

**Measuring the Incentive
to be Homeless**

by

Michael Cragg
Brendan O'Flaherty
Columbia University

Discussion Paper # 714
December 1994

45

Measuring the Incentive to be Homeless¹

Michael Cragg and Brendan O'Flaherty
Columbia University, Department of Economics

We study the incentives to enter and to leave homeless shelters. After two years of decline, the number of homeless families in New York City's shelter system began rising again in Spring 1990 and continued to rise until it hit an all-time record high in Summer 1993. The conventional wisdom about why this happened is that a flood of new families were attracted into shelters by the Dinkins administration's aggressive policy of placement into subsidized housing. We test the conventional wisdom and reject it. Better prospects of subsidized housing increase flows into the shelter system, but this incentive effect is not nearly large enough to offset the first order accounting effect -- taking families out of the shelters reduces the number of families in them. Why then did the shelter system population grow after Spring 1990? A major part of the reason is that the city responded to conventional wisdom and slowed placement into subsidized housing. Other major factors were higher unemployment (which slowed self-initiated exits), greater use of more attractive Tier II shelters instead of hotels, and possibly increasing cocaine use.

December, 1994

¹We thankfully acknowledge the research assistance of Leilynne Lau. Vinnie DiTisu, Ken Rosenberg and Janet Greenblatt also provided great assistance in assembling the data. We have received useful comments from the Columbia Labor Workshop and Ron Miller.

1. Introduction

How much do efforts to help the homeless induce people to stay or become homeless? This has been a major question in the study of homelessness. Main [1983], Ellickson [1990], and Filer [1992], for instance, have all argued that incentive effects are large. To our knowledge, though, no previous studies have tried to estimate the size of these effects.

The most famous incident used to support the view that incentive effects matter is the large increase in New York City's family shelter population that followed Mayor David Dinkins' April 1990 decision to make subsidized housing more easily available to families living in hotels and shelters. It is now part of the received wisdom of New York City life that the availability of subsidized housing caused this increase (which followed almost two years of steady decrease). This incident has been studied in Main [1993] and Berlin and McAllister [1994], and cited by Berlin and McAllister [1992] and Jencks [1994] *inter alia* as an example of how actions designed to help the homelessness can produce perverse results. On the other hand, White [1991] is an early critic of this view.

In this paper, we will test empirically the hypothesis that Dinkins' decision to increase placements into subsidized housing caused the rise in family shelter population. In the interests of alliteration, we call this the "Dinkins deluge hypothesis." We will reject the hypothesis. More placements into subsidized housing do cause more families to enter the shelter system, but the effect is not great enough to offset the simple accounting identity that placements out of the shelter system reduce the number of families in it. If placements into subsidized housing had not risen, the family shelter population would have increased more than it actually did.

What then was driving the increase? Our answers are more tentative here. Even though New York's public assistance caseload began rising at about the same time as family shelter population, and most families entering the shelter system come from the public assistance caseload, we find little evidence that either the public assistance caseload or the number of individuals in that caseload paying rents at least as great as their housing allowances has a significant effect on inflows into the shelter system. Our primary positive finding is that, aside from the reduced rate of placement into subsidized housing, the major causes of the 1990-1993 shelter population rise were higher unemployment (which slowed self-initiated exits), greater use of more attractive Tier II shelters instead of hotels, and possibly increasing cocaine use.

Perhaps our most surprising finding is that the dynamics of New York City family shelter population can be described very well by two simple (almost linear) equations, one for inflows, and one for (unassisted) outflows. Our method is essentially to estimate these two equations, and then to simulate

the evolution of family shelter population under various (counter-factual) assumptions about the affect of city policies, unemployment and cocaine usage. We rely on New York's monthly reports on family shelter system population for the period January 1984 to December 1992. Because our methods are so simple, they may be useful for understanding the dynamics of other shelter populations for which fairly long time series are now becoming available.

One should not be hasty to generalize our results. We are dealing with a specific population--families in New York City--and two specific aspects of shelter life--the possibility of placement into unsubsidized housing and the type of shelters. New York is unique within the United States in its large family shelter system (with over 17,000 people) and in its close link to subsidized housing. (Perhaps the only close analogy is statutory homelessness in London, but housing market institutions are so different in London that it is easy to imagine that parameter values would also differ.) Single adults may react differently from families, and other aspects of shelter life--for instance, privacy, space, comfort, sanitation, availability of treatment and counseling--may have different incentive effects. In particular, improvements in the quality of shelter life may induce people to enter shelters without any corresponding increase in the number leaving. More work needs to be done on this topic.

Still, the New York family shelter system accounts for about a tenth of the entire homeless shelter population of all kinds in the United States, and the rise after April 1990 brought more people into the New York family system than were in the entire shelter population of any other American city in 1990 (U.S. Bureau of the Census, 1992). So to understand the dynamics of the New York family shelter system would have been important in its own right, even if the Dinkins deluge had not become the national symbol of iatrogenic homelessness.

The plan of this paper is standard. Section 2 will present a brief overview of the New York family shelter system and its history. Section 3 explains the behavioral components of a model of shelter population, and section 4 explains the data we use to estimate that model. Section 5 presents results of that estimation, and then section 6 uses these results both to simulate the evolution of shelter population under various counter-factual scenarios and to analyze the dynamic properties of the shelter population process. Section 7 concludes.

2. History of the New York Family Shelter System

New York City has for many years housed needy families in shelters and hotels. During the 1970's, this activity was called emergency housing, and the number of families being housed each month varied between 500 and 1000. Most families were fire victims, or had been served notices to vacate premises unfit for human habitation, or were being moved as part of an urban renewal program.

The number of emergency housing families began to move out of this range in the end of 1982, rising to almost 2000 by the beginning of 1983, but they were still not being called homeless families. In March 1983 the Legal Aid Society filed a suit, *McCain v. Koch* (502 N.Y.S. 2d 720--N.Y. App. Division 1986) designed to extend the right-to-shelter, which had recently been recognized for single men and women, to families as well. It was at this time that the phrase "homeless families" started to be used. By June 1983, a new agency, Crisis Intervention Services, had been formed to deal with homeless families, and reporting systems had been established.

McCain v. Koch was not settled until 1986. Essentially it provided and still provides a vehicle for judicial oversight of the family shelter system. This oversight, however, is more concerned with access to the system and with living conditions than with placement into subsidized housing.

Originally a "family" was one or more adults accompanied by a child or children; adults who were not accompanied by children were housed in the separate shelter system for single adults. Later, eligibility was broadened to include both couples without children and pregnant women without any other children. Family shelters are generally believed to be safer and cleaner than the shelters for single adults.

The family shelter system consists of three types of facilities--tier I shelters, hotels, and tier II shelters. The Cuomo Commission [1992, p. 72] described the system in the following way:

Families enter the emergency system through either H.R.A. [Human Resources Administration] Income Maintenance Centers or EAU's [Emergency Assistance Units]. They are then referred to one of several different types of shelters: a Tier I, a Tier II, or a hotel. Tier I facilities are congregate or dormitory style shelters offering some services and little privacy. The physical plant is most often a converted building such as a school that has been adopted to serve as a shelter. . . . Tier I facilities are operated by the City and cost approximately \$145 per family per night from City, State, and federal sources. Tier II facilities have come into use more recently, The major policy reform for homeless families, these facilities offer private accommodations and services intended to expedite a family's return to mainstream society. They primarily are developed and operated by not-for-profits, and funded through AFDC by the City, State, and federal governments. The cost is approximately \$100 per night per family. The use of so-called welfare hotels has long been documented. Hotels have few services and many are in poor condition yet cost an average of \$75 per room per day. . . .

In this paper we will not make distinctions between hotels and the other facilities; "shelter" and "shelter population" will refer to the whole system. However, we will test for incentive effects of the different types of facilities.

After the current system was put in place in 1983, population grew rapidly, rising from about 2000 families to around 5200 families at the beginning of 1988. Then it fell even more rapidly, reaching a trough slightly above 3000 in spring 1990. Then it rose again, peaking at around 5700 families in the summer of 1993. Figure 2.1 illustrates.

Explaining this last rise is one of the major goals of this paper. The traditional explanation is that large numbers of new families were attracted into the system because Mayor Dinkins, who took office at the beginning of 1990, increased the rate at which shelter families were placed into subsidized housing.

Placement into subsidized housing has always been part of New York's system of family shelters, as befits its history of fire victims and of urban renewal relocatees. The first rise in shelter population, moreover, came at a time when the City had on hand a large stock of housing it had taken for failure to pay property taxes--88,500 units in June 1983, of which only 25,500 were thought to be occupied (In-Rem Housing Annual Report, FY 1983). These were called "in-rem" housing units, because the city had foreclosed on them in in-rem legal actions. As early as February 1983, in-rem housing stopped renting apartments to walk-in applicants; henceforth vacant and rehabilitated apartments would be used to move homeless families out of the shelter system.

New York has a second program as well, called EARP (Emergency Assistance Rental Program), which subsidizes private sector landlords who rent to families from the shelter system.

At first, both the in-rem program and EARP were very small. In-rem did not begin to house many families until about 1987, and EARP stayed insubstantial for several years after that. We refer to the sum of in-rem and EARP placements as "city placements." The time series is graphed as Figure 2.2. Following a bureaucratic reorganization that created a Department of Homeless Services in January 1993, the city stopped publishing statistics on city placements.

3. The Model

We build upon a fundamental accounting identity: shelter population at the end of month t (s_t) equals shelter population at the end of the previous month (s_{t-1}), plus new families who entered the shelter system during the month (n_t), minus city placements during the month (c_t), minus the number of families who exited on their own without a city placement (e_t):

$$s_t = s_{t-1} + n_t - c_t - e_t \quad (1)$$

To understand the evolution of shelter population, then, we must find out what determines n_t , c_t , and e_t .

3.1. New entrants

What makes families enter the shelter system? There are several different theories we can test. The most prominent one, of course, is that they are drawn by the opportunity to get subsidized housing. To measure this effect we will use a variable q_t defined as the ratio of shelter population to city placements during the previous month:

$$q_t = \frac{S_t}{C_{t-1}}$$

The Dinkins deluge hypothesis requires that q_t have a large negative effect on entries to the shelter system.

There are two different ways to think about q_t , but they both have the same implications. If the shelter system represents a stationary first-in-first-out (FIFO) queue for housing, then q_t is the expected number of months a family must stay in the shelter system before it get permanent subsidized housing; it is the duration of purgatory.

Alternatively if city placements are drawn randomly from the shelter population each month without regard for seniority, then $(1/q_t)$ is the probability of being picked (and q_t is the expected length of time before being picked). The higher this probability, the more families should be entering the shelter system. So once again q_t should have a negative effect on entries.

Both interpretations reach the same conclusion. On paper, the shelter system works by seniority, and so the first interpretation is the more relevant one; the second interpretation reminds us that the expected relationship is fairly robust if actual operations deviate from what is written on paper.²

Variation in the degree of shelter comfort may also matter. The more families sheltered in Tier I facilities, the more time a family can expect to be sheltered there. The same is true for Tier II facilities and for hotels. Since Tier I facilities are less attractive on all dimensions than Tier II facilities and hotels, we expect that higher proportions in Tier I housing will deter entries. About Tier II facilities and hotels our priors are less clear: hotels may be uncomfortable and unsafe, but they offer privacy, and for some, a touch of glamour; Tier II facilities are comfortable, safe, and offer counseling and other therapy, but they come with a paternalistic veneer that families may dislike.

Endogeneity problems mean that we will have to be careful in how we treat the distribution among the types of facilities. The distribution is not totally under the city's control. A large, unexpected surge

²At various times the city has also imposed administrative minima on the length of time a family must stay in the shelter system before it can be considered for subsidized housing. We test for these minima and find they have no independent effect. Either they were not binding, or they were not enforced.

of new entrants, for instance, would increase the use of hotels, because Tier I and Tier II capacities are pretty much fixed in the short run. To avoid these difficulties, we lag the distribution among facilities when we estimate the equation for entries.

The alternative theories about entries are that events external to the shelter system drive people to enter--that they are not being attracted by the system's internal workings. In turn, there are a variety of theories about what external events might matter.

One frequently mentioned possibility is poverty, and one way of measuring the extent of poverty is the size of the population receiving public assistance. The more people receiving public assistance, the more people entering the shelter system. Another interpretation of public assistance also implies the same relationship: since most families entering the shelter system are receiving public assistance or were recently cut off it, the public assistance caseload can be seen as a pool from which random families are drawn by bad luck into the shelter system. Holding the bad-luck process constant, the bigger the pool, the more people will be drawn.

Another closely related measure is unemployment. The New York public assistance caseload does not correlate well with unemployment, and so unemployment may in fact be a better measurement of the extent to which people lack the resources to secure housing on their own.

Housing prices may also matter: if housing prices go up, the same resources will not go as far. One measure of housing prices is the New York metropolitan area consumer price index for residential rent.

Another indicator of the tightness of housing market, possibly more relevant, is the proportion of public assistance households with rents at least equal to the maximum housing allowance. Public assistance grants in New York have two parts: one part is for the household's housing expense and the other is for all its other expenses. The housing expense part is the smaller of the actual rent a household pays, and an administrative maximum that is adjusted periodically. Thus the proportion of public assistance households constrained by the administrative maximum is one measure of the extent to which public assistance families lack the resources to obtain housing on their own. The higher this proportion, the greater the inflow into the shelter system. The product of this proportion and the size of the public assistance caseload may also matter, since the proportion of clients receiving the maximum housing allowance should be related to the probability that a household experiences the kind of bad luck that leads to homelessness.

A final external determinant of shelter entries may be the use of drugs. Jencks (1994) has argued that crack cocaine is an important cause of the rise in homeless single adults, and the Cuomo Commission (Mayor's Commission on the Homeless, 1992) found that a substantial proportion (29%) of the adults in

family shelters tested positive for the presence of drugs in their urine, mostly for cocaine. So indicators of cocaine use should be positively correlated with shelter entries. We use two such indicators: births to women using cocaine (since most of the families are headed by lone mothers), and emergency room incidents involving cocaine.

Thus for entries to the shelter system we will estimate an equation of the form

$$n_t = X^n(Z_t^n) - \alpha q_t + \epsilon_t^n \quad (2)$$

where $X^n(\cdot)$ is a (linear) function of events Z_t^n , external to the shelter system and of the previous month's distribution of shelter population among facility types. Possible indicators are public assistance unemployment, rents, public assistance clients receiving the maximum housing allowance, and cocaine use.

3.2 City placements

We will treat city placements as policy variable under the control of city government. This treatment is in accord with the popular story of the Dinkins deluge, and we will present evidence to support it.

3.3. Noncity exits

By noncity exits (e_t) we mean the number of families who left the shelter system on their own without a city placement into subsidized housing. Since noncity exits can come only from a fixed pool--families already in the shelter system--we estimate the noncity exit rate--(e_t/s_{t-1})--rather than the absolute number of noncity exits.

Many of the same things that affect new entries should affect the noncity exit rate as well. In particular, increases in queue-length should increase the rate at which families leave the shelter system on their own, since longer waits should be just as discouraging to families on the inside as they are to families on the outside. Indeed, families on the inside can be expected to have better information about queue-length than families on the outside, and so noncity exits should be more sensitive to changes in queue-length than new entries are.

Rents and the proportion of public assistance households at the housing allowance maximum should also affect noncity exits, since they indicate the extent of difficulties in the housing market. The size of the public assistance caseload, though, should not matter, since the relevant pool is the people already in the shelter system. Unemployment, however, may matter: a booming economy may make it easier for adults in the shelter system to find jobs and marriage partners, and easier for their friends and relatives to help them.

