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Three Essays on Understanding Welfare Reform

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2005

The dissertation of Kevin King is approved, and it is acceptable in quality and form for publication on microfilm:

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Chair

University of California, San Diego

2005

To my wife,

Sarah.

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ABSTRACT OF THE DISSERTATION

Three Essays on Understanding Welfare Reform

by

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Doctor of Philosophy in Economics

University of California, San Diego, 2005

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In 1996 the United States passed a major reform of welfare, the federal and state program that had provided and continues to provide money to poor, mostly single mothers since 1935. One element of the reform was that it capped benefit receipt at no more than five years regardless the age of a recipient's child. This dissertation focuses on understanding what led to these time-limits.

Chapter 1 makes the case that changes in the welfare caseload—brought on by population changes, the Supreme Court, and other government programs—could have led to its reform. The problem was that too many people receiving welfare were people for whom it was not intended. The solution Washington chose was to cut the program's generosity intertemporally by instituting five-year time limits.

Chapter 2 adds rigor to the welfare reform story in Chapter 1 by analyzing 1) how lack of observability affects the design of a social insurance program, and 2) how it

interacts with an increasing population who find going on social insurance attractive. It shows that a lack of observability affects the generosity and incentives of the program because what is preferred with observability often cannot be implemented when it is absent. Finally, it shows that a rising population of the poor can induce programs to switch from allowing the poor not to work to ones that do require them to work because the high types subsidizing the program slash the benefit to reduce excessive redistribution.

Chapter 3 examines our ability to use observable information to explain future welfare usage and finds that it has gone down since reform. I argue that this result is consistent with the social insurance function of welfare being more important than it was before reform. I note, however, that it is also consistent with a rise in the importance of unexplained variation.

Chapter 1

Why Time-Limited Welfare Reform?

1.1 Introduction

In 1996 the United States passed a major reform of welfare,[1] the federal and state program that had provided and continues to provide money to poor, mostly single mothers since 1935. The reform was called the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), and it changed one of welfare's longstanding features. It had been that a mother could receive welfare so long as one of her children was younger than 18 years old; after PRWORA the government capped this time period at no more than five years regardless of her children's age.

[1] "Welfare" serves as the general term for the program that has gone by many names. It has been called mothers' pensions, widows' pensions, Aid to Dependent Children (ADC), Aid to Families with Dependent Children (AFDC), and Temporary Assistance for Needy Families (TANF). When it makes more sense in historical context, I use the historically-appropriate name.

In so doing PRWORA ended welfare as a means-tested, open-ended cash entitlement. While PRWORA reformed other aspects of welfare,[2] I focus on time limits because I believe introducing them addressed welfare's chief political problem—that welfare was attracting too many people with characteristics for whom it was not intended.

The story begins with policymakers creating welfare primarily for a target population of mothers either widowed or with disabled husbands. While welfare mostly went to mothers with these characteristics in the beginning, by the 1970s it was mostly separated, divorced, and never-married mothers who received it. I hypothesize it was this development that principally fueled the calls to reform welfare and that time limits were one way of addressing it.

Despite welfare reform being almost a decade in our past, there are two important reasons for us to continue researching it. First, the federal government will have to eventually reauthorize PRWORA, and its success or failure should matter to that debate. To date I think researchers and commentators have misunderstood what PRWORA was meant to address so current efforts to judge its efficacy have been misdirected. Current efforts have focused on two strands of research. The first seeks to understand why the welfare case load has fallen so dramatically since reform. Recognizing that a booming economy accompanied this fall in case loads, this line of research wants to know what portion of the fall can be attributed to welfare reform and what portion to the economy.[3] Another strategy, embodied in Blank and Haskins (2001), is to look at individuals' outcomes before and after welfare reform to see if

[2]See Blank (1997) and Blank (2002) for a discussion of the other aspects of welfare reform.
[3]For a summary of this work, see Blank (2001).

they are better off. While this information in both cases may be worth knowing, it does not address the political aspects of welfare reform. The second reason to continue researching welfare reform is that it is likely that other programs will undergo similar caseload evolutions which may damage their respective popularities. Understanding the importance of caseload characteristics will help policymakers better design their programs in anticipation of and in response to such changes.

1.2 Welfare in the Beginning

Welfare started as a patchwork of state programs early in the 20th century. It was one result of a child welfare movement that sought better care for America's poor children. Its supporters argued that children of destitute families were better off when raised by their birth mothers rather than by orphanages (DeParle 2004) and that providing home-based support was cheaper than institutional care for the government (Bell 1965). What they proposed instead were mothers' pensions[4] whereby the state provided money to poor mothers so they could raise their children without having to work. The movement was remarkably successful. Between 1911 and 1935—the year the federal government started providing welfare—all but two states had enacted mothers' pensions (Skocpol 1992).

Welfare became a semi-federal program in 1935 when the U.S. government created Aid to Dependent Children (ADC) as an element of the Social Security Act (SSA). The SSA authorized the federal government to disburse money to the states according

[4]Less often they were called widows' pensions.

to a formula of what each state spent on its welfare recipients.[5] I call ADC semi-federal because the SSA did not initially revoke much of the autonomy states had over their mothers' pensions: the states still administered them, set their benefit levels, and wrote eligibility guidelines.[6] The Act did not even require the two states without mothers' pensions to offer ADC if they chose not to.

As indicated above states continued to set eligibility standards with the SSA providing only a broad standard upon which the states could further restrict. According to Title IV, Section 406 of SSA, a dependent child was

> a child under the age of sixteen who has been deprived of parental support or care by reason of the death, continued absence from the home, or physical or mental incapacity of a parent, and who is living with his father, mother, grandfather, grandmother, brother, sister, stepfather, stepmother, stepbrother, stepsister, uncle, or aunt, in a place of residence maintained by one or more of such relatives as his or their own home.[7]

This language gave states plenty of leeway to pass more restrictive eligibility guidelines or keep the more stringent standards of their mothers' pensions.[8] With the legal authority to do so many states chose to have a restrictive eligibility standard known as

[5]Under the SSA's cost-sharing formula, the federal government contributed one-third of the state programs' costs up to $6 per month for a family's first ADC-receiving child. For each additional child, the federal benefit was $4. Thus, the federal government contributed money to the states up to $18 and $12 per child per month. In 2004 dollars these combined federal-state benefit amounts would be $2970 and $1980 per annum. The Act permitted states to set monthly benefits above these levels although the cost-sharing formula implied the states alone would foot the additional cost.

[6]One minor exception was that the SSA required states with welfare programs to universalize them throughout the state (Cauthen and Amenta 1996). Before SSA, states let their localities decide if they wanted welfare programs or not (Bell 1965). In practice, there were states with welfare programs where but a few of their counties actually offered assistance. According to Bell (1965), six states with mothers' pensions offered welfare in less than 5% of their counties. Two of the six offered welfare in *none* of their counties.

[7]It is interesting to note that the SSA did not make a distinction between fathers and mothers, only that a parent be dead, absent, or incapacitated. In practice, the overwhelming majority of welfare recipients have always been mothers.

[8]All but three of them had done so, according to Bell (1965).

a suitable home policy. This standard demanded that eligible mothers be "physically, mentally, and morally" fit to raise their children with the government's cash assistance (Bell 1965). As a result administrators typically excluded from receiving welfare "divorced mothers and those with children born outside marriage, and it almost always excluded racial minorities" (DeParle 2004). In the end, the overwhelming majority of recipients were widows: both Cauthen and Amenta (1996) and Bell (1965) cite a federal survey from 1931 that found over 80% of mothers' pension recipients were widows. According to DeParle (2004) and Bell (1965), because many mothers found it difficult to qualify for welfare, the widows who received it were known as "gilt-edged" for the ease with which they were welfare-eligible.

1.3 The Welfare Population Changes

While the percentage of welfare recipients who were widows was over 80% in 1931, Figure 1.1 shows that the welfare population completely shifted to mothers who were divorced, separated, or not married by the 1990s. For example, widows were 37% of welfare's recipients in 1942 but had fallen to 2% by 1992. It was a similar situation for families with one or more disabled parents. In 1942, they were 22% of the welfare rolls; fifty years later they had fallen to 4%. What took the place of both groups were divorced, separated, or not married mothers. Together they grew from 37% in 1942 to 90% by 1992 with the largest gains coming from those not married.

What caused this radical evolution is the subject for the rest of this section where I discuss two reasons that probably explain it. First, single mothers flooded the welfare

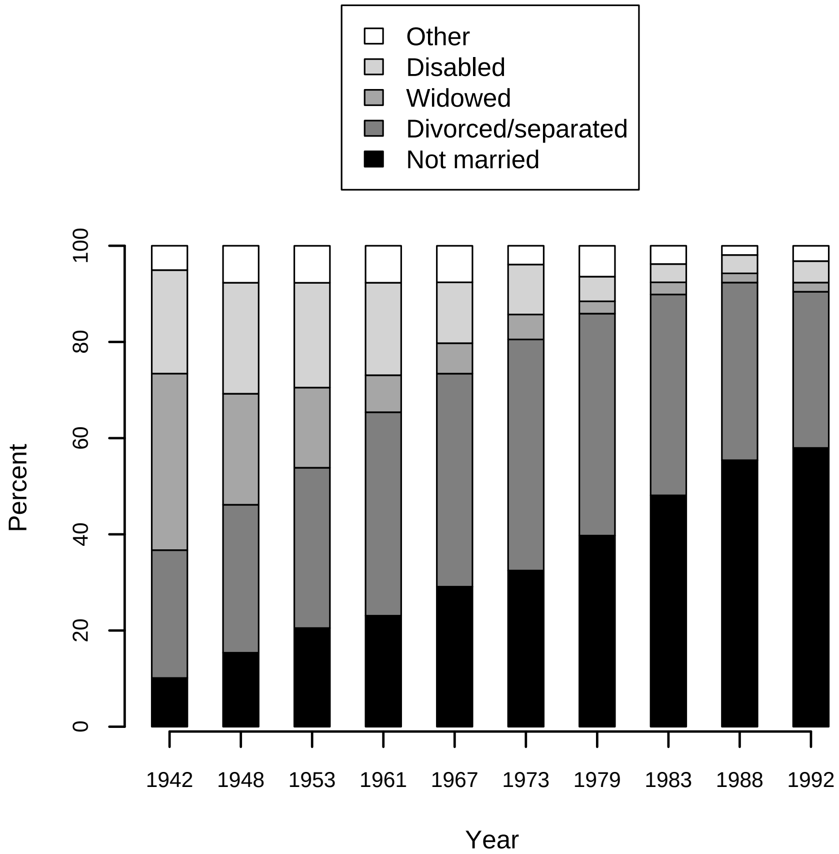

Figure 1.1: Reason for Welfare Eligibility, Selected Years, 1942–1992
[Note: see Appendix A for source descriptions of this dissertation's figures.]

rolls. They did so because there were many more of them in the general population and because the states could no longer use the suitable home provisions to keep them off welfare. Second, the federal government created new social insurance programs that were probably more attractive to widows and disabled parents than welfare. I should note that the extent to which these developments contributed to welfare's evolution is an open research question. I present them here because they strike me as likely explanations.

