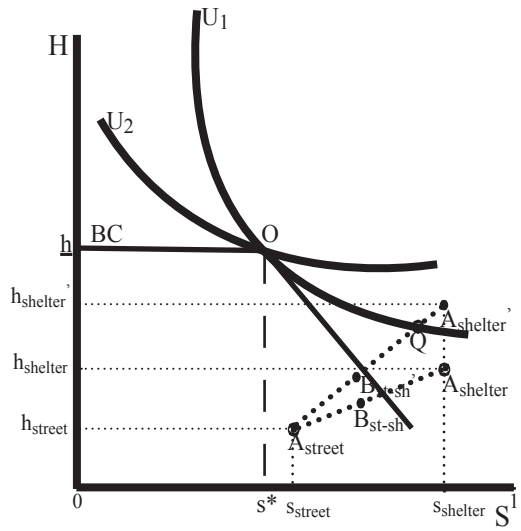

Figure 3.8: Improvement in Shelter Quality with Indifference Curves

5. When city streets improve in quality, the new expected payoff of the homelessness gamble B'_{st-sh} may lie above the indifference curve representing the utility-maximizing housing choice. In such a case, individuals will choose to enter the homelessness gamble (Not pictured).

6. When the relative probability of being placed in a shelter over the street increases, the expected payoff of the homelessness gamble increases. If the new expected payoff B'_{st-sh} lies above the indifference curve representing the utility-maximizing housing choice, individuals will maximize utility by entering the homelessness gamble. In Figure 3.8, the expected payoff of the homelessness gamble would have to be above point Q for Individual 1 to benefit by entering the gamble.

In the following section, we will be able to test the validity of this theory with data from the National Survey of Homeless Assistance Providers and Clients and the New York City Department of Homeless Services.

Chapter 4

Empirical Approach

The theoretical model of the interaction between domestic violence and homelessness presupposes that individuals who live with violence in the household face homelessness options different from those with greater safety levels at home. We therefore expect the domestic violence population to differ from the rest of the homeless population. Holding other factors constant, individuals with low safety threshold levels will choose to become homeless before individuals with high safety thresholds.

The model also explains homelessness in terms of factors external to the individual and the individual's in-housing safety level. The quality and quantity of available homeless or domestic violence support services affect the choice to become homeless.

In the coming section, we test the model using two sets of data. First, using univariate analysis on individual-level data from a national survey of the homeless population, we compare characteristics of individuals who became homeless because of violence in the household to individuals who became homeless for other reasons. Second, using data collected on New York City, we use multiple regression analysis to analyze changes in the size of the homeless population over time, testing the hypothesis that prevalence of domestic violence affects the size of the homeless population.

4.1 National Survey of Homeless Assistance Providers and Clients

4.1.1 Data and Methods

The primary data source for the univariate analysis of the characteristics of homeless individuals is the 1996 National Survey of Homeless Assistance Providers and Clients (NSHAPC), collected by the United States Bureau of the Census. Client data comes from in-person interviews with 4,207 clients conducted at homeless assistance service programs nationwide in October and November of 1996. Because the survey is not designed to act as a national homeless count and instead focuses on clients of homeless-assistance programs, many of the clients interviewed were not homeless at the time of interview, though they were using homeless-assistance programs. 2,998 clients, or 71% of the sample, are classified as currently homeless, 679 clients (16%) are classified as formerly homeless, and 530 (13%) are classified as never homeless. In the coming analysis, the sample is limited to clients who are classified as currently homeless or formerly homeless.

Clients were interviewed on a number of topics, including: current living situation, demographic characteristics, children, mental health, alcohol and drug dependency, history of victimization, income sources, veteran status, education, employment, and service use. Currently and formerly homeless clients were asked why they left the last place they were living before their most recent homeless spell; the same clients then listed one primary reason for leaving their last place of residence.

Geographical identifiers for clients surveyed were confidential, and so it was not possible to compare homelessness rates across cities using location-specific information. Instead, the author uses the survey to understand the unique characteristics of individuals who become homeless because of domestic violence.