Three other considerations, all internal to the shelter system may also help determine the noncity exit rate. First, the distribution among shelter types may matter -- people may be more eager to leave less

comfortable shelters. Second, congestion may be a problem if many people are in the system, and so absolute population may matter. Finally, duration dependence is probably the most important internal consideration: recent entrants to the system are much more likely to leave than families who have been in the system for several months. So the proportion of new entrants (n_t/s_{t-1}) should also affect the noncity exit rate (at the very least it includes families who entered during the month and left before it was over and so n_t matters even without duration dependence).

Thus we will estimate an equation of the form:

$$\frac{e_t}{s_{t-1}} = \beta q_t - \gamma s_t + \delta \frac{n_t}{s_{t-1}} + X^e(Z_t^e) + \epsilon_t^e \quad (3)$$

where $X^e(\cdot)$ is a (linear) function of the events Z_t^e , external to the shelter system and the previous month's distribution among shelter types. If $\beta = \gamma = 0$, equation (3) takes a particularly simple form which is useful for understanding the dynamics of shelter population.

$$e_t = \delta n_t + X^e(Z_t^e)s_{t-1} + \epsilon_t^e s_{t-1} \quad (4)$$

4. The Data

Our primary data source for all of the variables in equation (1) are the Monthly Shelter Reports of the City of New York. Although shelter exits and entrances are available from January 1984, we use only the period March 1986, to December 1992, because city placements in subsidized housing are available only in this period. In January 1993 responsibility for the shelter system was transferred from the Human Resources Administration to the Department of Homeless Services, and city placements stopped being published. After January 1993 we know what happened to shelter population and new entries, but we cannot use this data for estimating purposes because city placements are missing. These data provide us with city placements, the homeless shelter population and new entrants into the system. Because the shelter population is equal to last period's population plus entrants net of city placements and self initiated exits, the noncity placements are determined as the residual in this identity.

There are two chief weaknesses with these data. First while a full time series of entrants and the shelter population is available, several months are missing from the city placement series (Jan. Feb. 1986, and Sept.-Dec. 1987) largely because of conversion of the management information system. For these missing data we linearly interpolate to fill the missing values. Second, and more seriously, families who leave the shelter system and return within less than 30 days are treated somewhat inconsistently. If the period during which they were gone is completely within a month, neither an exit nor an entry is recorded. If the period during which they were gone spans two months, the shelter count is reduced by one at the

end of the first month. Since for most of the data set, we calculate noncity exits ourselves as a residual according to the accounting identity (1), this increases noncity exits by one in the first month. When they return in the second month they are not counted as new (because an absence of less than 30 days does not cost them their seniority in the queue), but at the end of the month shelter population goes up by one, and so we will reduce our figure for noncity exits by one.

For public assistance caseload and the proportion receiving the maximum housing allowance, we use HRA Facts, a monthly publication of the New York City Human Resources Administration. HRA runs two different public assistance programs: Aid to Families with Dependent Children (AFDC), the federally sponsored and partially funded program of assistance primarily to single-parent families with children; and Home Relief (general assistance), a locally funded program of assistance to other household categories, including childless couples, pregnant women, and single adults. The shelter system draws from both programs, but primarily from AFDC. On average, AFDC households have more members than Home Relief households. We use the number of persons receiving public assistance rather than the number of households because this construction implicitly puts greater weight on AFDC cases than Home Relief cases, a large number of whom are ineligible to use the family shelter system.

The proportion of public assistance households constrained by the housing allowance maximum is published only once every six months; for the other months we interpolated linearly.

For unemployment, we use the New York City unemployment rate from the U.S. Bureau of Labor Statistics. Once again, there is a gap from April 1988-October 1989, because the Current Population Survey sample was too small to provide estimates for New York City. We predict missing values from a polynomial extrapolation in time with month dummies. For rents we use the residential rent component of the consumer price index for urban workers in the New York metropolitan area, also from the U.S. Bureau of Labor Statistics. Because this series is published annually we fit a smooth polynomial in time to the annual data to generate monthly data.

Data on the distribution of the shelter population among types of facility come from the HRA Monthly Shelter Reports. The missing data for September to December in 1987 were filled in by linear interpolation.

Data on cocaine or cocaine-related emergency room episodes are from the Drug Abuse Warning Network of the federal Substance Abuse and Mental Health Services Administration. A consistent estimate based upon a representative sample of hospitals is available only after January 1988. The series is published semi-annually and so we generated monthly data by fitting a smooth polynomial in time. As an indicator of cocaine use or abuse in households at risk of entering the family shelter system, this series has several disadvantages: it includes many single adults, an individual who uses an emergency room ten

times in a six-month period gets counted ten times; the age and general physical condition of users matters as much as the number of users; and, alternatives to emergency room care also matter. Nationally, there are considerable divergences in the trends shown by the emergency room time series and trends in survey results on drug usage in the general population.

An alternative cocaine time series is free of some of these disadvantages -- births to women testing positive for cocaine. This series is available on an annual basis starting in 1988 from the New York City Department of Health. A major problem with this series is the suspicion voiced by health officials that an increasing number of women are hiding their use when they go to the hospital out of fear that their babies will be taken away and placed in foster care if they test positive.

The emergency room series and the birth series show quite different trends. The emergency room series falls from 1988 to early 1990, and then rises through 1992. The birth series is almost the opposite: it rises from 1988 to 1989, then falls through 1992. The national survey series on cocaine use is more like the birth series than the emergency room series. These data problems strongly suggest skepticism in interpreting the cocaine coefficients.

Summary statistics are presented in Table 4.1

Regressions involving these variables could be spurious if several of the processes these variables describe have unit roots -- that is, they follow random walks. Accordingly, we conducted Phillips-Perron tests for unit roots on all the time series we will be using. These results are presented in Table 4.2.³ Table 4.2 shows that for the two series we will be using as dependent variables, we can reject the null hypothesis of a unit root with drift.⁴ Since spurious regression is a problem only when *both* the dependent variable and the independent variable follow unit root processes, this rejection means that spurious regression of this sort will not be a problem for us. Also comforting from Table 4.2 is the rejection of the unit root null for queue, our most important independent variable.

5. Results

5.1. City placements

The question about city placements is whether we can consider them really under the control of city government. The journalistic story is that they are. In particular, the story is that placements were low under Mayor Koch; they went up when Mayor Dinkins took office but then fell back down again when the Dinkins administration realized the error of its ways in October 1990 and established the

³Phillips-Perron tests are described in Hamilton (1994), pp. 506-516.

⁴This is the appropriate null because the series are constrained to be greater than zero.

Alternative Pathways Program (APP). APP was designed to reduce new entries even more by making some subsidized housing available quickly to some families that had not yet entered shelters in the hope that they would not. (Main [1993]) is the most detailed telling of the story.)

To check this story, we regressed city placements on dummies for the Koch period (equal to 1 from August 1988 to March 1990), the Dinkins period (equal to 1 from April 1990 to October 1993) and the APP period (equal to 1 from October 1990 to December 1993) and a constant. Results are in table 5.1. Both coefficients are significant and the signs and relative magnitude are correct. The proportion of the variance explained by this extremely simple-minded specification is very large, about 73%.

An alternative hypothesis is that city policies are driven by the shelter population--for instance, when the shelter population is large officials panic and step up the placement rate. To test this hypothesis, we add shelter population to the equation with dummy variable for policy periods. See table 5.1. The coefficient is tiny and insignificant.

We obtained similar results when we took the proportion of city placements in total departures as the dependent variable. These results give us no reason to reject the hypothesis that city placements are an exogenous variable, as far as the workings of the shelter system are concerned.

5.2. New entrants

Table 5.2 presents our results about what causes families to enter the shelter system. Since cocaine data are available only after 1988, we run some regressions only on the shorter period.

When we look at the full period, the availability of subsidized housing as reflected in the queue variable has a positive and significant impact on inflows into the shelter system. This is a necessary condition for the Dinkins deluge hypothesis. Significance disappears on the shorter 1988-1992 period, but the size of the coefficient increases when emergency cocaine admissions and the proportion of shelter residents in hotels are included.

The rent component of the consumer price index is significant and positive, as expected, over the whole period, and is positive but insignificant over the shorter period. When the distribution of shelter types is introduced, however, the coefficient on rents switches signs and becomes negative.

Although the coefficient on the percent of the shelter population in Tier I facilities has the wrong sign and is insignificant both for the full period and the shorter period, the coefficient on hotels is negative and significant in the short period (but positive and insignificant in the full period). After 1988, people liked Tier II facilities more than hotels.

Emergency room cocaine admissions increase shelter inflows. The other coefficients are insignificant. In particular, nothing about public assistance makes a significant difference.

Not reported here are a series of regressions where we introduced the policy variables (Koch,

Dinkins and APP) into equations like those in Table 5.2. The coefficients on the policy variables were uniformly small and insignificant. City officials influenced the inflows through changes in the queue length and in the distribution of shelter recipients among different types of facilities. No other aspect of city policy mattered -- not "general attitude," not administrative minima on length of stay before placements, not attempts to divert flows elsewhere. As a homelessness prevention tool, the Alternative Pathways Program was a failure. Finally, we ran regressions which included lags and leads of the queue variable and unemployment. While there was an insignificant rise in the R^2 , the significance of the queue variable was eroded since it is highly correlated with its first and second lag (0.83 and 0.90 respectively).

5.3. Noncity exits

Table 5.2 also shows our preferred equations for noncity exits. A much more consistent picture emerges here: across both specifications and both time periods, only two variables matter: the proportion of new entrants in the shelter population, and the unemployment rate. The coefficients on the proportion of new entrants indicate that about a third of new entrants leave before the end of the month in which they enter; these coefficients are consistent with independent data on the duration of ongoing spells. The unemployment rate results may be somewhat surprising, since few of these family heads are directly connected to the labor market; indirect effects through the generosity of friends and relatives and through the marriage market may be more important than direct effects.

We also ran equations with queue and total shelter population as independent variables. Neither had a coefficient significantly different from zero. This means we can use the simple linear form (4) instead of (3). The failure of queue length to affect noncity exits is troublesome for the Dinkins deluge hypothesis: if people outside the shelter system know enough to respond to internal events, why don't inside people also (presumably they are better informed)?

Dummy variables for the different policy regimes also had no significant impact on noncity exits in equations not displayed here. Administrative minima on the length of time a family must stay in the shelter system before it can be considered for subsidized housing do not appear to affect families' decisions to leave on their own. We also interacted queue with the ratio of new entrants to last period's shelter population but this provided no additional explanatory power.

5.4. Shelter population

Figure 5.1 shows that our preferred equations (column 2) allow a very close simulation to actual shelter population. The confidence intervals in this figure were derived by Monte Carlo methods. The correlation between the actual and predicted population is 0.95. Of course both time series have unit roots.

6. Implications

6.1. Simulations

Since the dynamics of the shelter system are complex, simulation is the easiest way to find the effects of various policies and external events. For these simulations, we use the preferred behavioral equations for new entrants and noncity exits that we found in the previous section (specifically, from Table 5.2 we use column 1).

City placements are the most important policy variable we want to examine. The Dinkins deluge hypothesis says that city placements were responsible for most, if not all, of the rise in shelter population after 1990. To test this hypothesis we consider three simulations. First, we examine what would have happened to the shelter population if the Dinkins' administration had adopted Koch's March 1988 policy of 245 placements per month in January 1990, when they came into office. A second simulation considers a return to this policy in June 1990 and finally, we examine what would have occurred if the Dinkins' March 1990 placement rate of 521 families per month was continued. If the Dinkins deluge hypothesis were correct, simulated shelter population under this hypothesis would rise after 1990 using the March 1990 placement rate but it would fall if the March 1988 placement rate is used.

The results strikingly reject the Dinkins deluge hypothesis (see Figure 6.1). A policy of reduced placements would have in fact made the shelter population rise even more than it actually did. If placements continued at their March 1988 level, by 1993 the shelter population would have been over 8,000 families.

Alternatively, suppose that the Dinkins administration had continued after March 1990 the policies that have been so extensively pilloried. In particular, suppose that city placements stayed at the March 1990 level throughout the subsequent period. If the Dinkins administration had continued its original placement policy, the shelter population would have been far less in December 1993 than it actually was. In fact, our simulation indicates that the shelter population would have been almost half as large (3,000 versus 5,500 families). The difference is attributed to factors outside of the city placement policy. Thus we clearly reject the Dinkins deluge hypothesis: while placements do induce more entrants they are overwhelmed by the first order effect of a one-for-one reduction in the shelter population. In fact, the reduction in city placement activity was a major cause of the rise in the shelter population.

These results are robust. Figure 6.2 shows the same simulation but a different starting point for the simulation and experiments with different behavioral equations. In all three simulation we use January 1986 as the first year in the simulation. If city placements were at their March 1990 level throughout the period, the 1993 shelter population would have been substantially lower - on the order of 2,400 families.

A simulation using behavioral equations most sympathetic to the Dinkins deluge hypothesis sets the coefficient on queue-length on the new entrants equation and the coefficient on new entrants in the noncity placement equation both set at the bottom end (algebraically) of their respective 95% confidence intervals. Even then, the predicted shelter population would have been 23% lower than the actual levels. If the placement rate was held at its March 1988 level throughout the period, the shelter population would have been nearly 8,000 families.

If we reject the Dinkins deluge hypothesis, we still need to explain why shelter population rose after 1990. Of course, part of this is due to the fall in city placements in later 1990 but placements rose again through 1991 and 1992 nearly to the 1990 levels. Thus, the shelter population was rising during a period when it should have been falling *ceteris paribus*.

The rise in the shelter population following 1990 can be attributed to either a rise in new entrants or a fall in self-motivated exits. During the period following 1990, neither the number of families receiving public Assistance nor the fraction of families who were collecting the maximum shelter allowance changed and so neither can explain the rise in the shelter population. Although the rental component of the CPI rose steadily both before and after 1990, in no specification did it play an important role. Thus, four variables can potentially explain the rise: the rising NYC unemployment rate, the rising fraction of homeless families housed in hotels, the falling fraction of the caseload housed in Tier 1 shelters, and the rise in cocaine related emergency room admissions (see Figures 6.3-6.6 for the data).

Using the parameters from the full specification estimated in column 4 of Table 5.2, Figures 6.8 - 6.10 show the results of four simulations that explore the four separate explanations-- rents, cocaine, shelter quality and unemployment--for the increase. For each simulation, we hold the variable in which we are interested -- say unemployment -- fixed at its March 1990 level and simulate the evolution of the shelter population after March 1990 with all other variables taking their actual values. If a variable is important in explaining the post-1990 rise, then the simulated outcome will be significantly below the actual caseload. Figure 6.8 shows that the upward trend in the unemployment rate following 1990 had a large effect on the shelter population, but only after January 1991. While the fraction of the caseload housed in Tier 1 accommodations has no effect on the simulated caseload, the rapid drop in the fraction housed in hotels in 1990 led to a quite substantial rise in the simulated caseload (see Figure 6.9). Since the default value for accommodations is Tier II, an alternative interpretation of this simulation is that the increasing use of Tier II shelters attracts more families into the shelter system. Finally, the upward trend in cocaine related emergency room visits also can explain a large fraction of the post-1990 rise in the shelter caseload. However, because of the measurement problems with this variable, this conclusion should remain extremely tentative.