1.3.1 Single-Parent Families Dominate Welfare

Figure 1.2 shows that the growth of unwidowed single-parent families far outpaced widows and disabled-parent families on the welfare roles. In fact, while unwidowed single-parent families on welfare exploded, the other categories remained constant by comparison. The increase in unwidowed single-parents drove a result familiar to many welfare watchers: by almost any perspective the number of people receiving welfare grew enormously during welfare's post-World War II history. From 1936 to 1996, the number of welfare families increased by over 2900% as Figure 1.3 shows, and the number of recipients grew by more than 2200% during this time frame as Figure 1.4 shows. Figure 1.5 shows that individuals receiving welfare outpaced population growth as well, with per capita welfare receipt increasing from 0.4% to 4.6% from 1936 to 1996. Finally, these three figures demonstrate that welfare especially grew between the late 1960s and early 1970s, a period of time that corresponds with when Figure 1.2 shows that unwidowed single-parent welfare families sharply diverged from widows and families with a disabled parent.

Single-Motherhood in the General Population

The most important reason why unwidowed single parents came to dominate welfare is because there were so many more of them in the general population. Figure 1.6 shows that they increased by 500% from 1950 to 1996 with an especially large gain in the 1960s and 1970s. Figure 1.7 shows that as a percentage of all families, single-mother families also increased, by 250% in that case.

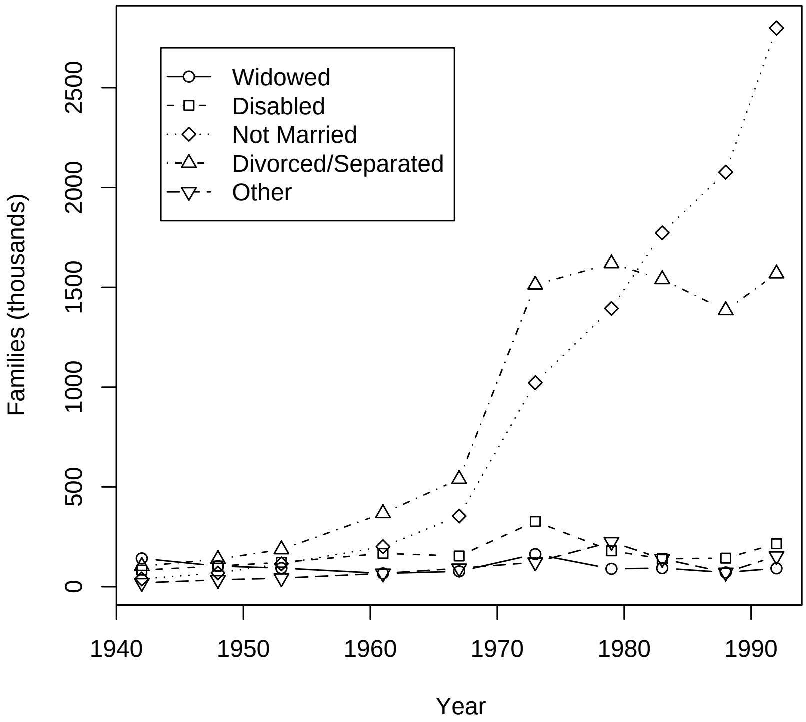

Figure 1.2: Families on Welfare by Reason of Eligibility, Selected Years, 1942–1992

Another factor that contributed to welfare's demographic shift was an increase in the rate at which single mothers received welfare. Figure 1.8 shows an estimate of the welfare participation rate among single-parent families from 1950 to 1996.[9] The participation rate increased slightly until the late 1960s, but then shot up dramatically

[9]Note: this estimate is derived from dividing the number of families on welfare by the number of single-parent families with children under the age of 18 and multiplying the result by 80%. As Figure 1.1 shows, a non-zero portion of families receiving welfare do so because one of the parents is disabled. Therefore, there are two parents and an unadjusted division results in a higher number than ought to be the case. The 80% roughly reflects the percentage of single-parent families in 1948 and 1953, which declined from there considerably. Therefore, the estimate presented here is likely to be an underestimate in the years after the 1950s. Moffitt (1992) uses the Current Population Survey (CPS) to calculate a welfare participation rate among single-parents for the late 1960s to the late 1980s. His numbers are extremely close to this estimate, lending it believability. One advantage of this estimate is that it allows us to investigate back to 1950 which the CPS does not go back to.

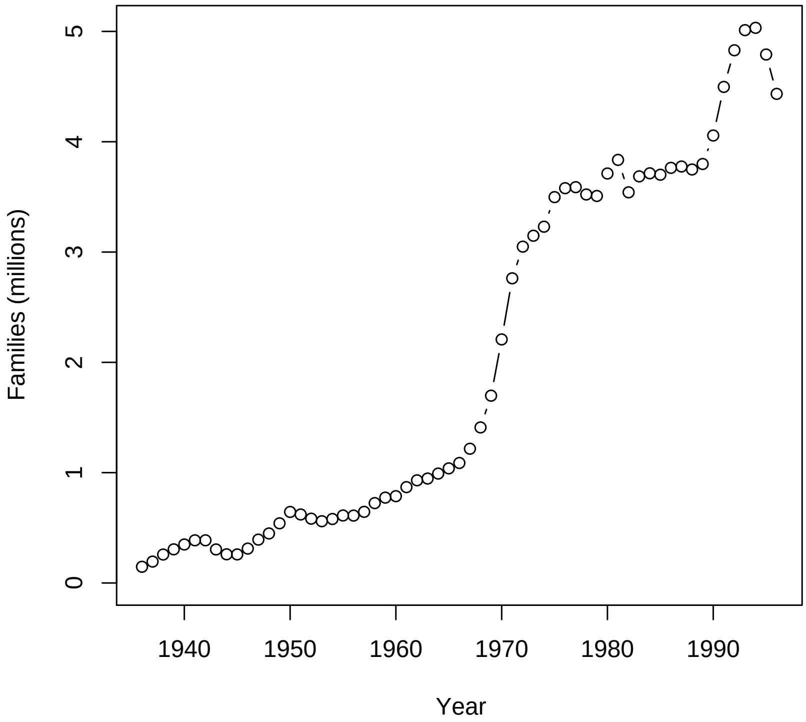

Figure 1.3: Families Receiving Welfare, 1936–1996

until well into the 1970s. It actually declined from there though it never fell below its level in the 1950s and early 1960s.

The evidence gathered here demonstrates that something changed about family formation in America, and there existed an increased pool of unwidowed single-mother families who lacked husbands. This change in the underlying population of single mothers contributed to a corresponding change in the welfare population. Some states had laws to counteract this effect, but as we will see, they eventually lost the ability to do so. Because of the growth in the population of such women and the statutory inability to keep them off of welfare, the profile of the welfare population

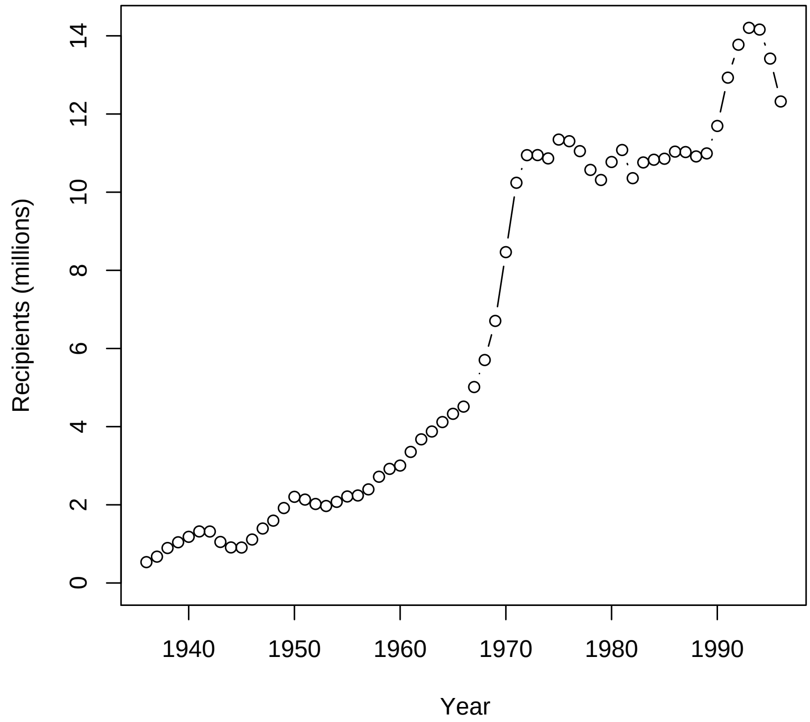

Figure 1.4: Welfare Recipients, 1936–1996

changed.