Primary reason for leaving last place lived	All n=3255	Men n=2167	Women n=1086	Women with Children n=451
Unable to pay rent	**14.02**[a]	**13.24**	**15.44**	**15.12**
Substance abuse[b]	**12.91**	**14.32**	**10.34**	5.09
Lost job/job ended	**12.27**	**15.91**	5.59	3.97
Landlord made client leave	6.32	5.24	8.31	9.39
Didn't get along with other people there	4.98	5.6	3.83	4.68
Pushed/kicked out	4.94	4.56	5.63	4.17
Violence in household	4.05	0.79	**10.02**	**14.83**
Left town	3.81	4.15	3.19	2.42
Problematic relationship w/ a partner/relative	3.73	4.56	2.22	2.83
Problem with location	3.55	2.14	6.13	**11.94**
Displaced because of building's conditions	3.23	2.1	5.25	5.6
Went to jail/prison	3.0	4.1	0.99	0.05
Asked to leave by the people client was staying with	3.0	3.99	1.19	1.47
Rent increased	2.48	2.79	1.91	1.52
Other	17.72	16.51	19.96	16.91

[a] Top three reasons for each sample are in bold. [b] "Substance abuse" is defined by the author as "was drinking," "was doing drugs," or "went into treatment program."
Source: National Survey of Homeless Assistance Providers and Clients

Table 4.1: Percentage of clients listing primary reason for leaving the last place they were living

4.1.2 Results

Of the individuals surveyed, 201 currently and formerly homeless listed "You or your children were abused, beaten; violence in household" as one of their reasons for leaving their last place of residence. Of those people, 145 listed violence as the primary reason they left their last place of residence. An additional 122 clients who did not list domestic violence as a reason for leaving their last place of residence reported using domestic violence support services in the thirty days preceding the survey.

In the following analysis, client data is weighted using weights generated by the NSHAPC survey administrator to represent the national population of homeless assistance program clients. Table 4.1 reports clients' answers to the question: "What was the main reason you left the last place where you lived?" Only reasons that were given by at least two percent of the full sample are listed. The most common primary reasons listed are "unable to pay rent," "substance abuse," and "lost job/job ended." The subpopulation of male clients lists "lost job/job end," "substance abuse," and "unable to pay rent" as the top three primary reasons for leaving, while women – who make up 33% of the study sample – list "unable to pay rent," "substance abuse," and "violence in household" as the primary reasons for leaving. Finally, women who are currently living with at least one of their own children (14% of the study sample) most often list "unable to pay rent," "violence in household," and "problem with location" as the primary reasons for leaving, with 14.83% listing violence in household as their primary reason for leaving.

The framing of this survey question is convenient for the rational choice model of domestic violence and homelessness. The question allows homeless individuals to define the circumstances that surrounded their decisions to become homeless, and so we can use the information to pinpoint the experiences that trigger the decision. The data indicates that individuals become homeless for a large variety of reasons. Still, there are defining patterns for different subgroups of the population.

In Table 4.2, currently and formerly homeless clients are divided into two subgroups based on their answer to the question described in Table 4.1. Specifically, clients who listed "You or your children were abused, beaten; violence in household" as the main reason for leaving the last place they lived are categorized as DV, Domestic Violence. All other currently and formerly homeless clients are categorized as NDV, or Not Domestic Violence.

As indicated in Table 4.1, domestic violence is not a problem for all subgroups

of the homeless population; it is more common among women, and particularly among women living with children. Therefore, the homeless clients are further divided into male and female subgroups in order to examine how victims of domestic violence differ from individuals of the same gender. Women who live with at least one of their own children are also listed as a subgroup.

We perform a z-test on two proportions to study the differences between the independent DV and NDV groups for various characteristics.[1] For variables with two possible outcomes, we compare the proportion of the DV population with a given characteristic to the proportion of the NDV population with the same characteristic. In each case, the z-test is a two-tailed test of the null hypothesis that the two groups are identical.