6.2 Analysis

Closer analysis confirms the result of those simulations. Since the behavioral equations allow us to set $\beta = \gamma = 0$ in equation (3), we can combine equations (1), (2), and (4), ignoring residuals, to obtain a first order linear difference equation for the evolution of shelter population:

$$\begin{aligned}
 s_t &= s_{t-1} + [X^n(Z_t^n) - \alpha q_t] - c_t - [\delta n_t + X^e(Z_t^e) s_{t-1}] \\
 &= s_{t-1} \left\{ 1 - (1 - \delta) \frac{\alpha}{c_{t-1}} - X^e(Z_t^e) \right\} + [(1 - \delta) X^n(Z_t^n) - c_t] \\
 &= s_{t-1} a_t + b_t
 \end{aligned} \tag{5}$$

From (5) we can see very quickly why the Dinkins deluge hypothesis fails. An increase in city placements in period $(t-1)$ decreases s_{t-1} one-for-one in period $(t-1)$ and most of this decrease carries over to period t because the expression in curly brackets a_t is pretty close to one. The incentive effect in period t , however, is only

$$\frac{\partial s_t}{\partial c_{t-1}} = (1 - \delta) \frac{\alpha s_{t-1}}{c_{t-1}^2} = (1 - \delta) \alpha \frac{q_t}{c_{t-1}}$$

With the estimates from column (4) and mean values of the variables, this expression is only 0.45. The estimates from column (4) are most favorable to the Dinkins deluge hypothesis; we cannot reject the null hypothesis that the incentive effect is one -- new entrants precisely offset city placements -- at the 95% level at mean values. Even with column (4) we can reject the null hypothesis that placements increase the shelter population.

With the estimates from column (2), on the other hand, the incentive effect is only 0.19 at mean values. Mean values, moreover are much more favorable to the Dinkins deluge hypothesis than actual values in the spring of 1990 when the Dinkins deluge is supposed to have been triggered. Using April 1990 values and column (4) gives an incentive effect of only 0.04; with column (2) the incentive effect shrinks to 0.01.

Figures 6.11a and 6.11b show how a_t and b_t evolve over the sample period. For most of the time, a_t is less than one and b_t is positive. This means that if external events Z_t^e and Z_t^n , and city placements c_t were to be stable for a long enough time, the shelter population would approach some steady state $s(Z^e, Z^n, c)$. From algebra

Call equation (6) the "implicit steady state population" at month t ; it is the steady state to which shelter

$$s(Z^n, Z^e, c) = \frac{b}{1 - a} = \frac{(1 - \delta)X^n(Z^n) - c}{X^e(Z^e) + (1 - \delta)\frac{\alpha}{c}} \quad (7)$$

population would converge if city policies and external conditions were to remain the same for a long enough time. The implicit steady state population depends only on city policies and external conditions at time t ; it is independent of the historical conditions that affect the actual shelter population. Changes in actual shelter population reflect partly adjustment to the implicit steady state, and partly changes in city policies and external conditions. Starting from any initial condition, the shelter population would adjust monotonically toward the steady state.

Figure 6.11 traces out how the implicit steady state population $b_t / (1 - a_t)$ changed during the sample period. This figure uses estimates from column (2) of Table 5.2. The implicit steady state rose rapidly in the spring of 1990, and most of the rise for the rest of that year was adjustment to the higher steady state. Since early 1991, the actual shelter population has been fairly close to the steady state.

Why did the steady state rise in the spring of 1990? Figures 6.11a and 6.11b show that the chief culprit was a steep rise in the b_t term, although a small rise in the a_t term also contributed a little. The b_t is externally induced entrants net of city placements, and so the incentive effects of city placements cannot be responsible for the rise. Rather it appears that the combined effects of a small hotel population (at first) and fewer city placements (later in the year) were what drove the increase in b_t and hence the rise in the implicit steady state population in 1990. After 1990, b_t fell but a_t continued to rise, largely because rising unemployment made unassisted exits from the shelter system less common.

Notice from figure 6.11a that a_t is very close to one; it never gets below 0.95 and was approaching 0.98 in 1992. These large values of a_t explain why the implicit steady state population is more volatile than the actual population in figure 6.11: b_t is being divided by a very small number. These large values of a_t also imply that convergence to the steady state population, while monotonic, is very slow -- much slower than changes in the steady state. With $a_t = 0.96$, the half life of a deviation from the steady state is 17 months. Since 1990, especially, the shelter population is best characterized as a random walk with positive drift (Table 4.2 confirms this characterization); transitory disturbances can have (almost) permanent repercussions. The Dinkins increase in city placements in early 1990 continued to depress the shelter population even in 1992, and the fall off in placements in late 1990 drove up the 1993 shelter population.

Figure 6.12 traces out the implicit steady state for the average values of the independent variables in the data set using estimates from the second column of Table 5.2. The figure shows that for almost the entire period more placements would have reduced implicit steady state population. The exceptions

come in early years when city placements were extremely low. Even in these years, though, a large but not ridiculous increase in placements--say, to the mean level of 277 a month--would have decreased implicit steady state population. Once again, this result is not supportive of the Dinkins deluge hypothesis.

Considering implicit steady states also gives another way of going about the positive task of trying to explain why shelter population rose after April 1990. Figures 6.13 and 6.14 provide simulations of the implicit steady state population for various values of c , for high and low values of the unemployment and percentage of the shelter population housed in hotels using the estimates in column 2 of Table 5.2 while Figure 6.15 provides the steady state for the extreme value of the number of cocaine related emergency room visits using estimates from the 4th column of Table 5.2.

7. Conclusion

It is easy to see why the story of Dinkins deluge is so appealing. The irony is deep. Dinkins, as borough president and mayoral candidate, had attacked Mayor Koch for not moving families out of the shelter system quickly enough, and then as mayor, found the policy he had fought for a disaster, and embraced the same policies he had attacked. "It took him a long while for him to accept that was going on,' First Deputy Mayor Norman Steisel said of Mr. Dinkins" (Roberts 1991). It is a classic story of good intentions gone awry, and hubris replaced by wisdom.

The only thing wrong with the story, we have argued, is that it is not true. Unemployment, more Tier II shelters and possibly cocaine use are more important reasons for the increase in family shelter population; more city placements in fact would have decreased shelter population. Some weak indirect evidence on this point comes from Essex County, New Jersey, only a few miles from New York City, where an aggressive policy of placement through a program like EARP reduced family shelter population drastically between January 1991 and July 1993--the same time when family shelter population was rising in New York (Walsh 1993).

Our findings, however, do not imply an endorsement for a policy of providing subsidized housing to homeless families. We have not explored the budgetary cost or housing market effects of alternative policies. The most serious issue is equity: as long as subsidized housing is rationed, jumping shelter families to the head of queue harms the interests of other families in the queue, even if it decreases shelter population. Perhaps this is unfair, but without a good principle for rationing fairly a small number of large subsidies among a group of poor people, it is difficult to say what is fair or unfair. At any rate, minimizing the shelter population should not be the only goal of social policy.

References

- Berlin, Gordon and William McAllister (1994). "Prevention and Population Dynamics: One Works, The Other Doesn't," Criminal Justice Research Center Discussion Paper, City University of New York.
- Berlin, Gordon and William McAllister (1992). "Homelessness," pp. 63-69 in Henry Aaron and Charles Schultze, *Setting Domestic Priorities: What Can Government Do?* Washington: Brookings Institution.
- Dugger, Cecilia (1993). "Search for Shelter: New York and its Homeless," *New York Times*, July 4, I, p.1; July 5, I, p.1; July 6, A-1.
- Ellickson, Robert (1990). "The Homeless Muddle," *The Public Interest*, 99, Spring, pp. 45-60.
- Filer, Randy (1990). "What Really Causes Family Homelessness?" *The City Journal*, pp. 22-31.
- Hamilton, James D. (1994). *Time Series Analysis*. Princeton: Princeton University Press.
- Jencks, Christopher (1994). *The Homeless*. Cambridge: Harvard University Press.
- Main, Thomas (1983). "The Homeless of New York," *The Public Interest*, 72, Summer, pp. 3-28.
- Main, Thomas (1993). "Hard Lessons on Homelessness: The Education of David Dinkins." *City Journal*, Vol. 3, No. 3, pp. 30-39.
- New York City, Commission on the Homeless (1992). "The Way Home: A New Direction in Social Policy."
- New York City, Department of Housing Preservation and Development, "Annual Reports," various years.
- New York City, Human Resources Administration, "HRA Facts," monthly publication.
- New York City, Human Resources Administration, "Monthly Shelter Reports," monthly publication.
- Roberts, Sam (1991). "What Led to a Crackdown on the Homeless," *New York Times*, October 28, pp. B1, B4.
- U.S. Bureau of the Census (1991). "Census Bureau Releases 1990 Decennial Counts for Persons Enumerated in Emergency Shelters and Observed on Streets," press release, April 12.
- Walsh, Diane C. (1993). "Essex shifting funds from hotels to more stable homeless housing," *The Star-Ledger*, August 15, p. 32.
- White, A. (1991). "Shelter Gridlock," *City Limits*, November, pp. 12-16.

Figure 2.1 - Shelter Population
Figure 2.2 - City Placements
Figure 2.3 - Queue
Table 4.1 - Summary Stats
Table 4.2 - Philps Peron Z stats
Table 5.1 - City placements on dummies
Table 5.2 - Estimates
Figure 5.1 - Shelter Population with confidence intervals
Figure 6.1 - Simulation with City Placements at March 1988 and 1990 levels
Figure 6.2 - Dinkin's Deluge Simulation
Figure 6.3 - Fraction of Caselaod in Tier1 and Hotels
Figure 6.4 - Time Series of Rents, PA and Percentage at Shelter Max
Figure 6.5 - NYC Unemployment Rate
Figure 6.6 - Cocaine Related ER Admissions
Figure 6.7 - Full Specification Simulation
Figure 6.8 - What Explains Post-1990 - Unemployment Rate Held at March 1990 Level
Figure 6.9 - What Explains Post-1990 - Hotels and Tier 1 Held at March 1990 Level
Figure 6.10 - What Explains Post-1990 - Cocaine Admissions
Figure 6.11 - Steady State versus City Placements
Figure 6.11a
Figure 6.11b
Figure 6.11c
Figure 6.12 - Steady State - High versus Low Unemployment
Figure 6.13 - Steady State - High versus Low Fraction Housed in Hotels
Figure 6.14 - Steady State - High versus Low Cocaine Related ER Admissions

Variable	Months	Mean	S.E.	Minimum	Maximum
Monthly Shelter Population	82	4571	602	3196	5591
New Entrants per Month	82	828	149	457	1171
City Placements in Subsidized Housing	82	287	133	34	581
Self-Motivated Exits from Shelters	82	523.3	97.5	229	769
Percentage of Exits which are City Placements	82	0.34	0.13	0.07	0.69
NYC Public Assistance Recipients (thousands)	82	891.8	64.4	813	1054
Fraction of Public Assistance Recipients at Maximum Shelter Allowance	82	62.9	8.1	39.7	74
Rental Component of CPI	82	145.2	13.1	121.23	164.45
NYC Unemployment Rate	82	7.1	2.1	3.7	12.09
Queue (months)	81	23.5	20.2	6.01	121.06
Number of PA Recipients at Shelter Maximum	82	56414	10543	33983	77996
Percentage of Shelter in Tier 1 Housing	82	0.1	0	0.01	0.16
Percentage of Shelter Population in Hotels	82	0.5	0.3	0.05	0.83
Number of Cocaine Related Emergency Room Visits	60	8099	1424	6178	11233

Variable	Rho	sigma	Z for Case 2	Significant
Dependent				
Nonrate	0.495	0.099	-41.39	*
New	0.762	0.066	-19.54	*
Independent				
Newrate	0.847	0.058	-12.59	*
Max	0.981	0.027	-1.60	
Rent	0.992	0.001	-0.62	
Unemp	0.958	0.040	-3.47	
Tier 1	1.014	0.036	1.18	
Hotel	0.990	0.010	-0.85	
Coke	0.987	0.043	-1.05	
City	0.880	0.048	-9.84	
q	0.743	0.057	-21.09	*
Load	1.000	0.019	0.00	
			0.025	0.975
Critical Value		n=50	-9.9	1.7
		n=100	-10.2	1.65
The unit root test is based upon a regression of the variable on its lag and a constant. The null hypothesis is a unit root with a drift. The alternative is a stationary process with a constant.				
* indicates series is stationary at the 5% level				

Table 5.1 - Regression Explaining Variation in City Placements		
(number in parentheses are t-statistics)		
Dependent Variable - City Placements		
Koch	218.21 (10.6)	230.94 (10.2)
Dinkins	315.49 (9.9)	348.34 (8.7)
APP	97.57 (3.0)	-130.40 (3.3)
Load		0.02 (1.3)
Constant	139.34 (10.6)	25.63 (1.3)
Number of Observations	82	82
R Squared	0.73	0.73
Dependent Variable - Fraction of Exits which are City Placements		
Koch	0.20 (9.7)	0.20 (8.7)
Dinkins	0.24 (7.5)	0.24 (6.0)
APP	0.03 (0.8)	-0.03 (0.7)
Load		0.00 (0.0)
Constant	0.20 (14.9)	0.20 (2.3)
Number of Observations	82	82
R-Squared	0.68	0.68

Table 5.2 - Estimates of Entry and Exit Equations				
	1986-1993		1988-1992	
Dependent Variable - New Entrants				
queue	-2.7319 (2.5)	-3.0600 (2.7)	-2.5960 (0.7)	-7.2221 (1.9)
maximum shelter allowance*PA pop	0.0019 (0.9)	0.0009 (0.4)	0.0008 (0.3)	-0.0019 (0.1)
rental cpi	5.2172 (2.3)	-0.5302 (0.1)	10.6746 (0.4)	14.1249 (0.7)
unemployment rate	-11.3241 (-0.8)	-7.6880 (0.6)	14.1262 (0.7)	14.1249 (0.5)
percent of shelter pop in Tier1 Housing		255.9041 (0.4)		1131.4230 (0.8)
percent of shelter pop in hotels		290.2000 (1.3)		-614.9530 (2.9)
Emergency room cocaine admits				0.0695 (2.6)
Constant	111.2630 (0.4)	1143.8010 (1.3)	-447.0800 (0.0)	2659.4100 (1.1)
Obs	81	81	54	0.54
R square	0.59	0.63	0.29	0.54
Box-Ljung-Pierce Tests for AR	no	no	no	no
Dependent Variable - Non City Placement Rate				
ratio of new entrants to last period shelter pop	0.3401 (6.7)	0.3800 (4.7)	0.3100 (5.0)	0.3681 (3.6)
maximum shelter allowance	0.0002 (0.5)	0.0002 (0.6)	-0.0004 (0.2)	0.0000 (0.1)
rental cpi	-0.0002 (0.9)	0.0003 (0.4)	-0.0002 (0.5)	0.0012 (0.5)
unemployment rate	-0.0048 (2.9)	-0.0045 (2.4)	-0.0057 (2.0)	-0.0081 (2.1)
percent of shelter pop in Tier1 Housing		0.0165 (0.1)		0.0500 (0.3)
percent of shelter pop in hotels		0.0326 (0.8)		0.0400 (0.6)
Emergency room cocaine admits				0.0000 (0.4)
Constant	0.1072 (3.7)	0.0082 (0.1)	0.0300 (0.1)	-0.2000 (0.5)
Obs	82	82	54	54
R squared	0.55	0.55	0.53	0.54
Box-Ljung-Pierce Tests for AR	no	no	no	no
t-statistics are in parentheses. Box-Ljung-Pierce Statistics are calculated from $Q=T(\text{sum of the first } P \text{ autocorrelations of the residuals})$ which are distributed chi-squared with P-p-q degrees of freedom for an ARMA(p,q).				