Suitable Home Ends

The other reason why many more unwidowed single parents received welfare was because Congress and the federal courts outlawed the suitable home provisions that would have kept some of them off. Moffitt (1992), among others, points to the court cases alone, but Congress played a role as well. By the end of the 1960s states could no longer prevent the burgeoning population of single mothers from receiving welfare, thereby cementing the shift in welfare's caseload composition. Some states

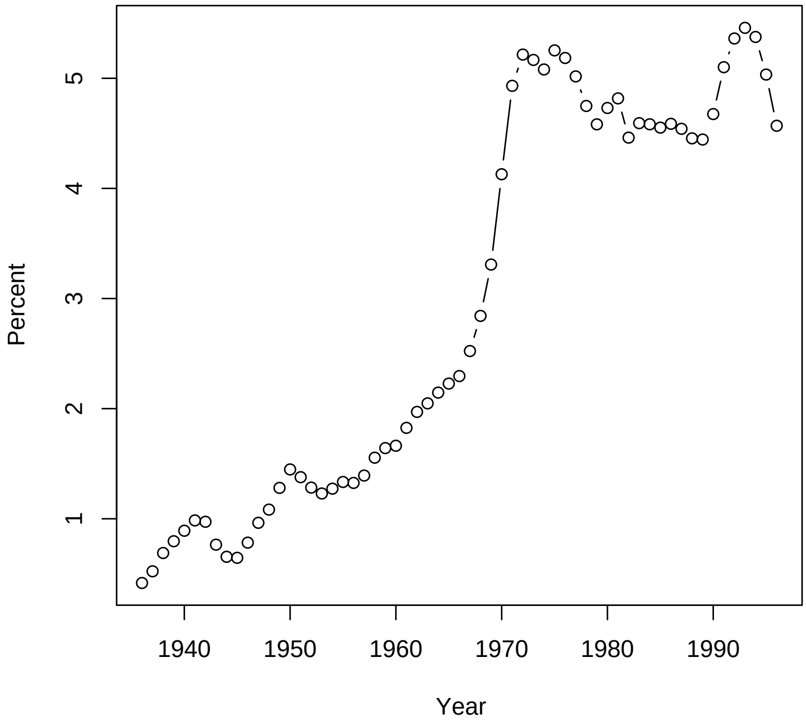

Figure 1.5: Welfare Recipients as Percentage of Population, 1936–1996

had tried to keep these morality-based eligibility guidelines well into the 1960s. One such example is a policy some states adopted known as the "man-in-the-house" rule. It prohibited otherwise eligible families from receiving welfare if there were a male who lived in a welfare recipient's house—even just part-time—and did not financially support the family. The effect was that mothers in these states could not have extra-marital relationships and still receive welfare. A second example is from Louisiana, which in 1960 decided that welfare recipients would lose their eligibility if the mother gave birth to an illegitimate child.[10]

[10] *King vs Smith* (1968)

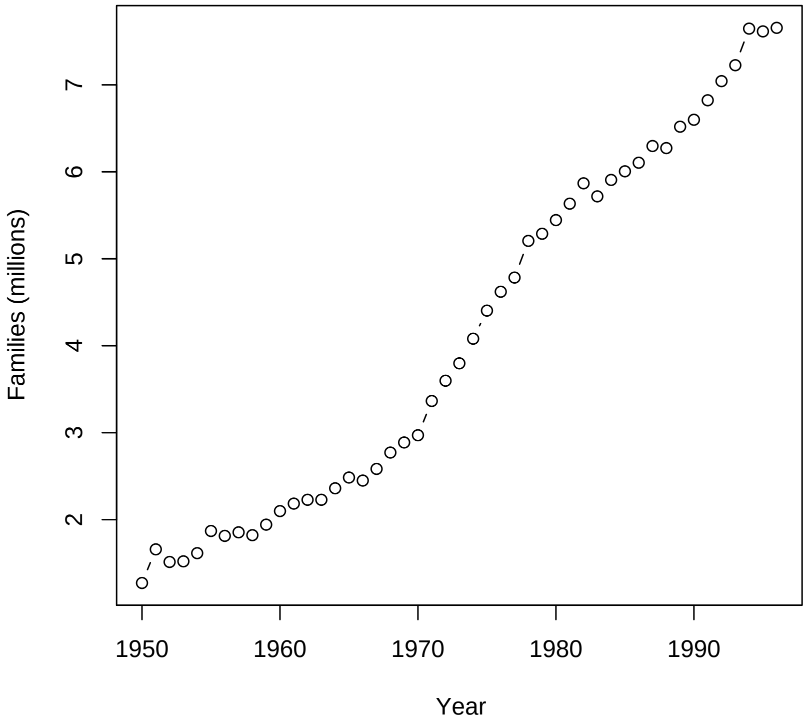

Figure 1.6: Families with Children Under 18 Headed by Single Females, 1950–1996

In the 1960s the federal government started to end such practices, and had succeeded by the end of the decade. The process began with Congress passing amendments to the SSA in 1961, 1962, and 1968 which weakened the states' authority in determining welfare eligibility.[11] Doing so laid the groundwork for the court case that outlawed the suitable home provisions once and for all. The Supreme Court in *King vs Smith* (1968)—which found Alabama's "man-in-the-house" law unconstitutional—cited these congressional amendments as the basis for its ruling against morally re-

[11] *King vs Smith* (1968)

Figure 1.7: Percentage of Families with Children Under 18 Headed by Single Females, 1950–1996

strictive eligibility standards.[12] The Court said that Congress' amendments meant that states could not use the prospect of losing welfare benefits to counter "immorality and illegitimacy" in their welfare populations. States now had to provide welfare to all poor single mothers who asked and otherwise qualified for it—suitable home had ended.

[12]It is noteworthy that the Mrs. Smith of the case—who had lost her benefits because she had a sexual relationship with a man who spent the night with her on weekends—was actually a widow. Her sexual behavior after her husband's death overrode her status as a widow in the eyes of Alabama's law.

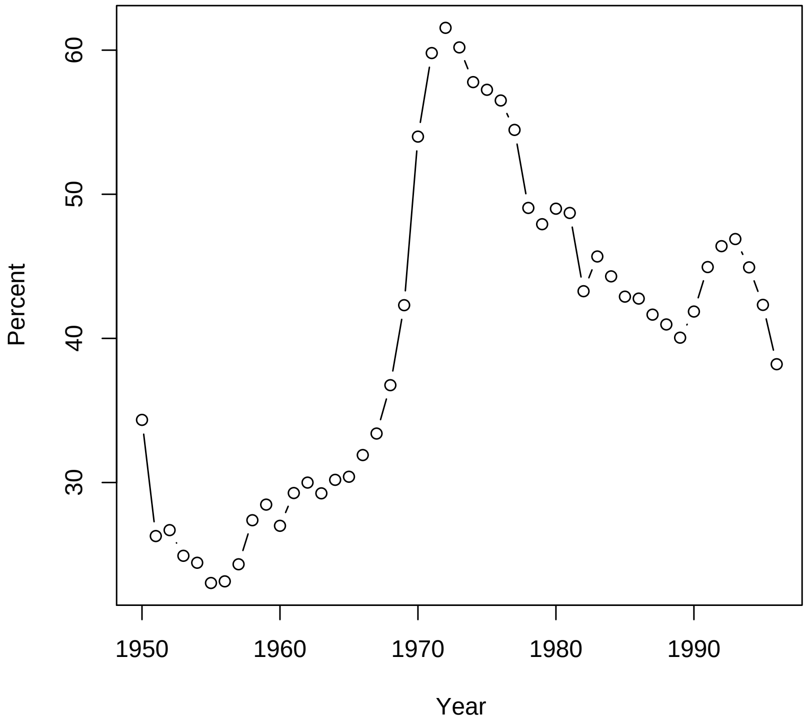

Figure 1.8: Estimated Welfare Participation Rate among Families with Children Under 18 Headed by Single Parents, 1950–1996

1.3.2 Feds Create Rival Programs

Weaver (2000) offers another explanation when he notes that post-SSA social insurance programs competed with welfare for widows and the disabled. In a little over twenty years after the US passed the original SSA in 1935, the federal government added Survivor's Insurance and a couple of forms of Disability Insurance (Berkowitz 2000). Specifically, with the 1939 amendments to the SSA, the government added Survivor's Insurance which extended benefits to those individuals who had lost spouses and later to the children they left behind. Disability Insurance began in 1956, and it provided benefits to individuals who could not work. Both of these programs in their various forms continue to exist to the present day and are more generous than welfare.

Though Weaver (2000) makes a credible case that these programs played some role in the evolution of welfare, their effect was probably not enough to explain all or even most of its changes. In Figure 1.2 we saw that it was the entrance of many more unwidowed single-parent families on welfare that tilted the welfare caseload in their direction than it was widows and the disabled departing the rolls. Changes in family formation probably swamped any change in the incentives for choosing one government program over another.

* * *

Welfare began as a program intended primarily for widowed mothers and families with one or more disabled parents, and the evidence shows they were its overwhelming recipients early on. It is important, though, to qualify the statement about who welfare was created for. As we have seen, the eligibility rules both before and after the SSA did not restrict welfare to only widows and disabled parents, something they very easily could have been written to do. Because neither the states nor the federal governments did so, it is hard not to conclude then that welfare began with a sense of confusion about who it was created for.

Perhaps it is best to think of the intended welfare recipient on a continuum of "worthiness," for lack of a better term. At the worthiest end were widows and disabled parents while at the other were never-married mothers, with varying degrees of worthiness in between. Because federal policymakers chose not to exclude anyone in that continuum, states were free to draw a somewhat arbitrary eligibility cutoff line within that continuum to separate worthy mothers from those that were not. It is not surprising that something so confused in theory would be unimplementable in practice, a point Bell (1965) makes clear. Even if the woman of the "suitable home" existed, locating her in that continuum without concrete guidelines was ultimately impossible to do.

What we have seen is that the failure of welfare's designers to figure out who it was for led to a striking outcome: the welfare population shifted almost totally from the "worthy" end of this spectrum to its opposite end. It should not surprise that this development accompanied welfare becoming an unpopular program and a constant target of reform.

1.4 How Caseload Characteristics Could Have Mattered

This section presents a few reasons for why the evolution in welfare's caseload may have contributed to the movement that sought to reform welfare. While other authors have attributed welfare's unpopularity to its caseload growth, its alleged encouragement of illegitimacy, and its disincentives to work, none has made that case on the basis of welfare's caseload transformation alone. This fact is somewhat surprising given that the people who typically received welfare in its early years were so different from the people who received it later on, and in fact were the very ones many states had fought to keep off welfare in the first place.

There are at least two possible reasons—one derived from preferences for social insurance, the other from preferences for morality in public programs—for why the caseload composition could have reduced support for welfare. In either case, voters would have thought that the program's design—which had not changed significantly since the 1910s—was inappropriate for the population and incentives of the 1990s when there were so many more unwidowed single-parent families whose mothers chose to receive welfare. It is a fact, as we have seen, that taxpaying voters funded a program far different from the one they and their predecessors had endorsed earlier in that century. If voters held the preferences I describe below, then they would have demanded change, something welfare's political history indicates voters did not have many opportunities to do.