Among all homeless clients, those who listed domestic violence as the primary reason for leaving the last place they lived were more likely to be female, live with at least one of their own children, have had mental health problems in their lifetime, been abused or neglected as a child, receive government benefits, and have slept in a homeless shelter in the week preceding the survey. They were less likely to have had drug or alcohol problems in their lifetime, and less likely to be veterans. Not reported in Table 4.2, though also shown to be statistically significant, is that DV clients were less likely to have slept on the street in the week preceding the survey or to have spent time in jail in their lifetime.

Of the 121 people listing domestic violence as their primary reason for homelessness, 16 are male. Statistically, those male clients closely resemble the male home-

[1]The NSHAPC has a Census Bureau design effect of 3. The design effect is the ratio of the variance of sample estimates for a particular sample design to the corresponding variance of a true random sample with the same sample size. Because the NSHAPC collected data by cluster sampling, the population surveyed is not as varied as it would have been had the homeless-assistance clients truly been selected randomly. A design effect of 3 indicates that the sample variance is three times bigger than it would be if the survey were truly selected randomly (Shackman, 2001). For the purposes of this report, the design effect is used to indicate how much larger the confidence interval must be in order to accurately draw conclusions from the data. Therefore, where data would have been reported at the 95% confidence level, it will be reported at the 99% confidence level, unless otherwise stated.

	All			Men			Women			Women with Children		
	DV n=121	NDV n=3556	*p*-Value	DV n=16	NDV n=2405	*p*-Value	DV n=98	NDV n=1154	*p*-Value	DV n=62	NDV n=451	*p*-Value
Female	.87	.35[a]	0	–	–	–	–	–	–	–	–	–
Live with children	.51	.15	0	.07	.04[b]	.7760	.57	.35[c]	0	–	–	–
Mental health problem in lifetime	.76	.57	0	.41	.53	.3137	.81	.63	.0003	.72	.50	.0012
Alcohol problem in lifetime	.44	.60	.0005	.59	.69	.3566	.42	.42	.9508	.20	.42	.0014
Drug problem in lifetime	.39	.55	.0005	.47	.61	.2442	.37	.42	.3657	.26	.44	.0079
Childhood abuse or neglect	.42	.26	.0001	.17	.23	.5891	.46	.33	.0093	.40	.29	.0599
Receive government benefits	.65	.53	.0086	.61	.45	.1947	.66	.68	.6227	.73	.85	.0185
Used a shelter in past week	.62	.52	.0220	.36	.53	.1832	.66	.50	.0016	.65	.51	.0473
Veteran	.03	.23	0	.11	.33	.0604	.02	.03	.7389	.04	.03	.7480

[a] n=3552 due to missing information [b] n=2359 due to missing information [c] n=1149 due to missing information
Source: National Survey of Homeless Assistance Providers and Clients

Table 4.2: Comparison of homeless who list "Domestic Violence" as primary reason for leaving their last place of residence (DV) to those who list other reasons as the primary reason (NDV)

less clients who did not list domestic violence as their primary reason for leaving their last place lived. Not reported, though noteworthy, is that DV males were less likely to have had an alcohol problem in the past month ($p = 0.0167$).

The 98 females who listed domestic violence as their primary reason for leaving – compared to those females who did not list domestic violence as their primary reason for leaving – were more likely to live with their children, have had mental health problems in their lifetime, been abused or neglected as children, and used a shelter in the past week. DV and NDV females were equally likely to have had problems with drugs or alcohol in their lifetime. More relevant to the time period of this study, assuming that homelessness is directly caused by short-term problems, DV females were less likely to have had an alcohol problem in the past month ($p = 0.0314$) or a drug problem in the past year ($p = 0.0281$) at the 95% confidence interval. DV females were also more likely to have had a mental health problem in the past month and year ($p = 0.0074$ for past month, $p = 0.0006$ for past year). Finally, women living with at least one of their own children were more likely to have had mental health problems in their lifetime, and less likely to have had alcohol or drug problems in their lifetime.

