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LIVING ARRANGEMENTS, EMPLOYMENT, SCHOOLING, AND WELFARE RECIPIENCY OF YOUNG WOMEN

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Chapter 1

Overview and Summary

Public assistance programs seek to strike a balance between two goals. They attempt to provide adequate financial support to needy families, and also endeavor to encourage adult recipients to support themselves. The challenge is to design programs that, to the greatest extent possible, attain both goals. To address this challenge we need to understand the forces that influence self-support. This project examines one aspect of that issue--the relationship between living arrangements on the one hand, and education, employment, and welfare use on the other.

The issue is important. Previous research indicates that welfare programs influence a young mother's choices among living arrangements.[1] For example, Ellwood and Bane (1983) find that higher welfare benefits are associated with an increased propensity for mothers to establish separate households and not share a household with parents or other relatives. It is conceivable that this phenomenon discourages self-support. By establishing a separate household, the mother may devote more time to child care and less time to work and schooling; had she stayed with her parents, there quite possibly would have been more hands to help with child care. If establishing a separate household leads to failure to invest in schooling or failure to obtain work experience, then that could contribute to welfare dependency in the future. Thus, to the extent that welfare programs encourage young mothers to establish separate households, they may discourage self-support. An important goal of the present research is to examine whether this scenario is consistent with the facts.

To accomplish this our work addresses several related research questions. At the outset, it is important to distinguish between them.

1. To what extent do states differ in their treatment of different living arrangements?

Since states administer the AFDC program, subject to broad federal guidelines, interstate differences may exist in the treatment of different living arrangements. That could be important for two reasons. First, if the states treat different living arrangements differently, then there could be important behavioral implications. For example, suppose that in some states the amount of AFDC benefits paid to mothers who live in separate households is higher than the amount paid to otherwise identical mothers who live with parents. That could affect a young mother's propensity to form a separate household. As such, in estimating models of a mother's choice among living arrangements, it is important to include an explanatory variable that measures within-state differences in payments to mothers in different living arrangements. To exclude that variable is to risk bias on the other coefficients. Second, if states do, in fact, differ in their treatment of different living arrangements, and that affects behavior, then there could be important policy implications. For example, the federal government may wish to dissuade states from structuring their benefits in a way that encourages formation of separate households. For both reasons, it is important to know whether there are within-state differences in the treatment of different living arrangements.

2. To what extent do welfare benefit levels affect a young woman's choices among living arrangements?

The above scenario begins with the idea that higher welfare benefit levels affect choices among living arrangements. While other research has confirmed this finding, it is important to begin our research with an attempt at replication. This is in part because our data differ from those used in previous work. Moreover, rejection of the hypothesis that welfare programs influence living arrangements would constitute rejection of the above scenario.

3. To what extent do welfare benefit levels affect a young woman's choices with regard to education, work status, and welfare?

Regardless of whether benefit levels influence living arrangements, we need to examine whether differences in benefit levels are associated with different choices with regard to education, work status, and welfare receipt. There is, of course, a good deal of evidence that higher benefits discourage work and encourage welfare receipt.[2] With regard to education, the only available evidence comes from the Negative Income Tax experiments, and that evidence is mixed.[3] For purposes of assessing whether our data yield results that are consistent with past results, it is important to examine this question.

4. To what extent do young women in different living arrangements differ in their propensity to work, go to school, and receive welfare?

If the above scenario is correct, then one would expect to observe that mothers who share households with parents or relatives are more likely to work and go to school, and less likely to receive welfare, ceteris paribus. That hypothesis can be tested with both univariate (e.g., a comparison of means) and multivariate (e.g., regression) methods.

5. If the federal government instituted policies that encouraged women with young children to live with parents or other relatives, what effect would that have on schooling, work, and welfare receipt?

The scenario implies that if young mothers were discouraged from forming separate households (perhaps through comparatively high benefits for mothers who share households with parents or other relatives), then they would be more likely to work and/or go to school. One would like to know the magnitude of this effect. If, for example, all states raised the benefits paid to mothers in these shared living arrangements by 10 percent, what would happen to the average young nonmarried mother's propensity to work, receive welfare, and go to school? One can conceive of multiple variations on such questions. For example, what effect does a 10 percent increase in the AFDC guarantee for all living arrangements have upon employment, schooling, and welfare status? Alternatively, what is the effect of moving all states to a "neutral" benefit structure--a benefit structure that provides the same benefits under all living arrangements?

These five questions form the organizational backbone of this report. Question 1, which asks to what extent states differ in their treatment of different living arrangements, is dealt with in Chapter 2. We pursued two strategies. First, we conducted a telephone survey of state administrative agencies that sought information on the level of benefits paid to families in several prototypical living arrangements. Second, we applied linear regression techniques to the 1982 AFDC Quality Control data in order to assess whether there actually is within-state variation in benefits paid to mothers in different living arrangements. Chapter 2 presents, compares, and interprets these two sets of data. It concludes that states do, in fact, differ in their treatment of living arrangements. Some states pay mothers who establish separate households much higher benefits than mothers who live with parents or other relatives. Other states pay the same benefit regardless of living arrangement. Of course, these interstate differences may have behavioral implications.

To address the remaining four questions, a theoretical model is imperative. A theory helps one to focus on the essential. It can motivate empirical specifications; it can provide a basis for establishing refutable hypotheses and for evaluating critical assumptions. Chapter 3 presents the theoretical model underlying our analysis. The model characterizes a young mother's decisions with respect to four choices: living arrangement, labor supply, schooling, and welfare receipt. It is an equilibrium model that begins with utility maximization subject to time and money constraints, and concludes with reduced-form and structural econometric specifications. These specifications are then implemented in Chapters 4 and 5.

Chapter 4 presents our answers to questions 2, 3, and 4. Most of the answers come from estimation of reduced-form models in a cross-sectional sample of young (under 35) mothers with children taken from the 1984 Current Population Survey. This empirical work is largely restricted to an assessment of the effects of the AFDC program. The Food Stamp program may also affect choices regarding living arrangements, schooling, work, and welfare receipt. However, because the program is uniform throughout the nation, it is difficult to detect its effects in a cross-sectional study. (See Appendix C of Chapter 4 for a detailed discussion.) Stated briefly, for the AFDC program we find the following:

- AFDC benefits influence the choice of living arrangement. If a state structures its benefits so that a young mother can obtain higher benefits by forming a separate household, then she is more likely to form that household. More precisely, we find that higher AFDC payments to recipients in separate households are associated with an increased tendency for recipients to reside in separate households and a decreased tendency for them to reside in subfamilies, ceteris paribus. However, we obtain no statistically significant evidence that an increase in payments to both subfamilies and separate households alters the propensity for mothers to live in subfamilies. In addition, we obtain no statistically significant evidence linking AFDC benefits to choices between married and nonmarried living arrangements.

- Higher AFDC benefits are related to a greater propensity to receive welfare and a lower propensity to work. We find no statistically significant relationship between AFDC benefits and the propensity to attend or not attend school.

- Unconditional means indicate that young mothers who form separate households are less likely to attend school, more likely to work, and more likely to receive welfare than young mothers who live in subfamilies. This is in part due to the fact that mothers who form separate households have different characteristics than mothers who live in subfamilies. In particular, the former are older than the latter. Once one controls for age, education, and several other independent variables, differences between the two groups are much less pronounced.

Chapter 5 seeks to test the structural model implied by the theory in Chapter 3. The reduced-form models in Chapter 4 provide certain kinds of information. In particular, they indicate how a change in an independent variable affects a dependent variable. That is extremely useful information; it underlies our answers to questions 2 through 4. Yet the reduced forms do not yield a complete test of the theory in Chapter 3. That theory implies specific relationships between the parameters of the reduced form; it implies a more parsimonious specification of the estimating equations. In Chapter 5 we estimate a structural model and thereby test whether that more parsimonious specification is valid. The results are not encouraging. For a model of living arrangement choice, the data reject the restrictions implied by the theory. The reason for this result is unclear. Perhaps there are problems with the imputed variables used in the structural model (e.g., imputed wage and nonwage income) or with the theory. It is important, however, to emphasize that this result does not affect the other conclusions in this report. Those conclusions are based on reduced forms. Chapter 5 simply indicates that we do not yet know how to specify the structural model that underlies the reduced forms. We plan to continue working on this.

Chapter 6 addresses the fifth question. Here we present a series of simulations that examine how changes in AFDC benefit levels affect choices of living arrangements, schooling, labor force participation, and welfare receipt. The goal is to provide a sense of the magnitude of the effects found in the earlier chapters. While interpretation of these simulations is clouded by technical issues, in general they suggest rather small effects. For example, holding the guarantee for householders constant, a 10 percent increase in the guarantee for women living in subfamilies leads to a slight (1 or 2 percent) increase in the proportion of all mothers who live in subfamilies. Similarly, labor force participation and schooling were but slightly affected by changes in AFDC benefit levels. We conclude that a policy which eliminates within-state differences in AFDC benefits across living arrangements by raising the level of AFDC benefits paid to women in subfamilies would both increase the number of subfamilies and decrease the number of female household heads. These changes would, however, be quite small. Moreover, this policy would have almost imperceptible effects on labor force participation and schooling.

The report closes with a presentation of conclusions, Chapter 7.

The present chapter began with a scenario that depicted how welfare programs may diminish self-support by encouraging mothers to form separate households. The essential supposition was that when mothers form separate households, they devote more time to child care and less time to work and schooling, thereby becoming more dependent on welfare. This research finds partial empirical support for that scenario. In some states the AFDC system penalizes mothers who live with parents or relatives by paying them lower benefits than they could receive as household heads. This leads to more welfare recipients who are female heads and fewer recipients in subfamilies. In addition, it is true that young mothers in subfamilies tend to be more likely to attend school than female household heads, ceteris paribus. They are not, however, more likely to work. That means that the scenario can only be applicable to schooling.

Stated cautiously, the evidence presented in this report is consistent with the claim that by structuring AFDC benefits in a way that encourages mothers to form separate households, states may effectively discourage school attendance.[4] That may, in turn, lead to greater dependence on welfare in the future. Yet, even though the evidence is consistent with this, the simulations suggest that we are dealing with minuscule effects. We find little basis for claiming that by changing the way the welfare system treats subfamilies, the government can dramatically alter schooling behavior and thereby patterns of dependence.

Notes to Chapter 1

[1]See Bane and Ellwood (1983a, 1983b), Bradbury et al. (1979), Danziger et al. (1982), Ellwood and Bane (1983), Honig (1974, 1976), Hutchens (1979), MacDonald and Sawhill (1978), Ross and Sawhill (1975), and Schwartz (1981).

[2]See Barr and Hall (1981), Danziger et al. (1981), Hutchens (1981), Levy (1979), Masters and Garfinkel (1977), Moffitt (1983), and Saks (1975).

[3]The New Jersey experiment provides partial evidence of a significant positive relationship between a negative income tax and investments in schooling, while the Seattle-Denver experiment finds no significant relationship. See Mallar (1978) and Robins and West (1983, Chapter VI).

[4]A caveat should be noted at this point. It is conceivable that the results on schooling are driven by unobserved heterogeneity. There may be unobserved differences between mothers who form separate households and mothers who live in subfamilies that cause the former group to be less likely to attend school than the latter. In this case an increase in benefits paid to women who live with parents or other relatives may cause a shift of women into that living arrangement without altering their propensity to attend school. Since we are relying on cross-sectional data, we have no way of refuting this hypothesis. Yet, while it is conceivable that unobserved heterogeneity drives our results, that seems quite unlikely. After all, there are obvious differences between the two living arrangements. In one there are more adults around to help with child care than in the other. It is reasonable to argue that that

difference leads to increased school attendance. Although unobserved heterogeneity may play a role in the schooling and labor supply results, we suspect that changes in living arrangements do in fact precipitate changes in behavior.

Chapter 2

AFDC Benefits Available to Women In Different Living Arrangements: A State-by-State Assessment

The Aid to Families with Dependent Children (AFDC) program is administered by the states, subject to federal guidelines. Under this administrative arrangement there is considerable variation in program characteristics across states. For example, one state may pay a mother and child a maximum benefit of $88 per month while another pays a similar family $453. There is also substantial interstate variation in the treatment of earned income, unearned income, assets, and work-related expenses.[1] This chapter examines such variation in one aspect of the AFDC program about which comparatively little is known: the extent to which states differ in their treatment of mothers who choose to live with parents or other relatives rather than establish their own households.

It is important to understand this aspect of the AFDC program. If a state structures its benefits in a way that encourages women to establish separate households, then it may inadvertently contribute to welfare dependency. As discussed in the previous chapter, if establishing a separate household leads to failure to invest in schooling or failure to obtain work experience, then this could contribute to welfare dependency in the future. Thus, to the extent that the AFDC program encourages young mothers to establish separate households, it may discourage self-support.

There is evidence indicating that the AFDC program influences a mother's propensity to establish a separate household. In particular, Ellwood and Bane (1983) present evidence that a recipient mother is more likely to establish a separate household if she resides in a high-benefit state. It is not clear, however, whether this effect is due to high benefits per se. It may be due to the structure of benefits within such states. Those states may dispense benefits in a way that encourages families to establish separate households. They may effectively penalize families that live with parents or other relatives. If we are to understand the effect of AFDC benefits on the propensity for a mother to establish a separate household, we need to understand how benefits vary across living arrangements within a state.

This Chapter provides two kinds of information on that issue. In Section 2.1, we present results from a telephone survey of state administrative agencies that investigated the level of benefits paid to families in several prototypical living arrangements. Section 2.2 presents results from an analysis of the 1982 AFDC Quality Control data. Using linear regression techniques, we are able to assess whether actual benefit levels vary across living arrangements within a state. This section also compares the two kinds of data and assesses whether high-benefit states do, in fact, tend to structure benefits in a way that encourages mothers to establish their own households.

2.1 Results of a Survey of State AFDC Administrative Agencies

A married woman is generally not eligible for AFDC, but if her husband is disabled and unable to provide for the family, then she and her children can receive benefits. If the husband has been unemployed for a prolonged period, then the family may receive AFDC benefits if they reside in one of the 25 states (as of September 1984) in which there is an AFDC program for unemployed parents.

When a woman lives with only her children, there are, by definition, no other adults in the household whose economic status need be considered. If the woman receives no support from sources outside her household (e.g., alimony, child support, or monetary gifts) and has no non-AFDC income, she will receive the maximum payment in her state of residence.

If the mother and her children live with relatives (e.g., the grandparents of the children) then federal policy provides no specific guidelines. But aside from the differential treatment of married women, the most important source of variation in payments across living arrangements is caused by variation among states in how payments change if a woman and child either live with or move in with "other adults" (usually the grandparents of the child.)

Suppose that the grandparents are not themselves poor. In practice, the most important economic assistance that they might then provide are in-kind benefits in the form of room and board. Since there are no specific federal guidelines governing the treatment of this form of "outside" assistance, each state must decide how to adjust AFDC benefits in this situation. Between May and July 1985 we contacted the relevant administrative agency for each of the 48 states in the continental U.S. plus the District of Columbia.[2] In each case we posed the following questions:

1. What was the maximum payment for an adult mother, living independently, with no non-AFDC income and a single child under 3 years old?

2. What would happen if that woman moved in with (or had always lived with) her mother, if the mother herself had no non-AFDC income?

3. Supposing that the mother and child moved in with the mother's own parents in a case where the grandparents had substantial (e.g., $20,000 per year) income:

   (a) How would her payment change if she received free room and board from her parents?

   (b) If she paid a nominal (e.g., $1 per month) amount for room and board?

   (c) If she paid a nontrivial amount (e.g., $100 per month) for room and board?

Table 2.1 summarizes the responses, showing that, in some states there is substantial variation in benefits across living arrangements, and in others there is very little.

The simplest cases are those in which a recipient's payment is unaffected by in-kind income in the form of room and board. Alabama pays our two-person prototypical unit $88 per month regardless of whether they receive free room and board or not.

By contrast, in New Hampshire the two-person maximum payment is $320, composed of a $183 basic maintenance allowance and a $137 shelter allowance. If the recipient mother receives free room and board, she no longer receives the $137 shelter allowance and her payment drops to $183. If she pays for room and board, her payment is adjusted upward, dollar for dollar, to the maximum of $320. In Kansas, the fact that a recipient shares a household implies a reduction of about $50 per month from the maximum. The reduction is made regardless of any payments that may be made for room and board.

In Colorado, the maximum need standard for a two-person family is $331 and each such family receives 82 percent of its needs standard, implying a $272 maximum. Since 27 percent of the need standard is

Table 2.1

Variation in AFDC Benefits
Across Living Arrangements by States

	Two-Person Maximum	Two-Person Unit Living with Poor Grandmother	Two-Person Unit Headed by Adult Mother Living with Nonpoor Grandparents: Free Room and Board	Two-Person Unit Headed by Adult Mother Living with Nonpoor Grandparents: Mother Pays Room and Board
	(1)	(2)	(3)	(4)
Alabama	$ 88	$118	$ 88	$ 88
Arizona	180	233	141	180
Arkansas	135	164	135	135
California	448	555	283	448
Colorado	272	361	198	272
Connecticut	440	546	440	440
Delaware	212	287	212	212
D.C.	257	327	257	257
Florida	185	240	126	185
Georgia	174	208	174	174
Idaho	245	304	123	123
Illinois	250	341	250	250
Indiana	196	256	132	132
Iowa	305	360	305	305
Kansas	288	347	233	233
Kentucky	170	197	170	170
Louisiana	138	190	138	138

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Table 2.1 (continued)

	Two-Person Maximum	Two-Person Unit Living with Poor Grandmother	Two-Person Unit Headed by Adult Mother Living with Nonpoor Grandparents: Free Room and Board	Two-Person Unit Headed by Adult Mother Living with Nonpoor Grandparents: Mother Pays Room and Board
	(1)	(2)	(3)	(4)
Maine	275	370	275	275
Maryland	244	313	244	244
Massachusetts	328	396	222	328
Michigan	416	498	348	416
Minnesota	431	524	431	431
Mississippi	96	120	96	96
Missouri	211	263	211	211
Montana	279	332	123	123
Nebraska	280	480	280	280
Nevada	187	233	187	187
New Hampshire	320	378	183	183
New Jersey	292	385	292	292
New Mexico	210	258	122	210
New York	486	573	150	150
North Carolina	194	223	194	194
North Dakota	301	371	226	301
Ohio	238	290	238	238
Oklahoma	218	282	218	218

-continued-

Table 2.1 (continued)

	Two-Person Maximum	Two-Person Unit Living with Poor Grandmother	Two-Person Unit Headed by Adult Mother Living with Nonpoor Grandparents: Free Room and Board	Two-Person Unit Headed by Adult Mother Living with Nonpoor Grandparents: Mother Pays Room and Board
	(1)	(2)	(3)	(4)
Oregon	328	386	230	230
Pennsylvania	285	364	285	285
Rhode Island	350	432	350	350
South Carolina	144	187	144	144
South Dakota	286	329	123	123
Tennessee	108	140	108	108
Texas	144	167	144	144
Utah	301	376	301	301
Vermont	438	532	182	295
Virginia	272	327	231	272
Washington	385	476	263	385
West Virginia	164	206	98	164
Wisconsin	453	533	453	453
Wyoming	320	360	205	320

attributed to shelter, the actual payment is reduced by 27 percent if the family receives free room and board. As is the case in several other states, however, no distinction is made between nominal, but positive, amounts paid for room and board. Even if the family pays only $5 per month, the 27 percent reduction is restored. Obviously, there is a considerable incentive to report a positive amount for room and board payments.

To summarize, the states can be divided into three categories according to how they treat the case of the prototypical family which lives with other adults.

1. Some states ignore this form of income entirely, so that AFDC benefits are unaffected by the receipt of in-kind income, as is the case in Alabama. There are 29 such states, constituting 53 percent of the national caseload:

Alabama	Arkansas	Connecticut	Delaware
D.C.	Georgia	Illinois	Iowa
Kentucky	Louisiana	Maine	Maryland
Minnesota	Mississippi	Missouri	Nebraska
Nevada	New Jersey	North Carolina	Ohio
Oklahoma	Pennsylvania	Rhode Island	South Carolina
Tennessee	Texas	Utah	Virginia
Wisconsin			

2. A second group of states, an example being New Hampshire, initially assumes that when a woman lives with "other adults" she receives free room and board. If this is so, her AFDC payment is substantially reduced. If the woman provides evidence that she pays for room and board, the actual amount paid is considered in determining her payment. Another prominent example is New York, where a woman with one child receiving free room and board would receive $150/month rather than $486/month. If she does pay for shelter, her payment is adjusted upward

dollar for dollar. The 10 states which treat in-kind income in this fashion (representing 20 percent of the national caseload), are

Idaho	Indiana	Kansas	Michigan
Montana	New Hampshire	New York	Oregon
South Dakota	Vermont		

3. The last group of states does consider in-kind income in the form of room and board but does so very leniently. If the woman reports receiving free room and board, her AFDC payment is substantially reduced. However, if she reports paying a nominal amount, her payment is restored to the two-person maximum. An example is Massachusetts, where a woman with free room and board would receive $222/month rather than the $328/month that she would receive if she lived alone. However, if she reports any positive payment for room and board, she would receive the $328/month maximum. These 10 states are

Arizona	California	Colorado
Florida	Massachusetts	New Mexico
North Dakota	Washington	West Virginia
Wyoming		

To conclude, the telephone survey of state administrative agencies indicated significant differences in the way states treat different living arrangements.

2.2 Analysis of the 1982 Quality Control Data

The second approach we used in examining state policies involved regression analysis. This complements the first approach. It permits one to assess whether actual (as opposed to prototypical) benefits vary across living arrangements within a state. Our data were the 1982 AFDC Quality Control data, which are collected by the federal government when checking the accuracy with which states compute AFDC payments. The data take the form of a sample of cases from each state's caseload along with detailed information on how payments were computed in each of the cases.

As such, the data contain considerable detail on how states determine benefits. Indeed, with the elimination of the biannual AFDC surveys, the QC data constitute the principal source of such information. A potential problem with these data is that sample sizes are sometimes too small for meaningful estimation. In the 1982 data, sample sizes range from 23 in South Dakota to 214 in Pennsylvania. They are therefore not unambiguously superior to the above telephone survey data.[3]

Using these data, we sought to estimate a model that would indicate how benefits vary across living arrangements within states. Our unit of observation was a recipient mother and her children. We chose the AFDC payment standard (PAYSTD) as a dependent variable. The payment standard is essentially the family's AFDC guarantee. It is determined through a complex process that includes an assessment of the family's needs along with consideration of state maximums and percentage reductions.[4] If the assessment of need is influenced by presence of other adults in the household, then this will be reflected in the payment standard.

We estimated a different regression for each state (including Hawaii but not Alaska) plus the District of Columbia and Puerto Rico. In each regression, the following were used as independent variables:

A variable (MAR) which was set equal to 1 when the recipient mother shared a household with a male who can reasonably be classified as a "husband" (i.e., a male who was father to the children (natural or adoptive)*, stepfather, nonrelative male or unknown male). Otherwise, MAR equaled zero.

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*The mother could be eligible despite presence of a father if the family receives AFDC-U or if the father is disabled.

A variable (SHARE) which was set equal to 1 when the recipient mother shared a household with an adult who could not be classified as a "husband." Otherwise, SHARE equaled zero.

The "published" maximum benefit (MXBEN) in the state for a family consisting of a mother and N children, where N is the number of children in the recipient family. These data are published in U.S. Department of Health and Human Services (1984).

Algebraically, for the ith recipient family in each state,

$$\text{(2.1)} \quad PAYSTD_i = B_0 + B_1MAR_i + B_2SHARE_i + B_3MXBEN_i + e_i$$

We include MXBEN in the specification for two reasons. First, the variable contains information on the determinants of AFDC benefits--information that is external to the 1982 Quality Control data. By including this variable, we are able to improve the model's predictive power. Second, although the model is estimated with the 1982 AFDC Quality Control data, it must eventually be used to impute benefits to women in different living arrangements in 1983, because our empirical work in Chapter 4 is based on 1983 data contained in the March 1984 Current Population Survey. With the above specification, the model can be estimated using 1982 values of MXBEN, and the imputations can subsequently be based on 1983 values.

Of course, if every AFDC recipient's payment standard were equal to the published value of MXBEN for her family size, this would be a nonsensical regression. In fact, actual payment standards can differ dramatically from MXBEN due to interfamily differences in housing costs or special needs. Thus, it is sensible to include MXBEN in the specification.