Considering welfare as a social insurance program is the first way in which the caseload could have been a problem. When thinking about why the welfare state exists in the way it does, there is a temptation to attribute it to mere benevolence on the part of voters. Another view argues for a self-interested motive in that the welfare state exists to provide protection from uncertainty for its citizens. As Dryzek and Goodin (1986) write, "[j]udging from their form, at least, the original initiatives of the welfare state seem to serve essentially an insurance (i.e., risk-sharing) function." By adopting this view, welfare was mostly created to provide insurance for two specific, negative outcomes. They were that a mother's financial provider husband died or became disabled, outcomes that would have forced her to work, move in with someone else, or give up her child. Unable to insure against these risks with private insurance, voters would have demanded the government to insure them.

Because of the way its caseload evolved, welfare began to increasingly insure people against additional risks—of separating, divorcing, and a having a child out of wedlock—that could have posed two interrelated problems for welfare as a social insurance program.

1. **Financial**—Voters had a program both more expensive and expansive than they may have wanted.

2. **Moral Hazard**—Separating, divorcing, and having an out-of-wedlock child leave more room for human agency than does dying or getting disabled. That welfare existed would have had more ability to encourage these behaviors than the ones that led to what welfare originally existed to insure against.

The second way the caseload composition could have mattered is if voters held preferences about the morality of public programs. In a society that says it values marriage—especially when it involves children—the evolution of the welfare caseload meant that welfare was supporting, and some thought promoting, an ever-increasing population of single parents. There are two ways this fact could have posed a problem for welfare.

1. ***Moral*** **Moral Hazard**—Voters may have believed that welfare encouraged family break-up and illegitimacy, behaviors they considered immoral.

2. **Suitable Home Redux**—Even for those voters who did not think that welfare encouraged family break-up and illegitimacy, they may not have wanted to support the single mothers who had made choices that led to these outcomes.

Of most apparent concern to PRWORA's drafters was the belief that AFDC encouraged out-of-wedlock childbearing. The "Findings" section of the bill discusses this issue at the exclusion of almost all others (U.S. House 1996, Sec. 101). For example, it says that the percentage of all live births that were to unmarried women grew from 10.7% in 1970 to 29.5% in 1991 (U.S. House 1996, Sec. 101(5)(C)). The law's drafters take one step further in hinting at a causal link between AFDC and this growth by saying, "The increase in the number of children receiving public assistance is closely related to the increase in births to unmarried women [Sec. 101(5)(C)]." They do not unequivocally say AFDC is the culprit, but it is certain from the text of the bill that its possibility was one of the more compelling reasons that legislators supported welfare reform.

It is obvious why they insinuated a link between AFDC and illegitimacy. By conditioning AFDC support on the recipient being a single parent, Moffitt (1992) notes

> the program provide[d] an obvious incentive to delay marriage, increase rates of marital dissolution, delay remarriage, and have children outside of a marital union, all of which [would] lower the percentage of the population that is married.

Despite AFDC's obvious incentives for unwed motherhood, the evidence has never supported this claim. Only a few studies found effects in the obvious direction, but even then, the estimates were rather small. Moffitt (1992, pg. 31) remarks, "The failure to find strong benefit effects is the most notable characteristic of this literature." The consensus among social scientists does not support the causal link insinuated by PRWORA's authors. Nevertheless, a belief unsupported by facts can still be a powerful force.

1.5 How Time Limits Would Have Addressed These Problems

What these four reasons share in common is that welfare money was being misspent on too many of the wrong people. Many taxpaying voters would have viewed this situation as wasteful because they were not deriving any benefit from it.[13] Of course, some money went to the "right" people but probably far from all of it did. Something had to be done to rebalance the distribution of welfare money between getting it to the "right" people and it not being too wasteful.[14]

One obvious way would be to reimpose a mechanism to screen between those who should and should not receive welfare. The Supreme Court's decision in *King vs Smith* (1968) would have prevented using an overt mechanism because it could probably be charged with countering the "immorality and illegitimacy" of welfare recipients. It

[13]Of course, this statement should not be construed to imply that this analysis ignores or even minimizes the benefits that welfare recipients derived from being on it. Their preferences obviously mattered and could have affected any political decision. Insofar as welfare was received by a narrow part of the population, however, their preferences would not overwhelmingly matter. The outcome of reform probably hinged on what the large majority of voters who did not and probably would never receive welfare wanted.

[14]Chapter 2 makes rigorous this non-mathematical analysis.

might have been possible to have instituted a less obvious screening mechanism with the use of work requirements as in Besley and Coate (1992), but it is not clear how that might have worked in this context. If unable to use a screening mechanism, the only option left would be to reduce the program's generosity.

Instituting time limits is one way of doing so. Rather than the more obvious choice of reducing benefits for a given unit of time, time-limits do so intertemporally. Why did policymakers choose time limits over cutting benefits for a given unit of time? One possibility is that doing the latter by the necessary amount would have rendered an already paltry benefit completely undesirable. Very few single parents would have chosen that kind of reformed welfare benefit over other available options. As such, time limits might have been the only way to reduce the program's generosity and still provide some benefits to the "right" people. Indeed, federal, state, and local cash assistance has gone down considerably since the early 1990s as we see in Figure 1.9, though most of the drop has been replaced with non-cash assistance.

1.6 Conclusion

This chapter has made the case that changes in the welfare caseload—brought on by population changes, Congress, the Supreme Court, and other government programs—could have led to its reform. The problem was that too many people receiving welfare were people for whom it was not intended. The solution Washington chose was to cut the program's generosity intertemporally by limiting benefits to no more than five years. In this view, PRWORA was an adjustment to the new

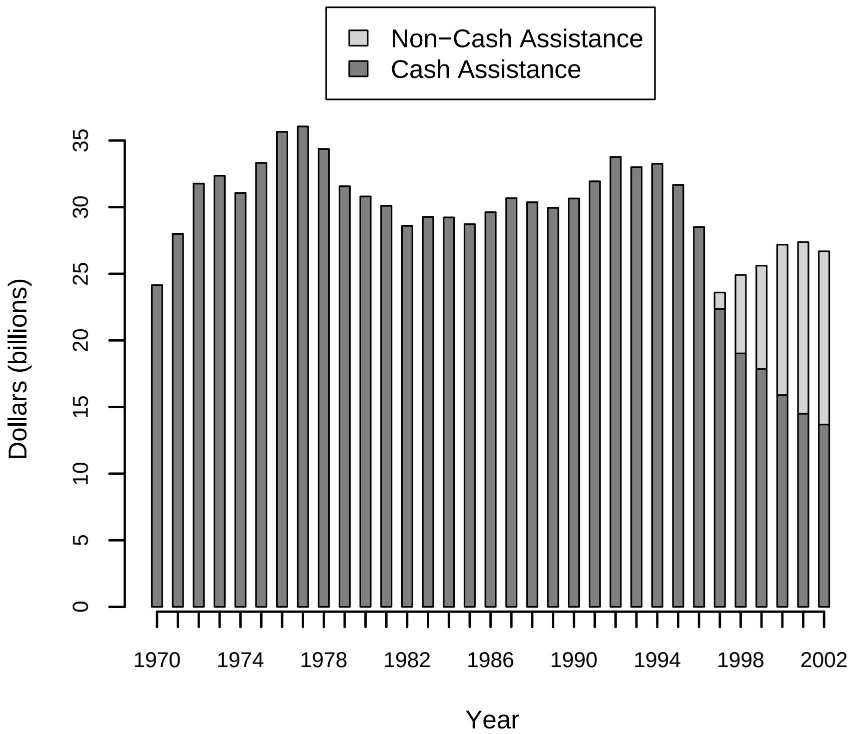

Figure 1.9: Federal, State, and Local Cash and Non-Cash Welfare Assistance (2004 Dollars), 1970–2002

reality of who was receiving welfare.

Chapter 2

Politics, Observability, and Social Insurance

2.1 Introduction

> The central element in the theory is information. Public policies apply to individuals only on the basis of what can be publicly known about them.
> —J. A. Mirrlees (1986)

In discussing the theory of optimal taxation Mirrlees reminds us that a government's inability to know everything about everybody constrains what it can implement. Nevertheless, Mirrlees and his colleagues showed us what government programs "should" look like in the presence of imperfect information by evaluating them according to a social welfare function (SWF). But a SWF does not reflect a satisfactory aggregation of preferences (Arrow 1950) so the programs they identified are not necessarily the ones voters would approve of. In ignoring voter preferences, their work does not tell us as much as we might like about how government's non-omniscience determines what actual programs look like.

I do not believe this point is trivial. For example, government programs are often intended for the benefit of a segment of the population like the disabled, the widowed, the victims of natural disasters, the jobless, the poor, and so on. Because of non-omniscience, government cannot ensure that all intended recipients get the benefit, nor can it exclude all unintended recipients from getting it either. Depending on the degree to which government misclassifies people, the politics of the program should affect its features. Voters usually do not like to waste their taxes, which is how they might consider program misclassification.

This paper models this situation with two goals in mind. The first is to investigate how limited information affects the program voters choose. The second goal—which relates the model to the welfare reform story in Chapter 1—is to see how a change in the population that increases the degree of misclassification further affects the program.

This paper uses a social insurance context to model this issue. There are two reasons for doing this. First, informational problems are inherent to social insurance—people always have an incentive to masquerade as qualifying for an insurance benefit which government often cannot prevent. Second, preferences for insurance provide a ready metric for judging the extent to which a program misidentifies recipients. Namely, a program that misclassifies people redistributes resources to people that are not supposed to receive the benefit. Preferences dictate how that individual would vote based on whether or not the program redistributes too much.

2.2 Model

Individuals face a risky situation with two possible outcomes. They are either "healthy," meaning they are capable of working and earning an income w or "sick" where they cannot work and earn 0. The probability of being "sick" is $p \in (0, 1)$ while the probability of being "healthy" is $1 - p$. Furthermore, there are two types of people in the model. When working, the high types earn w_{H} while the low types earn w_{L} with

$$w_{\mathrm{H}} > w_{\mathrm{L}} > 0. \tag{2.1}$$

Finally, the low types comprise a portion $\alpha \in (0, 1)$ of the population while the high types are $1 - \alpha$.

The government program consists of a pair (τ, b) where τ is the tax rate assessed on earned income, and b is the social insurance benefit provided to all those who do not work. This set-up leads to redistribution—(2.1) means the high types pay higher taxes (τw_{H}) if "healthy" than the low types do (τw_{L}) but earn the same benefit b if "sick." This assumption is crucial. As Casamatta, Cremer, and Pestieau (2000) show in their paper, a non-redistributive program does not produce interesting results. As a result, we adopt what constitutes the opposite polar case in their model where the program is fully redistributive. Most governments finance their social insurance programs through some degree of redistributive taxation so this assumption does not stray far from reality.