The disproportionate prevalence of mental health problems is interesting, and points to several different conclusions. Women with mental illness may be more inclined to be in abusive relationships, or the abusive relationship itself may cause mental health problems. Additionally, mental health problems may affect perceived safety or housing quality levels, lowering individual's safety threshold. There is also a likely relationship between mental illness and child abuse that is worthwhile to explore further.

Less drug and alcohol use among the DV population indicates that the DV group has a relatively lower threshold level for safety. Where other at-risk individuals without drug or alcohol problems would not choose homelessness, the experience

of domestic violence triggers some to enter homelessness. In the model, the trade-off between housing quality and safety begins occurs earlier due to a lower safety threshold.

4.2 New York City

In the following section, we will test the hypothesis that the prevalence of domestic violence will increase the size of the shelter population, using data collected on the size of the New York City homeless shelter population between 1998 and 2005.

When families become homeless in New York City, they begin the transition to shelter by applying for shelter at one of two centers managed by the New York City Department of Homeless Services (NYC DHS). Families go through a ten-day eligibility process to be placed into shelter in order to ensure that the family is in immediate need of emergency shelter. During the eligibility process, families are housed in temporary shelters; when the eligibility process is complete, families are placed into transitional housing or temporary shelters operated by non-profit organizations. DHS defines families as legally married couples with or without children, single parents with children, or pregnant women. However, more than 80% of families at DHS shelters have children, and children make up more than half of the family shelter population (Nunez, 2004).

Since the early 1990s, New York City has used Tier II shelters to house the majority of homeless families. Tier II shelters are transitional shelters that offer extra services including private rooms, meals, childcare, and health, job placement, and housing placement services. We will assume quantity of Tier II shelters to be a measure of family shelter quality as we examine concurrent changes in the New York City shelter system and population.

4.2.1 Data and Methods

Monthly data on the New York City homeless shelter population comes from the Average Daily Census in NYC DHS Shelters for the years 1998 - 2005. Data includes shelter counts for families in Family Shelters, and male, female, and total individual counts in Single Adult Shelters. Data on new entrants to the shelter system comes from the NYC DHS Critical Activities Reports for the fiscal years 2002 - 2006, and is provided monthly for the same subgroups listed above.

The test variable is the number of domestic violence hotline calls received by New York City's citywide domestic violence hotline. Data for domestic violence hotline calls comes from Safe Horizon, the social service organization that operates the hotline, for fiscal years 1999 - 2006.

In 1994, New York City created a twenty-four-hour, seven-day-a-week toll-free hotline for domestic violence victims, which has since been operated by contract by Safe Horizon. Over time, the number of calls received by the Domestic Violence Hotline has increased. In the first year of the time period covered by this data, the Hotline received 91,556 calls. By fiscal year 2005, the Hotline was receiving 139,860 calls per year, which is a 53% increase in six years. Safe Horizon officials credit the increase in hotline calls to citywide public education campaigns that increased awareness of domestic violence and encouraged more people to seek help. Ad campaigns in 1999 and 2000 featured advertisements on public buses and subways that provided the phone number of the citywide hotline (Thompson, 2002).

The number of calls received by the domestic violence hotline is not an ideal measure of either the prevalence of domestic violence or the availability of services. However, insofar as the attitude that causes an individual to seek support from a hotline changes over time, the same attitude trends may exist when individuals consider seeking support from homeless shelters. An ad campaign that encourages individuals to use a domestic violence hotline may also encourage individuals to seek housing

alternatives to their abusive living situations. That is, public awareness of domestic violence decreases the implicit cost of seeking support services. Monthly hotline calls thereby represent an indirect measure of the cost of seeking domestic violence services. Other available statistics about domestic violence – including police response to 911 calls and shelter population, requests, or capacity – were not available for a long period of time in monthly or quarterly increments.