Figure 2.1 - New York City Homeless Shelter Population

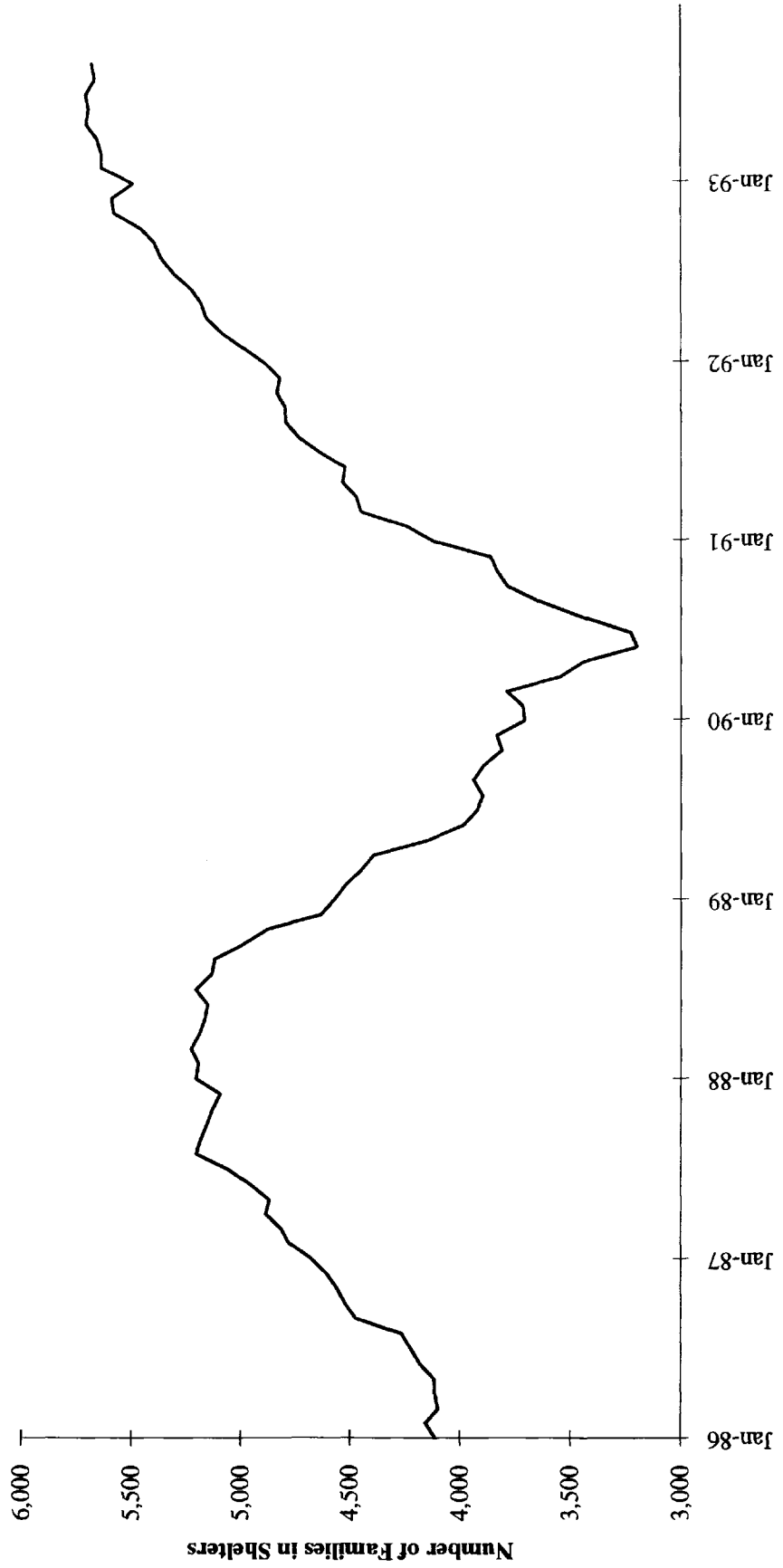


Figure 2.2 - New York City Placements in Subsidized Housing

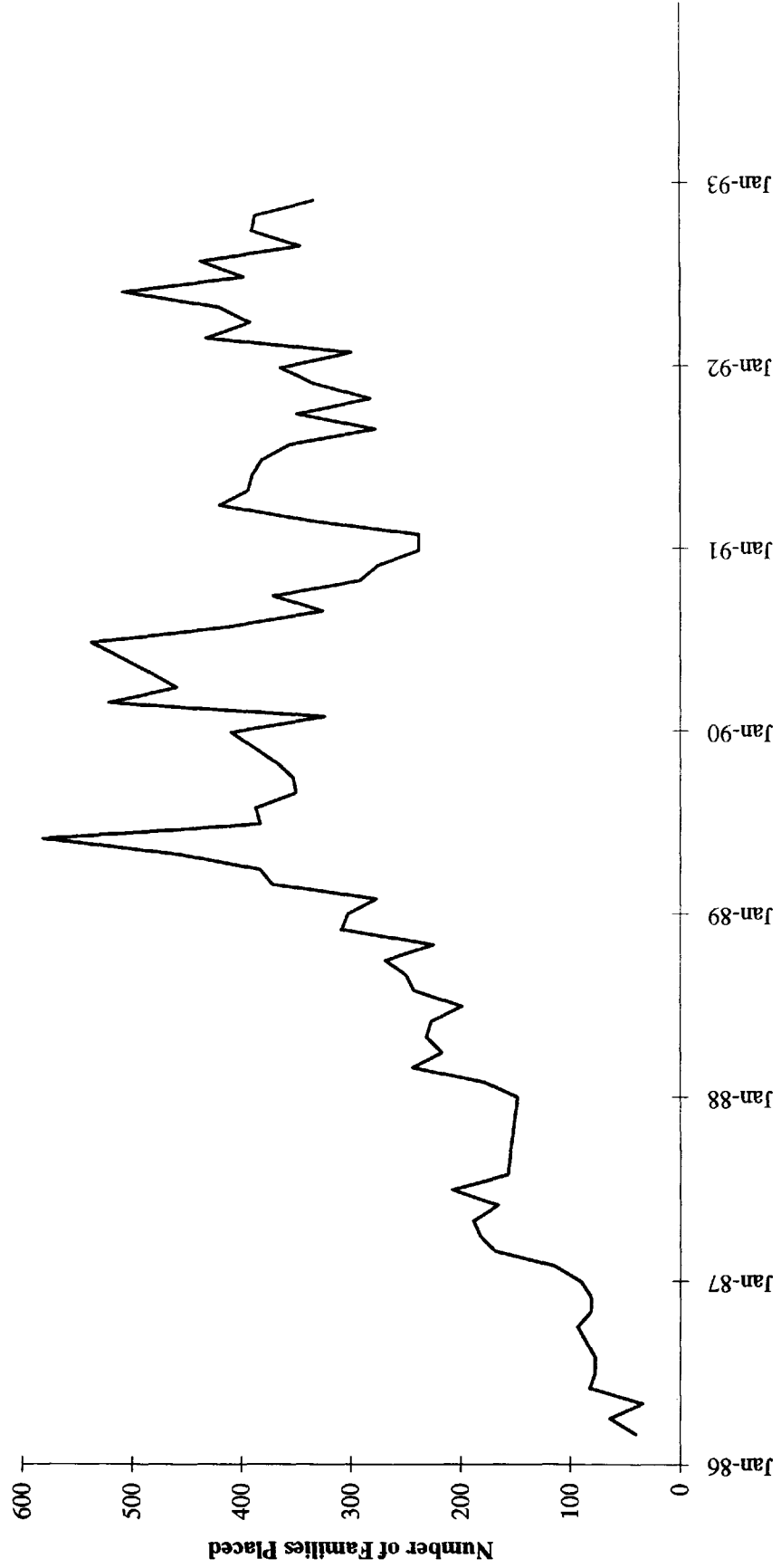


Figure 2.3 - New York City Shelter Queue

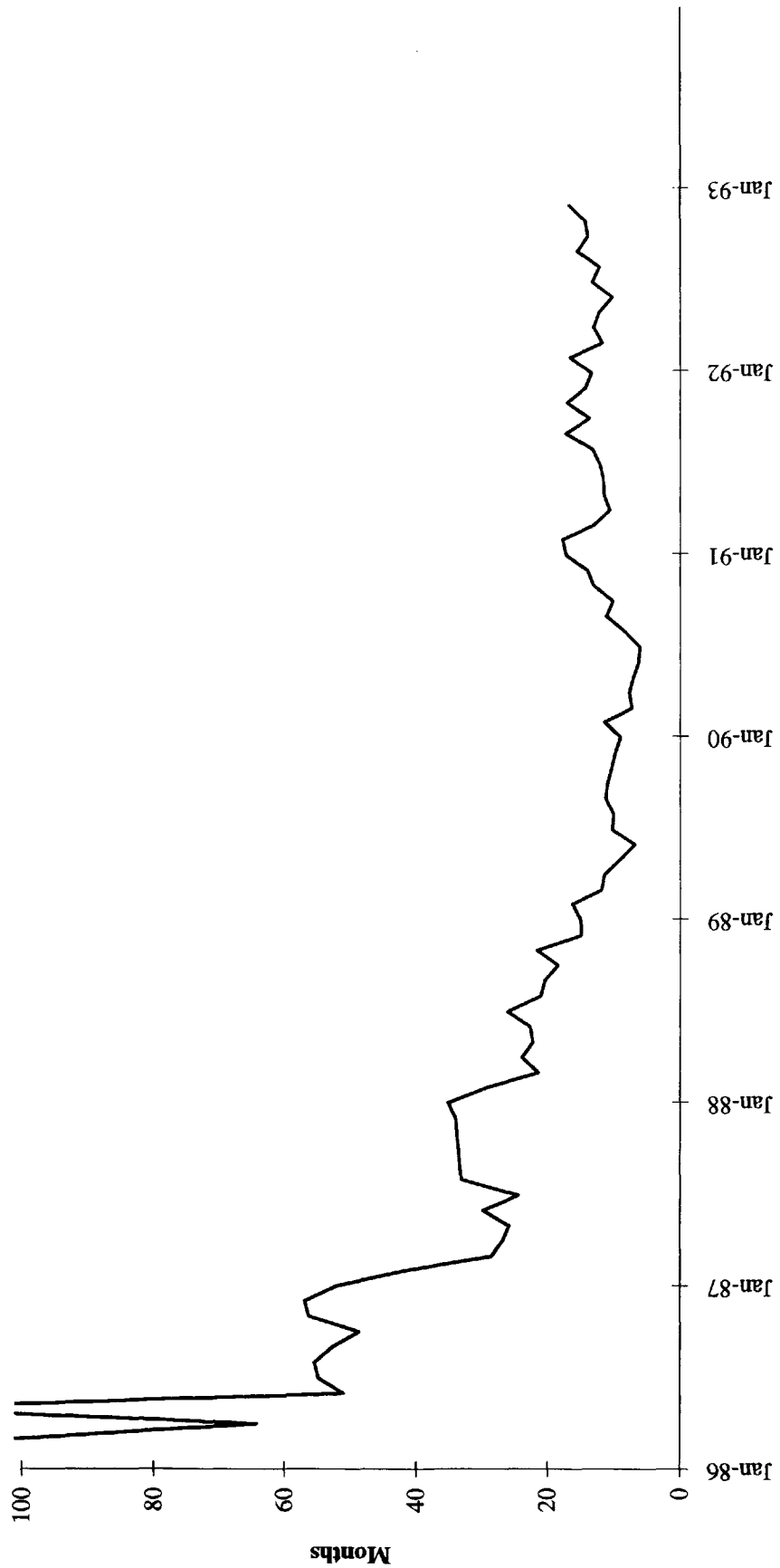


Figure 5.1 - New York City Homeless Shelter Population (Simulated and Actual)