Table 2.2 presents estimates of the coefficient on SHARE in each regression. We see that in most states, it is difficult to reject the

Table 2.2

Coefficients and t-Statistics on SHARE Variable
in Regression, Estimated with 1982 Quality Control Data

	Coefficient	t-Statistic
Alabama	-5.05	-1.5
Arizona	-6.45	-.8
Arkansas	-.37	-.5
California	-3.19	-.6
Colorado	3.39	.5
Connecticut	7.52	1.6
Delaware	.0	.0
Dist. of Columbia	2.56	1.1
Florida	-2.38	-.9
Georgia	-.51	-1.0
Hawaii	-25.68	-1.3
Idaho	-28.27	-.8
Indiana	-63.64	-4.6
Illinois	-.39	-.1
Iowa	6.46	.4
Kansas	-22.91	-1.4
Kentucky	-.40	-.9
Louisiana	-2.19	-1.3
Maine	-5.54	-.8
Maryland	-1.25	-1.1
Massachusetts	-5.97	-.4

-continued-

Table 2.2 (continued)

	Coefficient	t-Statistic
Michigan	-82.79	-4.2
Minnesota	0.55	.0
Mississippi	-3.10	-.6
Missouri	-0.31	-.2
Montana	-0.0	-.5
Nebraska	-3.86	-.5
Nevada	0.0	0
New Hampshire	20.51	.9
New Jersey	-4.88	-1.3
New Mexico	-13.96	-1.6
New York	-69.70	-4.5
N. Carolina	0.34	1.2
N. Dakota	8.77	0.3
Oklahoma	-0.96	-0.4
Ohio	3.22	1.9
Oregon	2.96	2.2
Pennsylvania	1.60	0.4
Puerto Rico	-15.14	-2.7
Rhode Island	0.05	0.5
S. Carolina	0.84	1.1
S. Dakota	-96.71	-2.8
Tennessee	-1.27	-0.6

-continued-

Table 2.2 (continued)

	Coefficient	t-Statistic
Texas	0.67	-1.0
Utah	-1.74	-0.6
Vermont	-122.05	-3.2
Virginia	-1.60	-0.3
Washington	4.96	1.0
West Virgina	-11.29	-1.7
Wisconsin	-6.55	-0.5
Wyoming	-57.50	-3.9

null hypothesis of a zero coefficient. Thus, in most states the AFDC guarantee for a mother who lives with parents or relatives is essentially the same as that for a mother who establishes her own household. There are, however, some states that unambiguously pay lower benefits to recipients living with relatives (namely, Indiana, Michigan, New York, South Dakota, Vermont, and Wyoming). Results from the latter three states are, however, based on very small samples. Similar regressions run on larger samples from the 1979 AFDC Surveys contradict the Wyoming result but support the others.

It is interesting to compare the Table 2.2 coefficients with the survey results summarized in Table 2.1. Recall that there are three ways in which states treat recipient families that live with parents or other relatives: (1) they ignore any in-kind income (e.g., room and board), (2) they count in-kind income as a resource and reduce payments accordingly, and (3) they count in-kind income as a resource only if the recipient obtains free room and board. The average unweighted value of the coefficient on SHARE for these three types of states are as follows:

Type of State	Average Value of Share Coefficient
(1)	(2)
1	-0.56
2	-37.25
3	- 8.96

Thus, the survey data and the regression results tell the same story: in the second type of state, mothers who live with parents or other relatives obtain smaller AFDC benefits than mothers who establish separate households. In these states there are clear incentives to establish one's own household.

Finally, to what extent are states that provide these incentives also high-benefit states? To address this issue, we estimated a weighted linear regression relating the share coefficient (SHARECOEF) from each payment standard regression to the maximum AFDC benefit for a two-person family (MAXTWO). The weights in this regression were the number of AFDC recipients in the jurisdiction. If states with generous AFDC systems are also those which give recipients an incentive to form their own households, the coeffficent on MAXTWO will be negative and significantly different from zero.[5] Our results were as follows (t-statistics in parentheses):

$$\underset{}{SHARECOEFj} = \underset{(0.6)}{6.54} - \underset{(2.0)}{0.08}\ MAXTWOj \qquad j=1,\ldots,49$$

$$R^2 = 0.0565$$

Thus, it is the more generous states that tend to encourage the formation of separate households.

It is conceivable that this is what lies behind the Ellwood and Bane finding of a positive relationship between benefit levels and the tendency to establish separate households. This issue is discussed in the Chapter 4 analysis of the relationship between AFDC benefits and choice among living arrangements.

Conclusion

This chapter used a telephone survey and the 1982 AFDC Quality Control data to establish the fact that some states structure their AFDC benefits in a way that encourages women with children to establish their own households. By paying lower benefits to mothers who live with parents or relatives, these states effectively penalize families that choose this living arrangement. Moreover, the penalty is related to the level of AFDC benefits. High-benefit states tend to be more likely to penalize mothers who live with parents or other relatives. The subsequent chapters take up the issue of whether this penalty affects a young mother's choice of living arrangement.

Notes to Chapter 2

[1]See Fraker, Moffitt, and Wolf (1985) and Department of Health and Human Services (1985).

[2]Data for Alaska and Hawaii were not collected.

[3]Because of this we also estimated similar models from the 1979 AFDC Survey. These data have larger sample sizes, but are clearly not as timely as the 1982 QC data.

[4]We also estimated models that used actual benefits received as the dependent variable. Such models must include the recipient family's earned and unearned income as independent variables, and that raises issues of truncation bias. Since truncation bias is not an issue when the payment standard is used as the dependent variable, and since the two models yielded similar results, we focus here on the payment standard models.

[5]The results from unweighted regressions were similar to those from the weighted regressions.

Chapter 3

A Conceptual Model

This chapter presents a conceptual model for dealing with the problems of choice of living arrangement, employment, schooling, and welfare recipiency for young women. It deals with the model in general terms; we defer discussion of concrete estimation issues, functional forms, etc., to Chapter 5.

3.1 A Sketch of the Model

We wish to model a young mother's decisions among four choices: living arrangement, market work, schooling, and welfare receipt. Our basic notion is that any given combination of these four yields some level of utility, and that "rational" women will choose that combination which maximizes utility (in a sense to be described below). We consider an equilibrium model of utility maximization, which will lead to an econometric specification for the choice of living arrangement, work, welfare, and schooling. The choice of an equilibrium framework is not without qualms--we discuss the advantages and disadvantages of an equilibrium approach below.

We consider three possible living arrangements for a woman with children: living independently as a household head, living with a husband, and living with others as a subfamily head. Within each living arrangement she makes choices with respect to labor supply, welfare recipiency, and schooling. The first two are, of course, closely tied. The attractiveness of these alternatives is directly affected by the income support program (AFDC) in place. It is clear that the guarantees and tax rates in the AFDC program affect her labor supply. They will also affect schooling decisions, through their effects on both the value of time as well as on the nonlabor income available to the household. Changes in living arrangement may affect the potential AFDC benefit, thereby affecting labor supply, welfare, and schooling. In addition, changes in living arrangements may change the availability and cost of child care as well as the nonlabor income available to the woman, and thereby affect labor supply and schooling.

We suppose that the woman has a utility function of the following form:

$$(3.1) \qquad U = U(C, L, S),$$

where C denotes consumption of a Hicks composite commodity, L denotes consumption of leisure, and S denotes consumption of schooling.[1] The utility function may also depend on some other variables which are "taste shifters" (e.g., race). These taste shifter variables will be left implicit in what follows. She faces a budget constraint:

$$(3.2) \qquad C + PS = Y + W(\overline{L} - L - S),$$

where P is the (money) cost of schooling, Y is nonlabor income, W is the (net) wage rate, and $\overline{L}$ is the leisure endowment per period. We have normalized the price of the consumption good to unity. We rewrite this budget constraint in the form of "full income"[2] and "full prices" in the following manner:

$$(3.3) \qquad Z = C + P_S S + P_L L,$$

where $Z = Y + W\bar{L}$ is full income, $P_S = P + W$ is the full price of schooling (incorporating both money and time costs), and $P_L = W$ is the full price of leisure (assuming that time is valued at the wage rate).

We can solve the utility-maximization problem of maximizing the utility function (3.1) subject to the budget constraint (3.3) to find the indirect utility function as a function of full income and full prices. This function gives the maximum utility attainable, subject to the budget constraint, as a function of (full) income and prices.[3] We denote the indirect utility function as

$$(3.4) \qquad v = v(Z,\ P_S,\ P_L) \ = \ v(\theta),$$

where θ denotes the vector $(Z,\ P_S,\ P_L)$. The vector θ characterizes the set of allocations which are feasible for the woman, that is, θ characterizes the budget set. We use Roy's Identity to solve for the demand functions for leisure and schooling, which we write as

$$(3.5a) \qquad L = L(\theta)$$

and

$$(3.5b) \qquad S = S(\theta).$$

Now, for each living arrangement, there is a different θ vector, reflecting differences in available income, etc. Consider the first element of θ—full income, which we denote as Z. There are three components which together make up Z. These are nonlabor income (Y), the (net) wage rate (W), and the leisure endowment ($\bar{L}$). Each of these might vary across living arrangements. A woman who lives independently as a household head may qualify for AFDC. The AFDC guarantee is then her "virtual income," or the appropriate nonlabor income (Y) to consider in the budget constraint (3.2).[4] Or a woman living as a subfamily head may have a claim over the income of other members of the household. Thus, Y might vary across living arrangements. Similarly, the net wage rate W might vary across living arrangements, due to the tax system, or the AFDC program, which taxes the earnings of the woman. A poor woman who lives alone with her children is AFDC eligible, and (at least in some ranges) her net wage is net of the AFDC tax rate, while this would not be true, in general, were she to be married.

Finally, the endowment of leisure time L may vary over living arrangements. We interpret the leisure endowment $\bar{L}$ not as the total time available in a day, as is common in this class of models, but rather as the total discretionary time which the woman can allocate to alternative uses.[5] The time devoted to such "necessities" as child care will vary across living arrangements. A woman who lives independently must spend either money or time to ensure that her children are cared for, while a woman who lives as a subfamily head may have others in the household who can take over the child care duties.

Similarly, the other elements of the vector θ may vary across living arrangements. The full prices of schooling and leisure also depend on the net wage rate W, and therefore will also vary across living arrangements.

Denote these different θ vectors as θ_j, j = 1, 2, ..., J, where J is the number of alternatives under consideration.[6] We can think of the vector θ_j as containing the information characterizing living arrangement j: the full income and prices which are relevant. Then for each living arrangement j there is a maximal level of utility $v_j = v(\theta_j)$. A utility-maximizing woman chooses living arrangement k if it provides the highest utility level, that is:

(3.6) Choose living arrangement k if

$$v(\theta_k) = \max \{v(\theta_j),\ j = 1, \ldots, J\}.$$

This is the class of models referred to as "probabilistic choice systems" by writers such as McFadden (1981).[7] In these models, a rational economic agent chooses that alternative from among a set of possible choices which yields the maximal level of utility. In our case, the woman chooses that living arrangement which yields the highest utility from among a set of possible living arrangements. The woman who chooses living arrangement k will then have leisure $L(\theta_k)$ and schooling $S(\theta_k)$, where θ_k refers to the full income and prices that characterize living arrangement k, as described above.

3.2 The Importance of the Counterfactual

Notice that it is imperative for the implementation of this model to "know" θ_k not only for the chosen alternative k, but also for all the other alternatives. (Remember that θ_j is the vector which characterizes the budget constraint for a woman in living arrangement j.) The problem we face is that in the data we can at most observe θ for the chosen state, and cannot observe θ for the counterfactual states. We therefore must devise a procedure for estimating the θ vector for the counterfactual states. Once we "know" θ_j for all possible living arrangements j, we can adopt an empirical model based on our theoretical model.

It is here that our use of an equilibrium model is critical. We use women who are in living arrangement j to estimate equations predicting the components of θ_j, and then use the estimated coefficients to impute $\hat{\theta}_j$ for each woman. A similar procedure was employed by Danziger et al. (1982), though they used a simpler model than that used below. Explicit details of the estimation and the imputation procedures appear in a later section of this report.

We impute the elements of the θ vector for all women for each living arrangement, for the following reason. Our starting point is the maximization of the utility from the "expected conditions" (see the discussion in Section 3.4, below). In this view of the world, decision makers choose living arrangements on the basis of the conditions which they expect to face in each arrangement. They choose the living arrangement which maximizes utility in that sense, and then, after they have chosen the living arrangement, they observe the actual conditions they will face. The relevant θ vector, then, is not the θ vector which we observe, but rather the θ vector which was expected when the decision was made, since the expected θ characterizes the conditions which she expected to face, and hence those relevant for the choice of living arrangement.

We add the rational expectations assumption that, on average, people are happy with their choices (i.e., on average, they face θ's which were expected—see the discussion in Section 3.4). For this reason, we can estimate prediction equations for θ_j from those women whom we observe to be in living arrangement j. The prediction equations predict the mean of θ_j (as a function of observed characteristics), which is the relevant quantity for the decision-making problem.[8,9] We then predict the elements of each vector r_j, for each living arrangement j, using observed characteristics of the woman.

3.3 Estimation Strategy

Reduced Forms. The approach above suggests that we can write each of the r vectors as $r_j(X)$, where X is the vector of predictor variables. Hence we can write a "reduced-form" version of equations (3.4) - (3.6) as

(3.7) $v(r_j) = v_j^*(X)$; $j = 1, \ldots, J$;

(3.8a) $L(r_j) = L_j^*(X)$; $j = 1, \ldots, J$;

(3.8b) $S(r_j) = S_j^*(X)$; $j = 1, \ldots, J$;

and

(3.9) Choose living arrangement k if

$$v_k^*(X) = \max \# v_j^*(X),\ j = 1, \ldots, J\$.$$

These equations define a reduced form for our model, one which is specified solely as a function of the predictor variables X. This is a model similar to that which has been estimated previously (Ellwood and Bane, 1983). In order to compare our results to previous results, our first set of estimates will reproduce a version of this reduced form. We will denote this model as "reduced-form I".

The second step in the estimation is to use the predicted r_j's in the reduced-form model. This step is similar to the models of Danziger et al. (1982) and Schwartz (1981). Here we will estimate the analogues of equations (3.7) - (3.9) using our predicted values for r (in conjuction with some of the X variables which we view as "taste shifter" variables). We will denote this model as "reduced form II".

<u>Structural Model</u>. The final step in the estimation is to propose a functional form for the indirect utility function v(r). This will imply functional forms for the schooling and leisure demand equations, as well as for the equation predicting choice of living arrangement. This model is developed in detail in Chapter 5. We also need to complete the specification of the probabilistic choice system by specifying the form of the idiosyncratic variation in utility, that is, the disturbances in the econometric model. To foreshadow what is to come, there are serious problems in specifying a tractable econometric model which is completely consistent with the theoretical model. A number of compromises will be made in the interests of tractability. In general, these will take the form of independence assumptions--disturbance terms in some equations will be assumed to be independent of the disturbance terms in other equations. To the extent that one views these simplifying assumptions as suspicious, the reduced-form models should be viewed in a positive light--by not making those assumptions, we can hope that their predictions are not as sensitive to ad hoc assumptions as those of a structural model might be.

Independence assumptions will allow us to write some elements of the model in a recursive structure. While theory suggests that in fact all four decisions (living arrangement, labor supply, welfare recipiency, and schooling) are made simultaneously, a model which incorporates all possible types of simultaneity is intractable. The substantive analogy of the independence assumptions is the following: Suppose that we assume that the disturbance terms in the choice of living arrangement equation

(equation 3.9) are independent of the disturbance terms in the schooling and leisure demand equations (equations 3.8). We interpret this as a hierarchical decision-making problem: The costs of changing living arrangement are viewed as large, relative to the costs of marginal adjustments in leisure.[10]

3.4 The Use of an Equilibrium Model

We now turn to a discussion of the assumptions that underlie the use of an equilibrium model for a problem such as ours. We view this problem in terms of a model of individual utility maximization. Such models have been used in connection with the choice of living arrangements in the past, by such authors as Becker (1975), Becker, Landes, and Michael (1977), Danziger et al. (1982), Schwartz (1981), and others. The essence of the model is very simple: Young women face an array of possible alternatives. These alternatives are characterized by a set of attributes, including living arrangement, employment status, welfare status, and schooling status. Within each alternative, there is an expected consumption of goods and leisure. This yields an "expected utility,"[11] given that the woman chooses that particular alternative. A woman behind the Rawlsian "veil of ignorance" then chooses that alternative which makes her best off, or maximizes her utility.

There is an important modeling issue here which should not be downplayed: the choice of modeling this problem as an equilibrium problem. This is why the paragraph above was couched in terms of the expected utility from each alternative. There are two lines of argument that can be used to justify this approach. The earliest is that of "costless compensation."[12]

The second line is the "expected conditions" class of argument,[13] and is the one used here. Here we argue that a woman confronts a number of choices. The actual conditions that she would face in making a given choice are not known with certainty; rather, the decision-maker has knowledge of the expected conditions associated with each possible choice. She is forced to make a decision before she knows the exact conditions associated with each choice, and we assume that she makes her decision on the basis of the expected conditions. She evaluates her utility at each possible position, based on the expected conditions, and chooses the alternative with the highest utility (calculated in this manner).[14]

We choose this line of argument for the following reason: Our aim is to estimate the effects of the parameters of the income support system on the decisions of young women with regard to living arrangement, employment, etc. Of particular interest is the question, discussed above, of the interrelated effects of choices of living arrangements, on the one hand, and employment and schooling, on the other hand, and of the effects of program parameters on this process. Hence, we need to be able to predict the conditions that would be faced by a young woman were she to change living arrangements, and we need the ability to predict how those conditions would change owing to changes in the parameters of the welfare system. The essence of our approach is to model not only the state of the world in which we actually observe a woman, but also to model her entire choice set, that is, the counterfactual states that we do not observe. In order to make this approach consistent with a theory of utility maximization, we use the "expected conditions" line of argument. While not entirely satisfactory (for reasons discussed in the note 14), it seems to us to be a useful approach.

A final argument is needed before we can use a model based on this approach to analyze data. We will be using cross-sectional data to estimate the model, and hence are implicitly assuming that what we see in a cross-sectional dataset is a world in equilibrium. We are not arguing that every individual who is observed is in fact in equilibrium. Rather, the argument is that, on average, the individuals whom we observe in a large cross section are in equilibrium, and that the departures from equilibrium are sufficiently small and random so as not to affect our empirical results. Implicit here, then, is a kind of rational expectations assumption. We model individuals as making choices on the basis of the expected conditions to be faced in each position in the world, and now we add the assumption that, on average, they do not wish to change their minds once they have observed the actual conditions associated with the choice that was made. This implicit assumption has important implications for the interpretation of our models, which are based on imputed values $\hat{\theta}_j$ for the full incomes and prices characterizing the conditions that the woman expects to face in the different living arrangements j. We decompose the realized θ_j into two components, a mean $\hat{\theta}_j$ and a prediction error. If the woman knows more than we are able to predict, that is, she knows part of our prediction error, then she will make her decision based on her (greater) knowledge, and not an our estimated mean $\hat{\theta}_j$.

Finally, we note that there is an alternative approach to that taken here. The alternative can be viewed as explicitly modeling <u>changes</u>, rather than levels, as is done here. That is, we could model the process of changing from one living arrangement to another.[15] While this approach to modeling does not suffer from the disadvantage of the equilibrium assumption, we believe that it is not as well suited to addressing the questions in which we are interested. We would like to make predictions about the effects of changes in program parameters on the stock of household heads, etc. To answer a question like this from a model of changes in living arrangements would require us to solve the dynamic system implicit in the model of changes for the new equilibrium. This requires that our model of the dynamic process be correct. Small departures from the assumed model will have much larger effects when we solve a dynamic model for the new equilibrium than will small departures from our assumed model of the stocks, we feel. Since it is difficult to know whether we have captured the "true" model of the process, we feel that it is safer to work with an equilibrium model.

Notes

[1]Schooling may enter the utility function for two reasons. First, it might enter the utility function as a consumption good--schooling as an enjoyable use of time. This may or may not be plausible. Second, time spent in school today may increase the wage rate in the future, increasing command over goods and services in the future. We do not build a dynamic model here, but one might interpret schooling in that light. In the context of a static model, this consideration suggests that schooling may enter the utility function as an investment good. For either or both reasons, then, we enter schooling as an argument of the utility function.

[2]This terminology can be traced to Becker (1975).

[3]See Varian (1984).

[4]The use of the terminology "virtual income" in this context is from Burtless and Hausman (1978).

[5]This is similar to the spirit of a Stone-Geary system of demand equations. In that model, there is a certain minimum consumption of each good which is viewed as not subject to allocation decisions. The allocation problem involves only the choice of quantities over and above the minima. Here we treat certain time commitments as necessities, for example, time committed to child care. In this context, the minimum quantity enters the utility maximization problem through the budget constraint, rather than in the more familiar Stone-Geary form.

[6]We use different choice sets in the empirical portion of the paper. In some sections we set J equal to 3--for household head, wife, and

subfamily head--which we denote as living arrangement one (LA3). In other sections we set J equal to 6, which is LA3 interacted with a dummy variable representing welfare recipiency, which takes the value one if the women is a welfare recipient, and zero if not. We denote the six-valued living arrangement variable as LA6.

[7]A probabilistic choice system contains two elements. The first is a specification of the deterministic portion of the indirect utility function. This has the interpretation of the utility of a "representative" individual. The second is the specification of the stochastic portion of the utility function. This has the interpretation of the "idiosyncratic" element of utility, and forms the disturbance term for the econometric model. The discussion above is couched in terms of the representative portion of the utility function. We defer discussion of the idiosyncratic element to a later section in which we discuss the stochastic structure of the model and the implied econometric model.

[8]This is the same procedure used by Danziger et al. (1982), and by Schwartz (1981) in a similar problem. Formally, our assumptions imply that there is no problem of "selectivity bias" (Heckman, 1979) in estimating the prediction equations for θ. Note, additionally, that Schwartz estimated prediction equations both with and without corrections for selectivity bias, and found very little difference in the empirical results. For these reasons, we will not employ the correction techniques in the prediction equations we use, in general. See below for a complete discussion of the imputation procedures used.

[9]There is an issue here which is formally similar to that faced in dynamic models of labor supply under uncertainty. We use a predictor

$\hat{\theta}$ in place of θ, and assume that the woman also used $\hat{\theta}$ when making her decision. Now, θ is equal to $\hat{\theta}$ plus a prediction error. To the extent that the woman knows (at least a portion) of the prediction error when making her decision, we are making incorrect predictions of θ, and basing our estimates of the parameters of the choice equation (i.e., the indirect utility function $v(\theta)$) on incorrect values of θ. See MaCurdy (1983) for a more complete discussion of this issue. Also, see the discussion below concerning the issues involved in using an equilibrium model for a problem of this type.

[10]An alternative interpretation might employ a partially lexicographic utility function which places primary importance on living arrangement. We do not feel comfortable with this approach. If utility functions were lexicographic in this way, then changes in the parameters of income support programs such as AFDC could not affect choice of living arrangement, by assumption.

However, if the source of income had an independent effect on utility, then one could view the model in the text as a partially lexicographic utility function. If, for example, there were a stigma associated with AFDC, this might be the case. Substantively, however, the stigma model does not differ in its implications for estimation from the model outlined above.

[11]Our use of the term "expected utility" is not the standard usage. See the discussion below for details.

[12]This argument was used, for example, by Becker, Landes, and Michael. The argument is that an individual who finds herself in an undesirable position--for instance, married when she would rather be a

household head--can freely change to the more preferred position. If there are others who prefer the original arrangement (in this example, perhaps the husband), then the woman, whom we model as the decision-maker, can costlessly compensate the other parties for their loss, and the change is made only if the gain to the woman exceeds the loss to the other parties. From this line of argument, it is argued that if all parties are so characterized, then the world which we see when looking at cross-sectional data is a world in equilibrium. In this world of equilibrium, it is reasonable to build models of individual maximization, and use the equilibrium conditions of those models to derive empirical implications.

[13]This line of argument was used by Danziger et al. (1982).

[14]Note that the use of the term "expected utility" is somewhat misleading in this context. As commonly used, the term refers to an individual who satisfies the von Neumann-Morgenstern axioms of behavior, and who acts so as to maximize the probability weighted average of the utility attainable in various states of the world. As used here, we refer to evaluating utility based on the expected value of the conditions to be faced in each possible state of the world. In some cases the two will coincide, but in general they may not. Implicit in our model is a special kind of "risk neutrality." Individuals, who may be risk averse, make decisions among alternative positions in the world (e.g., living arrangements) based on the expected value of the conditions they would face in that position. In the general case, only risk-neutral individuals make decisions solely on the basis of expected values. In general, a risk-averse individual takes into account the form of the probability

distribution faced. In principle, when we specify the form of the probability distribution while specifying the estimating model, we could solve the maximization problem with that distribution in mind, but we do not.

The reasons we do not are twofold. First, there are serious problems in the specification of a tractable econometric model (discussed in Chapter 5), and we do not wish to compound the theoretical model with more distributional baggage than we feel is needed in order to arrive at a useful model. Second, the reason that we proceed in this manner is to be able to model the counterfactual states, that is, the conditions that would be faced had the woman made a choice other than the one we observe (see discussion below). We feel no strong attachment to our notion of "expected utility" maximization, but feel that the inconsistency between that justification of our modeling strategy and the theoretical model used is relatively small.

[15]This approach is taken in models of marital dissolution. For examples, see Tuma et al. (1979) or Wolf (1977).

Chapter 4

Empirical Results

This chapter presents our empirical findings concerning the last three questions posed in Chapter 1. Section 4.1 describes the source of our data, defines the variables used in the remainder of the chapter, and where necessary details the construction of those variables. Section 4.2 contains our results concerning the determinants of the living arrangements of young women and, in particular, how the AFDC system affects the choice of living arrangement. In Section 4.3 we examine simple models of the determinants of labor force participation, schooling, and welfare recipiency. Finally, Section 4.4 describes the differences in labor force participation, schooling, and welfare recipiency of women in different living arrangements.