In order to test the hypothesis that the social costs of seeking domestic violence support services (as measured by the number of domestic violence hotline calls) affects the size of the homeless population, we control for unemployment, cost of living, the size of the at-ris population, temperature, and rental vacancy rate. All variables are measured in logarithms, so that coefficients represent elasticities of the size of the homeless population. Data on the non-seasonally-adjusted unemployment rate for New York City comes from the New York State Department of Labor. As far as homelessness is related to a lack of income – as predicted by the theoretical model – or the labor market in general, we expect the coefficient on unemployment to be positive.

To measure the cost of living, as well as the cost of other goods, we use the Consumer Price Index for the years 1998 - 2005 for the New York Metropolitan Statistical Area including New York, Northern New Jersey, and Long Island, reported by the United States Department of Labor Bureau of Labor Statistics. The CPI calculates housing expenses as 31.5% of the total index, and so can also represent the cost of housing. We predict that the coefficient on CPI to be positive.

To measure the size of the low income population, we use the monthly public assistance caseload, gathered from New York City Human Resources Administration Facts for 1998 - 2005.[2] The sign of the coefficient on public assistance is difficult to

[2]Public assistance caseload includes the number of households receiving Temporary Assistance for Needy Families (TANF) or Safety Net Assistance (SNA), the New York State assistance program for households that exceed TANF time limits.

predict. The public assistance caseload may accurately represent a crude measure of the size of the at-risk population. However, households receiving public assistance have a safety net against homelessness. Presumably, one of the goals of public assistance is to keep recipients housed, and so a large caseload could represent the effectiveness of the city in connecting at-risk households with appropriate support services.

Finally, we control for average monthly temperature using data from annual Local Climatological Data summary reports for the years 1998 through 2005, published by the National Climatic Data Center for New York City. Mean daily temperature for each month was calculated by averaging the month's mean daily maximum and mean daily minimum temperatures. We predict the coefficient on temperature to be negative.

Rental vacancy rates for the Metropolitan Statistical Area including New York, Northern New Jersey, and Long Island were available quarterly for 1998 - 2005 from the Current Population Survey/Housing Vacancy Survey Bureau of the Census. Because using observations on a quarterly rather than monthly level for the time period covered decreases the number of observations significantly, we first report regressions on monthly data without using a variable to describe rental vacancy rates. Later, the same methodology is applied to quarterly data, including rental vacancy rate as an independent variable. We predict coefficients on housing vacancy rates to be negative, as tighter housing markets should increase homelessness.

The model is specified using two different sets of dependent variables: total monthly homeless shelter population, and new shelter entrants. In each group, population counts are broken up to represent families and single adults, and then single male and single female homeless adults, to resemble the groups described with the NSHAPC survey data. Because the test variable measures a problem closely related to females and families, we expect to see positive results in the family and single

	Total Families	New Entrant Families		Total Families	
	(1)	(2)	(3)	(4)	(5)
DV calls received	0.0160	0.5683***	0.5795	0.0242**	0.0226**
	(0.011)	(0.335)	(0.350)	(0.335)	(0.010)
Average temperature	-0.0046	0.7442***	0.7148***	0.0058	0.0063
	(0.012)	(0.368)	(0.378)	(0.018)	(0.015)
Unemployment	0.0240**	0.3286	0.4310	-0.0135	-0.0017
	(0.016)	(0.410)	(0.412)	(0.017)	(0.014)
CPI	-0.0819	1.8990***	2.3374**	-0.2291*	-0.0649
	(0.068)	(1.013)	(1.065)	(0.067)	(0.065)
Public assistance	-0.0989*	-2.1333	-2.7692***	-0.1777*	-0.0741**
caseload	(0.024)	(1.397)	(1.526)	(0.030)	(0.033)
Homeless population	0.9291*	0.5229*	0.5800*	0.9504*	1.4943*
in period $(t-1)$	(0.024)	(0.118)	(0.152)	(0.023)	(0.111)
Homeless population	–	–	-0.1709	–	-0.5313*
in period $(t-2)$			(0.146)		(0.107)
Adjusted R^2	0.998	0.560	0.573	0.998	0.999
Durbin's h	5.770	-1.968	–[a]	4.654	2.676
Observations	90	53	52	72	72
Starting date	7/98	8/01	9/01	1/00	1/00