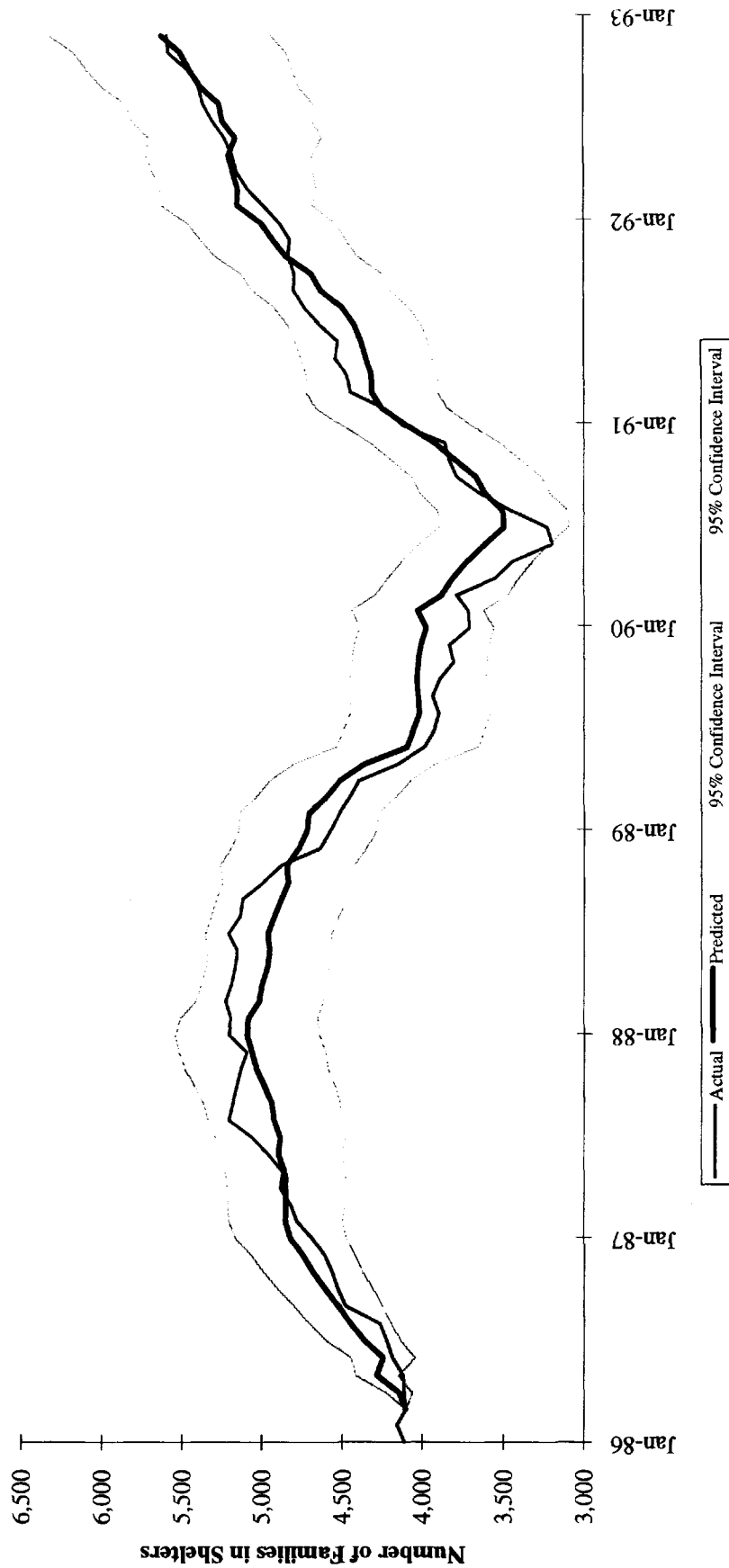


Figure 6.1 - Simulated Shelter Population using 1988 and 1990 City Placements

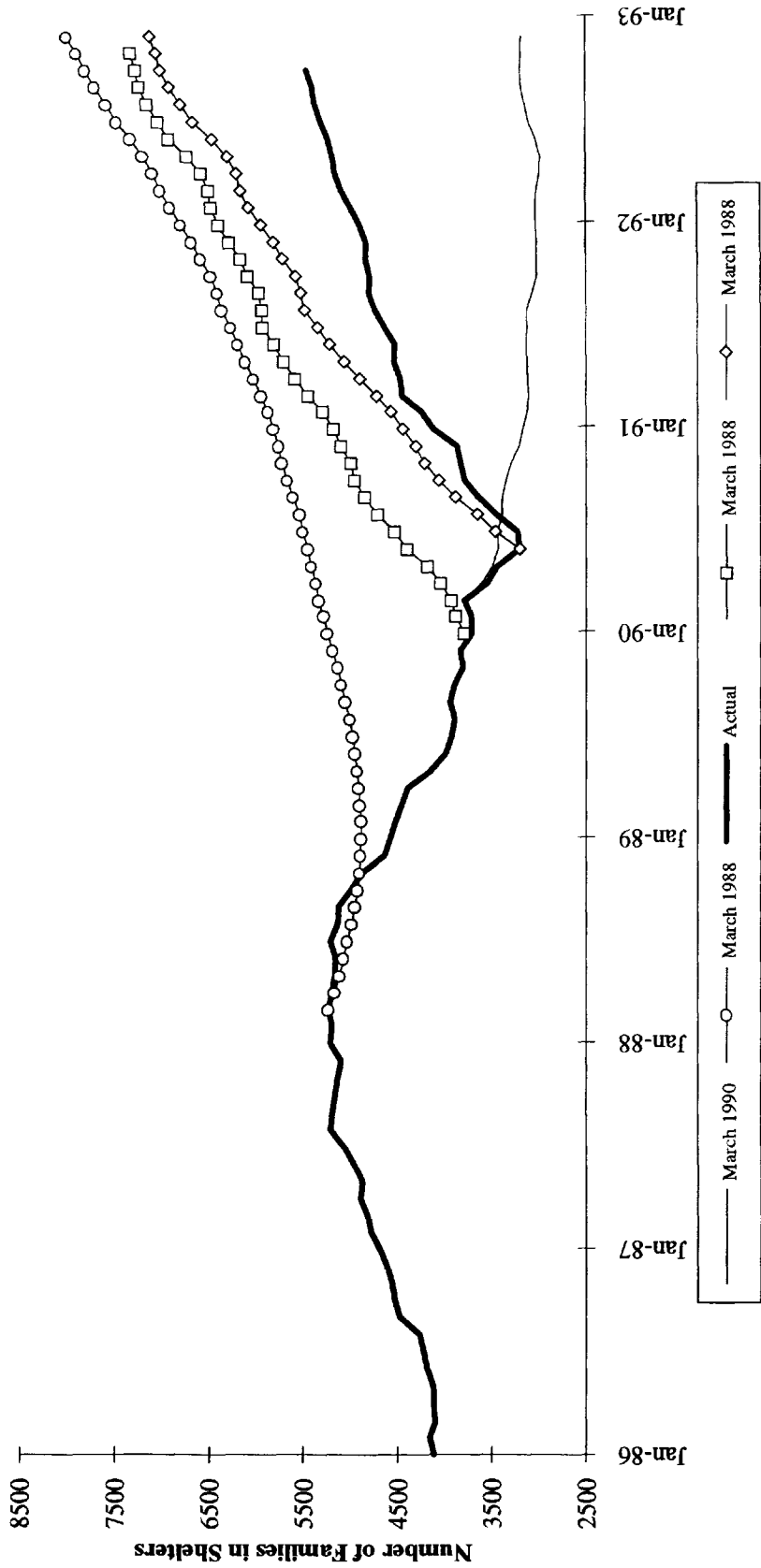


Figure 6.2 - Dinkins' Deluge Simulated Shelter Population using 1988 and 1990 Placements