4.1 Sources of Data and Definitions of Variables

Many of the variables used in this analysis are drawn from the March 1984 Current Population Survey (CPS).[1] Since our model focuses on the decisions of women with relatively young children, the basic unit of observation for our extract is women under 55 with at least one child who is 18 or under. For most of our work, we further limit the sample to those women who are 35 or younger. Each record consists of three parts: (1) information on the household of which the woman is a part; (2) information on the family (or subfamily) of which the woman is a part; and (3) information on the woman herself. Thus, for each woman with children 18 or younger, whether married, heading her own household or living in a subfamily, a variety of "household," "family," and "person" variables were selected.

If a household was composed of more than one family containing a woman and young children, we created two separate records for that household. To illustrate, suppose a CPS household consisted of 40-year-old woman and her three daughters aged 14, 16, and 18. Suppose the 18-year-old had a child of her own and was thus a member of a subfamily within the household headed by her mother. This multifamily household appears in our extract as two separate records, one for the 40-year-old and one for the 18-year-old. The household part of each of these two records is identical; the family part is different on each record, since it refers to the primary family for the 40-year-old and the subfamily for the 18-year-old. The "person" sections of the two records will contain data on the 40-year-old and the 18-year-old, respectively. The final extract consisted of 238 variables for each of 22,277 women. To those variables we added 13 others, drawn from other sources, as follows:

(a) One variable (UNEMPLOY) measuring state unemployment rates at the end of 1983.

(b) Two variables measuring effective state AFDC tax rates on earned income and unearned income estimated by Fraker, Moffitt and Wolf (1985). National averages were substituted in states for which Fraker, Moffitt and Wolf did not estimate tax rates.

(c) Ten payment standards (PAYSTD) for families of different sizes ranging from 1 to 10.

From this augmented data set, we constructed several other variables (see Table 4.1), which were then used in the analysis reported below.

In the multivariate, multiequation models of living arrangements constructed and estimated in this paper, we have used several imputed variables. For example, it is necessary to have estimates of the labor market wage which would be "available" to each woman in the sample, regardless of whether she is currently working or not. We observe actual

Table 4.1

List of Variables

Dependent Variables	Construction of Variables
Living Arrangements:	
Three-way categorization of living arrangements (LA3)	Each CPS respondent is asked to state his or her relationship to the householder. Those who were themselves householders were classified as LA3 = 1. Those who reported themselves as "spouse of householder" were classified as married and given LA3=2. Those who reported themselves as "child of householder," "other relative of householder" or "unrelated subfamily member" were classified as living in a subfamily (LA3=3). If any of those classified as living in a subfamily were married, they were reclassified as LA3=2.
Six-way categorization of living arrangements (LA6)	LA3, as defined above, was then broken down into six categories by distinguishing between those women who received income from public assistance and those who did not. If LA=1 and the woman received no public assistance, LA6=1. If she received public assistance, LA6=4. Married women not receiving public assistance were classified as LA6=2; otherwise, they became LA6=5. Those in subfamilies who did not receive any income from public assistance were LA6=3; otherwise LA6=6.
Four-way categorization of living arrangements (LA4)	If LA6=1, LA4=1; If LA6=3, LA4=2; If LA6=4, LA4=3; If LA6=6, LA4=4.
Two-way categorization of living arrangements (LA2)	If LA3=1, LA2=1; If LA3=3, LA2=0.

-continued-

Table 4.1 (continued)

Dependent Variables	Construction of Variables
Work and School:	
Full time (FULL)	If the woman worked more than 48 weeks per year and more than 35 hours per week and reported positive total earnings, FULL=1.
In Labor Force (INLF)	If the woman worked at all and reported positive earnings, INLF=1.
Currently in School (SCHOOL)	The CPS asks respondents to classify their reasons for (a) not working at all in the previous year; and (b) not working full time in the previous year. If that reason was "going to school," the woman was classified as being in school in the previous year (SCHOOL = 1).
Welfare Recipiency (WELFARE)	If the woman had personal income from public assistance, WELFARE=1. If not, WELFARE=0.

Independent Variables	Construction of Variables
Age and Education:	
Age (AGE) Age Squared (AGE2) Age Cubed (AGE3)	Based on the age, in years, of the woman in the family.
Education (EDUC) Education Squared (EDUC2) Education Cubed (EDUC3)	The CPS collects data on "highest grade attended" and on whether or not this grade was completed. From these two variables, we constructed a variable representing "completed years of education." This variable was then adjusted downward by one year for those who were in school in the previous year.

-continued-

Table 4.1 (continued)

Independent Variables	Construction of Variables
Age and Education: (continued)	
Age*Education Squared (AE2) Age*Squared*Education (A2E) Age*Education (AGE * EDUC)	These interactions were constructed using age and education as defined above.
Family Characteristics:	
Presence of Child	If there was a child (own or otherwise) in family who was between the ages of 0 and 5, inclusive, PRESCHOOL=1.
Presence of Teenaged Child (TEENAGER)	If there was a child of the woman in the family who was between the ages of 13 and 18, inclusive, TEENAGER=1.
Number of Dependents (DEPENDS)	The number of family members under 18 years old.
Family Size for AFDC Purposes (FAMSIZE)	The number of dependents (DEPENDS) plus 1.
Never Married (NEVERMAR)	If the woman was never married, NEVERMAR=1.
Region of Residence:	
Northeast (NEAST)	If the woman resides in the Northeast region, NEAST=1.
North Central (NC)	If the woman resides in the North Central region, NC=1.
West (WEST)	If the woman resides in the West region, WEST=1.
South (SOUTH)	If the woman lives in the Southern region, SOUTH=1.

-continued-

Table 4.1 (continued)

Independent Variables	Construction of Variables
Residence: (continued)	
SMSA	If the woman lives in a standard metropolitan statistical area, SMSA=1.
Race:	
Nonwhite (NONWHITE)	If the woman is not white, NONWHITE=1.
Hispanic (HISPANIC)	If the woman is Hispanic, HISPANIC=1.
Labor Force Participation:	
Part time/Full time/Not in Labor Force (WORK3PT)	If the woman worked full time, full year, WORK3PT=2. If she did not work at all, WORK3PT=0. Otherwise, she is assumed to have worked "part time, part year" and WORK3PT=1.
Income:	
Nonwage Income (NONWAGE)	Nonwage income, for each individual woman, is defined as the income derived by the family (not household) of which she is a member. The categories of income classified as "nonwage" are interest income, dividend income, retirement income and income from child support and alimony.
Others' Income (OTHERINC)	The income available to the woman from other family members was set equal to zero for household heads (LA=1). For married women (LA=2), it is total household income minus total personal income. For women in subfamilies, LA=3, others' income is total household income minus total family income.
Existence of Nonwage Income	If the family of which the woman is a part had any nonwage income, as defined above, NW=1. Otherwise, NW=0

-continued-

Table 4.1 (continued)

Independent Variables	Construction of Variables
Income: (continued)	
Preliminary estimate of AFDC benefits (AFDC)	This is an estimate of potential AFDC benefits based on the maximums reported in Department of Health and Human Services (1984) and FAMSIZE.

wages only, however, for those women who worked in the survey period. Because of this we must impute a wage to women who are not currently working. Similarly, for women who are not currently receiving income from AFDC, we would like to estimate the payment they would receive if they were to become eligible for the program. In this way, we can estimate the characteristics of the alternatives facing each woman. There are four magnitudes which are imputed for each woman:

(a) labor market wage;
(b) nonwage income;
(c) others' income;
(d) AFDC benefits.

Each is estimated for each of the three available living arrangements and each is discussed in detail in Appendix A.

4.2 Estimates of the Determinants of Living Arrangements

In this section we address the first question framed in Chapter 1: To what extent do welfare benefit levels affect a young woman's choices among living arrangements? We answer ths question by presenting coefficient estimates drawn from econometric models of increasing complexity. We begin, in Section 4.2.1, with a simple reduced-form model. Then, in Section 4.2.2, we move on to models containing our AFDC imputations, discussed in Section 4.1. Finally, in Section 4.2.3, we attempt to estimate the parameters of a model which is consistent with the theoretical model of Chapter 3 by including imputed wage rates and imputed nonwage income.

In general, we find that the level of AFDC benefits and the differential treatment of shared households by the various state AFDC programs does affect the choice of living arrangement.

4.2.1 Reduced-Form Multinomial Logit Models

The simplest model of the living arrangement choice is one which contains only exogenous variables. The dependent variable representing the observed choices among living arrangements is either LA2 or LA3, defined briefly here (see Table 4.1 for details):

In a sample of unmarried women: LA2 = 1 if the woman heads her own household; 0 otherwise.

In a sample of all women: LA3 = 1 if the woman heads her own household; 2 if the woman is married and her spouse is present; 3 if the woman lives in a subfamily (also called "sharing" here).

This variant of the multinomial logit model (see Appendix B for a discussion of the various types of logit models used here) does not contain any independent variables that vary across alternatives. For example, completed years of education (EDUC) does not change as the woman considers the merits of her alternative living arrangements. In contrast, the income available from other family members would change under the alternatives (especially for a married woman contemplating another living arrangement). But that type of imputed income variable is not included in the models we discuss in this section.

Table 4.2 presents our coefficient estimates from these reduced-form models. In columns 1 and 2, the dependent variable is LA3 and the sample contains women from all three living arrangements. In column 3, the dependent variable is LA2 and the sample consists entirely of unmarried women.[2]

The base case is "sharing," so that a positive coefficient in column 1 or 3 implies that an increase in the corresponding variable will

Table 4.2

The Determinants of the Living Arrangements of Young Women: Multinomial Logit Results, Reduced-Form with No Imputations

Independent Variables	Change in the Relative Odds of: Share versus Householder (LA3) (1)	Share versus Married (LA3) (2)	Share versus Householder (LA2) (3)
AGE	-.633 (.131)	-.435 (.112)	-.615 (.134)
AGE2	.011 (.002)	.007 (.002)	.011 (.003)
EDUC	.243 (.172)	.368 (.155)	.202 (.189)
EDUC2	-.006 (.005)	-.017 (.005)	-.003 (.005)
AGE * EDUC	-.007 (.005)	-.007 (.005)	-.008 (.006)
DEPENDS	-.562 (.082)	-.702 (.077)	-.559 (.082)
PRESCHOOL	.156 (.149)	-.584 (.139)	.155 (.154)
NONWHITE	.419 (.120)	1.85 (.113)	.344 (.128)
SMSA	-.006 (.133)	.271 (.118)	.115 (.141)
UNEMPLOY	-.053 (.026)	-.017 (.023)	-.062 (.027)
SOUTH	.374 (.122)	.101 (.108)	.469 (.131)
Constant	9.15 (2.31)	5.65 (1.84)	9.22 (2.37)
Dependent Variable	LA3	LA3	LA2

Note: The asymptotic standard errors for the coefficient estimates appear in parentheses below the estimates themselves.

increase the relative probability of sharing a household versus heading one's own household.[3] Column 2 indicates the effects of the variables on the relative odds of sharing versus being married. Finally, the effects of the variables on the relative odds of heading a household versus being married are the coefficients in column 2 minus the coefficients in column 1.

We see in Table 4.2 that age is the most important factor in distinguishing between women who live in subfamilies and women who are either married or householders. As a woman becomes older, she is less and less likely to live in a subfamily relative to being a householder. The coefficient on AGE in column 1 is large (-.633) and significantly different from zero. Older women are also considerably more likely to be married than to share a household.

Women with more children are more likely to head their own households than to share with others (the coefficient on DEPENDS in the first column is -.562) and are more likely to marry than to share with others (the coefficient in the second column is -.702). These coefficients are statistically significant. More children makes marriage somewhat more likely than household headship (the coefficient on DEPENDS in the second column minus the coefficient in the first column is -.140 (-.702+.562).

The large positive coefficients on the NONWHITE variable imply a greater prevalence of sharing among nonwhites, ceteris paribus. Nonwhites are more likely than similar whites to share than to be householders and are more likely to be householders than to be wives. Women in the South are significantly more likely to share than to be household heads, but no more likely to share than to be wives. Finally, sharing a household is not more likely in states with high unemployment rates. In fact, in such states household headship is more likely than sharing (although marriage is not more likely than sharing).

Education is not a determinant of the choice between sharing and being a householder but, at the mean, more education seems to imply higher probabilities of marriage. If we interpret the second-order polynomial in age and education as standing for a wage rate, then women with higher wages are less likely to share with others than to be either householders or wives, and are most likely to be householders, other things equal.

The coefficients in column 3 of Table 4.2 (where the dependent variable is LA2 and the sample consists of unmarried women) are the effects on the relative odds of sharing a household with others versus heading one's own household. The coefficients are quite close to those in the first column, both in magnitude and in statistical significance.

The results in Tables 4.2 are quite robust. They are not sensitive to the exclusion of the SMSA, South, and unemployment rate variables, nor are they sensitive to the addition of three region variables rather than just the one.

4.2.2 Multinomial Logit Models with Imputations as Independent Variables

Since one of our primary goals is to estimate the effects of AFDC on living arrangements, we continue our examination of the living-arrangement choice by including our estimates of potential AFDC benefits as independent variables.

Table 4.3 presents coefficient estimates from multinomial logit models which include the potential AFDC payments available to a householder (AFDC1). Columns 1 and 2 present the results for a model with LA3 as the dependent variable, while column 3 represents the LA2 model.

These models retain all the demographic variables from the first table. By including both potential AFDC payments and the variables indicating the presence and number of children, we can separate the effects of AFDC from those of family size.

The interpretation of the coefficients parallels that of the first table. Overall, the coefficients on the demographic variables change very little with the addition of AFDC1 to the equation. In particular, the coefficients on DEPENDS and PRESCHOOL are constant across the two specifications, supporting the notion that the coefficent on AFDC1 represents its impact, independent of family size.

As for the AFDC variable itself, the results from Table 4.3 suggest that the level of AFDC benefits, as measured by the potential benefit available to a household head, does not by itself affect the relative probability of household headship versus sharing a household with others, nor does it seem to have much effect on the relative probability of sharing versus marriage. There does, however, seem to be a weak effect of AFDC1 on the relative probability of household headship versus marriage. The difference in the coefficients on AFDC1 in columns 1 and 2 is .464, with a standard error of .357. This is similar to the finding of Ellwood and Bane that increases in the generosity of the AFDC program lead to increases in the number of female householders. As before,

Table 4.3

The Determinants of the Living Arrangements of Young Women: Multinomial Logit Results, Reduced-Form, with AFDC1

Independent Variables	Estimated Change in the Relative Odds of: Share versus Householder (LA3) (1)	Share versus Married (LA3) (2)	Share versus Householder (LA2) (3)
AGE	-.634	-.435	-.616
	(.131)	(.112)	(.141)
AGE2	.011	.007	.011
	(.002)	(.002)	(.003)
EDUC	.238	.367	.203
	(.172)	(.155)	(.188)
EDUC2	-.005	-.017	-.003
	(.005)	(.005)	(.005)
AGE * EDUC	-.007	-.007	-.008
	(.005)	(.005)	(.006)
DEPENDS	-.528	-.697	-.530
	(.089)	(.084)	(.091)
PRESCHOOL	.158	-.584	.154
	(.149)	(.139)	(.154)
NONWHITE	.424	1.86	.347
	(.120)	(.113)	(.128)
SMSA	-.010	.271	.110
	(.132)	(.118)	(.142)
UNEMPLOY	-.054	-.017	-.063
	(.026)	(.023)	(.027)
SOUTH	.264	.084	.376
	(.169)	(.152)	(.183)
AFDC1	-.572	-.108	-.511
	(.638)	(.590)	(.699)
Constant	9.35	5.69	9.39
	(2.17)	(1.85)	(2.39)
Dependent Variable	LA3	LA3	LA2

Note: The asymptotic standard errors for the coefficient estimates appear in parentheses below the estimates themselves.

restricting attention to the nonmarrieds in column 3 changes nothing of substance. The results of Table 4.3 are especially important, since including a variable such as AFDC1 is a typical procedure in measuring the impact of AFDC on economic behavior.

In Table 4.4, we come to the heart of the matter. This table presents multinomial logit models which involve both the AFDC benefit available to a householder (AFDC1) as well as that available to a woman living in a subfamily (AFDC3).

We incorporate the potential AFDC payment available to women in subfamilies by constructing a variable called ADCDIF (AFDC1 minus AFDC3).[4] ADCDIF measures the "wedge" between payments to a householder and a subfamily head. The coefficient on AFDC1 gives the impact of the level of AFDC benefits on the choice of living arrangements, holding constant the wedge (as measured by ADCDIF). The coefficient on ADCDIF gives the impact of changes in the wedge, holding constant the level of benefits.

The coefficients on AFDC1 in Table 4.4 are not very different from their counterparts in Table 4.3. Holding constant AFDC1, however, the difference between the benefit available as a household head and as a subfamily head has an effect on the relative probability of heading a household versus sharing with others. The coefficient on ADCDIF in the first column of Table 4.4 is -2.87, with a standard error of 1.71. The difference does not affect the relative probability of sharing versus marriage.

Thus, the treatment of subfamilies does seem to have an effect on household composition. The larger the loss of benefits due to sharing a household with others, the more likely a woman is to be a householder.

Table 4.4

The Determinants of the Living Arrangements of Young Women: Multinomial Logit Results, Reduced-Form, with AFDC1 and AFDC3 Estimates

Independent Variables	Change in the Relative Odds of: Share versus Householder (LA3) (1)	Share versus Married (LA3) (2)	Share versus Householder (LA2) (3)
AGE	-.627 (.131)	-.435 (.112)	-.611 (.141)
AGE2	.011 (.002)	.007 (.002)	.011 (.003)
EDUC	.253 (.172)	.366 (.155)	.214 (.189)
EDUC2	-.005 (.005)	-.017 (.005)	-.002 (.005)
AGE * EDUC	-.008 (.005)	-.007 (.005)	-.009 (.006)
DEPENDS	-.527 (.089)	-.698 (.084)	-.532 (.091)
PRESCHOOL	.162 (.149)	-.585 (.139)	.162 (.154)
NONWHITE	.423 (.120)	1.86 (.113)	.345 (.128)
SMSA	-.003 (.132)	.270 (.118)	.114 (.142)
UNEMPLOY	-.056 (.026)	-.018 (.023)	-.064 (.028)
SOUTH	.220 (.171)	.081 (.154)	.333 (.184)
AFDC1	-.583 (.638)	-.122 (.590)	-.420 (.698)
ADCDIF	-2.87 (1.71)	-.021 (1.61)	-3.80 (1.78)
Constant	9.22 (2.16)	5.70 (1.85)	9.29 (2.38)
Dependent Variable	LA3	LA3	LA2

Note: The asymptotic standard errors for the coefficient estimates appear in parentheses beside the estimates themselves.

Alternative Parameterization (see text note 4):

AFDC1	-3.45 (1.85)	-.100 (1.74)	-4.22 (1.89)
AFDC3	2.87 (1.71)	.021 (1.61)	3.80 (1.78)

Viewed the other way, holding constant the wedge between householders and women in subfamilies, higher benefits lead to higher probabilities of household headship. The same results obtain in column 3, which focuses only on nonmarried women.

4.2.3 Adding Wage Rate and Nonwage Income Imputations

We now turn to models that are more closely related to the theoretical framework outlined in Chapter 3. In this section we discuss models which use imputations for wage rates and nonwage income in addition to the AFDC benefit imputations.

Table 4.5 presents results from multinomial logit models which parallel the structure of the models in Tables 4.2-4.4. In this table we add our imputation of the wage rate (PWAGE1), as well as an imputation of the wage rate net of the AFDC earnings tax (PWAGE2). Variation in PWAGE2, independent of PWAGE1, is due solely to state-to-state differences in the AFDC program (see Table 4.1). We also add the sum of imputed others' income and nonwage income in each living arrangement as measures of nonwage, non-AFDC income. Specifically, "other income" if householder (OY1) is the sum of NWIMP1 and IOTHERS1 while "other income" for women living in subfamilies (OY3) is the sum of NWIMP3 plus IOTHERS3. The definitions of NWIMP1, NWIMP3, IOTHERS1, and IOTHERS3 are contained in Appendix A.[5] For two reasons we restrict the set of demographic variables in these models. First, if our conceptual framework is correct, many of the demographic variables in the preceding models were included solely as proxies for the prices and incomes that enter the indirect utility function. Second, the higher-order terms in age and

Table 4.5

The Determinants of the Living Arrangements of Young Women: Multinomial Logit Results, Reduced-Form, with Wage Rate and Other Income Imputations

	Change in the Relative Odds of:		
	Share versus Householder (LA3)	Share versus Married (LA3)	Share versus Householder (LA2)
Independent Variables	(1)	(2)	(3)
AGE	-.300 (.028)	-.522 (.027)	-.219 (.026)
DEPENDS	-.491 (.111)	-.903 (.107)	-.347 (.111)
PRESCHOOL	-.032 (.163)	-.820 (.158)	-.123 (.172)
NONWHITE	-.231 (.168)	-.340 (.162)	-.286 (.179)
OY1	-.492 (.343)	-1.16 (.326)	-1.14 (.384)
OY3	-.084 (.023)	-.348 (.022)	-.037 (.021)
PWAGE1	.550 (.120)	1.71 (.115)	.361 (.121)
PWAGE2	.073 (.121)	.171 (.115)	.129 (.125)
AFDC1	-1.14 (.586)	-.512 (.551)	-1.17 (.605)
ADCDIF	-3.41 (1.84)	.898 (1.77)	-4.23 (1.77)
Constant	7.22 (.611)	12.23 (.601)	5.21 (.558)
Dependent Variable	LA3	LA3	LA2

Note: The asymptotic standard errors for the coefficient estimates appear in parentheses beside the estimates themselves.

Alternative Parameterization (see text note 4):

AFDC1	4.55 (1.89)	.386 (1.82)	-5.40 (1.81)
AFDC3	3.41 (1.84)	-.898 (1.77)	4.23 (1.77)

education are highly collinear with the imputations. That collinearity becomes a serious problem when a number of imputations are used in the same equation. As a result, the coefficient estimates were very unstable when the full range of demographic variables was included.

We retain, however, those demographic variables from the reduced form which we believe have an independent effect on the choice of living arrangement. For example, age may well have an independent effect, owing solely to life-cycle considerations. A similar argument applies to race. The number of children (DEPENDS) is retained, both because we think it may have an independent effect, and also to ensure that we do not attribute to the AFDC variables an effect that is merely due to the number of children. We also retain the indicator of a young child (PRESCHOOL), because we think that the presence of a young child may affect the ability of a woman to form alternative living arrangements.

Columns 1 and 2 of Table 4.5 present the results from the model involving LA3 and column 3 presents the results from the LA2 model. In columns 1 and 2, we see that the strong age effect in the living-arrangement decision continues even when the wage rate and other income are held constant. The coefficient on DEPENDS in column 1 remains at around -0.5, as it has throughout these differing models. PRESCHOOL remains insignificant in determining the relative odds of sharing versus being a householder, but continues to significantly reduce the probability of sharing a household with others relative to living as a wife.

For the first time, however, nonwhites are less likely to share than to be married, now holding constant wage rates and nonlabor income. This last result is somewhat surprising, but is fairly robust to changes in specification.

Turning to the economic variables, we see the same AFDC effects as in the previous tables. The differential treatment of subfamilies in the AFDC program has a significant effect on the probability of household headship relative to sharing a household with others. Holding constant the level of benefits, the greater is the loss of AFDC benefits due to sharing, the less likely is sharing to occur, relative to being a householder. As before, the level of AFDC benefits has little or no effect on the marriage decision, holding constant our other imputations.

The coefficient on PWAGE1 is somewhat surprising. The higher is the wage, other things equal, the more likely is the woman to be sharing with others compared to be heading her own household, and she is much more likely to be married. Variation in the AFDC earnings tax has little effect--the coefficients on PWAGE2 are small and not significantly different from zero. Similarly, the coefficients on other income (OY1 AND OY3) in Table 4.5 are surprising, and not particularly plausible. Furthermore, these coefficients are very sensitive to the specification of the independent variables. If we include education as a taste-shifter variable, the coefficients on the wage and other income variables become insignificant. On the other hand, if neither age nor education appears in the equation, then their coefficients have the theoretically "correct" signs and are often significant.

In column 3 of Table 4.5, with a sample restricted to unmarried women, the results appear somewhat more plausible. The higher is the AFDC benefit "if a householder," the more likely is the woman to be a householder. Holding the benefit level constant, the treatment of subfamilies has a significant impact. The greater the loss of benefits due to sharing a household, the less likely is the woman to share.

We see the same wage effect as in columns 1 and 2. The higher the wage rate, the more likely is the woman to share rather than to head her own household. As above, this effect disappears entirely if education is added to the equation, and changes sign if age is excluded. The coefficients on other income make more sense here. The higher is other income "if householder," the more likely is the woman to be a household head. This coefficient is robust to the addition of education and the exclusion of age.

We find, then, that we are unable carefully to distinguish a wage effect from an effect due to age and education, and that the effect of other income on the living-arrangement decision cannot be estimated very precisely from our procedures.

The estimated effects of AFDC are robust, however, and are not due solely to the number of children. Differences in the AFDC program have an impact on living arrangements. In particular, the differential treatment of subfamilies seems to have a consistent effect in all of the equations we have estimated. The greater is the penalty for sharing a household with others, the less likely we are to see women sharing.