Standard deviations are in parentheses.
* indicates coefficient significant at 1%; ** indicates coefficient significant at 5%; *** indicates coefficient significant at 10%
[a] Durbin's h could not be calculated using standard procedure, so we regressed the least squares residual $\hat{e}_t$ on $\hat{e}_{t-1}$ and the above variables. The coefficient of $\hat{e}_{t-1}$ was significant at 5%, so we could reject the null hypothesis of autocorrelation.
Source: NYC DHS, Safe Horizon, NCDC, NYS DOL, US BLS, NYC HRA

Table 4.3: Logarithmic regressions of homeless shelter counts with lagged dependent variables using two specifications

women groups. For each specification, we omit the constant term and include twelve dummy variables for months in order to control for monthly effects.

4.2.2 Results

Table 4.3 presents findings of logarithmic regressions of family homeless shelter counts on the test variable and control variables. Running ordinary least squares regressions of family shelter counts on the test variable and control variables showed signs of positive autocorrelation (using the Durbin-Watson statistic, we could not

reject autocorrelation). We therefore try to correct for autocorrelation by including one or two lagged dependent variables representing the previous period's family shelter population. After adding in lagged dependent variables, we calculate Durbin's h to test for autocorrelation. [3] Only regressions for which it was possible to reject autocorrelation at the 95% confidence interval are described in the tables.

In Regression (1) in Table 4.3, as predicted, the coefficient on the previous period is relatively high and very significant. The previous month's shelter population is a good predictor of current shelter population. The coefficient on unemployment is positive and significant at 5%, while the coefficient on public assistance caseload is negative and significant at 1%.

In a second specification (not pictured), we further attempt to correct for autocorrelation by adding a dependent variable that is lagged two periods back. However, calculating Durbin's h and using the alternative procedure to test for autocorrelation showed that we could not reject autocorrelation.

We also ran regressions using the shelter population of adult singles, adult males, and adult females as dependent variables. In each sample, autocorrelation was a problem (we could not reject autocorrelation using the Durbin-Watson statistic.) After adding one or two lagged dependent variables, we were still not able to reject autocorrelation.

Ordinary least squares is then applied to the second set of dependent variables, new entrant families and single adults. Again, autocorrelation is a problem for each subgroup, and so the model is specified including one or two lagged dependent variables. For new entrant families, the lagged dependent variables allow us to reject autocorrelation (see Regression (2) and Regression (3) in Table 4.3). For new entrant single adults, males, and females, the included lagged dependent variable does not

[3] When it was not possible to calculate Durbin's h, we test for autocorrelation by regressing the least squares residual $\hat{e}_t$ on the lagged residuals $\hat{e}_{t-1}$ and the other independent variables and relevant lagged dependent variables. Using least squares estimates, we test the significance of the coefficient of the lagged residual term $\hat{e}_{t-1}$.

allow us to reject autocorrelation. In both cases, coefficients on temperature and on CPI are positive and significant. In the first specification, the coefficient on the test variable is positive and significant, indicating that decreasing the social costs of seeking domestic violence services is related to an increase in homeless population.

Finally, we return to the original specification of the model and estimate an AR(1) process for each subgroup, and look for white noise in the residuals. We also attempt to fit ARMA processes of of varying degress. In most cases, the coefficient on the AR(1) term is positive and highly significant ($p < 0.01$).

Anecdotal evidence indicates that the number of Tier II shelters increased substantially between 1999 and 2000. It was not possible to acquire information on the number of Tier II shelter beds for each month in the sample period. However, yearly counts indicate that the number of Tier II shelters increased by 60% between 1999 and 2000, from 87 to 140 shelters. To account for the dramatic increase in availability of services, we therefore run the same regressions on total homeless families while limiting the sample to the years 2000 - 2005. The results are found in Regression (4) and Regression (5) in Table 4.3. Including a single lagged dependent variable in the first specification and two lagged dependent variables in the second specification allows us to reject autocorrelation (Durbin's h equals 4.654 and 2.676, respectively). Again, coefficients on the first lagged variables are positive and significant. In the second specification, the coefficient on the second lagged dependent variable is negative and significant.