Requiring budget-balance limits the values of (τ, b) the government can set. A realistic assumption would require that the program's budget be balanced under every possible state of the world. For example, if there were an unusually large number of people who were sick, then the program would necessarily have to be less generous or would have to tax those who could work an extra amount in order for premiums to equal benefits. To require this kind of balance complicates the analysis to an undesired degree. Instead, what we require is that the budget be balanced in expected value—expected tax payments must be equal to the expected benefits paid out by the government. Though less realistic than the ideal budget balance, this one does place reasonable limits on the program's generosity.

The next step is to specify the preferences of the individuals in the model. In the interest of simplicity we assume that individuals evaluate uncertain events with the expected utility form

$$V_i = pU\big(b\big) + (1-p)U\big((1-\tau)\,w_i\big) \quad \text{for } i \in \{\mathrm{L}, \mathrm{H}\} \tag{2.2}$$

where $U(x)$ is a von Neumann-Morgenstern utility index. It is twice differentiable with $U'(x) > 0$ and $U''(x) < 0$. There is no disutility of labor in this model in order to simplify the analysis. Incorporating it would not alter the nature of the results.

The final step in setting up the model is to specify how the government chooses what policy to implement. The simplicity of this model provides a ready answer. The type with a higher proportion of the population is decisive in the electoral process. To be more specific the government policy (τ, b) equals $(\tau_{\mathrm{H}}, b_{\mathrm{H}})$ when $\alpha < \frac{1}{2}$ and $(\tau_{\mathrm{L}}, b_{\mathrm{L}})$ when $\alpha > \frac{1}{2}$. If α should equal $\frac{1}{2}$ then let it be the case that a tie-breaking mechanism exists that assigns equal probability to the two possible outcomes being the chosen government policy.

2.3 Observability Case

The analysis begins with the benchmark case where the government can observe an individual's condition. What this case implies is that the government costlessly and flawlessly delivers the insurance benefit to the "sick" while making the "healthy" work for their consumption—there are no misclassifications.

The first step is to satisfy the budget-balancing condition referred to in Section 2.2. Expected pay outs by the government program equal

$$pb \tag{2.3}$$

while expected tax receipts equal

$$\tau(1-p)\bar{w}(\alpha) \tag{2.4}$$

where

$$\bar{w}(\alpha) = \alpha w_{\mathrm{L}} + (1-\alpha) w_{\mathrm{H}}, \tag{2.5}$$

or average pre-tax earnings. Setting them equal and solving for b gives us the budget-balancing condition for the case with observability

$$b = \bar{w}(\alpha)\tfrac{1-p}{p}\tau = \bar{w}(\alpha)\varphi\tau \tag{2.6}$$

where

$$\varphi = \tfrac{1-p}{p}. \tag{2.7}$$

To decide upon a preferred government program individuals solve

$$\max_{(\tau,b)} \quad pU\big(b\big) + (1-p)U\big((1-\tau)\,w_i\big) \tag{2.8}$$
$$\text{s.t.} \quad b = \bar{w}(\alpha)\varphi\tau.$$

Substituting the constraint into the utility function and differentiating with respect to τ gives us the first order condition:

$$\frac{\bar{w}(\alpha)}{w_i} = \frac{U'\big(w_i - w_i\tau\big)}{U'\big(\bar{w}(\alpha)\varphi\tau\big)}. \tag{2.9}$$

The τ_i^{O} that solves (2.9) is the preferred tax rate for an individual of type i. We find b_i^{O} by substituting τ_i^{O} into the constraint (2.6).

Before deriving some comparative statics let us define the degree of relative risk aversion $\rho(x)$ as

$$\rho(x) = -\frac{xU''(x)}{U'(x)}. \tag{2.10}$$

Implicitly differentiating the first order condition (2.9) with respect to α and solving for $\frac{\partial \tau_i^{\mathrm{O}}}{\partial \alpha}$ gives

$$\frac{\partial \tau_i^{\mathrm{O}}}{\partial \alpha} = \frac{(w_{\mathrm{H}} - w_{\mathrm{L}})\left(1 - \rho\left(\bar{w}(\alpha)\varphi\tau_i^{\mathrm{O}}\right)\right)}{U'\left(\bar{w}(\alpha)\varphi\tau_i^{\mathrm{O}}\right)\left\{\bar{w}(\alpha)^2\varphi U''\left(\bar{w}(\alpha)\varphi\tau_i^{\mathrm{O}}\right) + w_i^2 U''\left(w_i - w_i\tau_i^{\mathrm{O}}\right)\right\}}. \tag{2.11}$$

By assuming the second derivative of $U(\cdot)$ the denominator is negative, the sign of $\frac{\partial \tau_i^{\mathrm{O}}}{\partial \alpha}$ depends on whether $\rho\left(\bar{w}(\alpha)\varphi\tau_i^{\mathrm{O}}\right)$ is greater than or less than 1. If less than 1, the optimal tax rate decreases as α increases—if greater than 1, the optimal tax rate increases.

The sign of $\frac{\partial b_i^{\mathrm{O}}}{\partial \alpha}$ is trickier and less satisfying. Differentiating the constraint (2.6) leads to

$$\frac{\partial b_i^{\mathrm{O}}}{\partial \alpha} = \varphi\left(\bar{w}(\alpha)\frac{\partial \tau_i^{\mathrm{O}}}{\partial \alpha} - (w_{\mathrm{H}} - w_{\mathrm{L}})\tau\right). \tag{2.12}$$

Only when $\rho\left(\bar{w}(\alpha)\varphi\tau_i^{\mathrm{O}}\right)$ is less than 1 do we know for certain the preferred benefit will decline as the low types increase. When $\rho\left(\bar{w}(\alpha)\varphi\tau_i^{\mathrm{O}}\right)$ is greater than 1, we cannot sign the effect.

Figure 2.1 and Figure 2.2 illustrate how changes in α affect the preferred program for a high-type individual.[1] In both figures we graph the "healthy" consumption on the y-axis and the "sick" consumption on the x-axis. We graph the budget-balancing constraint (2.6) as the lines B_1 and B_2 for two different values of α with $\alpha_1 < \alpha_2$, respectively. Both intersect the y-axis at w_{H} which corresponds to the consumption

[1] In this and all figures we model $U(x)$ as having the iso-elastic form where

$$U(x) = \tfrac{1}{1-\rho}x^{1-\rho} \tag{2.13}$$

and ρ is equal to the coefficient of relative risk aversion for all $x > 0$.

pair when $\tau = 0$. The two constraints then intersect the x-axis at the value of the insurance benefit when $\tau = 1$ and all earned income is taxed to finance the "sick" consumption. We know B_2 intersects closer to the origin because the derivative of (2.6) with respect to α evaluated at $\tau = 1$ is negative. As the reader can observe in both figures, a rise in α is analogous to a price increase in the rational choice framework. The redistribution inherent in the model implies that as α rises, the high types finance relatively more of the government program. While Figure 2.1 and Figure 2.2 are modeled from the perspective of the high types, this analogy holds for the low types as well.