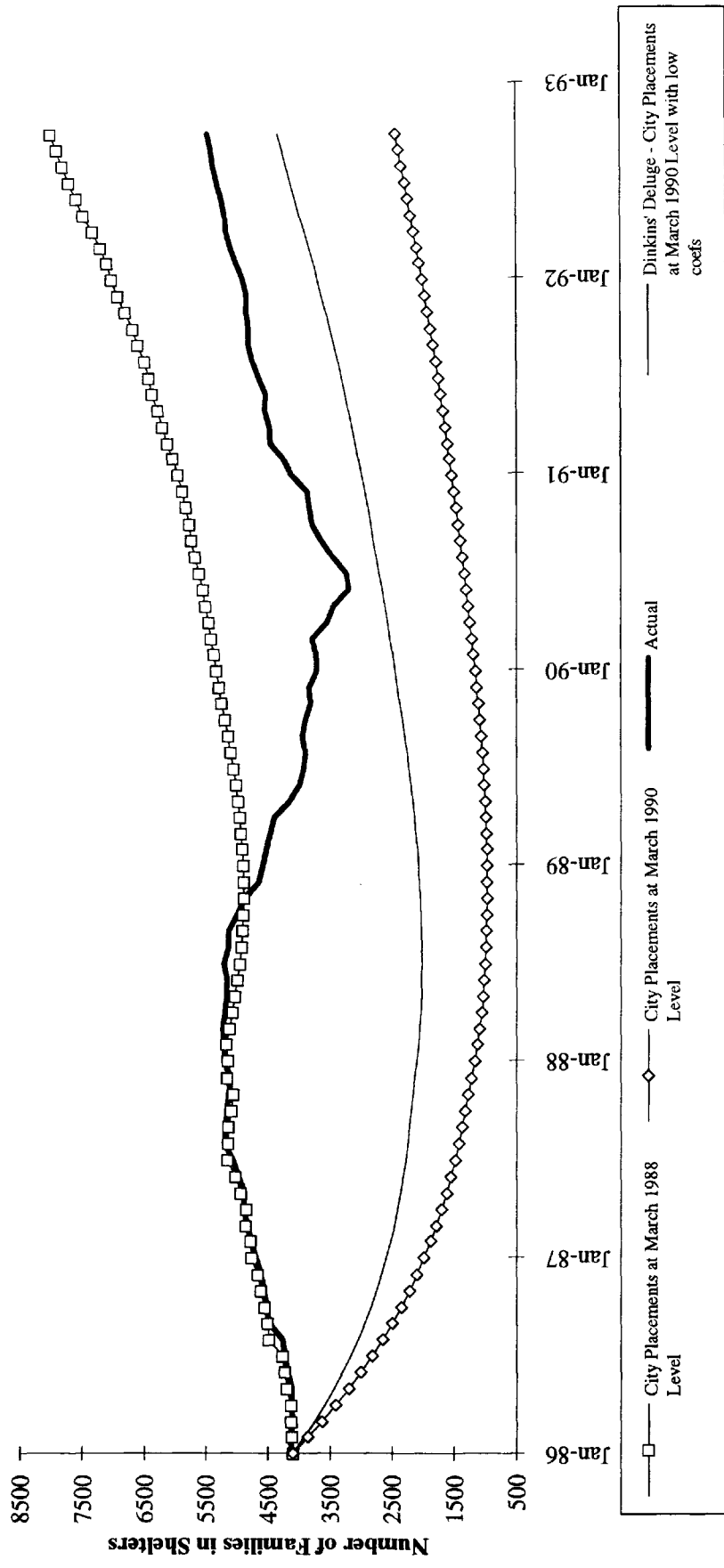


Figure 6.3 - Percentage of Caseload in Tier1 and Hotels

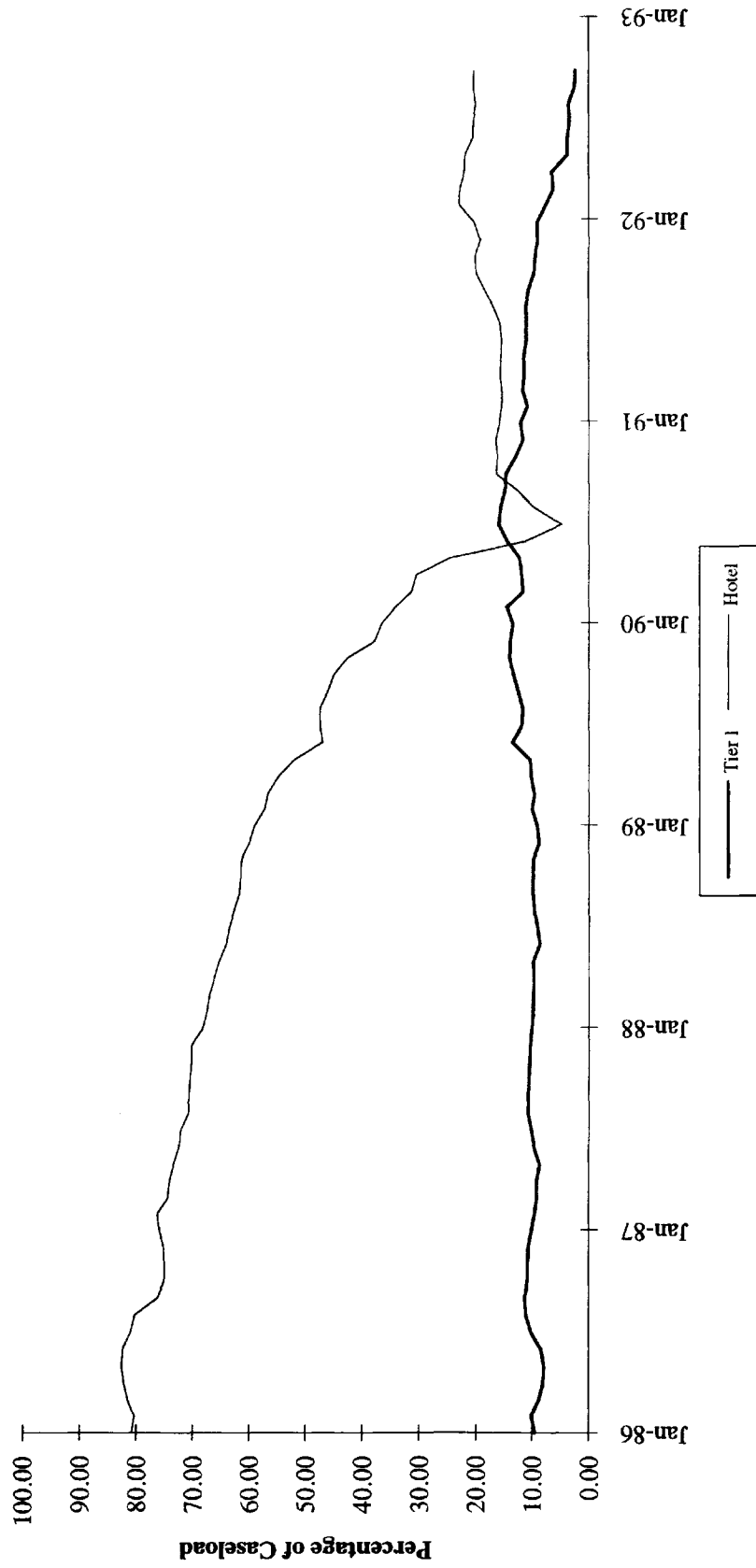


Figure 6.4 - Time Series

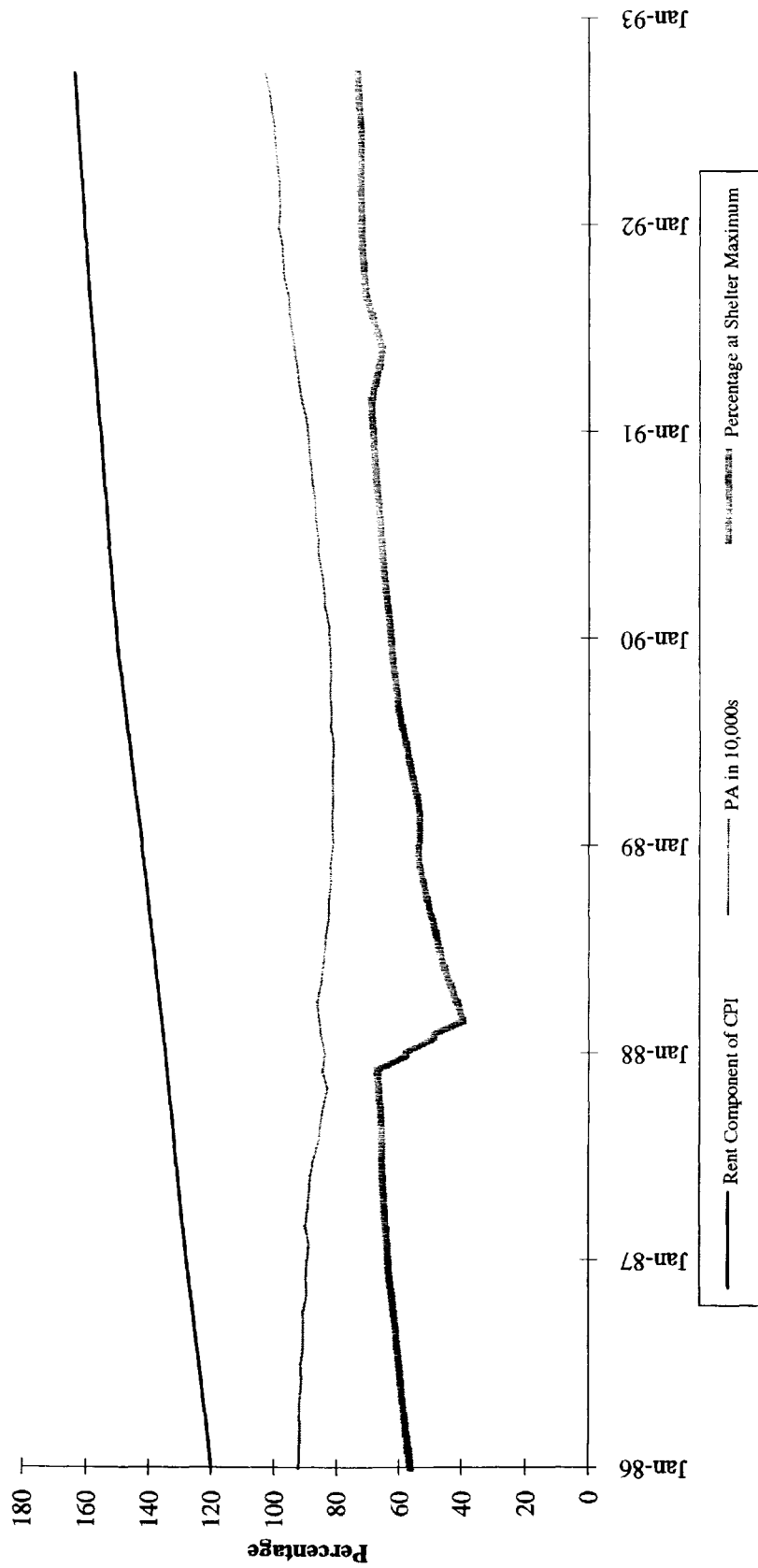


Figure 6.5 - NYC Unemployment Rate

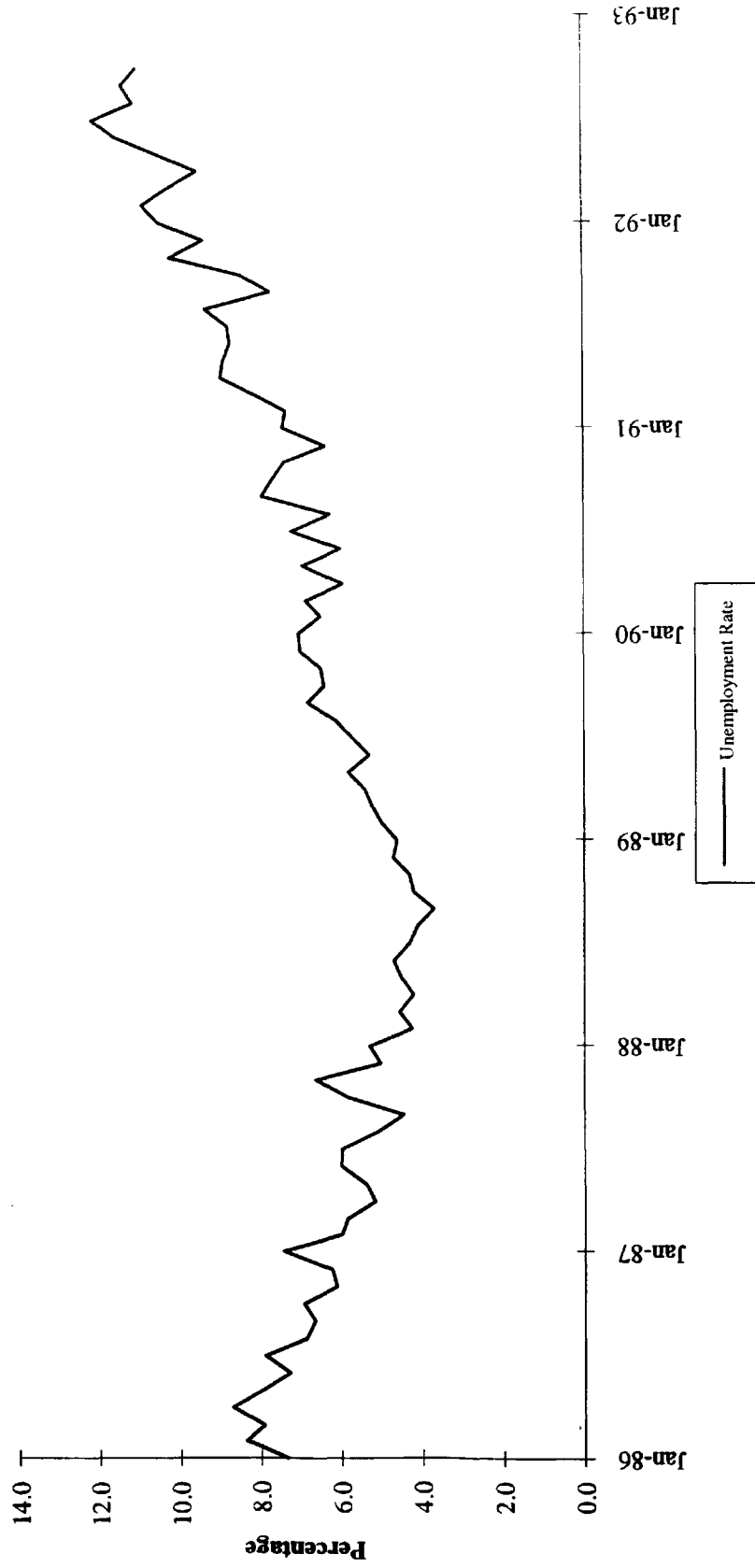


Figure 6.6 - Cocaine Related Emergency Room Admissions

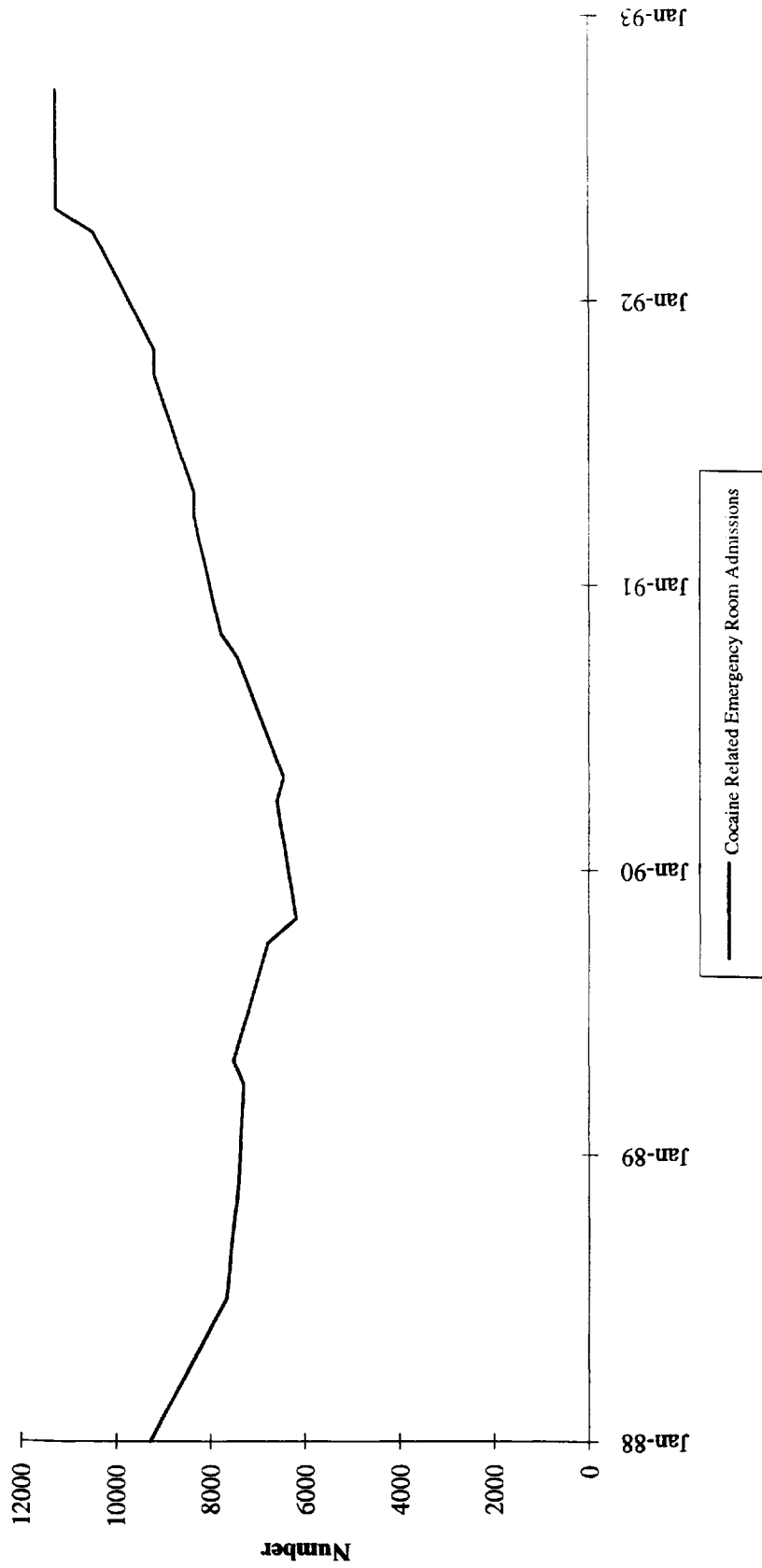


Figure 6.7 - New York City Homeless Shelter Population (Full Specification)