Our last multinomial models are an attempt to estimate jointly the choice of living arrangement and welfare participation. To do this, we expand the definition of the living-arrangement variable to differentiate between those receiving and not receiving public assistance. We first restrict our attention to the nonmarried subsample and then turn to a model which also includes married women.

Table 4.6 presents the results of a model which parallels that in Tables 4.5. The living-arrangement variable (LA4) takes on four values:

LA4 = 1 if householder, not receiving public assistance;
2 if living with others, not receiving public assistance;
3 if householder, receiving public assistance;
4 if living with others, not receiving public assistance.

The last category is taken as the base case, and the coefficients are to be interpreted as the effects of the explanatory variables on the probability that LA4 = i, i=1,2,3, relative to LA4 = 4.

The second column of the table is, in essence, a welfare participation equation for those who share a household with others. Holding constant ADCDIF, the level of AFDC benefits has a positive effect on the probability of AFDC receipt. One might worry, however, that this may be due to a mechanical effect on the break-evens. Higher guarantees mean high break-evens, other things equal, and this may be what we are seeing in the coefficients. The third column of the table is a living-arrangement equation for welfare recipients. There we see the same AFDC effects on household composition as before (although neither coefficient is significantly different from zero.) These effects are similar to those found by Ellwood and Bane. These results suggest that the estimates discussed in the previous paragraph were not due simply to mechanical effects of changes in AFDC guarantees on break-evens. It is not true that householders and subfamily heads are just located at different points in the income distribution, and that changes in the AFDC break-evens simply pick up the new population. Further, we see similar AFDC effects when we run the analog of the model containing the demographic variables plus the two AFDC benefit variables (not shown). The AFDC

Table 4.6

The Determinants of the Living Arrangements of Young Women: Multinomial Logit Results, Reduced-Form, with Wage Rate and Other Income Imputations

Classification of Dependent Variable (LA4):

1 = Householder not receiving public assistance
2 = Woman in a subfamily, not receiving public assistance
3 = Householder receiving public assistance
4 = Woman in a subfamily, receiving public assistance

Independent Variable	Change in the Relative Odds of: 4 vs. 1 (1)	4 vs. 2 (2)	4 vs. 3 (3)
Constant	9.05 (.986)	2.41 (.978)	4.15 (.964)
AGE	-.364 (.048)	-.102 (.050)	-.198 (.048)
DEPENDS	-.326 (.184)	-.033 (.194)	-.334 (.176)
PRESCHOOL	.439 (.296)	.507 (.304)	-.103 (.299)
NONWHITE	-.488 (.299)	.024 (.294)	.002 (.291)
OY1	-.776 (.662)	1.06 (.670)	-.276 (.653)
OY3	-.246 (.040)	-.172 (.040)	-.026 (.040)
PWAGE1	.737 (.210)	.266 (.219)	.297 (.206)
PWAGE2	.038 (.211)	-.128 (.220)	.093 (.211)
AFDC1	2.39 (.959)	2.39 (1.00)	-1.56 (.909)
ADCDIF	-3.00 (2.64)	-.027 (2.96)	-4.88 (2.45)
Sample Size	1599		

Note: The asymptotic standard errors for the coefficient estimates appear in parentheses beside the estimates themselves.

Alternative Parameterization (see text note 4):

AFDC1	-.611 (2.73)	2.36 (3.05)	-6.46 (2.57)
AFDC3	3.00 (2.64)	.027 (2.96)	4.88 (2.45)

benefit variables are important in determining the choice between heading one's own household and sharing with others.

The wage variables are generally not statistically significant. The one significant effect is in the first column. The higher is the wage, the less likely is the woman to be a nonwelfare householder. This implausible result is similar to that noted above. It disappears when education is added to the model, and changes sign when age is excluded from the model. The coefficients on other income are neither robust nor plausible.

Table 4.7 presents our final model of living arrangements and welfare recipiency. This model is especially important. Not only is it the most general model presented thus far, but it is also the basis for our policy simulations in Chapter 6. The dependent variable takes on five values, as opposed to four, since married women are now included in the model.

The key coefficients are those on AFDC1 and ADCDIF. The positive coefficients on AFDC1 in columns 1-3 imply that an increase in the guarantee "if householder" (AFDC1) will decrease the number of women in the nonwelfare categories (i.e., married, householder not on welfare, and subfamily woman not on welfare). The increase in guarantee "if householder" will also shift welfare recipients into the householder category as indicated by the negative coefficient on AFDC1 in column 4. The results of simulation 1 in Chapter 6 are driven by that pattern of coefficients.

The coefficients on ADCDIF are less encouraging. An increase in ADCDIF amounts to an decrease in AFDC3 relative to AFDC1, holding

Table 4.7

The Determinants of the Living Arrangements of Young Women: Multinomial Logit Results, Reduced-Form, with Wage Rate and Other Income Imputations

Classification of Dependent Variable (LA5):

1 = Married woman
2 = Householder not receiving public assistance
3 = Woman in a subfamily, not receiving public assistance
4 = Householder receiving public assistance
5 = Woman in a subfamily, receiving public assistance

	Change in the Relative Odds of:			
	5 vs. 1	5 vs. 2	5 vs. 3	5 vs. 4
Independent Variable	(1)	(2)	(3)	(4)
AGE	-.665 (.049)	-.553 (.050)	-.174 (.053)	-.282 (.051)
DEPENDS	-.994 (.163)	-.513 (.176)	-.026 (.189)	-.349 (.172)
PRESCHOOL	-.326 (.269)	.648 (.282)	.546 (.292)	-.102 (.288)
NONWHITE	-.421 (.255)	-.540 (.276)	-.086 (.278)	-.012 (.275)
OY1	-.164 (.529)	.239 (.577)	1.139 (.574)	-.136 (.574)
OY3	-.518 (.038)	-.346 (.040)	-.196 (.041)	-.041 (.040)
PWAGE1	2.148 (.193)	1.258 (.204)	.500 (.215)	.474 (.203)
PWAGE2	.112 (.191)	.029 (.203)	-.068 (.216)	.030 (.207)
AFDC1	1.058 (.850)	1.642 (.927)	2.052 (1.00)	-1.424 (.913)
ADCDIF	1.226 (2.64)	-1.098 (2.87)	-.102 (3.18)	-4.974 (2.77)
Constant	14.588 (.980)	12.535 (1.03)	3.357 (1.05)	5.778 (1.02)
Sample Size	6341			

Note: The asymptotic standard errors for the coefficient estimates appear in parentheses beside the estimates themselves.

constant the level of AFDC1. This implies an overall decline in the generosity of the AFDC system and we would expect the number of welfare recipients to fall. Furthermore, there should be a switch of women in subfamilies into household headship. Thus the expected sign of all of the coefficients on ADCDIF is negative. The relative odds of being on welfare should fall as should the odds of being in a subfamily relative to being a household head. Three of the four coefficients are indeed negative. But the coefficient in the married equation (column 1) is positive, suggesting that a decrease in the generosity of AFDC will encourage married women to move to the "subfamily on welfare" status. While this coefficient is not significantly different from zero, its perverse sign will play an important role in simulations 2-4 in Chapter 6. The remaining coefficients in Table 4.7 are similar to those in Table 4.6.

4.2.4 Conditional Logit Models

Our theoretical model (see Chapter 3) suggests that we model the (indirect) utility attainable in any particular living arrangement as a function of the incomes and prices faced in that arrangement. In particular, we assume that each woman has a single indirect utility function which she uses to evaluate the attributes of each alternative living arrangement. Our goal, then, is to estimate the parameters of this indirect utility function in order to measure the impact of varying AFDC benefits across living arrangements.

In this section, we try to estimate these parameters with a conditional logit model.[6] In that model, the choice of living arrangement is a function of the AFDC income, other forms of nonwage income, and the wage rate available in each living arrangement. The logit coefficient on AFDC income is then interpreted as its parameter in the indirect utility function. In addition to the income variables, we add a number of "taste-shifter" variables, including such variables as family size and composition, race, and region of residence.

The results from models of this form are highly unstable (not shown). The AFDC coefficient can be made to be positive or negative, and significant or not significant, simply by changing the set of taste-shifter variables included in the model. The same is true for the coefficients on nonwage income and the wage rate.

There are two possible reasons for the failure of this model to perform well. The first is that the assumption of independence of irrelevant alternatives (IIA), implicit in all conditional logit models, is not true. This assumption states that the only variables that affect the relative probability of choosing between any two of a set of alternatives are attributes of those two alternatives, and that the attributes of any other alternative are irrelevant. In our case, for example, this would mean that the AFDC income available if the woman were to share a household with others does not affect her choice between marriage and heading a household.

Why might this assumption be violated in our model? Suppose that the living-arrangement decision occurs in two stages. In the first stage, the woman chooses between marriage and nonmarriage. If she chooses not to be married, then in the second stage she chooses between heading her own household and sharing a household with others. In this world, the

IIA assumption would be violated. The conditional logit model would be inappropriate and would not perform as well as expected.

The second possible reason for that the conditional logit model does not perform well is our reliance on the "expected conditions" class of model outlined in Chapter 3. In this class of model, we not only need to know the attributes of the living arrangement in which we actually observe the woman, but also the attributes of the other living arrangements which she did not choose. Since we only observe the attributes of her chosen living arrangement, we must impute the attributes of the nonchosen alternatives. For reasons discussed in Chapter 3, we then use the imputed attributes for all potential living arrangements, including the one which the woman is actually occupying. The efficacy of this technique depends in a crucial way on the accuracy with which we predict the wage rate, the AFDC income, and the nonwage income which the woman could receive in any living arrangement. If our imputations are poor, then one would expect the resulting empirical estimates to be unstable.

For two related reasons, our imputations may not be accurate measures of the true alternatives facing each woman. First, if the woman makes her choices based on more information (variables) than we have available to us (as we should expect to be the case), then our imputations may not reflect her assessment of the characteristics of the alternative living arrangements, even on average. If our errors are systematic, then we would expect the conditional logit results to be "wrong" and/or unstable.

In addition, even if we assume that we are not making any systematic errors in imputing the characteristics of the alternatives, we still have only a limited set of variables with which to construct our imputations.

Some of the variables used are also important in the woman's living-arrangement decision. For example, the woman's age affects not only her imputed wage but also the probability that she lives in a subfamily. Because we are imputing so many different things with the same limited number of explanatory variables, the imputations are highly collinear, and the results are likely to be unstable for that reason.

4.3 The Effect of Potential AFDC Benefits in Reduced-Form Models of the Employment, Schooling, and Welfare-Recipiency Decisions of Single Women

The question addressed in this section is "To what extent do welfare benefit levels affect a young single woman's choices with regard to employment, schooling, and welfare recipiency?" In answering this question, we use sets of four probit models, focusing on a subsample of young women (aged 35 or less) who are unmarried. We do not distinguish between householders and women living in subfamilies. That distinction will be the focus of Section 4.4.

The four probit models do not account for the simultaneous relationships that exist among employment, schooling, welfare recipiency, and living arrangements. Instead, each of the four dependent variables, INLF, FULL, SCHOOL, and WELFARE (defined in Table 4.1.) are fitted on a set of exogenous variables. Those variables (defined in Table 4.1), include age and education variables, region of residence variables, and several variables measuring the presence, number, and ages of children.

As in Section 4.2, the AFDC system is represented by the estimated payment that would be received by the woman if she were to become a householder (AFDC1). In addition, we include the variable ADCDIF, measuring the difference between potential AFDC benefits "if householder" and "if living in a subfamily." Results from models in which ADCDIF is excluded are almost identical to those reported here. Table 4.8 presents our results.

The role of potential AFDC benefits in determining employment differs according to whether we look at women who work full time, full year or at women who work only part time. In distinguishing between those who work and those who do not work at all (column 1), the level of potential AFDC benefits is an important factor. The coefficient on AFDC1 is large, negative, and significantly different from zero, implying that higher potential AFDC benefits lead to smaller probabilities of working. For women who work full time, full year (column 2), however, the level of benefits is not as important. Their attachment to the labor force dominates the change in potential benefits. This is reflected in the smaller and statistically insignificant coefficient on AFDC1. The difference in potential AFDC benefits across living arrangements (ADCDIF) has no bearing on either labor force participation decision.

Nonwhites are significantly less likely to be in the labor force than whites, ceteris paribus, but that distinction vanishes when we look at the determinants of working full time, full year. The coefficient on NONWHITE is large, negative, and statistically different from zero in column 1 of Table 4.8, but small and insignificant in column 2. This suggests that white women are considerably more likely than nonwhite women to work part time, but not more likely to work full time.

Table 4.8

The Determinants of Employment, Schooling, and Welfare Recipiency -
Reduced-Form Probit Models
(standard errors in parentheses)

Nonmarried Women (N = 1599)				
Independent Variables	INLF (1)	FULL (2)	SCHOOL (3)	WELFARE (4)
AGE	.178 (.079)	.494 (.111)	-.746 (.114)	.233 (.077)
AGE2	-.002 (.0014)	-.007 (.002)	.011 (.002)	-.003 (.001)
EDUC	-.014 (.121)	.252 (.175)	.312 (.214)	.596 (.129)
EDUC2	.009 (.003)	.001 (.005)	-.023 (.012)	-.023 (.004)
AGE * EDUC	-.001 (.004)	-.003 (.005)	.010 (.008)	-.009 (.003)
SOUTH	.092 (.108)	.208 (.114)	-.046 (.166)	-.390 (.110)
SMSA	-.133 (.082)	.104 (.088)	.138 (.133)	-.036 (.082)
UNEMPLOY	-.031 (.016)	-.036 (.017)	-.032 (.025)	.063 (.016)
NONWHITE	-.408 (.075)	-.093 (.082)	.280 (.114)	.466 (.076)
DEPENDS	-.208 (.046)	-.179 (.051)	-.209 (.087)	.195 (.046)
PRESCHOOL	-.331 (.088)	-.271 (.087)	.243 (.156)	.259 (.089)
AFDC1 ($000)	-.965 (.372)	-.667 (.415)	.315 (.624)	1.059 (.380)
ADCDIF ($000)	-.852 (.925)	-.385 (1.06)	.246 (1.64)	.579 (.933)
Constant	-2.43 (1.42)	-10.10 (2.19)	6.90 (1.64)	-6.60 (1.38)
Mean of Dependent Variable	0.59	0.29	0.07	0.40

As expected, having children of preschool age (PRESCHOOL) significantly reduces the probabilities of working; the more children a woman has (measured by DEPENDS), the less likely she is to work.

Also as expected, the primary determinant of school attendance (column 3) is age. The older the woman, the less likely she is to be in school. Potential AFDC benefits play no role in the schooling decision, as indicated by the small and statistically insignificant coefficients on AFDC1 and ADCDIF in column 3. The more children the woman has, the less likely she is to be in school. Nonwhites are more likely to be in school than whites.

A controversial issue of the past few years has been the extent to which the availability of welfare benefits encourages welfare recipiency. While our results (column 4) cannot shed any light on the relationship between availability and recipiency, we can see if differing levels of potential benefits affect the probability of welfare receipt. For single women, the effect of differing AFDC benefits across states is positive and significantly different from zero. Higher benefit levels lead to greater probabilties of receiving welfare.

Education has a significant and negative relationship to welfare recipiency. More years of education imply lower probabilities of being on welfare (since the positive coefficient on EDUC is outweighed by the negative coefficient on EDUC2). The more children a woman has, the more likely she is to be on welfare. Finally, nonwhites are significantly more likely to be on welfare than whites.

In the models reported in Table 4.8, a key independent variable has been omitted. If it were available, we would like to include the wage that a woman would receive if she worked. This wage is clearly an important determinant of whether a woman works, goes to school, or receives welfare. However, we observe the woman's wage only if she is actually working. As described in Section 4.1, we have used these observed wages to assign an estimated wage to each woman, regardless of her current employment status. This estimated wage is based on regressions of observed wages on age, education, race, and region of residence variables, where the sample for the regressions was women who worked.

Also omitted from the specification in Table 4.8 are any measures of income available to the woman from nonwage sources or from other household members. As described in Section 4.1, we also impute nonwage and others' income to each woman. These imputations are combined into a single measure of "other income" in the models discussed below (see Appendix A for details).

Table 4.9 reports the results of models in which our nonwage income and wage imputations are included. (This specification was discussed in more detail in the latter part of section 4.2.3.)

Comparing Tables 4.8 and 4.9, we see that the significance and direction of the coefficients on the AFDC variables has been maintained. In the equation for FULL, potential AFDC payments still negatively affect the probability of working full time, but the coefficient is now significantly different from zero. Potential AFDC payments remain irrelevant to the schooling decisions; they are still a large factor increasing the probability of receiving welfare.

The magnitude of the coefficient estimates on the AFDC variables is uniformly higher in the equations containing the predicted wages and the predicted nonwage and others' income.

Table 4.9

The Determinants of Employment, Schooling, and Welfare Recipiency:
Reduced-Form Models using Estimated Wages as an Independent Variable
(standard errors in parentheses)

Nonmarried Women (N = 1599)

Independent Variables	INLF (1)	FULL (2)	SCHOOL (3)	WELFARE (4)
AGE	.057	.055	-.031	-.070
	(.014)	(.014)	(.022)	(.014)
NONWHITE	.141	.374	.495	-.178
	(.106)	(.113)	(.157)	(.106)
DEPENDS	-.195	-.094	-.227	.008
	(.061)	(.068)	(.104)	(.062)
PRESCHOOL	-.214	-.241	.154	.337
	(.099)	(.100)	(.166)	(.101)
OY1 ($000)	.520	.210	.314	.086
	(.217)	(.246)	(.335)	(.224)
OY3 ($000)	.055	.053	.025	-.118
	(.013)	(.013)	(.018)	(.013)
PDWAGE1	.037	.173	-.188	.208
	(.065)	(.073)	(.101)	(.066)
PDWAGE3	.014	-.030	-.139	-.052
	(.073)	(.073)	(.115)	(.073)
AFDC1 ($000)	-1.554	-1.755	.281	-2.126
	(.315)	(.372)	(.529)	(.337)
ADCDIF ($000)	-.998	-.467	-.150	1.216
	(.912)	(1.05)	(1.59)	(.906)
Constant	-1.86	-3.356	-.058	1.863
	(.315)	(.333)	(.457)	(.318)
Mean of Dependent Variable	0.59	0.29	0.07	0.40

Interestingly, nonwhites are <u>more</u> likely to be in the labor force when potential wages and other income are held constant. The coefficient on NONWHITE in column 1 is positive (although not significantly different from zero) where it had been negative and significantly different from zero in column 1 of Table 4.8. Similarly, in the equation predicting the probability of working full time, full year (column 2), the coefficient on NONWHITE is positive and significant in Table 4.9 as compared to being negative though not significant in Table 4.8.

Our confidence in these results is tempered somewhat by the coefficient estimates on the wages and other income estimates themselves. We expect that higher wages should imply higher probabilities of working (columns 1 and 2 of Table 4.9). This expectation is borne out by the coefficient estimates on PWAGE1, in column 2. But in column 1, the coefficient is small and not significantly different from zero. The coefficients on the wage adjusted for the AFDC tax rate have the wrong sign in column 2 and are not significantly different from zero in either equation. Even more troubling are the coefficents on other income. We expect that more income from nonwage sources should lead to lower probabilities of working. Instead, the coefficients on other income are positive and significantly different from zero.

In the schooling equation (column 3), higher potential wages imply lower probabilities of being in school, as we would expect. In the welfare equation, higher wages (unadjusted for the tax rate on earned income) are positively correlated with the probability of receiving welfare.

While the equations containing predicted wages and nonwage income (Table 4.9) are theoretically superior to those with only exogenous variables (Table 4.8), we are inclined to put more faith in the latter.

4.4 The Effect of Living Arrangements on Employment, Schooling, and Welfare Recipiency in Simple, Reduced-Form Linear Models

The question that this section tries to address is: "To what extent do young women in different living arrangements differ in their employment, schooling and welfare recipiency?" This question differs from that in the previous section in that we do not focus on the effect of potential AFDC benefits and in that a dependent variable, living arrangement, is introduced into the analysis. In addition, the large group of married women, omitted from the discussion in Section 4.3, is analyzed here.

We begin by showing the proportion of women in the labor force (INLF), working full time, full year (FULL), in school (SCHOOL), and receiving welfare (WELFARE), broken down by living arrangement (Table 4.10). These proportions can be interpreted as unconditional mean probabilities of employment, schooling and welfare recipiency, since none of the exogenous variables are being held constant.

While being married is the dominant living arrangement for young women with children (74.7 percent), women in subfamilies constitute a fairly large subgroup (8.3 percent). Women householders are 16.9 percent of the sample.

There are three clear implications of Table 4.10:

1. Women in subfamilies are considerably more likely to be in school than either of the other groups.

Table 4.10

Descriptive Statistics from 1984 CPS for Employment, Schooling, and Welfare Recipiency, by Living Arrangement: Women, Aged 35 or Younger, with Children 18 or Younger

Living Arrangement[a]	Sample Size (1)	INLF (2)	FULL (3)	WELFARE (4)	SCHOOL (5)
Householder	1072	0.62	0.33	0.43	0.04
Public Assistance	464	0.28	0.03	1.00	0.04
No Public Assistance	608	0.89	0.56	-	0.03
Married	4742	0.61	0.24	0.03	0.02
Public Assistance	136	0.32	0.02	1.00	0.04
No Public Assistance	4606	0.62	0.25	-	0.02
Living in Subfamiliy	527	0.51	0.22	0.33	0.13
Public Assistance	176	0.24	0.01	1.00	0.13
No Public Assistance	351	0.65	0.32	-	0.13
All Unmarried Women	1599	0.59	0.29	0.40	0.07
All Young Women	6341	0.60	0.25	0.12	0.03

[a]Variable definitions can be found in Table 4.1

Note: These statistics are based on a randomly chosen group of 11,138 women, drawn from the overall CPS sample of 22,277 women. See Section 4.1.1.

2. Women in subfamilies are considerably less likely to work than either householders or married women. Householders are more likely to work than any other group, especially if they receive no public assistance.

3. Women who live in subfamilies, even though they have access to the income of other household members, are very likely to receive welfare. One-third of women in subfamilies receive welfare, as opposed to 43 percent among female householders.

Of course, these women differ in more ways than simply in living arrangements. Table 4.11 shows the means of the independent variables for each subgroup. As is clear from the table, women in subfamilies tend to be considerably younger than either householders or married women. Perhaps because of this, they tend to have fewer children (and thus lower predicted AFDC benefits). Another reflection of their lower age is their lower average level of education, almost a full year below the average for married women. The percentage of nonwhite women is considerably higher among householders and women in subfamilies than it is among married women.

Will the differences in unconditional means remain when the independent variables are held constant? A simple, although potentially misleading, way to check is to reestimate the employment, schooling, and welfare-recipiency equations of Section 4.3, adding variables indicating living arrangement.

Table 4.12 presents the results of this simple analysis. The four dependent variables are identical to those defined and analyzed in Section 4.3. The set of independent variables is virtually identical to that in Table 4.8. In Table 4.12, however, the sample includes all young women rather than only single women, as in Section 4.3. Further, we have added two dummy variables (HEAD and SHARE), reflecting the living arrangement of the woman.

Table 4.11

Means of Independent Variables Used in Models of Employment, Schooling, and Welfare Recipiency

Independent Variable	Householders (1)	Married Women (2)	Women Living in Subfamilies (3)
AFDC1[a] ($)	335.75	332.20	278.68
ADCDIF ($)	14.49	9.74	8.90
AGE (years)	28.43	28.82	24.68
EDUC (completed years)	12.60	13.30	12.09
SOUTH (1 = South)	0.29	0.31	0.41
SMSA (1 = SMSA)	0.75	0.69	0.74
UNEMPLOY (Percentage)	9.74	9.54	9.51
NONWHITE (1 = Nonwhite)	0.32	0.11	0.41
DEPENDS (Number of children)	1.93	2.00	1.43
PRESCHOOL (1 = Yes)	0.60	0.74	0.75
Sample Size	1072	4742	527

[a]AFDC1 is the maximum payment available to a householder in each woman's geographic state, adjusted for family size. Because of this, the average of AFDC1 for women in subfamilies is considerably smaller than that for householders, owing to the smaller average number of children among mothers in subfamilies.