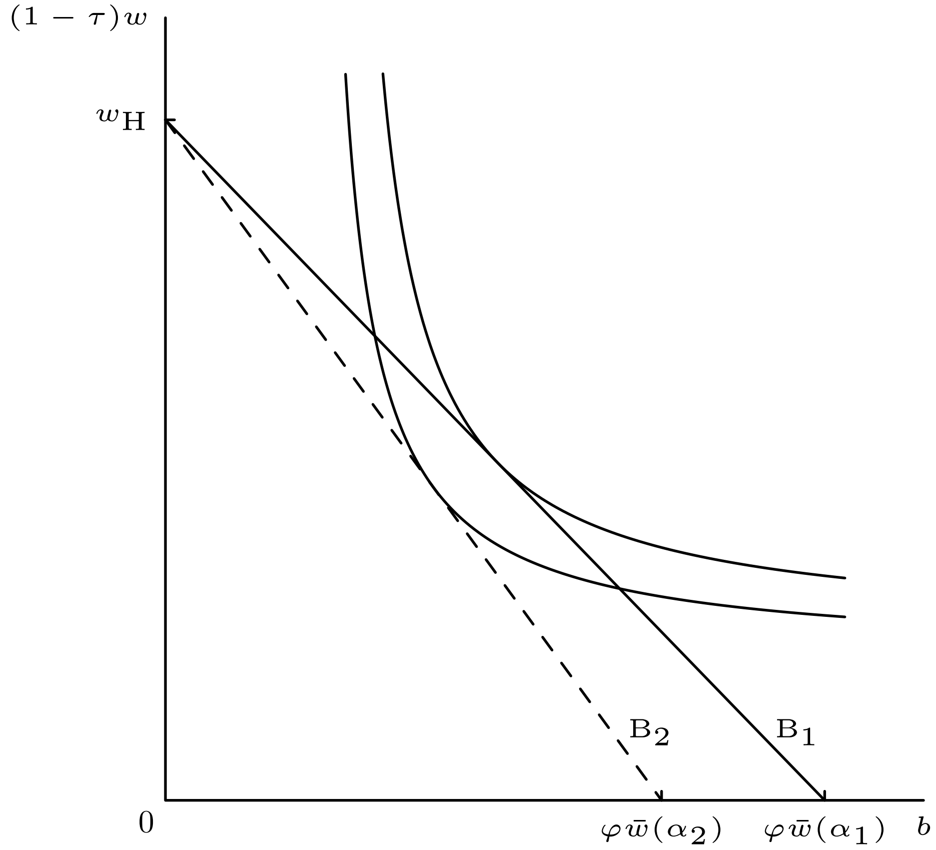

Figure 2.1: Effect of α Increasing, $\rho > 1$

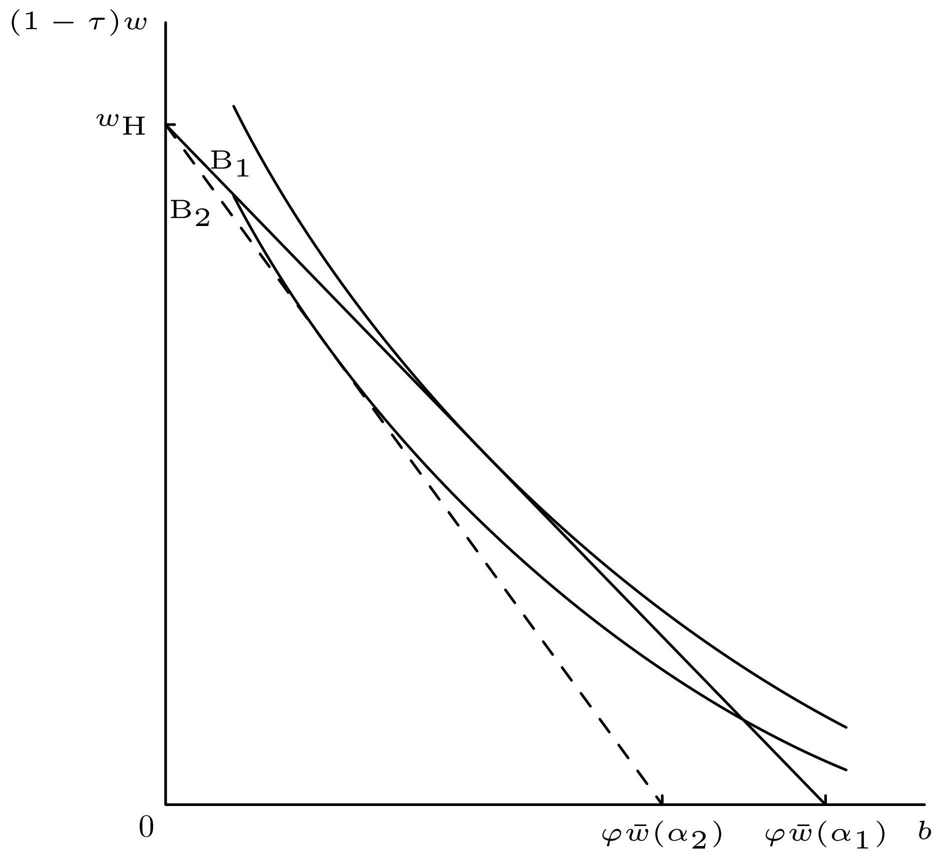

Figure 2.2: Effect of α Increasing, $\rho < 1$

Figure 2.1 indicates that the increase in α causes this individual to prefer both less "healthy" *and* "sick" consumption. Because after-tax "healthy" consumption is inversely related to the tax rate, this confirms the earlier result showing that the tax rate should rise. Figure 2.2, on the other hand, shows the opposite effect on "healthy" consumption when $\rho < 1$. "Healthy" consumption rises while "sick" consumption falls which means the the chosen tax rate falls.

The two figures clarify the role that risk aversion and α play in affecting the preferred government program. One interpretation is that ρ determines whether "healthy" and "sick" consumption are complements or substitutes. That a rise in the relative price of social insurance causes a decrease in "healthy" consumption when $\rho > 1$ indicates that the two are complements while the opposite effect when $\rho < 1$ implies that they are substitutes.[2]

Figure 2.3 and Figure 2.4 simulate how the program changes in response to changes in the poor population over the range of α. There are four things to note about these two figures. First, no matter what the risk aversion is, either type will prefer to almost exactly smooth consumption when it is approximately the only type, or when α is close to 0 or 1. This result is a consequence of the first order condition in equation (2.9) where the left-hand side would equal 1 for $\alpha \in \{0, 1\}$. Second, the observed preferences are consistent with the results about "healthy" and "sick" consumption being complements or substitutes. When ρ is greater than 1, it is apparent that individuals prefer to have the two forms of consumption close together. When ρ is less than 1, however, the relative price becomes a more important consideration, leading to quick divergence of the two types of consumption. Third, the only discontinuities in benefits or after-tax consumption are when the high types cede decisiveness to the low types at $\alpha = \frac{1}{2}$. The lack of discontinuities stands in contrast to the model without observability which appears in Section 2.4.4. Fourth, the low-type's after-tax wage in either figure only exceeds the benefit for a small region in Figure 2.4 when $\rho < 1$. The implication is that the low types would almost always prefer to appear "sick" to the government so that they could enjoy higher consumption. When they are able to do so, it will affect the program's generosity.

[2]The relative curvature of the indifference curves implies this as well.

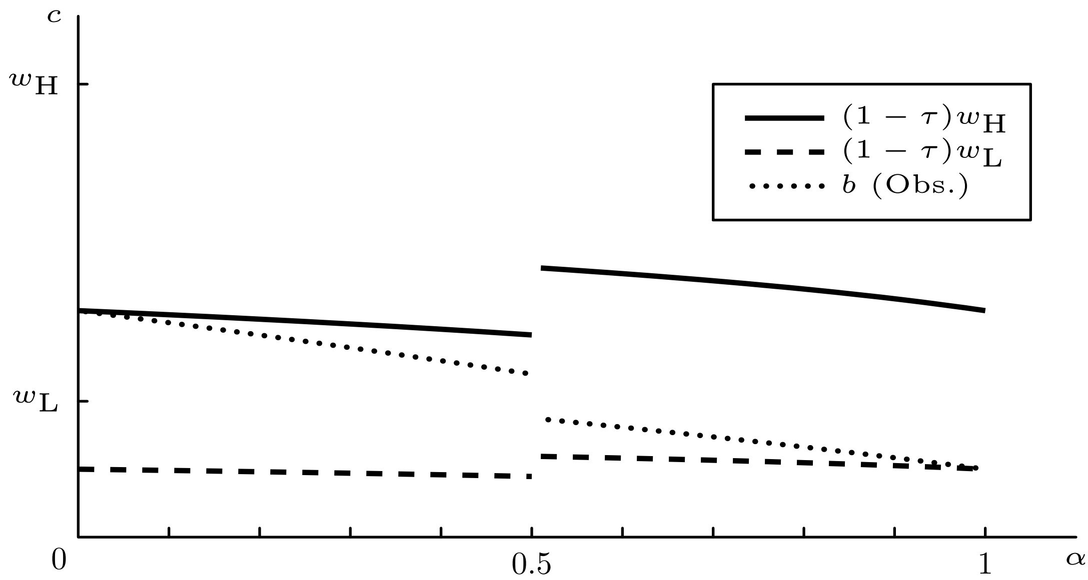

Figure 2.3: Observability Case Program, $\rho > 1$

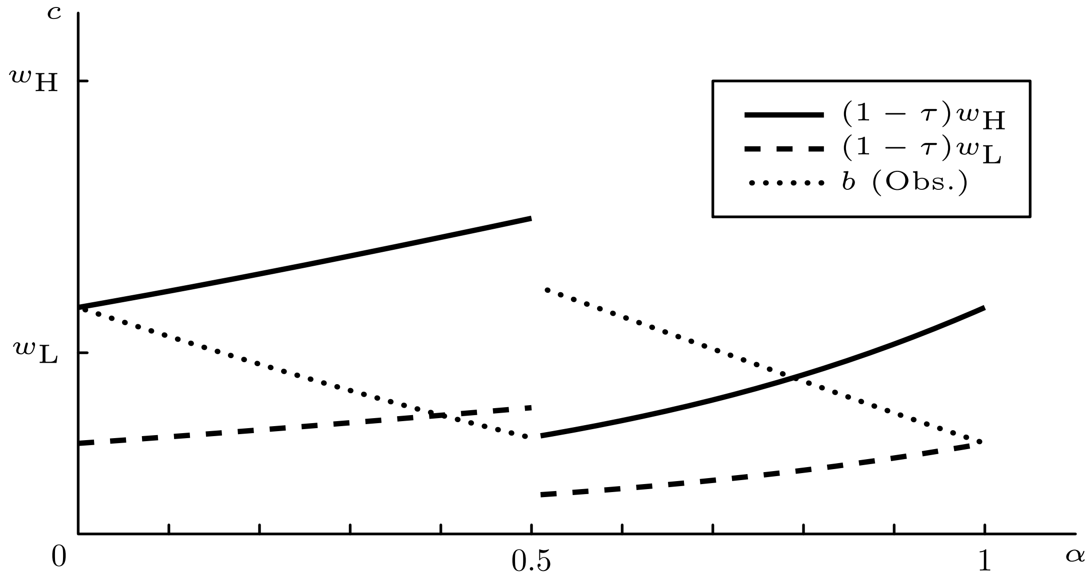

Figure 2.4: Observability Case Program, $\rho < 1$

2.4 No Observability Case

The difference between the observability and no observability cases is that individuals in the latter may claim the "sick" benefit even when "healthy" because the government is not able to observe their state. We assume that individuals do so when the insurance benefit is greater than or equal to their after-tax incomes

$$b \geq (1-\tau)w_i. \tag{2.14}$$

This constraint is not trivial as we observed in Figure 2.3 and Figure 2.4. There the benefit mostly exceeded the low types' after-tax incomes, which would cause them not to work in this case. By not working they would never pay taxes which would invalidate the budget-balancing condition on which the program was based. In other words, most of the programs with observability are not possible in the no observability case. We will have to check whether a program is internally consistent with both budget balance *and* incentive compatibility.

2.4.1 Budget Balance and Incentive Compatibility

When the low types do not work, the constraint will not be (2.6) because both expected payouts and receipts are different and no longer equal. The expected payouts would equal

$$b\,(\alpha + (1-\alpha)p) \tag{2.15}$$

while expected receipts would equal

$$(1-\alpha)(1-p)w_{\mathrm{H}}\tau. \tag{2.16}$$

Setting them equal to each other and solving for b gives

$$b = \frac{(1-\alpha)\varphi w_{\mathrm{H}}}{\alpha\varphi + 1}\tau. \tag{2.17}$$

The next step is to incorporate incentive compatibility into the budget constraints to find the regions where either (2.6) or (2.17) is the appropriate constraint. We can find these conditions in terms of b if we substitute versions of the work condition (2.14) into the budget-balancing constraints. By assumption, the low types work whenever the benefit is less than after-tax income,

$$b < (1-\tau)w_{\mathrm{L}}. \tag{2.18}$$

If we combine (2.18) with the budget-balancing condition when both types work (2.6), we obtain

$$b < \frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}} + \bar{w}(\alpha)\varphi}. \tag{2.19}$$

Similarly, the high types find it in their interest to work when

$$b < \frac{w_{\mathrm{H}}\bar{w}(\alpha)\varphi}{w_{\mathrm{H}} + \bar{w}(\alpha)\varphi}. \tag{2.20}$$

Because the right-hand side of (2.20) exceeds that of (2.19), it is (2.19) that defines the region where both types work and a budget-balanced program is possible.