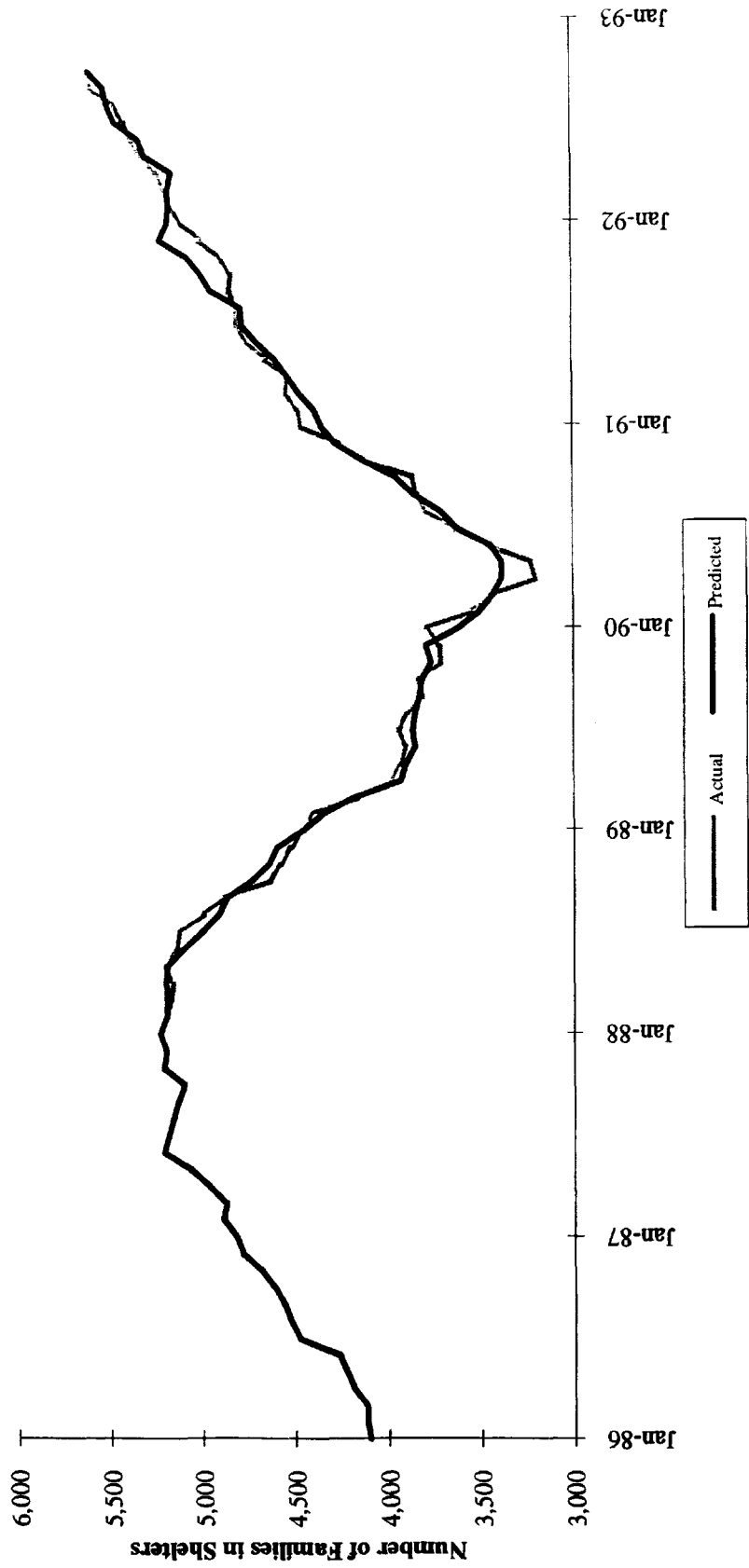


Figure 6.8 - New York City Homeless Shelter Population using March 1990 Levels

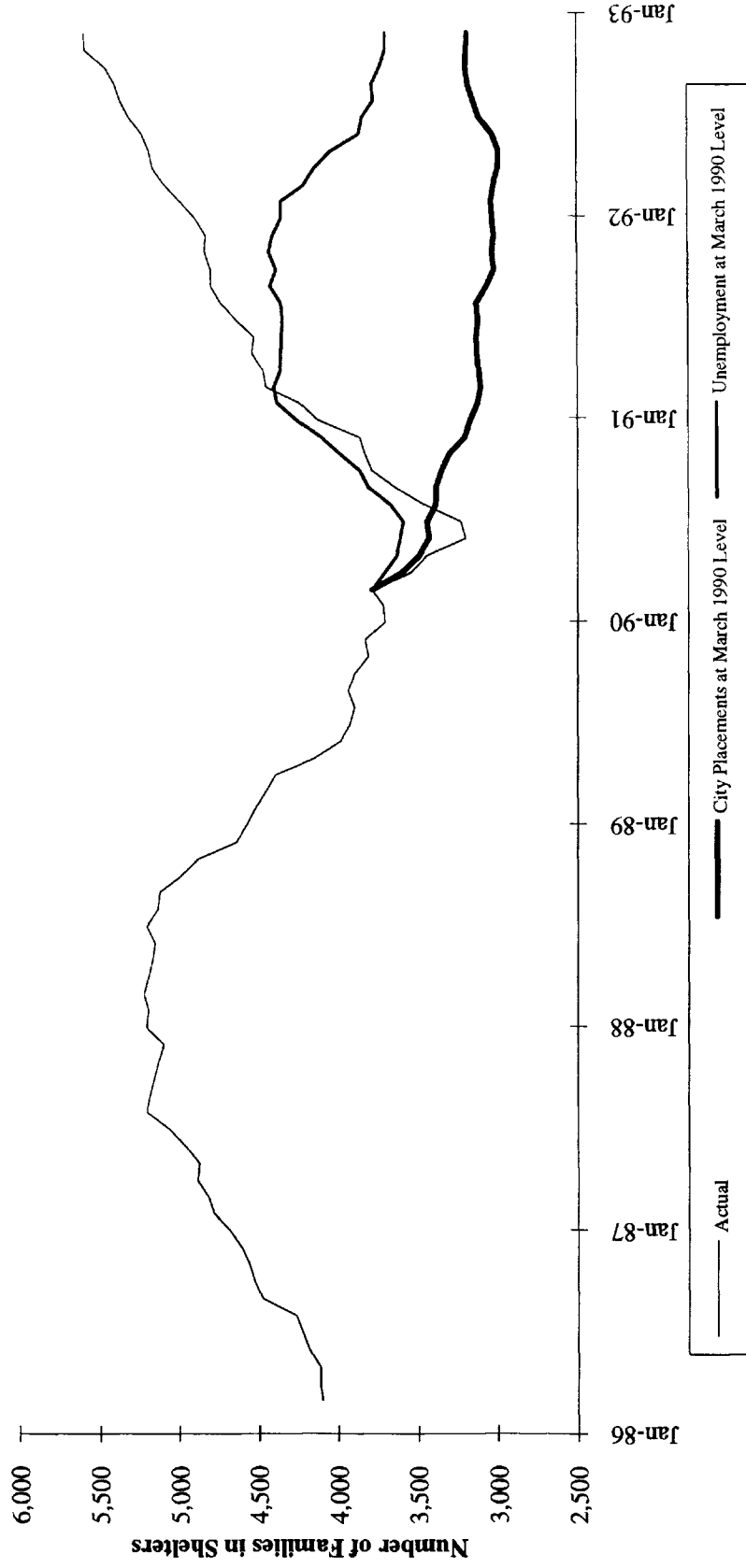


Figure 6.9 - New York City Homeless Shelter Population using March 1990 Levels

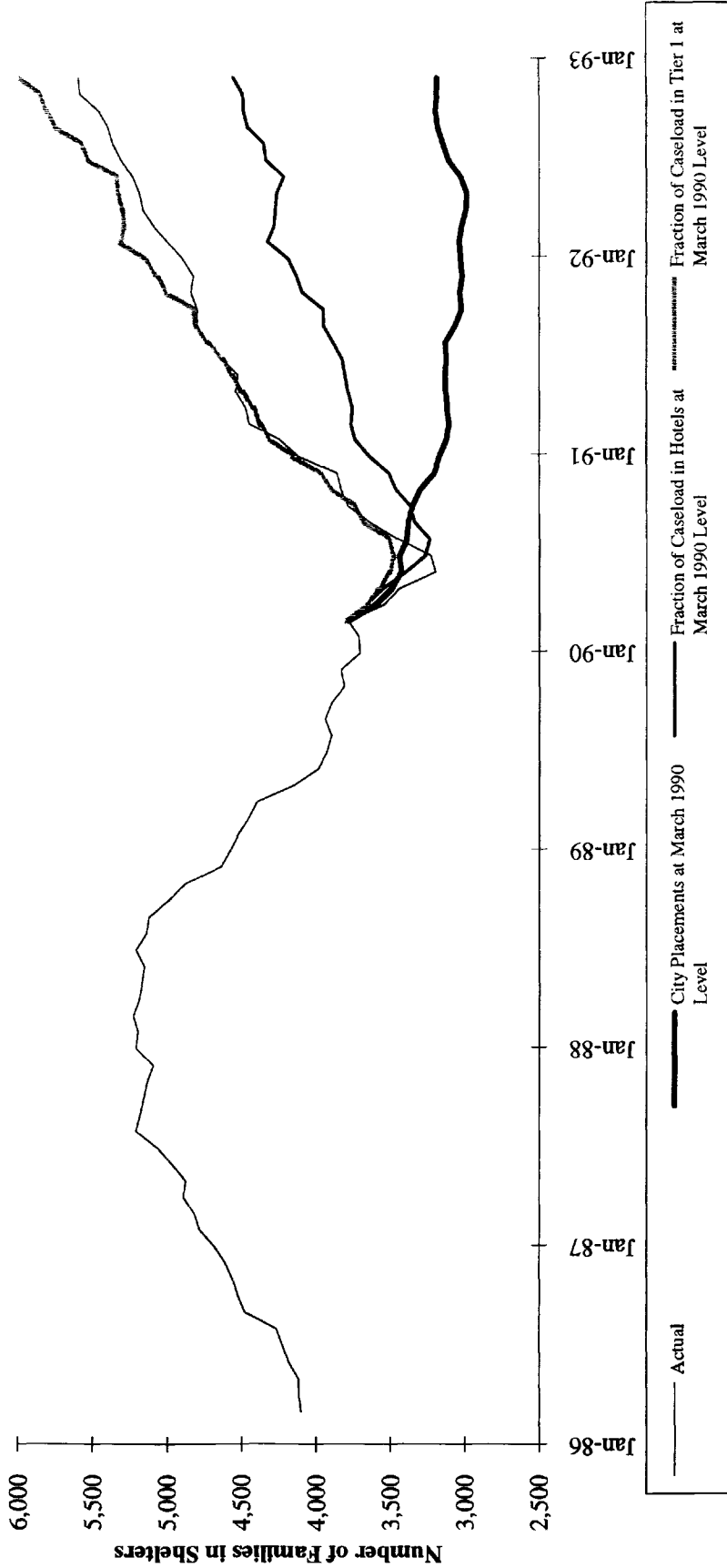


Figure 6.10 - New York City Homeless Shelter Population using March 1990 Levels

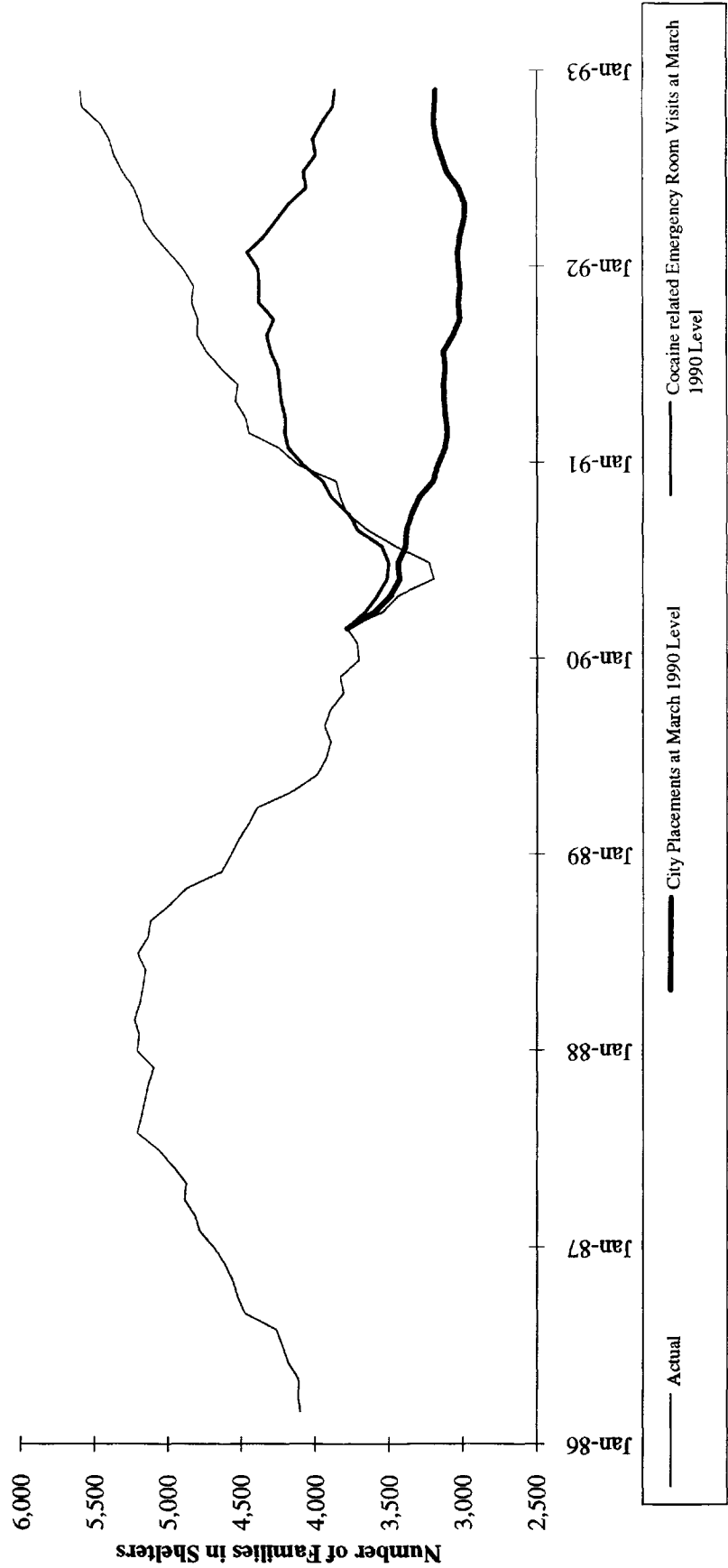


Figure 6.11a - New York City Homeless Shelter - at Term in Implicit Steady State

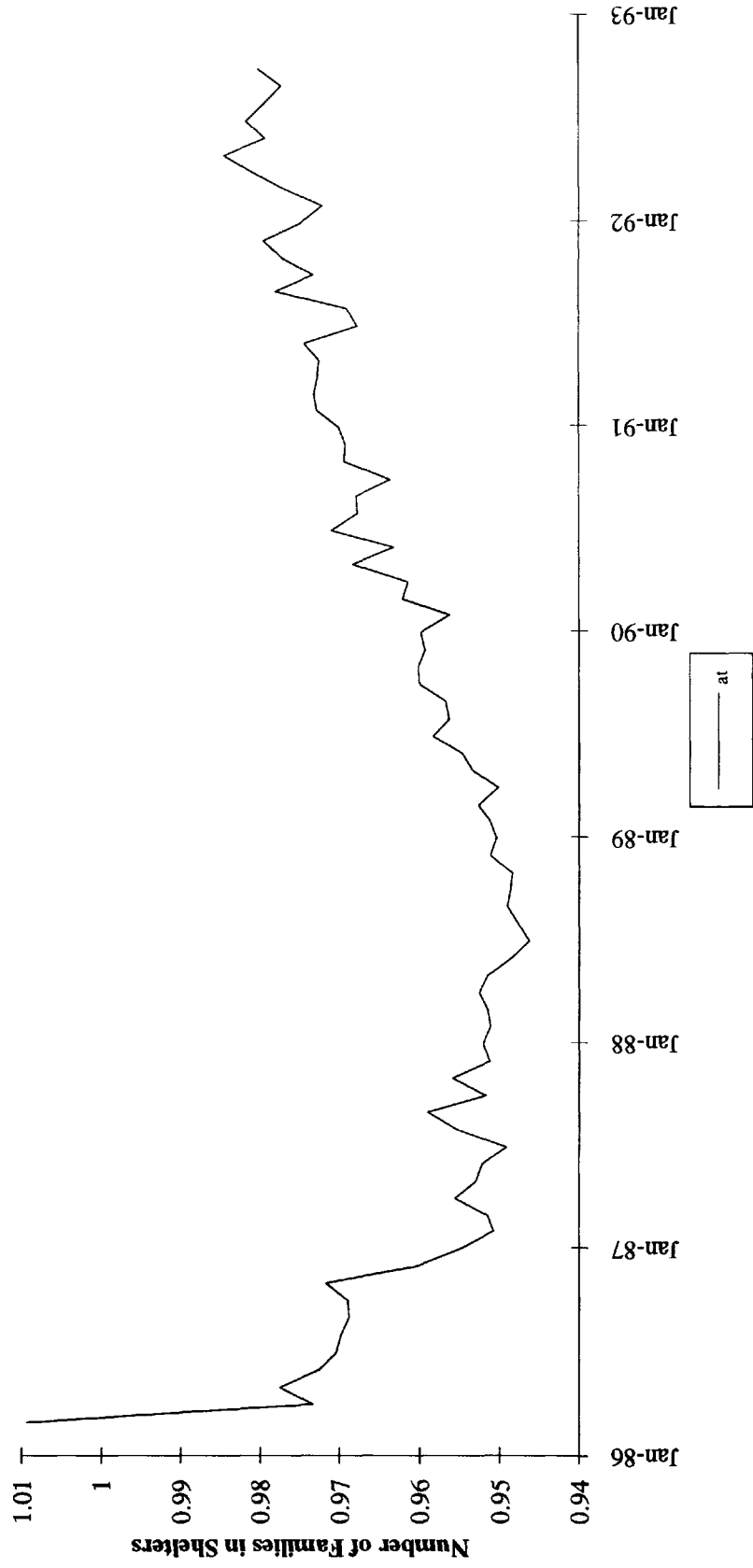


Figure 6.11b - New York City Homeless Shelter - bt Term in Implicit Steady State

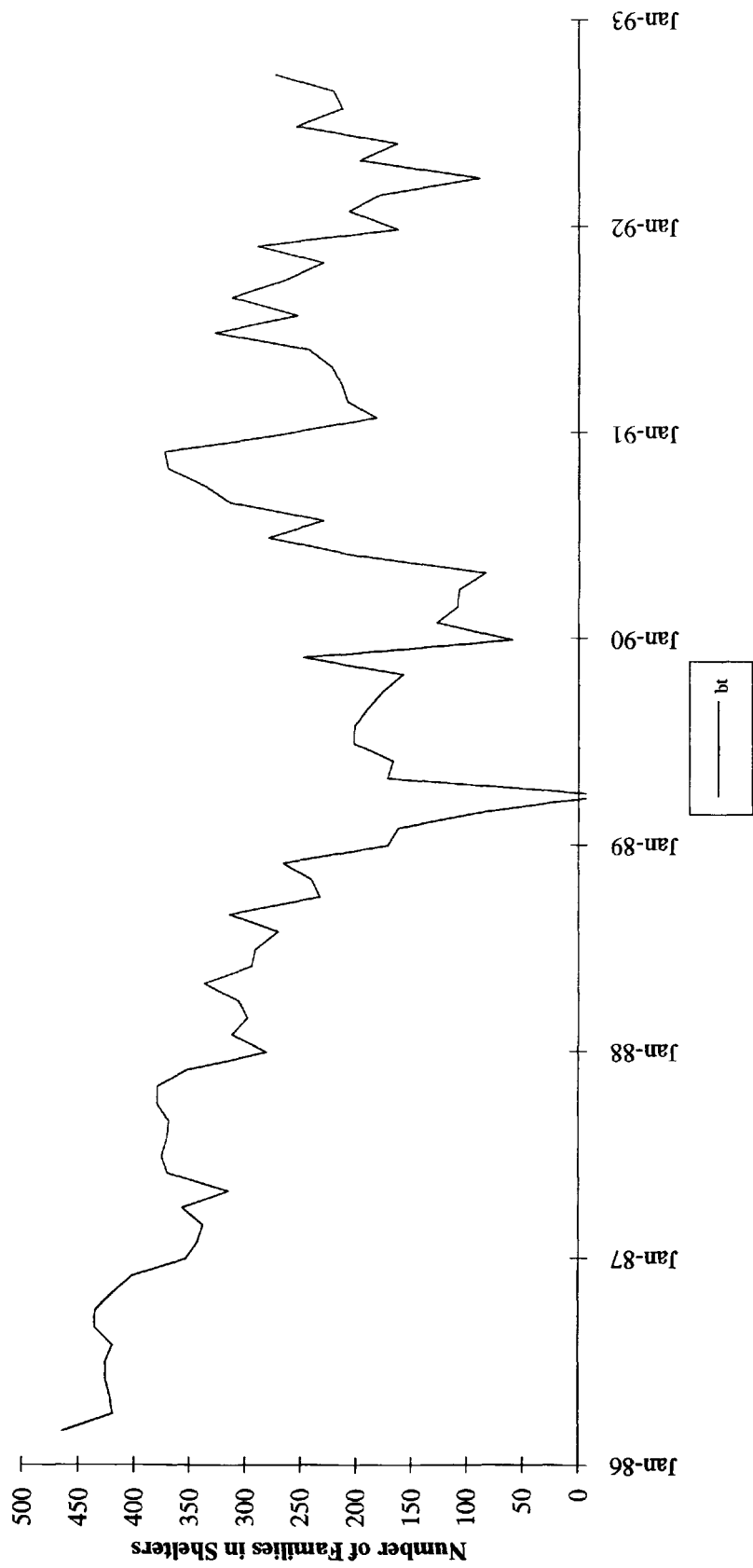


Figure 6.11c - New York City Homeless Shelter - at*load and bt Terms in Implicit Steady State