Table 4.12

The Determinants of Employment, Schooling, and Welfare Recipiency with HEAD and SHARE Controls, Full Sample (N = 6341)
(standard errors in parentheses)

Independent Variables	INLF (1)	FULL (2)	SCHOOL (3)	WELFARE (4)
AGE	.237 (.043)	.448 (.057)	-.519 (.069)	.077 (.061)
AGE2	-.002 (.001)	-.006 (.001)	.008 (.0015)	-.001 (.001)
EDUC	.249 (.055)	.315 (.078)	.001 (.095)	.417 (.094)
EDUC2	.001 (.001)	-.002 (.002)	-.006 (.004)	-.018 (.003)
AGE * EDUC	-.006 (.002)	-.006 (.002)	.005 (.004)	-.005 (.003)
SOUTH	.057 (.051)	.192 (.054)	-.112 (.104)	-.313 (.082)
SMSA	-.120 (.038)	-.025 (.041)	.079 (.080)	-.030 (.060)
UNEMPLOY	-.026 (.007)	-.018 (.008)	-.007 (.015)	.040 (.011)
NONWHITE	-.073 (.047)	.217 (.049)	.222 (.085)	.416 (.062)
DEPENDS	-.210 (.021)	-.264 (.025)	-.178 (.053)	.144 (.032)
PRESCHOOL	-.420 (.044)	-.288 (.044)	-.019 (.093)	.179 (.070)
AFDC1 ($000)	-.229 (.372)	-.072 (.191)	.107 (.378)	.572 (.253)
ADCDIF ($000)	-1.03 (.422)	-.773 (.497)	.938 (1.00)	.851 (.599)
HEAD	.086 (.047)	.236 (.049)	.258 (.088)	1.75 (.061)

-continued-

Table 4.12 (continued)

Independent Variables	INLF (1)	FULL (2)	SCHOOL (3)	WELFARE (4)
SHARE	-.140	.023	.477	1.33
	(.065)	(.074)	(.101)	(.079)
Constant	-4.33	-9.45	5.64	-6.60
	(.734)	(1.06)	(1.09)	(1.38)
Mean of Dependent Variable	0.60	0.25	0.03	0.12

The only important coefficients here are those on HEAD and SHARE. Since we believe that the determinants of employment, schooling, and welfare-recipiency are different for married and single women (see Section 2), it is economically inappropriate to pool the samples as we have done here. Regardless of the lack of an economic interpretation, the coefficients on HEAD and SHARE indicate the differences in the conditional means of the dependent variables, holding the other variables constant at their respective group means. By pooling the data, we are constraining the coefficients on the other variables to be equal.

Surprisingly, the differences in schooling behavior (point 1 above) remain even after the differences in age between women in subfamilies and other women have been held constant. Women in subfamilies remain more likely to be in school than either householders or married women.

Point 2 was that women in subfamilies are considerably less likely to work than are householders (0.51 versus 0.62) or married women (0.51 versus 0.61). The difference with regard to working full time, full year was 0.22 versus 0.33 for householders and 0.22 versus 0.24 for married women. In contrast to the schooling equation, these differences do <u>not</u> persist when other variables are taken into account. A considerable amount of the difference in means for INLF disappears; the difference in conditional means for women in subfamilies versus married women drops from 0.10 to 0.05 (0.61 - 0.51 minus the derivative of -.05 implied by the coefficient of -0.14 on SHARE in column 1 of Table 4.12).[7] Similarly, the difference in mean labor force participation between subfamilies and householders drops from 0.11 to 0.09.

The simple mean for full-time, full-year work for married women was 0.24 versus 0.22 for subfamily women. The direction of this relationship changes in Table 4.12: women in subfamilies are slightly more likely to work full time, full year than married women. The difference between subfamily women and householders drops from .11 to .07.

Point 3 above was that women in subfamilies are more likely to be on welfare than married women (0.33 versus 0.03), but less likely to be on welfare than householders (0.33 versus 0.43). Holding the other variables constant, these differences diminish. The conditional mean for women in subfamilies is only 0.11 higher than that for married women. The difference between the conditional mean for women in subfamilies and householders drops from 0.10 to 0.04, when the other variables are held constant.

Including dummy variables for HEAD and SHARE allows only the intercept of the equations to vary while constraining all of the other coefficients to equality across living arrangements. If these coefficients are substantially different, the above results may be misleading. Tables 4.13 through 4.16 present the results of running separate regressions for our four dependent variables on the three distinct subsamples of householders, married women, and women in subfamilies. This procedure allows all of the coefficients to vary and leads to very different and more plausible results. Significance levels are not reported, since these are intended as descriptive regressions only.

It is apparent from Tables 4.13-16 that the coefficients differ considerably in magnitude. For example, the coefficient on AGE in the SCHOOL equations is considerably larger in the sample of women in subfamilies than it is in the other samples. Similarly, the coefficients on NONWHITE vary considerably in all the equations. And, of course, the

Table 4.13

Reduced-Form Models of Labor Force Participation (INLF), Subsamples of Householders, Married Women, and Women in Subfamilies

Independent Variables	Householders (1)	Married Women (2)	Women Living in Subfamilies (3)
AGE	0.071	0.331	0.224
AGE2 (000)	-0.681	-4.952	-1.687
EDUC	-0.166	0.175	0.345
EDUC2 (000)	0.014	-0.604	-2.702
AGE * EDUC (000)	0.280	-2.532	-5.728
SOUTH	0.180	0.169	0.054
SMSA	-0.136	-0.024	-0.149
UNEMPLOY	-0.040	-0.045	-0.019
NONWHITE	-0.370	0.355	-0.470
DEPENDS	-0.192	-0.242	-0.370
PRESCHOOL	-0.382	-0.381	-0.154
AFDC1 ($000)	-1.075	-0.230	-0.538
ADCDIF ($000)	-1.405	-0.623	1.453
Constant	0.161	-5.108	-5.224
Sample Size	1072	948	527

Source: Computations by authors. The married subsample is a randomly chosen subset of the complete sample.

Table 4.14

Reduced-Form Models of Working Full Time, Full Year (FULL), Subsamples of Householders, Married Women, and Women in Subfamilies

Independent Variables	Householders (1)	Married Women (2)	Women Living in Subfamilies (3)
AGE	0.337	0.437	0.629
AGE2 (000)	-3.786	-5.241	-9.628
EDUC	0.360	0.263	0.133
EDUC2 (000)	0.496	0.564	1.598
AGE * EDUC (000)	-6.044	-7.684	-0.695
SOUTH	0.279	0.113	0.077
SMSA	0.098	-0.030	0.151
UNEMPLOY	-0.043	-0.029	-0.020
NONWHITE	-0.174	0.440	0.119
DEPENDS	-0.171	-0.381	-0.261
PRESCHOOL	-0.325	-0.252	-0.127
AFDC1 ($000)	-0.530	-0.103	-0.997
ADCDIF ($000)	-0.508	-1.758	-1.160
Constant	-8.417	-8.382	-11.361
Sample Size	1072	948	527

Source: Computations by authors. The married subsample is a randomly chosen subset of the complete sample.

Table 4.15

Reduced-Form Models of Schooling (SCHOOL), Subsamples of Householders, Married Women, and Women in Subfamilies

Independent Variables	Householders (1)	Married Women (2)	Women Living in Subfamilies (3)
AGE	-0.342	0.152	-0.761
AGE2 (000)	4.727	6.528	9.976
EDUC	0.394	2.084	0.329
EDUC2 (000)	-20.737	-36.832	-0.026
AGE * EDUC (000)	5.649	-38.995	11.730
SOUTH	0.022	-0.051	-0.078
SMSA	0.282	0.074	-0.068
UNEMPLOY	-0.011	-0.075	-0.046
NONWHITE	-0.233	-0.046	0.796
DEPENDS	-0.123	-0.105	-0.454
PRESCHOOL	0.257	0.140	-0.123
AFDC1 ($000)	0.143	-2.686	1.081
ADCDIF ($000)	-0.851	3.826	1.537
Constant	0.380	-16.891	7.847
Sample Size	1072	948	527

Source: Computations by authors. The married subsample is a randomly chosen subset of the complete sample.

Table 4.16

Reduced-Form Models of Welfare Recipiency (WELFARE), Subsamples of Householders, Married Women, and Women in Subfamilies

Independent Variables	Householders (1)	Married Women (2)	Women Living in Subfamilies (3)
AGE	0.020	-0.044	0.117
AGE2 (000)	1.018	-0.144	-1.396
EDUC	0.587	0.151	0.683
EDUC2 (000)	-20.914	-11.293	-29.502
AGE * EDUC (000)	-11.082	0.436	-5.750
SOUTH	-0.514	-0.181	-0.268
SMSA	0.016	-0.024	-0.132
UNEMPLOY	0.080	0.018	0.014
NONWHITE	0.701	0.253	0.255
DEPENDS	0.155	0.130	0.217
PRESCHOOL	0.321	-0.011	0.176
AFDC1 ($000)	1.124	0.367	0.667
ADCDIF ($000)	1.203	0.831	-0.834
Constant	-3.393	-1.320	-2.639
Sample Size	1072	948	527

Source: Computations by authors. The married subsample is a randomly chosen subset of the complete sample.

coefficients on the AFDC variables are very small in the sample of married women. These variations in coefficients make a considerable difference in calculating conditional means for the dependent variables.

In Table 4.17, we compare the mean probabilities of employment, schooling, and welfare recipiency for three "typical" women who are assumed to be identical in the sense that the values of the independent variables are the same. These "typical" women differ only in their living arrangements. In the model reported in Table 4.12, the effect of different living arrangements is entirely captured by the coefficients on HEAD and SHARE. Here, however, all of the coefficients may differ. The values of the independent variables assumed in this discussion are the overall means:

AFDC1	=	328
ADCDIF	=	10
AGE	=	28
EDUC	=	13
SOUTH	=	0.3
SMSA	=	0.7
UNEMPLOY	=	9.5
NONWHITE	=	0.17
DEPENDS	=	1.9
PRESCHOOL	=	0.7

In Table 4.17, the second line for each dependent variable is the calculated conditional mean using the coefficients in Table 4.13-16 and the values listed above. The third line is the conditional mean, calculated in the same way as the second, except that age is set equal to 20 rather than 28. The first line is the unconditional mean reprinted from Table 4.10.

As Table 4.17 indicates, holding all the independent variables constant while letting the coefficients vary has a pronounced leveling

Table 4.17

Predicted Probabilities, at the Means, of the Independent Variables of Employment, Schooling, and Welfare Recipiency, by Living Arrangement

	Householder (1)	Married Woman (2)	Woman Living in Subfamily (3)
Probability of Being in the Labor Force			
Unconditional Mean	0.62	0.61	0.51
Conditional Mean (Age = 28)	0.68	0.66	0.63
Conditional Mean (Age = 20)	0.55	0.47	0.42
Probability of Working Full Time, Full Year			
Unconditional Mean	0.33	0.24	0.22
Conditional Mean (Age = 28)	0.34	0.25	0.30
Conditional Mean (Age = 20)	0.15	0.09	0.04
Probabilty of Being in School			
Unconditional Mean	0.04	0.02	0.13
Conditional Mean (Age = 28)	0.04	0.01	0.01
Conditional Mean (Age = 20)	0.07	0.02	0.09
Probability of Receiving Welfare			
Unconditional Mean	0.43	0.03	0.33
Conditional Mean (Age = 28)	0.36	0.03	0.31
Conditional Mean (Age = 20)	0.60	0.06	0.39

effect on the mean probabilities of employment, schooling, and welfare recipiency. This is primarily because of the different age and education composition of subfamilies versus householders and married women.

With regard to point 1, stated at the beginning of this section, the difference in schooling behavior depends critically upon age. At younger ages, women in subfamilies are somewhat more likely than other women to be in school, while at older ages, women in subfamilies are less likely to be in school. The reason that the conditional and unconditional means differ so greatly is a combination of (a) the difference between the average age of women in subfamilies (about 24) and the value assumed here (28); and (b) the large coefficient on age in the SCHOOL equation for subfamilies (see Table 4.15).

On point 2, the three groups are closer in terms of the probability of working full time, full year once the independent variables are held constant at their means (where age equals 28). When age is held constant at 20, however, the differences remain quite pronounced. This is also the case for those who work less than full time, full year.

On point 3, the gap between the probability of receiving welfare for householders and women in subfamilies becomes somewhat narrower at age 28 and wider at age 20. Not unsurprisingly, the probability that married women receive welfare remains near zero.

In conclusion, if we compare economic behavior at the sample means, the fairly wide differences in economic behavior which seem to be implied by simple averages do not appear as wide. If, however, we compare economic behavior at the sample means, but set age equal to 20 years, the wide differences remain. At least for younger women then, there seem to be important differences in economic behavior across living arrangements.

Notes

[1]In making our extract, we utilized the now correct coding of subfamilies (see Ellwood and Bane, 1983). The data file was constructed at the Institute for Research on Poverty.

[2]All of the models discussed in this section are based on a half sample of our CPS extract. We utilize a half sample in order to reduce computational costs.

[3]It is important to note, in reading the tables in this section, that the coefficients we present are the negative of the coefficients discussed in the Appendix. The discussion will make clear the appropriate interpretation.

[4]There is another way to parameterize this model, which is to enter AFDC1 and AFDC3 separately. If that were done, the coefficient on the benefits available to a subfamily head (AFDC3) would be the negative of the coefficient on ADCDIF. The coefficient on the level of benefits available to a household head (AFDC1) would be the sum of the coefficients on AFDC1 and ADCDIF. These are shown, with standard errors, below Tables 4.4 and 4.5.

[5]The results were unchanged when measures of nonwage income which net out the AFDC tax on unearned income (NWIMP4, NWIMP6, IOTHERS4 and IOTHERS6) were substituted.

[6]See Appendix B for details on the various forms of logit models and their interpretations.

[7]The effect of a one-unit change in an independent variable on the probability of being in the labor force (or working full time, being in school or on welfare) is the coefficient from the probit equation multiplied by the constant $k*(1-k)$, where k is the mean of the dependent variable.

Appendix A

Detailed Description of the Construction of Imputations

Wage Imputations

To estimate wages for those women who are not working, we examine the determinants of the wages of those women who do work. That is, we estimate an earnings function for the women who work and then use that earnings function, in combination with the characteristics of the women who do not work, to estimate wages for the latter group.

The wage variable itself was constructed from the CPS data in the following way. For those who worked full time, full year, a variable representing their "annual hours worked" was constructed by multiplying "weeks worked" by average "hours worked per week." "Wage" was then calculated as total annual earnings divided by annual hours worked. The natural logarithm of this variable was then used as the dependent variable in the wage equations.

The specification of the earnings function follows the standard human capital model. Education and age figure prominently in that specification; they are entered linearly, as squares, as cubes and in interactions up to the third order. The "residence" variables (NEAST, NC, WEST and SMSA) were included, along with the race variables (NONWHITE and HISPANIC).

Because the possibility of selection bias is introduced by the restriction of the subsample to working women, we followed the technique for correcting for selectivity bias made popular by Heckman (1979). For each subsample, we estimated an equation for the probability of working full time, full year and then used that probability to compute the "hazard ratio" for each woman. This "hazard ratio" was then used as a regressor in the earnings function. If the "hazard ratio" was significantly different from zero, this regression was used for the imputation. If it was not significantly different from zero, an earnings function estimated without the "hazard ratio" term was used to produce the imputation. In either case, the actual "hazard ratio" was not itself used in the imputation.

This general specification was used in two different ways which lead to two different imputed wages. The first method involved using the specification on each of the three subgroups-household heads (LA3=1), married women (LA3=2), and subfamily members (LA3=3). Using these three separate regressions, a wage was then imputed to each member of the entire sample. The imputed wage for household heads (married women, subfamily members) was imputed using the regression run on the subsample of working household heads (married women, subfamily members). The result of this procedure is PWAGE1, used in our analyses in Chapter 4.

The second method consisted of estimating a single wage function using a subsample of all working women regardless of living arrangement, and then using it to impute a wage to all those who were not working.

Nonwage Income Imputations

"Nonwage income" is income received directly by the family of each woman, which is not the result of working in the market and not the result of government transfers. Specifically, NONWAGE is "family income" received from interest, dividends, rental income, retirement benefits, child support and alimony. Each living arrangement is characterized by a different expected "nonwage income." For example, women who head their own households will have higher expected "nonwage income" than married women, ceteris paribus, since child support is one source of nonwage income. We therefore impute an estimated nonwage income for each of the living arrangements.

We impute nonwage income by looking at the determinants of nonwage income for those in each living arrangement who actually receive nonwage income. That is, we run three separate regressions on the three subsamples consisting of those women who are married, heading their own households and living in subfamilies, respectively.

The independent variables used to predict nonwage income for each living arrangement are similar to those used in imputing wages. However, in addition to the age, education, race and residence variables listed in Table A.1, we include a set of variables reflecting the age and number of dependents (PRESCHOOL, TEENAGER, and DEPENDS) and a variable which indicates whether the woman was unemployed (UNEMPLOY). A variable indicating whether or not the woman had ever been married (NEVERMAR) was included in the regression for women who were either heading their own households or living in subfamilies. No correction was made for selectivity bias in these equations. Table A.2 reports the regression used to construct nonwage income imputations.

Using the coefficients reported in Table A.2, we computed an estimated nonwage income "if heading own household," "if married," and "if living in a subfamily" for each woman in our sample.

Table A.1

Wage Imputation Regressions:
Sample Used for Wage Regression

Full Sample	LA3=1		LA3=2		LA3=3		Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AGE	0.442*	0.425*	0.554*	0.487*	0.152	0.0918	0.398
AGE2	-0.00959*	-0.00898*	-0.0134*	-0.0129*	-0.00302	-0.00193	-0.00935
AGE3 (000)	0.0739*	0.0690*	0.109*	0.116*	0.0121	0.00364	0.0736
EDUC	0.340	0.465	0.0369	-0.0991	0.410	0.234	0.153
EDUC2	-0.010	-0.0183	0.0111	0.0139	-0.0357	-0.0243	-0.0005
EDUC3 (000)	0.0334	0.188	-0.373	-0.461	1.160	0.949	-0.0735
AE	-0.00978	-0.0119	-0.00789	-0.00233	0.00372	0.00664	-0.00691
AE2 (000)	0.275	0.339	0.169	0.169	-0.212	-0.353	0.16676
A2E (000)	0.0396	0.0468	0.0570	-0.019	0.0111	-0.012	0.046089
NONWHITE	-0.039	-0.0124	0.0750	-0.0199	-0.0691	-0.0529	0.0071
HISPANIC	-0.154*	-0.142*	-0.103	-0.117	-0.00403	-0.0124	-0.0309
NEAST	0.0368	0.0885	0.0202	0.0775	0.00604	0.0324	0.00795
NC	0.0515	0.0992	-0.0832	-0.0364	0.07	0.106	-0.0291
WEST	0.0938*	0.140*	0.0864	0.141	0.0704	0.100	0.0159
SMSA	0.136*	0.121*	0.182*	0.173*	0.096	0.0771	0.171
LAMBDA[a]	-	0.109	-	0.326*	-	0.103	-
Constant	-5.791	-5.994	-5.828	-4.517	-2.824	-1.509	-4.323
Adjusted R^2	0.110	0.113	0.109	0.114	0.214	0.214	
Std. Error	0.520	0.519	0.729	0.728	0.380	0.380	
Mean LNWAGE	1.818	1.818	1.807	1.807	1.714	1.714	
Sample Size	1562	1562	1234	1234	257	257	

*Significantly different from zero at the 1% level of significance.
[a]This is the "hazard ratio," described in the text.

Table A.2

Nonwage Income Imputation Regressions:
Living Arrangement Subgroup, Given NW=1

	LA3=1 (1)	LA3=2 (2)	LA3=3 (3)
AGE	702.592	- 845.461	-1031.846
AGE2	- 10.650	19.607	4.969
AGE3 (000)	50.01	- 131.13	- 23.99
EDUC	3152.532	-1316.446	-6732.804
EDUC2	- 180.145	81.571	394.174
EDUC3 (000)	3814.82	-2003.14	-7124.49
AE	- 101.2878	7.112	109.989
AE2 (000)	2609.64	369.77	-3867.54
A2E (000)	846.5	- 101.55	81.52
NONWHITE	-1173.520*	- 545.649	296.817
HISPANIC	-1032.247	- 690.785	-67.211
NEAST	363.969	- 544.807	-41.521
NC	8.824	- 780.958*	-23.967
WEST	120.655	- 488.676	419.635
SMSA	24.927	146.217	268.496
DEPENDS	400.076*	- 74.650	226.718
TEENAGER	166.442	- 199.996	-262.939
PRESCHOOL	- 481.914	- 205.668	-232.939
UNEMPLOY	- 67.072	31.001	- 10.101
NEVERMAR	- 351.912	-	-671.404

-continued-

Table A.2 (continued)

	LA3=1 (1)	LA3=2 (2)	LA3=3 (3)
Constant	-13351.485	16789.053	40388.210
Adjusted R^2	0.113	0.045	0.069
Std. Error	5341.02	5149.22	2066.62
Mean NONWAGE	2802.73	1828.42	1374.83
Std Dev NONWAGE	5671.09	5268.96	2141.52
Sample Size	2011	3071	295

*Significantly different from zero at the 1% level of significance.

To account for the fact that not all women receive nonwage income, we compute an alternative estimate of expected nonwage income using a two-stage method. We first create a dummy variable (named NW) which takes the value 1 if the woman receives nonwage income. We then run a logit model using NW as the dependent variable. Using the coefficients from this model, we compute an estimated probability of receiving nonwage income in each living arrangement. We then compute our alternative measure of expected nonwage income as the imputation from Table A.2 multiplied by the estimated probability of receipt.

Imputed Income from Other Household (Family) Members

One of the most striking changes in income when families split up is the loss to the family or household of income generated by the adult who leaves the household. This is especially true for households or families headed by women. The expected income "if heading own household" is clearly an important factor in living arrangement decisions.

We impute to each woman in our sample an income which she expects to have available to her from other family or household members in each of the three living arrangements. As before, we observe "others' income" only in one of the three living-arrangement statuses. We therefore regress observed "others' income" on a set of explanatory variables in each of the three subsamples and then use the result to impute an "others' income" to women in other living arrangements.

For all women (whether currently heading their own households or "imagining" doing so) we set others' income "if household head" equal to zero. For married women, others' income is defined as total household income less total personal income. For women who live in subfamilies, others' income is defined as total household income less total family income. The set of independent variables is identical to that used in the nonwage income equations reported in Table A.2. Table A.3 reports our results.

The coefficients in column 2 and 3 are then used on the full sample of women to impute others' income "if household head" and "if living in a subfamily."

AFDC Benefit Imputations

A key element of our work is to estimate the AFDC benefits which would be available to each woman were she to head her own household. Chapter 2 summarizes our efforts collect data on how AFDC benefits vary by geographic state and by living arrangement. Using the methods described there, we computed estimates of the potential benefits available to householders (AFDC1), married women (AFDC2) and women in subfamilies (AFDC3).

Estimates of the AFDC payments which would be available in each living arrangement are derived from equation (2.1) and the associated parameter estimates (Table 2.2). The benefit available to women who head their own households is $B_0 + B_3$MXBEN; to married women, the estimated payment is $B_0 + B_1$MAR + B_3MXBEN; and for women in subfamilies the estimated benefit is $B_0 + B_2$SHARE + B_3MXBEN.

A second set of estimates was also generated using the 1982 Quality Control data. These estimates are identical to those described immediately above except that two interaction variables (SHARE*MXBEN and

Table A.3

Others' Income Imputation Regressions:
Living Arrangement Subgroup

	LA3=1[a] (1)	LA3=2 (2)	LA3=3 (3)
AGE	-	-2026.528	-2386.406
AGE2	-	35.545	62.505
AGE3 (000)	-	- 205.84	- 571.57
EDUC	-	-9252.731*	-3244.316
EDUC2	-	555.573*	250.381
EDUC3 (000)	-	-12719.04 *	195.98
AE	-	204.032	48.951
AE2 (000)	-	-2172.	-3600.42
A2E (000)	-	-1554.8	16.98
NONWHITE	-	-5015.785*	-4560.867*
HISPANIC	-	-2612.012*	-1733.445
NEAST	-	593.455	1347.008
NC	-	- 454.125	1763.034
WEST	-	709.690	2045.279
SMSA	-	3711.264*	1446.902
DEPENDS	-	- 643.796	-1248.387
TEENAGER	-	343.442	467.905
PRESCHOOL	-	- 676.663	839.072
UNEMPLOY	-	77.669	- 719.439*
NEVERMAR	-	-	-2822.363*

-continued-

Table A.3 (continued)

	LA3=1[a] (1)	LA3=2 (2)	LA3=3 (3)
Constant	-	58378.203	56044.693
Adjusted R^2	-	0.173	0.116
Std. Error	-	15454.93	13914.48
Mean NONWAGE	-	24504.46	17799.01
Std Dev NONWAGE	-	16997.04	14800.82
Sample Size	-	4378	1141

*Significantly different from zero at the 1% level of significance.

[a]Imputed others' income "if household head" is set equal to zero (see text).

MAR*MXBEN) were added to the PAYSTD regression specified above, in equation (2.1).

As a check on both the Quality Control data and on the institutional data, we also estimated the parameters of equation (2.1), both with and without the interaction terms, using the 1979 AFDC Survey.

Summary

Table A.4 contains a list of all the variables which we have imputed and which are used in Chapter 4.