When the benefit equals or exceeds the right-hand side of (2.19), the low types will not work and thus (2.17) becomes the relevant budget-balancing constraint. We now must check that the low types are not willing to work and that the high types are. As before we have to substitute the relevant work condition

$$b \geq (1-\tau)w_{\mathrm{L}} \tag{2.21}$$

into the appropriate budget-balancing constraint (2.17). Doing so gives

$$b \geq \frac{w_{\mathrm{L}} w_{\mathrm{H}} \varphi(1-\alpha)}{(\alpha\varphi+1)w_{\mathrm{L}} + (1-\alpha)\varphi w_{\mathrm{H}}}. \tag{2.22}$$

The right-hand side quantity in this equation is less than that of (2.19) which implies that if (2.19) is false, then (2.22) is true and a budget-balanced government program that has the low types not working *can* be implemented with respect to the low types' incentives.

Finally, to find the work constraint for the high types we need to substitute their work condition

$$b < (1-\tau)w_{\mathrm{H}} \tag{2.23}$$

into (2.17) to obtain

$$b < (1-p)(1-\alpha)w_{\mathrm{H}}. \tag{2.24}$$

In the event that there is no b such that (2.19) is false and (2.24) is true, then there is no budget-balancing pair (τ, b) where the high types are willing to work while the low types are not. This will be the case if

$$(1-p)(1-\alpha)w_{\mathrm{H}} \leq \frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}}+\bar{w}(\alpha)\varphi}. \tag{2.25}$$

Figure 2.5 graphs the relevant information. $\mathrm{B}_{\mathrm{H}}^{\mathrm{O}}$ is the locus of budget-balancing consumption for the high types when both types work. $\mathrm{B}_{\mathrm{H}}^{\mathrm{N}}$ is the high types' consumption when they work but the low types do not. $\mathrm{B}_{\mathrm{L}}^{\mathrm{O}}$ is the locus of consumption for the low types if both types work. Finally, $\mathrm{B}_{\mathrm{L}}^{\mathrm{N}}$ is the consumption line for the low types if they do not work while the high types do.[3] The 45°-line helps determine whether individuals are going to work or not. The line represents the locus of consumption where $b = (1-\tau)w$. As such, any consumption bundle on or below this line along the appropriate budget constraint is a region where an individual will opt to report themselves "sick" even if "healthy."

The point A represents equation (2.19) because it is the point where insurance benefits to the right of it will cause the low types not to work—moving to the right from A along $\mathrm{B}_{\mathrm{L}}^{\mathrm{O}}$ induces after-tax consumption to fall below the insurance benefit. B represents (2.20) and point C depicts (2.22), respectively. Finally, D represents (2.24) and the point at which the high types will stop working if the low types are already not working. One observes this by noting that traveling rightward along $\mathrm{B}_{\mathrm{H}}^{\mathrm{N}}$ will put the high types' after-tax consumption below the benefit level at D. When D is to the left of A, then (2.25) will be true and no implementable region would exist

[3]The low types never actually consume along this constraint because their consumption is equal to the benefit regardless of their being "healthy" or "sick."

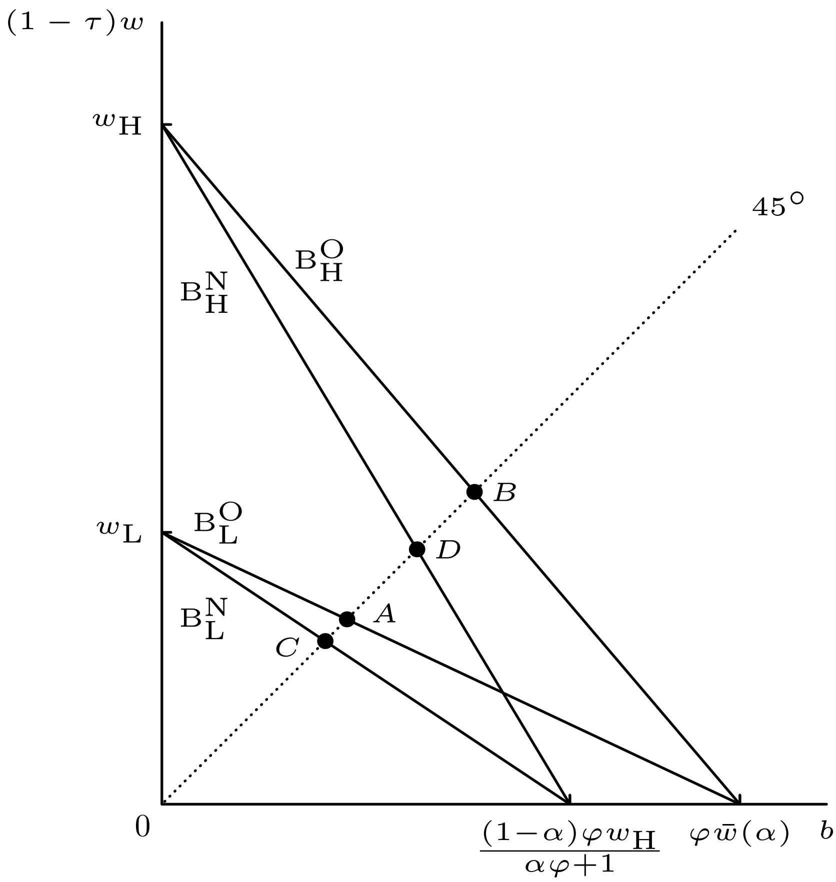

Figure 2.5: Incentive Compatibility Constraints

where the high types would work while the low types would not.

2.4.2 High Types' Preferred Program

Whether (2.25) is true or not affects the maximization problem the high types solve to determine their preferred program. When (2.25) is not true, the maximization problem for the high types is

$$\max_{(\tau,b)} \quad pU\big(b\big) + (1-p)U\big((1-\tau)\,w_{\mathrm{H}}\big) \tag{2.26}$$
$$\text{s.t.} \quad b = \bar{w}(\alpha)\varphi\tau \ \text{ for } \ b \in \left[0, \frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}} + \bar{w}(\alpha)\varphi}\right), \text{ and}$$
$$b = \frac{(1-\alpha)\varphi w_{\mathrm{H}}}{\alpha\varphi + 1}\tau \ \text{ for } \ b \in \left[\frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}} + \bar{w}(\alpha)\varphi}, (1-p)(1-\alpha)w_{\mathrm{H}}\right)$$

When (2.25) is true then the second part of the constraint cannot apply so the maximization problem would be

$$\max_{(\tau,b)} \quad pU\big(b\big) + (1-p)U\big((1-\tau)\,w_i\big) \tag{2.27}$$
$$\text{s.t.} \quad b = \bar{w}(\alpha)\varphi\tau \ \text{ for } \ b \in \Big[0, (1-p)(1-\alpha)w_{\mathrm{H}}\Big)$$

Figure 2.6 and Figure 2.7 remove extraneous information from Figure 2.5 to indicate the incentive compatible budget constraint the high types face in the maximization problems as represented by (2.26) and (2.27). The dashed lines represent the original budget constraints which do not account for incentive compatibility while the thicker lines superimposed on the dotted lines do. Figure 2.6 reproduces Figure 2.5 so (2.25) does not hold and represents the maximization problem in (2.26). What we see from this figure then is that the budget constraint for the high types may be neither linear nor continuous. Figure 2.7 displays the budget constraint when (2.25) does hold so it represents the maximization problem in (2.27).

There are three possible solutions to this problem. The first is that the solution

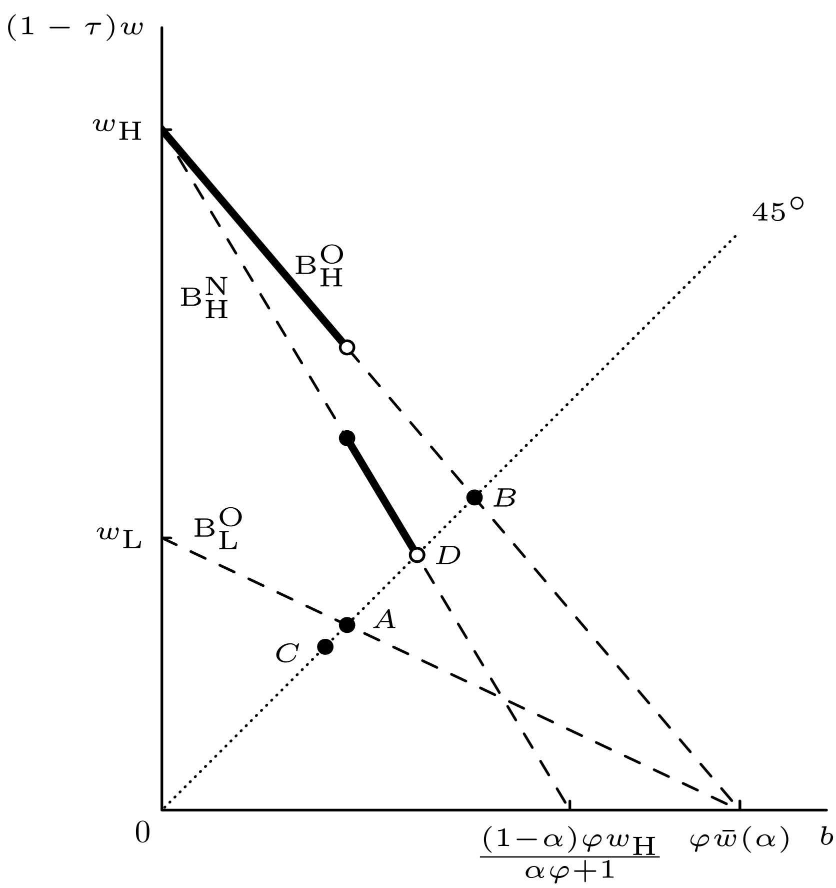

Figure 2.6: Budget Balance and Incentive Compatibility, (2.25) does not hold

lies in the interior of $\left[0, \frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}}+\bar{w}(\alpha)\varphi}\right)$ and the indifference curve is tangent to the budget constraint. This solution satisfies the first order condition with observability (2.9) and is only a possibility if the individuals' relative risk aversion is below 1. The next possible solution is poorly defined from a mathematical perspective but should should satisfy an economist.[4] That is the corner solution that also lies in the interior of $\left[0, \frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}}+\bar{w}(\alpha)\varphi}\right)$ but where there is not a tangency. That is, one sets the benefit slightly below $\frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}}+\bar{w}(\alpha)\varphi}$ so that the low types are just willing to work. The third solution is a

[4]If we assumed that money could only take on discrete values, as it does in real life, then a well-defined solution would exist.