Most noteworthy for the purposes of this study in Regression (4) and Regression (5) is that including a lagged dependent variable (or variables) on the shortened sample period produces positive and significant coefficients on the test variable. When we account for the dramatic increase in high-quality shelters by eliminating the period previous to the increase, domestic violence hotline calls show a positive relationship to family shelter population. For the time period in which high-quality shelters are

in greater abundance, decreased social costs of seeking domestic violence services (measured as hotline calls) are associated with larger shelter populations.

Examination of the control variables reveals negative and significant coefficients on public assistance caseload. Estimates for average temperature coefficients are positive and insignificant, most likely because significant coefficients on monthly dummies account for changes in temperature. Estimates on unemployment coefficients are negative and insignificant. In the first specification, the coefficient on CPI is negative and significant. Including a second lagged dependent variable reduces the magnitude of the coefficient on CPI, and makes it insignificant.

By plotting the shelter population series, we know that the shelter population increased over time. It is possible that the independent variables that are trended over time (either upward in the case of domestic violence hotline calls and CPI, or downward in the case of public assistance cases) show a relationship to the size of the shelter population because of their trend. If that is the case, then coefficients do not capture the direct effect of the variable on the size of the shelter population; rather, they capture series trends. Therefore, we specify trended variables using percent change between months instead of level measurements.

Table 4.4 presents logarithmic regressions using percent change of trended independent variables (domestic violence hotline calls, CPI, and public assistance caseload). We use percent change of total shelter population and subgroups as the dependent variable.

Again, we specify the regressions with the processes described above. Only results for which it was possible to reject autocorrelation at the 95% confidence interval are pictured. For total shelter population, we were only able to reject autocorrelation for the single adult female population in the shortened time period, 2000 - 2005. In that case, the coefficient on the test variable was positive and significant at the 95% confidence interval. That is, percent change in hotline calls between months was pos-

	%Δ Female	%Δ New Adult	%Δ New Female
	(1)	(2)	(3)
%Δ DV calls	0.0297**	0.1403	0.1668
	(0.014)	(0.179)	(0.232)
Average temperature	-0.0197	-0.0537	0.1303
	(0.017)	(0.179)	(0.236)
Unemployment	0.0060	0.0620	0.0718
	(0.007)	(0.081)	(0.107)
%Δ CPI	-0.1179	2.7770	7.7708
	(0.401)	(4.287)	(5.644)
%Δ Public assistance caseload	-0.1106	3.3651***	2.6151
	(0.152)	(1.961)	(2.572)
%Δ Homeless population in period $(t-1)$	0.2654**	-0.3764**	-0.3842**
	(0.131)	(0.161)	(0.159)
Adjusted R^2	0.275	0.419	0.285
Durbin's h	_[a]	_[a]	_[a]
Observations	72	52	52
Starting date	1/00	9/01	9/01

Standard deviations are in parentheses.
** indicates coefficient significant at 5%; *** indicates coefficient significant at 10%
[a] Durbin's h could not be calculated using standard procedure, so we regressed the least squares residual $\hat{e}_t$ on $\hat{e}_{t-1}$ and the above variables. The coefficient of $\hat{e}_{t-1}$ was significant at 5%, so we could reject the null hypothesis of autocorrelation.
Source: NYC DHS, Safe Horizon, NCDC, NYS DOL, US BLS, NYC HRA

Table 4.4: Logarithmic regressions of shelter counts using percent change of independent and dependent variables

itively related to percent changes in single female shelter population for the period following the citywide increase in Tier II high-quality shelters. The coefficient on the lagged dependent variable was also positive and significant, indicating that changes in shelter population between months were related.

For new entrants, we could reject autocorrelation for the single adult and single female populations. In each case, the coefficient on the lagged dependent variable was negative and significant. The coefficient on the test variable was positive, but insignifcant.