Table A.4

List of Imputations Used in Chapter 4		
PWAGE1	-	Imputed wage constructed from three subsample wage regressions.
PWAGE2	-	Imputed wage, net of AFDC tax rates on earned income. State-specific tax rates drawn from Fraker, Moffitt, and Wolf (1985).
OY1	-	Estimated "other income" available to each woman as a householder. This is NWIMP1.
OY3	-	Estimated "other income" available to each woman as a subfamily member. This is the sum of NWIMP3 and IOTHERS3.
AFDC1	-	Estimated AFDC benefits available to each woman as a householder.
AFDC3	-	Estimated AFDC benefits available to each woman as a subfamily member.
ADCDIF	-	AFDC1 - AFDC3

Appendix B

Notes on Logit Models

1. Conditional Logit Model (CL)

This is a model of probabilistic choice. Suppose that an individual must choose one of J alternatives. Each alternative j, j = 1, ..., J is characterized by a vector of alternative-specific characteristics, x_j. For example, if there are two alternatives, married or not married, then the x vector contains the determinants of utility (income, leisure, etc.) specific to that alternative. We assume that there is a representative component of utility, common for all individuals, and then idiosyncratic taste variation around the representative component. Let U(j) be the utility attainable in alternative j, and write

(1) $$U(j) = \mu_j + \varepsilon_j,$$

where μ_j is the representative component of utility and ε_j represents idiosyncratic taste variation. We might interpret μ_j as the average utility in alternative j. We expect that average to depend on the alternative-specific characteristics of the state x_j, as well as on some unknown parameters, say β. The parameters β have the interpretation of parameters of an indirect utility function. We therefore write

(2) $$\mu_j = \mu_j(x_j, \beta).$$

The Standard Form

In most applications (as in the original paper by McFadden, 1981) the μ_j function is assumed to be linear in x_j, and we therefore write the utility associated with alternative j as

(3) $$U(j) = \beta.xj + \varepsilon j.$$

We now must specify the probability distribution of the idiosyncratic component of utility. This has the interpretation of a disturbance (in econometric terminology). We will assume that the ε_j ($j = 1, \ldots, J$) are independent and identically distributed random variables, each of which is extreme value (Type I). Substantively, the major restriction which is imposed at this step is the assumption that the idiosyncratic component of utility in one alternative is independent of its counterpart in a different alternative, for the same economic agent. This is known as the IIA (Independence of Irrelevant Alternatives) assumption, and has received much criticism. The force of the IIA assumption is that the relative odds of choosing alternative j over alternative k do not change when another possible alternative, say i, is added to the set of possible choices. We will discuss this assumption in more detail below. The power of the IIA assumption is that it (1) yields econometric models which are quite tractable, and (2) allows one to predict the probability of choosing a new alternative which does not currently exist, given knowledge of its attributes.

Given these assumptions, we can write the probability of observing the individual in state j as

(4) $$P(j) = \exp\{\beta . x_j\} \;/\; [\Sigma_k \exp\{\beta . x_k\}],$$

where the summation is over the set of possible alternatives. Define the indicator variables $d_k = 1$ if state k is chosen and 0 otherwise, for each of the possible choices $k = 1, \ldots, J$. Then the log likelihood function is (for a single observation):

(5) $$L = \Sigma_k d_k . (\beta . x_k) - \log\, [\Sigma_k \exp\{\beta . x_k\}].$$

The score vector $S = \partial L/\partial \beta$ can be written as

$$(6) \qquad S = \Sigma_k\, d_k\, x_k - [(\Sigma_k\, x_k \exp\{\beta . x_k\}) \,/\, (\Sigma_k \exp\{\beta . x_k\})].$$

A Minor Extension

Note that there is nothing sacred about the linear "utility" function in equation (3). Linearity is used for ease of computation. The key to this specification is that the disturbance term, which is interpreted as idiosyncratic taste variation, is (1) additive, (2) independent of the deterministic part of the utility function, and (3) follows the assumed distribution. Hence, if we write down a "structural" form for the deterministic part of the utility function, and then add a stochastic term to it, we can still use the conditional logit formulation.

Suppose that a theoretical model yields a function $g(x_j, \beta)$ as the representative portion of U(j) (i.e., the mean μ_j), the utility realized in state j. In order to reduce notational clutter, we utilize the following conventions:

$$g_k = g(x_k, \beta)$$
$$G_k = \partial g(x_k, \beta) \,/\, \partial \beta.$$

Then we can rewrite the equations for the probability of state j, the log likelihood function, and the first-order conditions for the maximum likelihood problem as follows:

$$(4a) \qquad P(j) = \exp\{g_j\} \,/\, [\Sigma_k \exp\{g_k\}]$$

$$(5a) \qquad L = \Sigma_k\, d_k\, g_k - \log\, [\Sigma_k \exp\{g_k\}]$$

$$(6a) \qquad S = \Sigma_k\, d_k\, G_k - [(\Sigma_k\, G_k \exp\{g_k\}) \,/\, (\Sigma_k \exp\{g_k\})].$$

Note that in the special case in which $g(x_k, \beta)$ is linear, the derivative G_k is simply the attribute vector x_k, and these forms reduce to the forms shown above for the linear utility model.

The Choice Set

Note that, due to the IIA assumption, there is no requirement that the choice set be the same for all individuals in the conditional logit model. When the choice set varies among individuals ($n = 1, \ldots, N$), then we simply denote by B_n the set of choices available to individual n, and the summations above are simply summations over the set of choices in the budget set B_n (J_n of them).

Testing the IIA Assumption 1

There is a "standard" test of the IIA assumption in the literature: If the IIA assumption were true, then the parameter estimates are invariant to the inclusion of nonchosen alternatives. The proposal is then to estimate the parameters of the CL model using only a subset of the possible alternatives. Under the null, this estimator, call it β_1, is consistent, but not efficient. The CL estimator which uses all possible alternatives, call it β_0, is efficient, under the null. One then performs the standard Hausman-Wu type test, testing whether the two parameter vectors are the same.

Let V_1 and V_0 denote the variances of β_1 and β_0, respectively. Because β_0 is efficient while β_1 is consistent, it follows that the variance of $(\beta_0 - \beta_1)$ is $(V_1 - V_0)$. [Theorem: Any efficient estimator is uncorrelated with any random variable with mean zero. Hence, $\mathrm{Cov}[\beta_0, (\beta_0 - \beta_1)] = 0 = \mathrm{Var}(\beta_0) - \mathrm{Cov}(\beta_1, \beta_0)$.] The form of the test statistic is then

$$(\beta_0 - \beta_1)' \ (V_1 - V_0)^+ \ (\beta_0 - \beta_1),$$

where the "+" denotes a generalized inverse. Under the null, this statistic is asymptotically distributed as a chi-square with parameter m, where m is the rank of the difference of the variance matrices. As usual, the asymptotics are unaffected by replacing V_1 and V_0 by consistent estimators. Note that this test depends crucially on the maintained hypothesis that only attributes of a particular alternative affect the "utility" associated with that alternative.

2. The Multinomial Logit Model (MNL)

This model can be interpreted in a number of ways: (1) It is a flexible approximation to the log odds function, that is, the logarithm of the relative probability of choosing one alternative over another. (2) It is a reduced-form version of the conditional logit model described above. (3) It is a model which provides the "best" method (in a particular Bayesian sense) of discriminating among different populations. We will focus on the first two interpretations here.

Log Odds Function Interpretation

One can view the multinomial logit model as a flexible approximation to a log odds function. Let p_j denote the probability of choosing alternative j, and let p_k denote the probability of choosing alternative k. Suppose that there are J possible choices, and further suppose that the choice probabilities depend on some characteristics of the chooser, call them z. The multinomial logit model assumes the following form for the log odds function:

$$\text{(7)} \qquad \log\,[p_j \;/\; p_k] = z.(\gamma_j^{*} - \gamma_k^{*}).$$

The attribute vector z may have nonlinear functions (e.g. polynomial terms) of the attributes of the chooser, and is hence an approximation to an arbitrary log odds function in the same way that a least squares model is an arbitrary approximation to an unknown function. Equation (7) implies that the choice probabilities take the following form:

(8) $P(\text{choose } j) = \exp\{z.\gamma_j^*\} \,/\, [\Sigma_k \exp\{z.\gamma_k^*\}], \; j = 1, \ldots, J$;

where, as in the conditional logit model, the summation is over the possible alternatives $k = 1, \ldots, J$. While this probability is of a similar form to that of the conditional logit model above, there is a fundamental difference between them. In the conditional logit model the parameter vector β is the same for all alternatives, and it is the <u>attribute vector x_j which varies</u>. In the multinomial logit model, in contrast, the attribute vector z is the same for all alternatives, and it is the <u>parameter vector γ_j^* which varies</u>.

In the multinomial logit model we require a normalization in order to define the parameters. Because the probabilities must sum to one, if we know (J-1) of the probabilities, then we know all J of them. Hence there cannot be J free parameter vectors γ_j^*. There are a number of possible normalizations. One could make the γ_j^* vectors sum to zero. An easier (more interpretable) normalization is to set one of the parameter vectors equal to zero. The interpretation derives as follows:

One can manipulate the probability in equation (8) in the following manner: Choose a particular alternative to be the base case, for instance, the last alternative J. Then divide both the numerator and the denominator of the probability in equation (8) by $\exp\{z.\gamma_J^*\}$. This yields the following alternative form of the multinomial logit model:

$$\text{(8a)} \qquad P(\text{choose } j) = \exp\{z.(\gamma_j^* - \gamma_J^*)\} \;/\; [\Sigma_k \exp\{z.(\gamma_k^* - \gamma_J^*)\}],$$
$$j = 1, \ldots, J \;;$$

Note that when we are dealing with alternative J, the base case, the difference in the parameter vectors in the equation above is zero, and we have the term $\exp\{0\} = 1$. In order to reduce the amount of notation, let us define the normalized parameter vectors as γ_k, where

$$\text{(9)} \qquad \gamma_k = \gamma_k^* - \gamma_J^*,$$

and $\gamma_J = 0$ by construction. The log odds interpretation in equation (7) follows by dividing P(choose j) by P(choose k) and then taking logs. We can then rewrite the multinomial logit model in the following form:

$$\text{(8b)} \qquad P(\text{choose } j) = \exp\{z.(\gamma_j^* - \gamma_J^*)\} \;/\; [(\Sigma_k \exp\{z.(\gamma_k^* - \gamma_J^*)\}) + 1],$$

where the summation now goes from 1 to (J-1) (because γ_J is zero).

The parameters γ_j give information on the effect of a variable in z on the relative odds of choosing alternative j over the base case, alternative J. Thus, if a coefficient γ_j on a variable in z is positive, then a large value of that variable in z makes alternative j more likely than the base case, alternative J. We can also get information on the relative odds of choosing alternative i over alternative k, as follows: The log of the relative probability of choosing alternative i over alternative k is, by equation (7), equal to $z.(\gamma_i^* - \gamma_k^*)$. The difference $(\gamma_i - \gamma_k)$ (that is, the difference in our normalized parameters), is, by substitution, equal to $(\gamma_i^* - \gamma_k^*)$. Therefore, if $(\gamma_i - \gamma_k)$ is positive for a variable in z, a large value of that variable makes alternative i relatively more probable than alternative k.

Reduced-Form Interpretation

We can interpret the multinomial logit model as a reduced form of the conditional logit model which loosens the IIA assumption (subject to some limitations, described below). That is, in the multinomial logit model we allow the attributes of a third alternative to influence the relative odds of choosing between any other two alternatives. If the conditional logit model were correct, then we would see a particular pattern in the multinomial logit coefficients.

Maintain the same setup as for the conditional logit model. An individual must choose from among J alternatives. However, we now take all the attribute vectors for each possible alternative and consider them as a single large vector, say z. That is, we define

$$(10) \qquad z = (x_1, x_2, \ldots, x_J)'.$$

If there are q elements in each of the alternative-specific attribute vectors x_j, then the dimension of z is qJ.

If the conditional logit model were correct, then we would be able to express the multinomial logit parameters γ_k as a function of the conditional logit parameter β. As a concrete example, consider the situation in which there are three possible choices ($J = 3$). Then the vector z consists of x_1, x_2, and x_3. For simplicity, suppose that each of x_i's is a scalar. Then there will be two parameter vectors in the multinomial logit model, γ_1 and γ_2 (remember that $\gamma_3 = 0$), which will take on the following values:

$$(11) \qquad \gamma_1 = (\beta, 0, -\beta); \quad \gamma_2 = (0, \beta, -\beta).$$

If the conditional logit model were correct (in particular, if the IIA assumption is correct), then the attribute of alternative 2 (x_2) does not affect the relative odds of choosing between alternatives 1 and 3, and hence its coefficient in γ_1 is 0. For the same reason, the coefficient on x_1 is 0 in γ_2. This is the sense in which the multinomial logit model can be considered a reduced form for the conditional logit model.

Testing the IIA Assumption 2

We can use the multinomial logit model to test the IIA assumption of the conditional logit model. Simply estimate the MNL model, and then test the restrictions of the form of equation (11). This can be done using a simple Wald test on the unrestricted reduced form. Let γ be the vector of multinomial logit coefficients $\gamma_1, \gamma_2, \ldots, \gamma_{J-1}$, and let V be the variance matrix of γ. Then we can write the restrictions of equation (11) in the form $\gamma = H\beta$, where H is a matrix of 1's, 0's, and -1's which imposes the restrictions. The statistical problem is then to find a parameter vector β which comes "closest" to reproducing the observed reduced form $\hat{\gamma}$. Formally, the problem is

(12) choose $\hat{\beta}$ to minimize $D(\beta) = [\hat{\gamma} - H\beta]' \, V^{-1} \, [\hat{\gamma} - H\beta]$.

Since the restrictions H are linear, this problem is equivalent to generalized least squares, and the solution is

(13) $\hat{\beta} = [H' \, V^{-1} \, H]^{-1} \, [H' \, V^{-1} \, \hat{\gamma}]$,

with the variance of $\hat{\beta}$ equal to $[H'V^{-1}H]^{-1}$. The test statistic (Wald) for the restrictions is just $N.D(\hat{\beta})$, that is, the minimized value of the distance between the observed reduced form and that which is implied by the "structural" parameter estimate $\hat{\beta}$. Under the null hypothesis that the restrictions are correct, this statistic has a chi-square distribution with parameter equal to the number of restrictions.

For the example of equation (11), where the x_k's are assumed to be scalars, the H matrix would be the following:

$$(14a) \qquad H = (1 \quad 0 \quad -1 \quad 0 \quad 1 \quad -1)'.$$

If there were two elements in each of the x_k's, then H would take the form

$$(14b) \qquad H = \begin{bmatrix} 1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 1 & 0 & -1 \end{bmatrix}',$$

and $\beta = (\beta_1, \beta_2)'$.

Objections to the Alternative Test

Strictly speaking, we cannot view the multinomial logit model as an econometric model which corresponds to a probabilistic choice system (PCS) in the sense of McFadden. He displays a set of conditions necessary for an econometric model to correspond to a model of rational choice among discrete alternatives. The multinomial logit model violates one of these conditions and therefore cannot be viewed as an econometric model which corresponds to a rational PCS.

The condition which is violated is the following: In the McFadden setup, we view any alternative as yielding a utility level at some price. The rationality conditions require that any alternative which does not exist be able to be viewed as one which does exist, but with an infinite price. Hence, such an alternative will never be chosen by a rational individual, and its attributes are irrelevant to the choice probabilities. In the MNL model, in contrast, all the attributes of all alternatives are relevant to the choice probabilities (see equation 8), and hence the model violates McFadden's rationality conditions. The power of that setup is that it allows one to predict the choice probability for a new alternative, on which there is no experience, given knowledge of its attributes.

However, one can view the multinomial logit model as corresponding to a restricted PCS, where the restriction is that the set of possible choices is limited to those currently in existence. Hence we cannot use the results of the multinomial logit model to predict the probability of choosing some new alternative which is to be introduced into the choice set in the future.

Choice Sets

We may or may not require that the set of possible alternatives be the same for each individual (so that the vector z has the same dimension for each, and hence there are the same parameters $\beta_1, \beta_2, \ldots, \beta_{J-1}$). If we wish to view the MNL model as a probabilistic choice system, then we must require that the choice sets be the same for all individuals.

If, on the other hand, we only want to test the null hypothesis that the conditional logit model is correct, then we need not restrict ourselves to the case in which all individuals face the same set of alternatives. We would simply group the observations so that all those with the same choice set are in the same group, and then estimate the MNL model separately for each group. If the CL model were correct, there would be the same pattern of coefficients as we have outlined above, group by group, and the conditional logit parameter β would be the same for all groups. The test then would proceed as before, since the individuals are assumed to be independent. The test statistic can be viewed as the optimal weighted average of the test statistics which are obtained group by group. Note that this is not the standard test proposed in the literature.

3. Mixed Models

From the structure of the conditional logit model in Section 1, particularly for the usual case in which $g(x_k, \beta) = \beta . x_k$, it appears that any variable in the x_k's which is the same for all alternatives k will not affect the choice probabilities, i.e., will have a coefficient in β which is identically zero. In particular, such variables as attributes of the chooser (rather than attributes of the choice) appear to have no place in the model, for instance, a variable such as an individual's race.

In fact, we can allow a fixed variable to enter the choice equations, provided that we allow its coefficient β to be different for different alternatives. Formally, one can think of writing a vector x_k^* which contains x_k and the interactions of the choice indicators d_j ($j = 1, 2, \ldots, J$) with the attributes of the chooser (e.g. race). The conditional logit model can then be written using the x_k^* rather than the x_k as the attribute vectors.

This amounts to a mixture of the conditional logit model and the multinomial logit models described above. The parameters of this model have the same interpretations as before: The coefficients on alternative specific variables are interpreted as conditional logit parameters, and the coefficients on the chooser specific variables are interpreted as multinomial logit parameters. (Note that the multinomial logit model can be interpreted as a conditional logit model with a complete set of interactions.) As in the ordinary multinomial logit model, there must be a normalization for the coefficients of the chooser specific variables. The easiest might be to again choose a base case (e.g. alternative J) and interpret the coefficients as we did above.

4. Implementation of the Logit Choice Model

In order to implement the logit choice model, it is necessary to have information on the attributes x_k of the possible alternatives. In some cases these can be readily obtained. For example, in the choice of travel mode problems, the x_k's typically contain such variables as the time required for the trip under each travel mode and the money cost of each travel mode.

In other cases, we observe x_k only for the alternative which is in fact chosen. In these cases, we must impute the attributes x_j of the alternatives which we do not observe. The need to impute raises serious questions about the IIA assumption implicit in the conditional logit model. If we could impute exactly, that is, if we knew the exact x_j faced by the individual, then there would be no problem. However, when we impute we will make errors. We can hope to correctly estimate the mean of the x_j, but that is all. If the individual, at the time the decision is made, also only knows the mean x_k associated with each choice, then one should use imputed x_k's for all the choices in the estimation.

However, if the individual knows the exact x_k associated with each alternative (or at least knows them more precisely than we can estimate), then part of what we think of as ε_k (i.e., idiosyncratic taste variation) is known to the chooser (i.e., is part of the attribute vector), and there is an errors-in-variables bias in our conditional logit model. This is true in any model which uses imputations. If our imputations are systematically wrong in a way that is correlated with the included predicted attributes x_k, then there is an omitted variables bias as well.

Moreover, if the errors we make in predicting x_k are correlated with the errors we make in predicting x_l, then we would expect the IIA assumption to fail in our estimated models even if it were true for the individual. The reason is that the disturbance in the econometric model has two parts: the idiosyncratic term in the indirect utility function, and the imputation errors. Even if the idiosyncratic components of utility are independent across different alternatives, if the imputation errors are correlated across alternatives, then the disturbances in the econometric model will be correlated.

Appendix C

The Treatment of Food Stamps

We do not impute food stamps to the AFDC estimates used in the estimating equations in the model. We do this for two reasons. First, it is not clear that we can impute the potential food stamps for subfamilies with even the level of accuracy with which we can impute AFDC income and nonwage income. Second, given our first problem, we feel that there would be no gain to imputing food stamps. We have considered the problem of imputing food stamps and we outline a procedure for doing so below.

I. The Imputation Procedure

Definitions: Let TAE = AFDC earnings tax rate

TAN = AFDC tax rate on nonearned income

TF = Food Stamps tax rate (.30)

DED = Food Stamps standard deduction (89/month)

RDEDE = Food Stamps earnings exclusion (18%)

AFDCG = AFDC guarantee

FSG = Food Stamps guarantee

FSADCG = combined AFDC+Food Stamps guarantee

TFULLE = combined tax rate on earnings

TFULLN = combined tax rate on nonearned income

Step 1: Compute Food Stamp guarantees (FSG) by household size.

For 1983, the monthly guarantees are

Household Size	1	2	3	4	5
FSG	76	139	199	253	301

Household Size	6	7	8	9	10
FSG	361	399	457	514	571

Step 2: Calculation of the combined guarantee (FSADCG)
Food Stamps taxes AFDC at a rate of .3, after a standard deduction of $89, so

$$FS = MAX\ [\ FSG-TF(AFDCG-DED),\ 0]$$
$$= MAX\ [\ FSG-.3(AFDCG-89),\ 0]$$

and the combined guarantee is then

$$FSADCG = FS + AFDCG.$$

Step 3: Tax Rates

Assume that we are past the standard deduction in the Food Stamp program. The AFDC guarantee will surely take us past the standard deduction.

Step 3A. Tax on Nonearned Income (TFULLN)

Suppose that there is no nonearned income. Then add a dollar and see what happens:

AFDC: goes down by TAN

FOOD STAMPS:

Before the change: $FS1 = FSG-TF(AFDCG-DED)$

After the change: $FS2 = FSG - TF(1 + AFDCG - TAN - DED)$
$= FS1 - TF(1-TAN)$,

where the 1 is the additional dollar of nonearned income. Hence the combined tax rate on nonearned income is

$$TFULLN = TAN + TF(1-TAN).$$

Example: $TAN = .95$, then $TFULLN = .95 + .3(1-.95) = .965$

Step 3B. Tax on Earned Income (TFULLE)

Suppose that there is no earned income. Then add a dollar and see what happens:

AFDC: goes down by TAE

FOOD STAMPS: This is messier, since FOOD STAMPS excludes RDEDE (18%) of earnings from the taxable base

Before the change: FS1 = FSG-TF(AFDCG-DED)

After the change: FS2 = FSG - TF(1-RDEDE+AFDCG-TAE-DED)

= FS1 - TF(1 - TAE),

where the 1 is the additional dollar of earned income. Hence the combined tax rate on earned income is

TFULLE = TAE + TF(1-RDEDE-TAE).

Example: TAE = .5, then TFULLE = .5+ .3(1-.18-.5) = .596

II. Problems in Doing the Food Stamp Imputations

The problem in the imputation of Food Stamps arises because the Food Stamp program uses a different filing unit than the AFDC program. The Food Stamp filing unit is, roughly, the household, or at least those sharing cooking facilities. For a female household head, there is probably not much error in assuming that her family is the entire Food Stamp unit, and the same is true for a wife.

The major problem in doing the imputation of Food Stamps occurs when we consider subfamilies. There are two possibilities. First, the entire family could be the Food Stamp unit, with the subfamily as a potential AFDC unit as well. Alternatively, the subfamily could be its own Food Stamp unit, assuming it kept its food and cooking separate from the main family.

Under the first possibility, we would have to impute the number of people in the Food Stamp unit, in addition to all of the other imputations we are currently making. Given our set of potential explanatory variables in the imputation equations, we are not likely to be able to do this well. We are most likely to wind up essentially assuming a fixed number (the mean) for the number of other individuals in the family who are not subfamily members, and basing the Food Stamp imputation on that number. Under the second possiblity, we would simply treat the AFDC unit as the Food Stamp unit. In either case, we would essentially be adding a constant to the AFDC guarantee.

Further, while imputing the number of people in the Food Stamp unit is sufficient to impute the combined AFDC plus Food Stamps guarantee, in order to impute the tax rates and the net wage rate and net nonwage income, we would need to separate the income of the others in the household into earned and nonearned income. We would then separately impute the earned income and the nonearned income of others in the household, based solely on the woman's characteristics. This seems to be a hopeless task.

III. The Value of Food Stamps

The final issue which arises concerning the imputation of Food Stamps is the value to the recipients of Food Stamps. If Food Stamps are less valued by recipients than AFDC, perhaps owing to the additional stigma of receiving a voucher rather than cash, then it would not be correct to simply add the potential Food Stamp benefit to the AFDC guarantee. Further, the participation rate in the Food Stamp program is much lower than that of the AFDC program. For these reasons, one would prefer to estimate a Food Stamp participation equation, in each living arrangement, and then use those results in the imputation procedure. Given our results with the imputations, we do not feel that we could do a good job at that with the data at hand. In essence, we feel that we are already pushing the limits of our ability to impute.

IV. Effects of Failing to Impute Food Stamps

We do not appear to be able to impute the combined effects of AFDC and Food Stamps with any degree of accuracy, and choose not to do so for that reason. We now consider the effects on our procedures of the failure to impute Food Stamps.

We feel that the failure to impute the value of Food Stamps is not particularly damaging to our modeling. There are basically two parts to our modeling effort thus far. Living arrangements on the one hand, and schooling, welfare recipiency, and labor force participation on the other.

Consider the living arrangements modeling first. The important variation here is variation in welfare income, for a given woman, across different living arrangements. If, as argued above, we would end up treating Food Stamps essentially as a constant, then the variation in welfare income across living arrangements for a given woman would be reduced only slightly (owing to the leveling effect of the Food Stamp program). The rank ordering of welfare income "if householder" and welfare income "if subfamily" would be the same as when we use AFDC income in the two living arrangements. In fact, given the relatively small dollar differences, the welfare income measures would be highly correlated with the AFDC income measures. Thus, we would not expect the substantive results of the estimation to change.