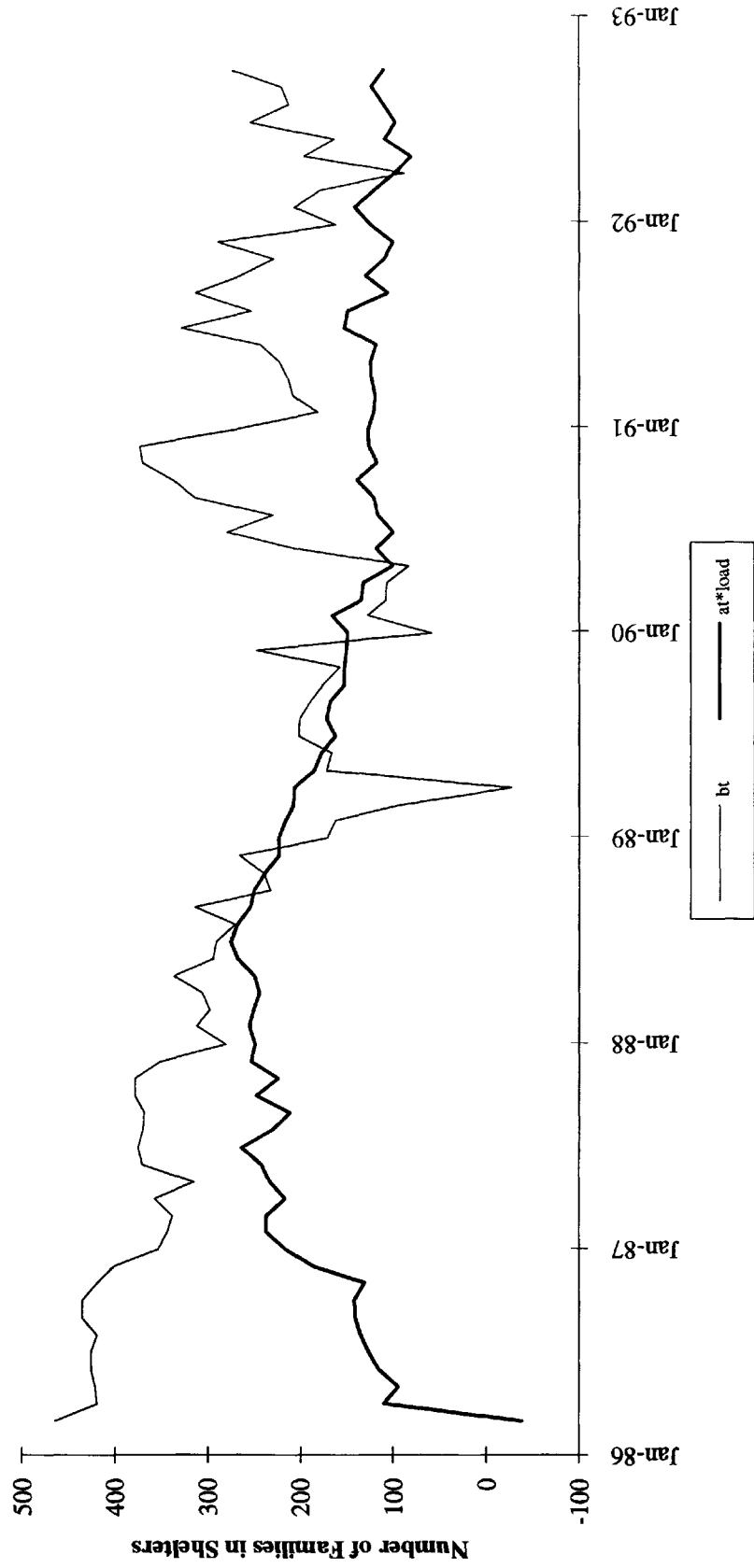


Figure 6.12 - New York City Implicit Steady State for the Homeless Shelter Population - Average Values of Covariates : High Versus Low Unemployment

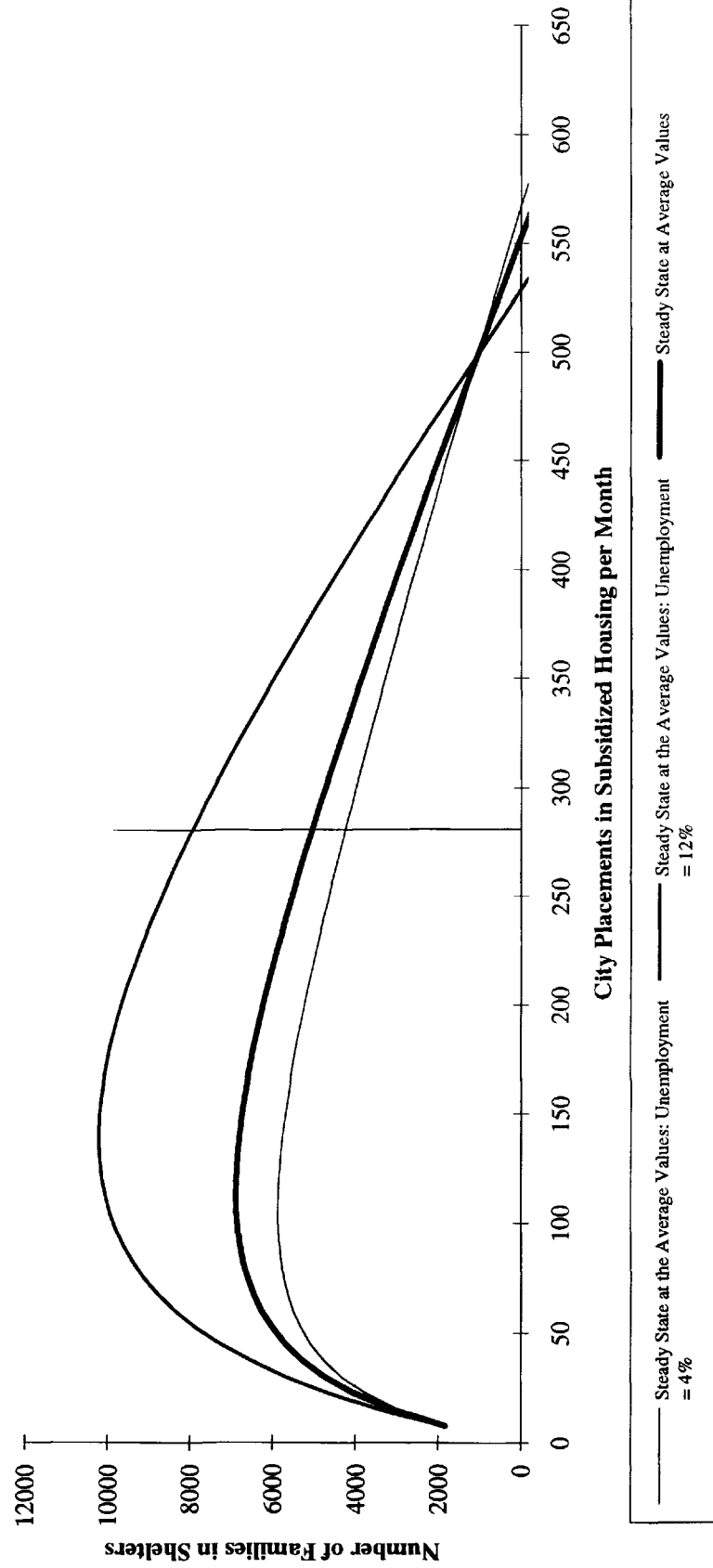


Figure 6.13 - New York City Implicit Steady State for the Homeless Shelter Population - Average Values of Covariates : High vs Low Fraction of Shelter Pop. Housed in Hotels

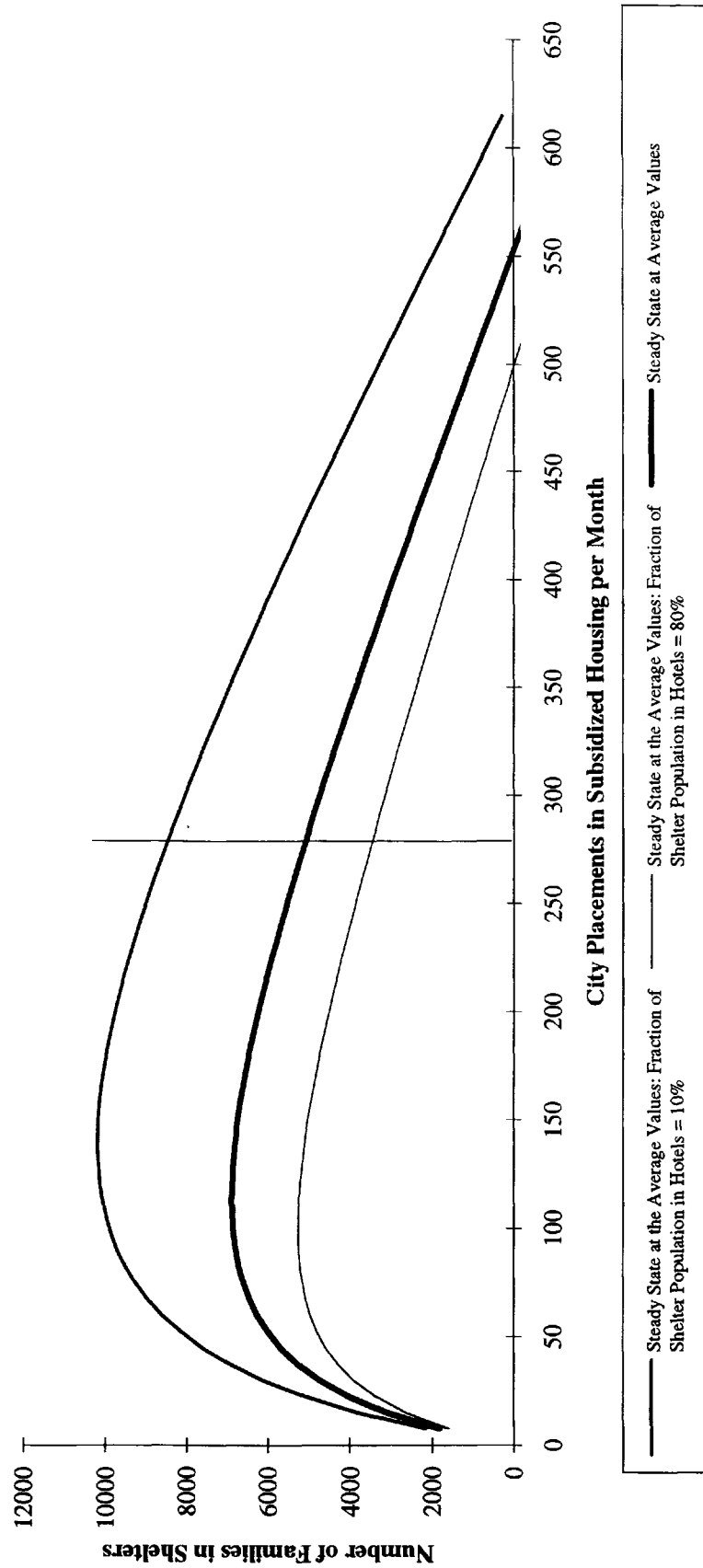
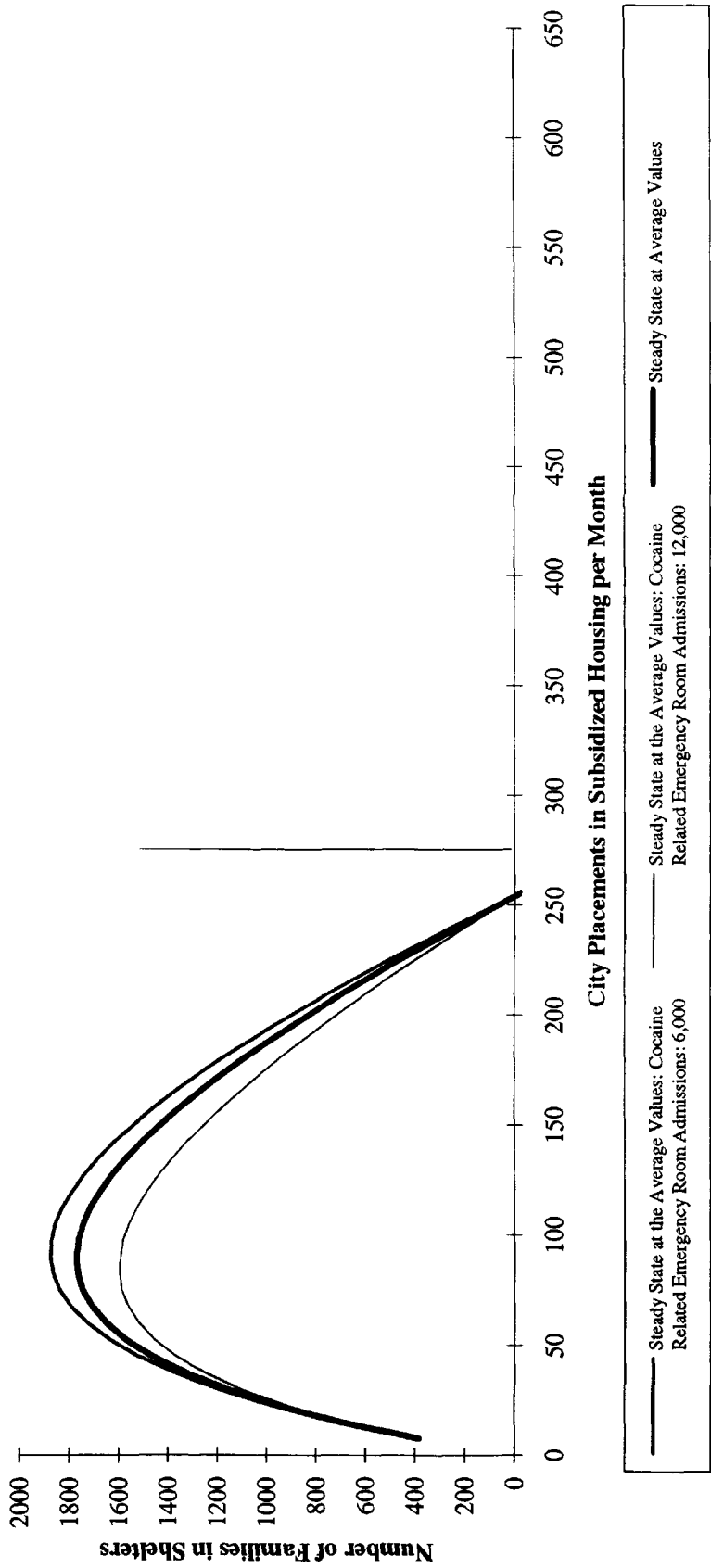


Figure 6.14 - New York City Implicit Steady State for the Homeless Shelter Population - Average Values of Covariates : High vs Low Cocaine Related ER Admissions



1994-1995 Discussion Paper Series
Department of Economics
Columbia University
420 West 118 Street, Rm 1022
New York, NY 10027

The following papers are published in the 1994-95 Columbia University Discussion Paper series which runs from early November to October 31. Domestic orders for discussion papers are available for purchase at \$8.00 (US) each and \$140.00 (US) for the series. Foreign orders cost \$10.00 (US) for individual paper and \$185.00 for the series. To order discussion papers, please send your check or money order payable to Department of Economics, Columbia University to the above address. Be sure to include the series number for the paper when you place an order.

- 708. Trade and Wages: Choosing among Alternative Explanations
Jagdish Bhagwati
- 709. Dynamics of Canadian Welfare Participation
Garrey F. Barret, Michael I. Cragg
- 710. Much Ado About Nothing? Capital Market Reaction to Changes in
Antitrust Precedent concerning Exclusive Territories.
Sherry A. Glied, Randall S. Kroszner
- 711. The Cost of Diabetes
Matthew E. Kahn
- 712. Evidence on Unobserved Polluter Abatement Effort
Matthew E. Kahn
- 713. The Premium for Skills: Evidence from Mexico
Michael Cragg
- 714. Measuring the Incentive to be Homeless
Michael Cragg, ~~Mario Epstein~~
B. O'FLAHERTY