In order to include more information on the housing market, we re-specified the model using quarterly data for each variable. Monthly data was converted into quarterly data by averaging observations for each quarter. We included rental vacancy rate as an independent variable, and went through each of the specification processes previously described for the monthly observations. Unfortunately, using quarterly data for 1998 - 2005 for the whole shelter population – and for fiscal years 2002 - 2006 for the new entrant population – leaves us with very few observations. We could not reject autocorrelation for any specification of the model.

Before concluding, it is important to emphasize that the data on the homeless population only describes those homeless that use Department of Homeless Services shelters for families or single adults. The precise relationship between the number of homeless in shelters and the number on the street is unclear. Since 2003, New York City has performed citywide Annual Homeless Street Counts to approximate the number of unsheltered individuals living on streets and in other public spaces. The "S-Night" counts estimated the street homeless population to be 1,780 in 2003, 2,694 in 2004, and 4,395 in 2005. The street homeless counts represent 4, 6, and 12 percent of the total shelter populations in 2003, 2004, and 2005, respectively. The sharp increase in S-Night counts is more likely the effect of changes in the data-collecting process, than of changes in the ratio of street to shelter homeless. We therefore cannot use the counts to infer about the total homeless population in New York City over time. Also, the shelter populations of a number of privately-owned shelters that do not contract with the Department of Homeless Services are not available. It is likely that changes in non-city-run shelters affect the size of the population in city shelters.

Nonetheless, under certain specifications, regression analysis reveals results consistent with the model's predictions. Improvements in the available options of homelessness, as well as increases in domestic violence (or decreases in the social costs of seeking domestic violence services), are related to a larger homeless population.

Chapter 5

Conclusions

Though individuals at risk of homelessness face constrained housing options, they still act rationally in order to maximize utility. This paper addresses homelessness as it relates to domestic violence using a rational choice framework. We find that individuals who become homeless because of domestic violence differ from those who become homeless for other reasons. Besides being more likely to be female and have children, individuals who are homeless because of domestic violence are more likely to have mental health problems, and less likely to have drug or alcohol problems. Clearly, the needs of this subset are different from those of the homeless population as a whole.

The rational choice framework demonstrates that it can be constructive and revealing to use a simple model to explain a complex situation. Future research might continue within the same framework to explore the more complex relationship between childhood abuse, adult abuse, mental illness, and homelessness. In this paper, rational choice theory predicts that individuals will choose housing quality and safety level in order to maximize utility. It would be interesting to break down the utility function further to isolate other choice variables related to homelessness and mental well-being.

In addition to describing the homeless population, this paper offers some revealing empirical information. The results presented in Tables 4.3 and 4.4 exhibit a few patterns. For one, it is clear that there is a close relationship between the size of the homeless shelter population in any period and the size of the shelter population one or two periods previous. Though the homeless population is dynamic over time, for the most part, shifts are not dramatic between short periods of time.

Quantitative analysis also showed that under certain circumstances, the quality and quantity of support services available to the homeless are related to the incidence of homelessness. Specifically, we find a positive relationship between the number of domestic violence hotline calls received and the size of the total shelter population. In the context of the rational choice model of homelessness, this relationship is beneficial to society's well-being because the increase in shelter population reflects individual utility-maximizing behavior.

However, it is very difficult to separate shelter-quality measures from the array of other economic, environmental, and personal characteristics that cause individuals to become homeless. If anything, this study ultimately reflects the complexities inherent in exploring a population as underrepresented and diverse as the homeless population. Despite our best quantitative efforts, it was difficult to isolate the conditions that surround an individual's path to homelessness; homelessness, therefore, must be considered within a larger context. In order to develop meaningful analysis of homelessness, more data on the subject must be made readily available. The National Survey of Homeless Assistance Providers and Clients could be a very valuable resource if used to compare the characteristics of homeless individuals across locations. As our regression analysis showed, local characteristics – including the quantity and quality of services offered to the homeless – are related to the size of the homeless population. It would be interesting to explore that relationship given more specific information about homeless and formerly homeless individuals.

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