Our estimated coefficients will not be correct in magnitude, however. Let welfare income (W) be the sum of AFDC (A) and Food Stamps (F), where we write Food Stamps as g(A) to emphasize their dependence on the level of AFDC benefits. If, in the correct model, welfare income entered linearly with coefficient B, i.e., $BW = B\,[A + g(A)]$, the coefficient which we estimate using only AFDC would be $B[1+ dg(A)/dA]$. While Food Stamps are not a linear function of AFDC, particularly since the family size will change across living arrangements, the term $dg(A)/dA$ is not likely to vary too much, and hence we are off by something which is almost constant.

A similar argument can be made with respect to the modeling of schooling, welfare recipiency, and labor supply. While it is certainly true that we do not have the correct measure of welfare income, one could view our estimated coefficients as being upper bounds.

Chapter 5

A Structural Model

In this chapter we lay out a more structural model of the choice problem faced by a young woman. The approach was outlined in general terms in Chapter 3; we provide a specific example here. Section 5.1 lays out a theoretical model; Section 5.2 discusses estimation issues; and Section 5.3 presents some empirical results. Those results, unfortunately, are not encouraging. The final section discusses possible avenues for future work.

5.1 The Theoretical Model

As in Chapter 3, we employ the following notational conventions:

C = consumption,
L = leisure,
$\bar{L}$ = leisure endowment,
S = schooling,
P = money price of schooling,
W = wage rate,
Y = nonlabor income,
Z = "full income" = $Y + W\bar{L}$,
P_L = "full price" of leisure = W,
P_S = "full price" of schooling = $W + P$, and
$\theta_j = (Z, P_S, P_L)_j$ = vector of attributes for choice j .

As in Chapter 3, the price of consumption has been normalized to unity.

The woman's problem is then to choose C, L, and S to maximize utility subject to the budget constraint. In order to operationalize the model, we must specify the form of the utility function, or equivalently, specify the form of the indirect utility function. That choice is essentially arbitrary. We make our initial choice on the following grounds.

The labor force participation and school attendance equations in Chapter 4 are estimated as probit equations. These probit equations correspond to linear schooling demand and leisure demand equations in a theoretical model. Hence, we choose a form for the indirect utility function that will yield linear leisure demand and schooling demand equations.

In particular, we choose the following indirect utility function:

$$(1) \qquad v(Z,\ P_L,\ P_S) =$$
$$\exp\{\delta_1 P_L + \delta_2 P_S\}\ [Z + (\alpha_1/\delta_1)P_L - (\alpha_1/\delta_1{}^2) + (\alpha_2/\delta_2)P_S - (\alpha_2/\delta_2{}^2)],$$

where exp{.} is the exponential function. If leisure and schooling are both normal goods, and if we can go uniquely from the indirect utility function to the demand functions and back, then we require some parametric restrictions in equation (1). A sufficient set of conditions for the indirect utility function in equation (1) to represent well-behaved preferences is the following:

(2a) $\delta_1 < 0$,

(2b) $\delta_2 < 0$,

(2c) $\alpha_1 > 0$, and

(2d) $\alpha_2 > 0$.

This formulation for the indirect utility function implies the following forms for the schooling demand and leisure demand equations, applying Roy's identity to equation (1):

$$(3) \qquad L = -\alpha_1 P_L - (\alpha_2\delta_1/\delta_2)P_S - \delta_1 Z, \text{ and}$$

$$(4) \qquad S = -(\alpha_1\delta_2/\delta_1)P_L - \alpha_2 P_S - \delta_2 Z.$$

From the sign restrictions in equations (2a) through (2d), we have the following predictions: The higher is the full price of leisure, holding full income constant, the less leisure and the less schooling are demanded. The higher is the full price of schooling, holding full income constant, the less leisure and the less schooling is demanded. The higher is nonlabor income, the more leisure and the more schooling are demanded.

In the estimation, we also add a set of "taste-shifter" variables to the utility function, with parameters that are allowed to vary by living arrangement and welfare status. The specification of these variables, and the interpretation of their coefficients, parallels that of the reduced-form living arrangement equations in Chapter 4.

5.2 Econometric Issues: Specification of the Stochastic Structure

In this section we discuss issues concerning the specification of the stochastic structure of the econometric model. The theoretical model of the previous section results in a "representative" utility function. The randomness we see in the data is interpreted as coming from variation in preferences among individuals. The exact manner in which that variation is introduced into the theoretical model will determine the structure of the econometric model.

In order to simplify the notation, we will use the following shorthand:

$$A = \exp\{\delta_1 P_L + \delta_2 P_S\} = A(P_L, P_S) \tag{5}$$

$$B = [Z + (\alpha_1/\delta_1)P_L - (\alpha_1/\delta_1^2) + (\alpha_2/\delta_2)P_S - (\alpha_2/\delta_2^2)] \tag{6}$$
$$= B(Z, P_L, P_S).$$

A general form for preferences, allowing for random variation in tastes, is the following:

(7) $$v(\theta_j) = v_j = A_j\ [B_j + \eta_j] + u_j$$

$$= A_jB_j + A_j\eta_j + u_j.$$

In the general form, we allow for two sources of taste variation, the terms η and u. In addition, we allow there to be alternative-specific taste shocks of each type, where the alternatives are indexed by j. It is clear that this most general form cannot be estimated. We now consider different ways of simplifying the problem down to something which is tractable empirically.

<u>Case 1</u>: $u_j = 0$ for all j, and $\eta_j = \eta$ for all j.

In Case 1, we restrict the random taste variation to enter through only a single parameter, the common η. In this model, the probability that alternative j is chosen is

(8.1) $$P(\text{choose } j) = P\ \{[\eta(Ak-Aj) < AjBj - AkBk] \text{ for all } k \neq j\}.$$

This formulations leads to inequalities of the form

(9.1) $$\eta < (A_jB_j - A_kB_k)\ /\ (A_k - A_j)\ ;\ \text{if } A_k > A_j\ ;\ \text{and}$$

(10.1) $$\eta > (A_jB_j - A_kB_k)\ /\ (A_k - A_j)\ ;\ \text{if } A_k < A_j.$$

Since the A terms are functions of both data and unknown parameters, there may be no parameter vector which can satisfy the appropriate inequality for all possible comparisons. That is, it is unlikely that we can find a parameter vector which can rationalize the choices among living arrangements which we observe in the data. The problem arises here because there are more than two alternatives; were there only two, then this would not be a problem.

Case 2: $u_j = 0$ for all j, and η_j distributed i.i.d.

In this model, we again restrict the random taste variation to enter only through the η term, but now we allow the η terms to be independent and identically distributed (i.i.d). Here we see that we gain nothing, for we will still end up with a set of inequalities in the living arrangements equation which resemble those in equations (9.1) and (10.1) above, and it is unlikely that we will be able to find a parameter vector to satisfy the inequalities.

Case 3: u_j distributed i.i.d., and $\eta_j = 0$ for all j.

In this model we allow the random taste variation to enter through the u term rather than the η term. The disadvantage of this class of model is that there is no disturbance left in the schooling and leisure demand equations. Unless we add randomness to the demand equations in some ad hoc manner, this formulation will not allow for stochastic demand equations. The manner in which this can be done will be outlined below.

This class of model is more tractable than those above. The probability of choosing alternative j in this model is

$$(8.3) \qquad P(\text{choose } j) = P\,\{[(u_k - u_j) < (A_jB_j - A_kB_k)] \text{ for all } k \neq j\}.$$

Given J possible choices, we have (J-1) random variables $\tau_k = u_k - u_j$. The probability in equation (8.3) then requires the evaluation of a (J-1) dimensional probability integral. This model is similar to many of the polychotomous choice models in the literature, but with an important difference. The τ_k are not independent, because each of them contains u_j. Therefore, the evaluation of the (J-1) dimensional probability integral can present some formidable computational difficulties if J is four or greater, as is the case here.

<u>Case 4</u>: $\eta_j = 0$ for all j; u_j distributed i.i.d. extreme value. This model is a tractable one, though unattractive for a number of reasons. It is a modification of the conditional logit model which is commonly used in polychotomous choice problems. Appendix B in Chapter 4 discusses this variant of a logit model in more detail. This model is tractable for estimation purposes, though somewhat more difficult than the usual conditional logit model.

There are two reasons that this model is unattractive. The first is that, like the model in Case 3, there is no structural source for the randomness in schooling and leisure demands. One can "fix" that problem in one of two ways: One could posit the existence of random "optimization error" in the schooling and labor supply decisions. That optimization error would generate the randomness needed to estimate an econometric model. Alternatively, one could allow for new taste variation, which is independent of the taste variation which enters the living arrangements decision. Once the living arrangements decision is made, then this new source of taste variation generates the stochastic structure for the schooling and leisure demand equations.

The second reason that this model is unattractive is that the estimation requires that we assume the alternative-specific taste components to be independent from one another. The independence assumption, and its implications in actual use of these models, are discussed more fully in the appendix to Chapter 4. Briefly, if there are components of utility which we do not capture in the variables included in the econometric model, then the independence assumption is not likely to hold. Given the imputation procedures that were described in Chapter 4, this seems plausible.

Our Choice

Despite these reservations, the model in Case 4 is the one we have chosen, primarily for its tractability. We will estimate the model on a sample of nonmarried women. The results in Chapter 4 suggest that not much is lost in so doing. For example, the reduced-form living arrangement equations are not very different when we include the married women or not. Given the highly nonlinear nature of this model, the reduction in sample size afforded by the exclusion of the married women is very helpful.

5.3 Estimation of the Model

Having chosen a stochastic specification which yields a conditional logit type of model, we now specify in more detail exactly what is to be estimated, and then present the empirical results.

5.3.1 Specification of the Estimating Equation

The theoretical model is written in terms of full income and full prices. We must first rewrite the indirect utility fuction in equation (1) in terms of the observed prices and incomes. Substitute the definitions of the full prices into equation (1) to obtain

$$(11) \qquad v(\theta) = \exp\{(\delta_1 + \delta_2)W + \delta_2 P\} \times$$
$$[(Y + W\bar{L}) + W(\alpha_1\delta_2 + \alpha_2\delta_1)/(\delta_1\delta_2) + P(\alpha_2/\delta_2)].$$

Two issues arise here. The first is that we do not observe the dollar price of schooling. Appealing to the principle that in choice models like this, only the differences between various alternatives affects the choice probabilities, we replace the terms in P with a shift parameter γ_0, which represents the additional costs incurred by a household head. These costs might take the form of child care expenses, for example. We therefore expect γ_0 to be positive.

The second issue is that, as discussed in Chapter 3, we wish to allow the leisure time endowment, $\bar{L}$, to vary for women in different living arrangements, reflecting different levels of time precommitted to activities such as child care. We represent the difference between the leisure time endowments of household heads and subfamily heads by the shift parameter γ_1. We expect γ_1 to be negative.

Let H be a dummy variable which takes the value 1 if the living arrangement under consideration is one in which the woman is a household head. The indirect utility function which we estimate is then

$$(12) \qquad v(\theta) = \exp\{(\delta_1+\delta_2)W + \delta_2\gamma_0 H\} \times$$
$$[(Y+W\bar{L}) + W(\alpha_1\delta_2+\alpha_2\delta_1)/(\delta_1\delta_2) + H(\alpha_2\gamma_0/\delta_2) + \gamma_1 HW].$$

We rewrite the function to be linear in the parameters, using the following definitions:

$$(13a) \qquad \pi_1 = (\delta_1+\delta_2) < 0,$$

$$(13b) \qquad \pi_2 = \delta_2\gamma_0 > 0,$$

(13c) $\pi_3 = (\alpha_1\delta_2+\alpha_2\delta_1)/(\delta_1\delta_2) < 0$,

(13d) $\pi_4 = (\alpha_2\gamma_0/\delta_2) > 0$, and

(13e) $\pi_5 = \gamma_1 < 0$.

The function used in estimation is then

(14) $$v(\theta) = \exp\{\pi_1 W + \pi_2 H\} \times [(Y+W\overline{L}) + \pi_3 W + \pi_4 H + \pi_5 WH].$$

5.3.2 Data

We restrict the sample to nonmarried women under 36 years of age. The sample was described in more detail in Chapter 4. There are four possible living arrangements: head not receiving welfare, sharing with others and not receiving welfare, head receiving welfare, and sharing with others and receiving welfare.

The full income measure was constructed by summing the imputed values of own nonwage income, the AFDC guarantee, and the income of others in the household, for each potential living arrangement. To this was added the product of the appropriate imputed net wage rate (depending on welfare status) and the leisure endowment $\overline{L}$. We took $\overline{L}$ to be 5840 hours (16 hours per day times 365 days per year). The results were not sensitive to the choice of $\overline{L}$. The full income measure was then divided by 10,000 in order to prevent scaling problems in the estimation.

We allowed for demographic taste shifter variables to enter the utility function, with their own living arrangement-specific coefficients. As in Chapter 4, we took as the base case sharing with others and receiving welfare. The taste-shifter variables included are age (AGE), the presence of a preschool child (PRESCHOOL), the number of dependents

(DEPENDS), and an indicator variable which takes on the value 1 if race is not white (NONWHITE). The coefficients on these variables reflect the change in the relative odds of choosing that particular living arrangement relative to the base case (sharing with others and receiving welfare). We also allowed for an intercept in the parameters for household heads and sharing with others and not receiving welfare. (Due to the presence of the H term in the estimating equation, it is not possible to allow for three intercepts, as was done in Chapter 4).

5.3.3 Estimation Results

The results of maximum likelihood estimation of equation (14), augmented by the taste-shifter variables, appear in Table 5.1. The log likelihood function is not globally concave, and different starting values did yield different local maxima. The results presented here are those which correspond to the largest value of the log likelihood function found. Whether this is in fact the global maximum is inherently unknowable.

The results are not in accord with our theoretical predictions. The chart below summarizes the results on π_1, π_2, π_3, π_4, and π_5:

Chart 5.1

Summary of Results on the π Parameters

Parameter	Expected Sign	Result
π_1	negative	negative, significant
π_2	positive	positive, significant
π_3	negative	negative, significant
π_4	positive	negative, significant
π_5	negative	positive, significant

Table 5.1

The Determinants of the Living Arrangements of Young Women: The Structural Model

(Asymptotic standard errors in parentheses beside the estimates)

Classification of Dependent Variable (LA4):

1 = Householder not receiving public assistance
2 = Householder receiving public assistance
3 = Woman in a subfamily, not receiving public assistance
4 = Woman in a subfamily, receiving public assistance

Structural Parameters Common to All Living Arrangements

π_1	- .087	(.026)
π_2	3.607	(.142)
π_3	-1.126	(.201)
π_4	- .162	(.028)
π_5	.538	(.197)

Demographic Variables

Change in the Relative Odds of

Independent Variable	4 vs. 1 (1)		4 vs. 2 (2)		4 vs. 3 (3)	
Constant	.151	(.030)	3.735	(1.044)	------	
AGE	-.0147	(.0017)	-.3090	(.0430)	-.0066	(.0011)
DEPENDS	.0192	(.0052)	.8225	(.2529)	.0075	(.0042)
PRESCHOOL	-.0064	(.0111)	.2143	(.4340)	-.0051	(.0091)
NONWHITE	-.0004	(.0093)	-.0162	(.2899)	.0022	(.0064)

We see in the chart that for three of the five parameters our theoretical predictions were obtained in the data. For two of the five, however, the estimates do not match the theoretical predictions. In particular, consider the parameter $\pi_5 = \gamma_1$. This is a measure of the difference in the leisure endowments of household heads and subfamily heads. The estimated parameter should be negative, according to theory, but is positive and significantly different from zero. We do not find these results to be particularly plausible.

The estimated effects of the taste-shifter variables also differ substantially, in many ways, from the results from the reduced forms in Chapter 4. The age effects are similar, but the results for PRESCHOOL and DEPENDS, when significantly different from zero, are of opposite sign in the structural model to those of the reduced form. Again, we do not find these plausible. The effect of NONWHITE is generally not significantly different from zero.

In summary, the structural model does not seem to provide a good basis for predicting living arrangements. The estimated parameters are generally not plausible when compared to either the theoretical predictions and/or the reduced-form estimates. This points out the importance of estimating both the reduced form and the structural versions of a model. Estimating the reduced form provides a benchmark against which the structural model can be checked.

It is possible that the results would improve if we were to estimate the labor force participation and schooling equations jointly with the living arrangement equation, but we hold little hope for that strategy. Furthermore, we would be very suspicious if these implausible results suddenly reversed themselves when the other equations were added to the system. For this reason, the policy simulations in Chapter 6 will be done with the reduced-form model.

5.4 What Went Wrong, and Where to Go Next?

We had similar kinds of problems with a more structural form of the living arrangement equation when we used the standard conditional logit model. Those problems were discussed in Chapter 4. Most of the comments there apply to this chapter as well. The most likely sources of problems are the following: (1) There is probably a failure of the Independence of Irrelevant Alternatives assumption implicit in our estimating model. (2) The functional form we chose for the indirect utility function may have been a poor choice. (3) The lack of data on key variables, including the price of schooling and the different leisure time available for householders and those who share a household with others may have prevented us from obtaining reasonable estimates. (4) We have only a limited set a variables to use in order to impute wage rates, own nonlabor income, and the income of others in the household. It is probable that our imputations are highly collinear, and, in consequence, the results are both unstable and implausible.

Future work should attempt to remedy the shortcomings of our own. A different choice of indirect utility function, together with better data with which to make the imputations, seems a desirable first step. The extent to which it is possible to gather data on the money cost of schooling, or on the different leisure times available to women in different living arrangements, is unclear, but information there would also be of help.

Chapter 6

Simulating the Effect of Policy Changes

This chapter addresses the fifth question asked in the introductory chapter. If the federal government instituted policies that encouraged single women with young children to live with parents or other relatives, what effect would that have on schooling, work, and welfare receipt? While the plethora of parameter estimates in the previous chapters are crucial for answering certain types of questions, they can leave one uncertain about the magnitude of the behavioral change that would follow a change in government policy. This chapter uses microeconomic simulation techniques to help resolve that uncertainty.

6.1 Simulations of the Effects of Changes in the AFDC System

We simulate the effect of three changes in government policy:

1. Introduction of a uniform national rule that increases the AFDC guarantee for female householders by 10 percent, without altering the difference between the subfamily and householder guarantee.

2. Introduction of a uniform national rule that increases the AFDC guarantee for single mothers in subfamilies (but not householders) by 10 percent.

3. Elimination of any difference in guarantees due to living arrangements by

   (a) setting guarantees for single mothers in subfamilies equal to those of householders, or;

   (b) setting guarantees for householders in all states equal to those of single mothers in subfamilies.

In each case we examine the effect of the policy change upon choice of living arrangement, propensity to receive welfare, propensity to work, and propensity to attend school, holding other factors constant.

Moreover, we do this for all mothers under 36 and for all mothers under 22.

We focus on these three policies for two reasons. First, they provide a sense of the magnitude of the effects found in the previous chapters. Are we dealing with huge behavioral shifts that must be considered in any policy decision, or are the effects so small as to be safely ignored? Second, these policies come close to politically feasible policy changes. While a national rule regarding guarantees is unlikely, guarantees do increase as a result of state decisions. Moreover, since states can decide to raise guarantees for mothers in one type of living arrangement and not in another, it is important to have information about the potential consequences of such changes. Finally, if there are beneficial effects from eliminating differences in guarantees across living arrangements, one can conceive of federal or state legislation that does just that.

Of course such policy decisions involve normative judgments about the type of behavior that the elected governments wish to foster. In particular, one can reasonably question whether it is appropriate to encourage mothers of young children to work and/or go to school. Perhaps their time is best spent at home with their children. The analysis in this chapter does not address such important normative issues. It is strictly a positive analysis. It examines the effect of a change in policy on the behavior of mothers, without claiming that one behavior is better than another. While such information is necessary for informed policy decisions, it is most emphatically not sufficient.

Our simulation methodology is relatively straightforward. It involves using the models in Chapter 4 to predict the probability that a given mother is in one of several alternative living arrangement-welfare-school-work "classifications." These probabilities depend in part upon the AFDC benefits available in specific living arrangements. By summing the probabilities over all mothers in our sample, we obtain an estimate of the number of mothers in each of the several classifications.[1] Our simulations involve changing the guarantee in a specific living arrangement, and recalculating the probabilities and the associated sums. In doing this, we are able to examine the effect of a change in the AFDC guarantee on the number of women in the alternative living arrangement-welfare-school-work classifications, holding other variables constant.

The subsequent section explains the methodology in greater detail. The final section presents the simulations and draws conclusions.

6.2 Methodology and Results from Policy Simulations

Our policy simulations are based on reduced-form estimates of the joint probability distribution of the living arrangements, employment, schooling, and welfare recipiency for women with young children. Table 6.1 describes the actual distribution of our sample in the various categories of our four dependent variables. There are three possible living arrangements ($j=1,2,3$), two employment statuses ($k=0,1$), two schooling statuses ($m=0,1$) and two welfare recipiency categories ($n=0,1$). The exact definitions of the categories appear in Table 4.1.

Based on the conceptual model presented in Chapter 3, we have assumed that the probability that the i^{th} woman occupies any of the 24 cells of Table 6.1 is a function of a vector of exogenous variables, Z_i, specific to the woman and unchanging across cells, and a vector of variables,

Table 6.1

The Distribution of Sample Respondents into Living Arrangement, Labor Force Participation, Schooling, and Welfare Recipiency Categories

	Householder (j=1)		Married Woman (j=2)		Woman in a Subfamily (j=3)	
	Welf. (n=1)	No Welf. (n=0)	Welf. (n=1)	No Welf. (n=0)	Welf. (n=1)	No Welf. (n=0)
	(1)	(2)	(3)	(4)	(5)	(6)
In Labor Force (k=1)	129	539	43	2835	42	227
Not in School (m=0)	124	526	41	2790	40	212
In School (m=1)	5	13	2	45	2	15
Not in Labor Force (k=0)	335	69	93	1771	134	124
Not in School (m=0)	320	61	89	1733	114	94
In School (m=1)	15	8	4	38	20	30
Total	434	608	136	4606	176	351

X_i, which can vary across the cells as well as across individuals. For example, the woman's age is an element of Z_i, since it does not vary across the categories of the dependent variables. But her estimated AFDC payment is an element of X_i, since it varies among the living arrangement, employment, schooling, and welfare recipiency categories.

We denote the joint probability that the i^{th} woman occupies the j^{th} living arrangement, the k^{th} employment status, the m^{th} schooling status and the n^{th} welfare recipiency category as: $Pr_i(j,k,m,n) = f(Z_i,X_i)$.

Given the Chapter 4 estimates of the functional relationship between $Pr_i(j,k,m,n)$ and Z_i and X_i, our simulation of the effect of a change in the AFDC system proceeds in two steps:

1. Given the current values of X_i and Z_i, compute the sum of the $Pr_i(j,k,m,n)$ for each of the 24 cells. This yields the current distribution of women in the sample across the 24 categories.

2. Given <u>new</u> values of X_i associated with a change in the AFDC system and the <u>current</u> values of Z_i, compute new values of the $Pr_i(j,k,m,n)$ and sum these for each of the 24 cells. This yields a new distribution of women in the sample across the 24 categories.

By comparing (2) to (1) one can assess the effect of changes in the AFDC program on living arrangements, employment, schooling, and welfare recipiency of young women.

Of course, one strategy for estimating $Pr_i(j,k,m,n)$ is to estimate a conditional logit model with a dependent variable which has 24 possible values. Not only would this be computationally complex, but in addition the results would be almost impossible to understand at an intuitive level. Instead we estimated various "pieces" of the joint probability distribution. These "pieces" enable us to answer the questions relevant to our research.

The conditional probabilities used in this chapter are (dropping the i subscript):

1. Pr(j,n), j=1,2,3; and n=0,1;
2. Pr(k:j,n), k=0,1; j=1,2,3; and n=0,1;
3. Pr(m:j,n), m=0,1; j=1,2,3; and n=0,1.

Each of these probabilities is discussed in turn below.[2]

(1) The Living Arrangement/Welfare Recipiency Probabilities [Pr(j,n),j=1,2,3 and n=0,1]

We begin by combining the living arrangement and the welfare recipiency variables into a single living arrangement/welfare recipiency variable. The small number of married women who receive welfare are combined with the other married women. Because of this combination, each woman can be classified as being in one of only five living arrangement/welfare recipiency categories:

1. Householder, not receiving public assistance;
2. Householder, receiving public assistance;
3. Woman in a subfamily, not receiving public assistance;
4. Woman in a subfamily, receiving public assistance;
5. Married woman.

These probabilities are the conditional probabilities of being in one of five living arrangement/welfare recipiency categories. In calculating and interpreting these probabilities, no distinction is made between the different possible employment and schooling statuses for each of the five living arrangement/welfare recipiency categories. For this reason, the probabilities can also be thought of as marginal probabilities of being in each living arrangement/welfare recipiency category.

Our estimates of the probabilities are derived from the five-valued logit model of living arrangements/welfare recipiency presented in Chapter 4. The parameter estimates from that model are reported in Table 4.7.

(2) The Probabilities of Being in the Labor Force (k) Conditional upon Living Arrangement/Welfare Recipiency Category (j,n), [Pr(k:j,n)]

The conditional probabilities of working, given a particular living arrangement/welfare recipiency category, are estimated using probit models in which the dependent variable takes the value 1 if the woman works full time, full year, and 0 otherwise. Five such probabilities are calculated using subsamples containing those women in each of the five living arrangement/welfare recipiency categories. The five sets of parameters are reported in Appendix Table A.6.1.

(3) The Probability of Being in School (m) Conditional upon Living-Arrangement/Welfare Recipiency Category (j,n), [Pr(m:j,n,)]

The conditional probabilities of being in school, given a particular living arrangement/welfare recipiency category, are calculated in the same way as the Pr(k:j,n), except that the dependent variable takes the value 1 if the women is currently in school and 0 otherwise. The five sets of parameter estimates are shown in Appendix Table A.6.2.

The three sets of probabilities just discussed can be used to compute the marginal probabilities of being in each living arrangement/welfare recipiency/employment cell as well as the marginal probabilities of being in each living arrangement/welfare recipiency/schooling cell. In particular:

$$Pr\ (j,k,n) = Pr(j,n) * Pr(k:j,n); \text{ and}$$
$$Pr\ (j,m,n) = Pr(j,n) * Pr(m:j,n).$$

To see how these probabilities are then used in the simulations, consider the effect of a change in the AFDC guarantee on the probability that the i^{th} woman lives in a subfamily, does not work, and receives public assistance [Pr(j=3,k=0,n=1)]. This probability can be expressed as the product of (1) the probability of living in a subfamily and receiving public assistance Pr(j=3,n=1) and (2) the probability of not working, given that j=3 and n=1, Pr(k=0:j=3,n=1). When this probability is computed and summed over all women in the sample, we obtain an estimate of the number of women in the sample who are living in a subfamily, not working, and receiving public assistance.

Now, suppose that a counterfactual AFDC system is simulated by raising the AFDC guarantee for each women by 10 percent. This change implies a new (different) probability that the i^{th} woman living in a subfamily does not work but does receive public assistance. As before, we can compute that probability for each woman in the sample, sum the probabilities, and obtain a new estimate of the number of such women in the sample. The difference between this new estimate and the previous estimate is a prediction of the effect of a 10 percent change in the AFDC guarantee on the number of women living in subfamily, not working and receiving public assistance.

It is clear that all of the subsequent simulations are based upon computed probabilities--probabilities that are computed from estimated coefficients. It is important to recognize that these estimated coefficients are <u>point estimates</u>. As indicated by the standard deviations associated with the coefficients, these point estimates may be quite imprecise. For example, we may compute probabilities and run simulations using the coefficient +1.00. If the standard deviation on this coefficient is 2.00, then there is a .95 probability that the "true" population coefficient lies within the interval -2.92 to 4.92. Obviously, the results of a simulation can depend on whether the coefficient is set at -2.92, 1.00, or 4.92. It follows that simulations are most credible when they are based on precisely measured (statistically significant) coefficients. This becomes an issue in the subsequent discussion.

6.4 Discussion of Simulation Results

Each of Tables 6.2-6.5 represents one of the four policy simulations introduced in Section 6.1. Each of the columns of the tables represents one of the dependent variables of interest to us. The effects of the proposed policy change on different subgroups within the sample are shown on the different lines of the table. The result is a matrix of policy impacts. For example, the effect of the policy simulation on the welfare recipiency of householders is represented in row (2) and column (5) of each table. Similarly, the effect of the simulated AFDC changes on the school attendance of women in subfamilies is represented in row (3), column (7) of each table. Our discussion here focuses on the first two simulations.[3]

Simulation 1: Raising AFDC1 by 10 Percent without Altering ADCDIF

Each woman in our sample has been assigned an AFDC "householder" guarantee (AFDC1) as well as an AFDC "subfamily" guarantee (AFDC3), both of which are based on the size of her family and the state in which she lives. Suppose the householder guarantee is raised by 10 percent and the

Table 6.2

Policy Change 1: Raising the AFDC Guarantee for Householders by 10 Percent

	Sample Size (1)	House-holders (2)	Living in Subfamilies (3)	Married Women (4)	Welfare Recipients (5)	In Labor Force (6)	In School (7)
1. Full Sample							
Before	6341	0.169	0.083	0.748	0.101	0.596	0.025
After	6341	0.173	0.082	0.746	0.107	0.591	0.024
After/Before	6341	1.021	0.983	0.997	1.058	0.991	0.962
Women Under 22							
Before	549	0.111	0.217	0.672	0.162	0.409	0.091
After	549	0.115	0.215	0.670	0.167	0.405	0.090
2. Householders							
Before	1072	1.000	NA	NA	0.433	0.621	0.038
After	1094	1.000	NA	NA	0.455	0.601	0.038
3. Subfamilies							
Before	527	NA	1.000	NA	0.334	0.518	0.102
After	518	NA	1.000	NA	0.346	0.512	0.108
4. Women on Welfare							
Before	640	0.725	0.275	NA	1.000	0.262	0.064
After	677	0.736	0.264	NA	1.000	0.264	0.062
5. Women Not on Welfare							
Before	5700	0.107	0.062	0.832	0.000	0.634	0.020
After	5664	0.105	0.060	0.835	0.000	0.630	0.019

Table 6.3

Policy Change 2: Raising AFDC Guarantees to Women in Subfamilies by 10 Percent

	Sample Size (1)	House-holders (2)	Living in Subfamilies (3)	Married Women (4)	Welfare Recipients (5)	In Labor Force (6)	In School (7)
1. Full Sample							
Before	6341	0.169	0.083	0.748	0.101	0.596	0.025
After	6340	0.150	0.084	0.766	0.087	0.606	0.023
After/Before	6341	0.886	1.011	1.024	0.866	1.017	0.943
Women Under 22							
Before	549	0.111	0.217	0.672	0.162	0.409	0.091
After	549	0.101	0.218	0.681	0.154	0.412	0.089
2. Householders							
Before	1072	1.000	NA	NA	0.433	0.621	0.038
After	950	1.000	NA	NA	0.393	0.655	0.043
3. Subfamilies							
Before	527	NA	1.000	NA	0.334	0.518	0.102
After	533	NA	1.000	NA	0.340	0.508	0.103
4. Women on Welfare							
Before	640	0.725	0.275	NA	1.000	0.262	0.064
After	554	0.673	0.327	NA	1.000	0.274	0.069
5. Women Not on Welfare							
Before	5700	0.107	0.062	0.832	0.000	0.634	0.020
After	5786	0.100	0.061	0.839	0.000	0.638	0.019

Table 6.4

Policy Change 3a: Raising the AFDC Guarantee for Women in Subfamilies to the Guarantee for Householders

	Sample Size	House-holders	Living in Subfamilies	Married Women	Welfare Recipients	In Labor Force	In School
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Full Sample							
Before	6341	0.169	0.083	0.748	0.101	0.596	0.025
After	6341	0.164	0.084	0.753	0.097	0.599	0.024
After/Before	6341	0.969	1.006	0.997	0.961	1.005	0.962
Women Under 22							
Before	549	0.111	0.217	0.672	0.162	0.409	0.091
After	549	0.107	0.218	0.676	0.158	0.410	0.089
2. Householders							
Before	1072	1.000	NA	NA	0.433	0.621	0.038
After	1039	1.000	NA	NA	0.421	0.632	0.039
3. Subfamilies							
Before	527	NA	1.000	NA	0.334	0.518	0.102
After	530	NA	1.000	NA	0.336	0.515	0.102
4. Women on Welfare							
Before	640	0.725	0.275	NA	1.000	0.262	0.064
After	615	0.711	0.289	NA	1.000	0.268	0.065
5. Women Not on Welfare							
Before	5700	0.107	0.062	0.832	0.000	0.634	0.020
After	5726	0.105	0.061	0.833	0.000	0.634	0.019

Table 6.5

Polcy Change 3b: Lowering the Guarantee for Householders to the Guarantee for Women in Subfamilies

	Sample Size	House-holders	Living in Subfamilies	Married Women	Welfare Recipients	In Labor Force	In School
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. Full Sample							
Before	6341	0.169	0.083	0.748	0.101	0.596	0.025
After	6342	0.163	0.084	0.746	0.096	0.600	0.024
After/Before	6341	0.966	1.011	1.007	0.948	1.007	0.987
Women Under 22							
Before	549	0.111	0.217	0.672	0.162	0.409	0.091
After	549	0.105	0.219	0.676	0.156	0.411	0.090
2. Householders							
Before	1072	1.000	NA	NA	0.433	0.621	0.038
After	1036	1.000	NA	NA	0.415	0.637	0.041
3. Subfamilies							
Before	527	NA	1.000	NA	0.334	0.518	0.102
After	533	NA	1.000	NA	0.332	0.518	0.099
4. Women on Welfare							
Before	640	0.725	0.275	NA	1.000	0.262	0.064
After	607	0.708	0.292	NA	1.000	0.267	0.068
5. Women Not on Welfare							
Before	5700	0.107	0.062	0.832	0.000	0.634	0.020
After	5735	0.106	0.062	0.832	0.000	0.636	0.020

difference between the householder and subfamily guarantee (AFDC1 - AFDC3 = ADCDIF) is held constant (which, of course, implies an increase in AFDC3). This increase in benefits for all living arrangements should make the welfare system more attractive to both householders and subfamilies.

The effect of this change is shown in Table 6.2. For the full sample of women under 36, household headship would rise from 16.9 to 17.3 percent, a mere 2 percent increase (the "After/Before" row), while the number of women in the "married" and "subfamily" living arrangements would decline slightly (line 1, columns 2, 3, and 4). Among welfare recipients (line 4), there would be a slight shift toward household headship from living in subfamilies. Before the change, the breakdown is 72.5 percent heading households and 27.5 sharing. After the policy change, we predict it would be 73.6 percent heading households and 26.4 percent sharing.

Of course, although these numbers appear quite precise, they are really rough predictions. They are based on the AFDC1 coefficients in Table 4.7, several of which are not statistically significant at conventional confidence levels. As such, one should not place too much faith in these predictions.

We estimate that the increased level of AFDC benefits will lead to a 5.8 percent increase in the number of recipients (column 5). The tables also allow us to see how this 5.8 percent "welfare effect" is distributed among the living arrangement categories. For example, line 2, column 5 tells us that under the current AFDC system, 43.3 percent of householders received public assistance. After the proposed policy change, we predict that 45.5 percent of householders will receive public assistance. The comparable change in welfare recipiency for women in subfamilies (line 3, column 5) is from 33.4 percent to 34.6 percent.

What would be the effect of the proposed policy shift on labor force participation and schooling? In our model the "labor supply" effect of this more generous AFDC program is quite modest. Overall (line 1, column 6) labor force participation would decline only slightly, from 59.6 percent to 59.1 percent. Despite the small overall effect, labor force participation among householders declines somewhat more, from 62.1 percent to 60.1 percent. Presumably because the higher benefits alter the composition of the welfare population, the labor force participation of women on welfare actually rises by a small amount (line 4, column 6). The labor force participation of women in subfamilies (line 3, column 6) and that of women "not on welfare" (including married women) declines slightly.

The estimated effect of changes in the AFDC system on schooling (column 7) must be viewed with considerable caution. In our sample of women with young children, there were very few respondents (only 197 out of 6341) who met our definition of "being in school." Because of this, our coefficient estimates in the schooling equations are very imprecise. (See the Appendix Table A.6.2.) Keeping this in mind, we see that increasing the AFDC guarantee to householders by 10 percent has a negligible overall impact (line 1, column 7) on schooling.

Simulation 2: Raising the Guarantee for Women in Subfamilies by 10 Percent

The second simulation involves raising the AFDC guarantee "if living in a subfamily" (AFDC3) by 10 percent and holding constant the AFDC guarantee "if householder" (AFDC1).[4] This should make the AFDC system as a whole more attractive and, within the system, make living in a subfamily more attractive than being a householder.

Consistent with these expectations, the simulation (Table 6.3) reveals an increased proportion of mothers who are single and living in subfamilies and a decreased proportion living as householders. The changes are, however, rather small. The proportion of women living in subfamilies rises from .083 to .084, while the proportion living as householders falls from .169 to .150.

Also consistent with expectations, there is a shift in living arrangements among those on welfare (line 4). The increase in AFDC3 causes the proportion of welfare recipients living in subfamilies to increase from 27.5 percent to 32.7 percent.

Yet not all of the results in Table 6.3 are plausible. In particular, the increase in AFDC3 leads to,

a) an increase in the proportion of mothers who are married (from .748 to .766),

b) a decrease in the proportion of mothers who are on welfare (from .400 to .390),

c) an increase in the proportion of mothers who are in the labor force (from .596 to .606), and

d) a decrease in the proportion of mothers who are in school (from .025 to .023).

None of these results make much sense. Why would an increase in the level of AFDC benefits available to women in subfamilies lead to more marriages, fewer welfare recipients, more labor force participation, and less schooling? Although small, these effects are somewhat troubling.

They are also easily explained. Each of the curious results is a product of imprecisely estimated coefficients on the ADCDIF variable.

Consider the marriage effect (point a above). That effect is strongly influenced by the coefficient on ADCDIF in column 1 of Table 4.7. The estimated coefficient is +1.23 with a standard deviation of 2.64. That implies a .95 probability that the "true" (population) coefficient lies within the range $1.23 \pm 1.96 \times 2.64$, i.e., the 95 percent confidence region for this coefficient is -3.95 to +6.40. Of course this has implications for the simulations. In fact, it can be shown that if the coefficient on ADCDIF were -2.0 instead of 1.23, then we would not have observed (a) above, i.e., the simulations would not indicate that an increase in AFDC3 leads to an increase in the proportion of women who are married. Thus, because a key coefficient is imprecisely estimated, one can not have much confidence in the simulation results.

The same point can be made for (b), (c), and (d) above. The key coefficient for (b) is the coefficient on ADCDIF in column 3 of Table 4.7; that coefficient is -.102 with a standard deviation of 3.18. The key coefficient for (c) and (d) are the coefficients on ADCDIF in the Appendix tables.[5] In each case a different coefficient on ADCDIF--a coefficient that falls well within the 95 percent confidence region--would yield more plausible results.

To conclude, the most meaningful results in this set of simulations are those that are based on precisely estimated (statistically significant) coefficients. Given this, we have two meaningful results. First, a 10 percent increase in AFDC3 will precipitate a rather large increase in the proportion of AFDC recipients who are living in subfamilies (from .275 to .327). Second, this increase in AFDC3 will cause a rather small decline in the proportion of all women who are living as household heads (from .169 to .150). In our view, because they are based on imprecisely estimated coefficients, the other results in this set of simulations (a through d above), are not credible.

Simulation 3: Elimination of Difference in Guarantees Due to Living Arrangements

Tables 6.4 and 6.5 indicate the effects of eliminating the difference between the AFDC "subfamily" and "householder" guarantee (reducing ADCDIF to zero). In 6.4 we increased the subfamily guarantee to the level of the householder guarantee. In 6.5 we decreased the householder guarantee to the level of the subfamily guarantee. Since the Table 6.4 simulation involves a decrease in AFDC3, its results are similar in direction (although smaller in magnitude) to those in Simulation 2. In like manner, the results in Table 6.5 are related to those in Simulation 1. Consequently, the major qualitative results in these two tables have already been discussed. Perhaps the most interesting aspect of the tables are the magnitudes. The effect of eliminating the difference in guarantees is invariably minuscule. This is true for living arrangements, welfare receipt, schooling, and labor force participation.

Conclusion

This chapter illustrates a problem in running simulations: imprecise parameter estimates lead to imprecise predictions. Because of this, some of the simulated results are more believable than others. By combining the Chapter 4 information on standard deviations with the results in this chapter, we arrive at the following conclusions:

- Changes in AFDC benefits have discernible but small effects on the choice of living arrangement. Simulation 1 indicates that holding the difference between the household and subfamily guarantee (ADCDIF) constant, a 10 percent increase in the guarantee for household heads leads to a slight (2 percent) decrease in the proportion of all mothers who are single and living in subfamilies. Simulation 2 indicates that, holding the guarantee for household heads constant, an increase in the guarantee for mothers living in subfamilies leads to a slight increase in the proportion of all mothers who are single and living in subfamilies. Perhaps the most significant effects were found for the AFDC recipient population. There, a 10 percent increase in the subfamily guarantee led to a 5 percentage-point rise in the fraction of recipients who live in subfamilies (from .275 to .327).

- We have little to say about the effect of AFDC benefits on schooling. The coefficient estimates in Chapter 4 often had implausible signs and large standard deviations. When those coefficients were employed in simulations, they indicated small, often implausible, effects. This is certainly consistent with the claim that AFDC benefit levels have little effect on the propensity to engage in schooling.

- An increase in the AFDC guarantee for household heads, holding ADCDIF constant, leads to large increases in the probability of recipiency and small decreases in the probability of labor force participation. Neither outcome is new or surprising.

- A policy that eliminates within-state differences in AFDC benefits across living arrangements by raising the level of AFDC benefits paid to women in subfamilies would increase the number of subfamilies and decrease the number of female household heads. It appears, however, that these changes would be quite small. Moreover, this policy would have almost imperceptible effects on labor force participation and schooling.

Notes

[1]Note that this assumes that changes in AFDC benefits do not affect the number of mothers in the sample. In consequence, these simulations abstract from any effect of AFDC on the propensity for women to give birth to and keep children.

[2]The probabilities are set equal to zero for $j=2$ and $n=1$ (married women on welfare).

[3]The third and fourth simulation show patterns of changes that are similar to those of the second simulation, although the changes are smaller.

[4]Since the model of living arrangements (Table 4.7) is parameterized in terms of ADCDIF = AFDC1 - AFDC3, we actually perform the simulation by setting ADCDIF* = (1.1)*ADCDIF - (.1)*AFDC1, where ADCDIF* represents the simulated change in the system.

[5]The problem of imprecise parameter estimates causing (b), (c), and (d) is not simply a product of our rather elaborate simulation methodology. The problem was present in the simple Chapter 4 models--note the coefficients on ADCDIF in Table 4.8. All are imprecisely estimated and several have unexpected signs.

[6]The first result is based on the coefficient on AFDCIF in Column 4 of Table 4.7. While the second is not based on any one coefficient in Table 4.7, it is backed up by the statistically significant coefficients on AFDCIF in Table 4.4. As a further check on this we ran the simulations in the nonmarried population using the 4 category logit in Table 4.6. While the results were essentially the same as those discussed in the text, the increase in the proportion of the all women living in subfamilies was slightly lower than that presented in Table 6.3.

Appendix Table A.6.1

Coefficients from Labor Force Participation Equations by Living Arrangement Subgroup[a]

	Householders		Subfamily Heads		
	No Welfare	Welfare	No Welfare	Welfare	Married
	(1)	(2)	(3)	(4)	(5)
AFDC1	-.0017**	-.00017	-.0013*	-.0016*	-.00023
ADCDIF	.0013	-.0021*	-.00071	.0034	-.00062
AGE	.21	.056	.37**	.11	.33**
AGES2	-.0030	.00057	-.0043*	.0036	-.0049**
EDUC	.034	.17	0.46*	1.54*	.18
EDUCS2	.0061	.0033	-.0068	-.049*	-.00060
AGE*EDUC	-.0016	-.0074*	-.0069	-.018*	-.0025
SOUTH	-.17	-.064	-.27*	.39*	.17*
SMSA	-.022	-.26*	-.29*	.020	-.024
UNEMLOY	-.0045	.010	-.022	.044	-.045**
NONWHITE	.12	-.086	-.35**	-.64**	.35**
DEPENDS	-.14*	-.15*	-.20*	-.73**	-.24**
PRESCHOOL	-.20*	-.33*	-.27*	.44*	-.38**
CONSTANT	-2.12	-1.86	-7.06**	-11.63*	-5.11**
Number in Sample	608	464	351	176	948
Number in Labor Force	69	129	124	42	569
-2 log likelihood	44.2	28.5	77.5	28.0	130.4

*t-stat > 1
**t-stat > 1.96

[a]All coefficients shown with two significant digits to the right of the decimal.

Appendix Table A.6.2

School Participation Equations
by Living Arrangement Subgroup[a]

	Householders		Subfamily Heads		
	No Welfare	Welfare	No Welfare	Welfare	Married
	(1)	(2)	(3)	(4)	(5)
AFDC1	.0015*	-.0017*	.0018*	.0016	-.0027*
ADCDIF	-.0028	-.00097	.00012	-.000016	.0038
AGE	-.75**	.0049	-.45	-.87**	.15
AGES2	.011*	-.00091	-.017	.0041	.0065*
EDUC	.46	.0025	-.60*	1.90*	2.08*
EDUCS2	-.025*	-.0023	-.040*	-.14*	-.037*
AGE*EDUC	.0080	.0065	.078*	.056*	-.039*
SOUTH	.13	-.021	-.11	.20	-.051
SMSA	.14	.63*	-.32*	.63*	.074
UNEMLOY	-.031	-.012	-.034	-.079	-.075*
NONWHITE	-.31*	-.40*	.74**	1.23**	-.046
DEPENDS	-.37**	.0044	-.26	-.72**	-.10
PRESCHOOL	.11	.45*	-.54*	.42	.14
CONSTANT	6.05*	-2.97	11.01**	-1.28	-16.89*
Number in Sample	608	464	351	176	948
Number in Labor Force	21	20	45	22	11
-2 log likelihood	19.8	15.7	113.2	36.0	15.2

*t-stat > 1
**t-stat > 1.96

[a]All coefficients shown with two significant digits to the right of the decimal.

Chapter 7

Conclusion

The goal of this project was to examine the relationship between living arrangements on the one hand, and education, employment, and welfare use on the other. While the first chapter summarizes our basic findings, a brief review may be helpful here. The foregoing chapters yield seven conclusions:

1. State AFDC programs differ in their treatment of various living arrangements. Some states impose a substantial penalty on poor mothers with children who choose to live with parents.

2. This "subfamily penalty" affects behavior. An increase in the penalty decreases the probability that a mother will reside in a subfamily and increases the probability that she will head her own separate household. In addition, an increase in the subfamily penalty decreases the probability that a mother will reside in a subfamily and receive welfare, and increases the probability that she will be a female household head on welfare.

3. Higher AFDC benefits are related to a greater propensity to receive welfare and a lower propensity to work. We find no statistically significant relationship between the level of AFDC benefits and either the propensity to attend school or the propensity to choose a specific living arrangement.

4. Mothers who live in subfamilies have lower labor force participation rates and lower welfare recipiency rates than mothers who are female heads of households. Not only is this true when the rates are computed as unconditional means, it is also true for conditional means (which hold other factors such as age, education and race constant). Differences in conditional means are, however, most pronounced for young mothers; the differences tend to disappear as mothers age (see Table 4.17).

5. Although a comparison of unconditional means indicates that mothers who live in subfamilies are more likely to attend school than mothers who are female heads of households, the result largely disappears when other variables such as age and race are held constant.

6. The data reject a structural model of living arrangement choice that is based on the theory in Chapter 3.

7. A policy that eliminates within-state differences in AFDC benefits across living arrangements by raising the AFDC benefits paid to women in subfamilies would lead to a small increase in the number of subfamilies and a small decrease in the number of female household heads. This policy would have almost imperceptible effects on labor force participation and schooling.

As is usually the case, the process of answering questions leads to new ones. It is fitting to conclude this report with a discussion of what more could be done on the topic.

One area for future work concerns data. The Current Population Survey is not a particularly good data set for addressing the questions posed here. For example, in analyzing choice of living arrangements, one would like to have information on a woman's options. The ideal survey would ask young women such questions as:

--Do your parents live nearby?

--Do other relatives live nearby?

--If times became particularly hard, could you move in with your parents or other relatives?

Such information could lead to improved empirical specifications and better estimates of how changes in the AFDC program affect behavior.

A second data problem concerns sample size. The Current Population Survey contains a surprisingly small sample of young mothers who are either heads of household or who reside in subfamilies; there are fewer than 200 such women under age 22. Of course, from a policy perspective, that is the population of interest. To learn more about that population, a larger sample is requisite. Both this problem and the previous data problem could perhaps be addressed with a supplement to the Survey of Income and Program Participation.

Such data could be used to estimate structural models of a young mother's choices concerning living arrangements, labor force participation, schooling, and welfare receipt. While this project sought to estimate structural models, it did not succeed. We are by no means finished with this line of work. We are not yet convinced that the structural model implied by the theory in Chapter 3 is inappropriate. Still, that remains a direction for future research, and better data may help. Research into choice of living arrangement badly needs an empirically verifiable theory. Too often work in this area involves an ad hoc model and a sign test on one or two parameters in a reduced form. As indicated in Chapters 3 and 5, the assumption of utility maximization yields several strong refutable hypotheses. If we are to make progress in understanding how living arrangements are chosen, then we need to take such hypotheses seriously.

Another direction for future research would be dynamic modeling. While we believe that the equilibrium models presented here address important questions, the questions addressed by dynamic models are also important. For example, one would like to develop behavioral models of the sequence of choices that a young mother makes as she moves from teenage pregnancy to adulthood. How are choices of living arrangements, schooling, labor force participation, and welfare receipt linked through time? While this is a very complicated modeling problem, it could help to indicate how the welfare system influences the timing of a mother's decisions. And it has the potential to reveal the fundamental mechanisms of dependency--it could reveal how today's choices affect tomorrow's options.

To conclude, this research has extended our understanding of the relationship between living arrangements on the one hand, and education, employment, and welfare use on the other. While we believe we made progress--perhaps even substantial progress--many interesting and socially important questions remain.

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