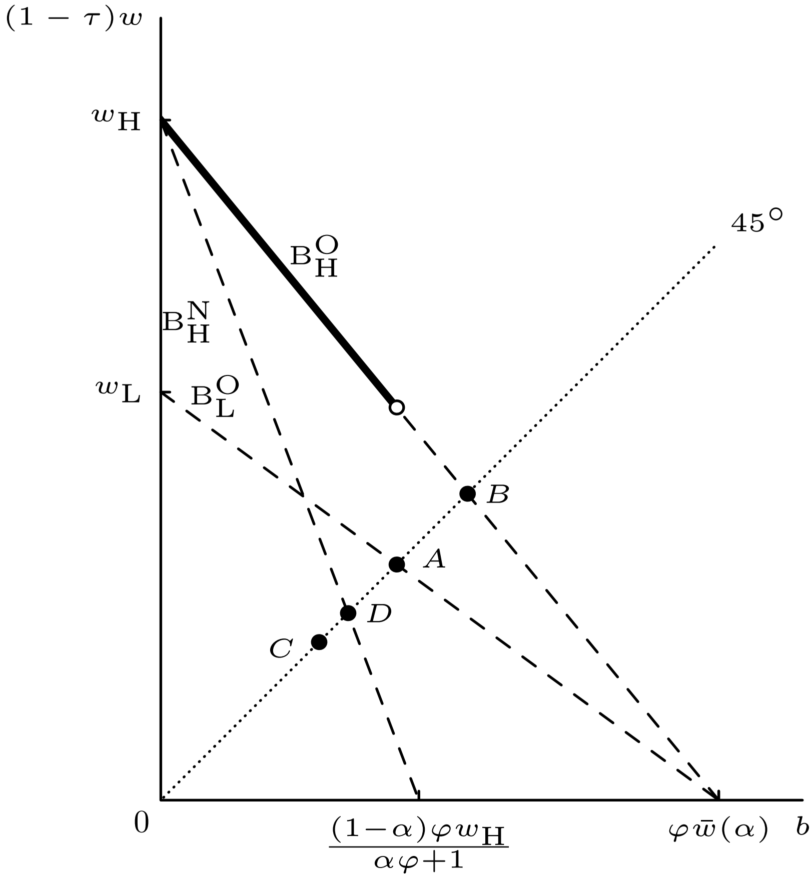

Figure 2.7: Budget Balance and Incentive Compatibility, (2.25) holds

tangency on the second portion of the constraint, $\left[\frac{w_L\bar{w}(\alpha)\varphi}{w_L+\bar{w}(\alpha)\varphi}, (1-p)(1-\alpha)w_H\right)$ so is only possible when (2.25) is not true. If this is an implementable solution, then the first order condition is

$$\frac{1-\alpha}{1+\alpha\varphi} = \frac{U'\Big(w_H - w_H\tau\Big)}{U'\Big(\frac{(1-\alpha)\varphi w_H\tau}{1+\alpha\varphi}\Big)}. \tag{2.28}$$

It is perhaps best to view the solution to (2.26) graphically as the problem does not lend itself to easy analytical results. In Figure 2.8, we set α to be a relatively low number. The figure graphs the high types' budget constraint as a thick, dark line along with the indifference curves associated with the possible solutions. The outermost indifference curve is the solution with observability. As this tangency lies on a dashed portion of the budget constraint, this government program is not implementable. The innermost indifference curve is the utility associated with the corner solution where the government policy is set so that the insurance benefit is just less than the after-tax wage of the low-types. Greater than this utility is the indifference curve representing the outcome where the high types work while the low types do not. As this tangency falls in a region where the budget constraint is thick, this outcome balances the budget and is implementable. Finally, because this utility exceeds the utility of the outcome that just induces the low types to work, the high types will vote this point as their preferred policy.

Figure 2.9 displays a similar situation with a different outcome. Here we increase the value of α to α'. The result is that the utilities associated with the two implementable possibilities have flipped. Now the innermost indifference curve is associated with the low types not working. Exceeding this point is the outcome where the low types are just willing to work when "healthy." Thus, when the low types comprise a higher portion of the population, the high types may find it optimal not only to decrease the generosity of the insurance benefit but to change the nature of the program as well. Where before they found it optimal to allow the low types to cheat the system, they no longer want that outcome to happen. In general, the only way to determine the preferred outcome is to either graph the possibilities or directly compare the utilities of the two implementable solutions and see which one is higher.

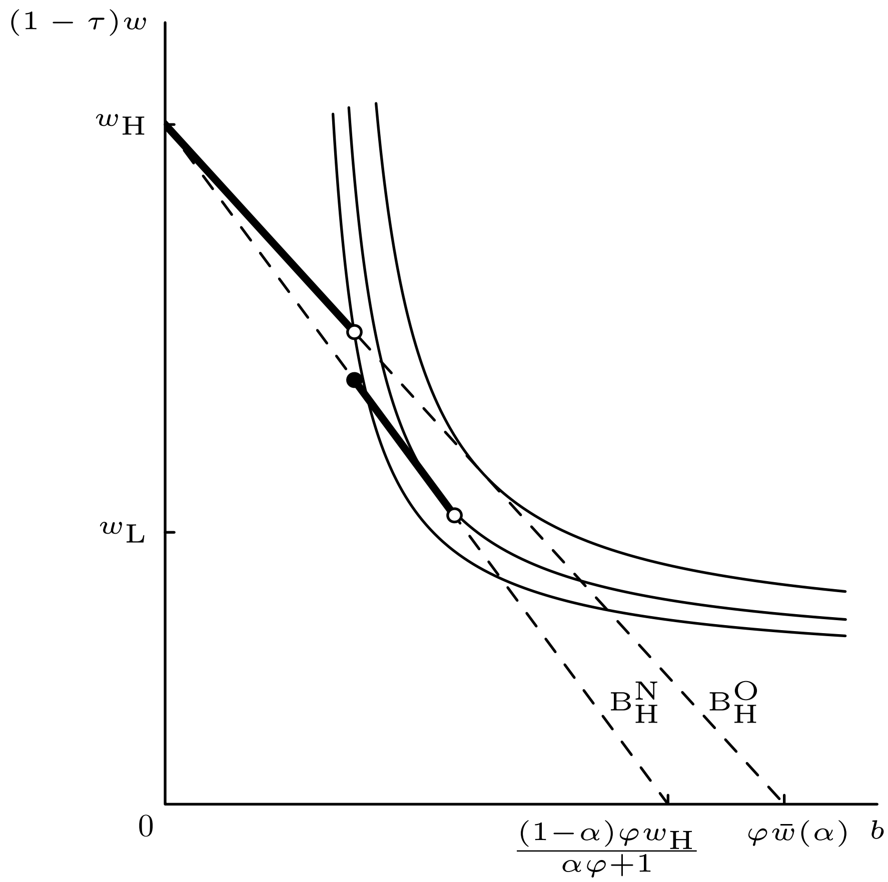

Figure 2.8: An Example of the Low Types Not Working

2.4.3 Low Types' Preferred Program

The constraints the low types face are similar to that of the high types but with slightly different outcomes. As before, equations (2.19) and (2.24) still define the regions where the low types work. That is, for budget-balancing b such that

$$b \in \left[0, \frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}} + \bar{w}(\alpha)\varphi}\right) \tag{2.29}$$

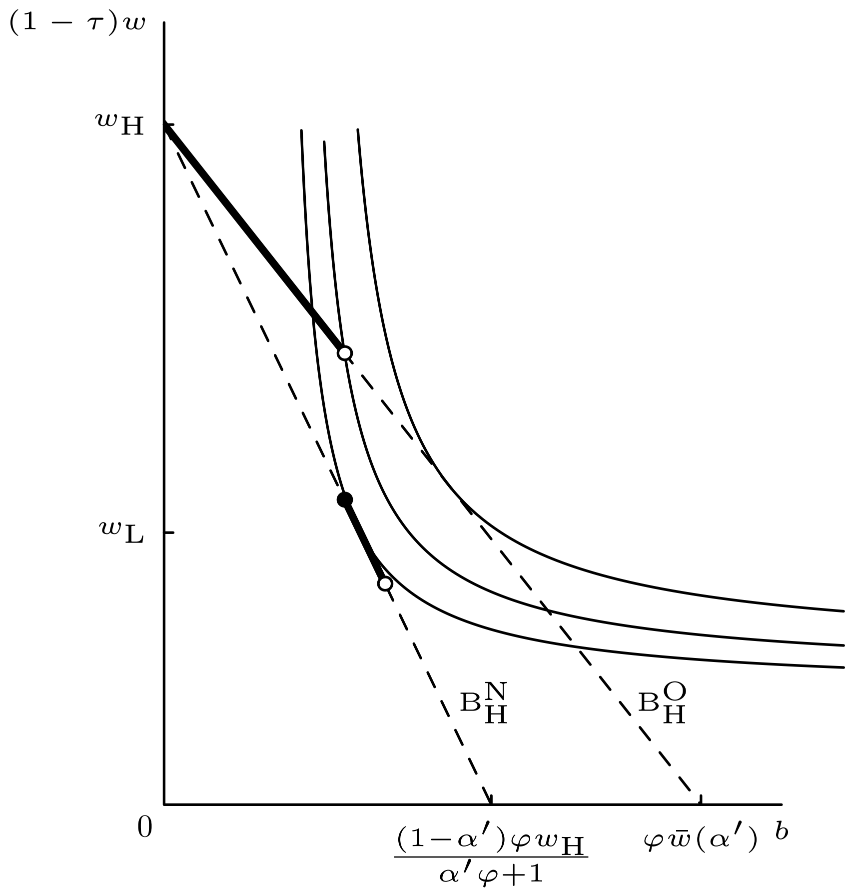

Figure 2.9: An Example of the Low Types Working

the low types will work and for

$$b \in \left[\frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}}+\bar{w}(\alpha)\varphi}, (1-p)(1-\alpha)w_{\mathrm{H}}\right) \tag{2.30}$$

the low types will not.

The low types maximize utility differently than the high types do. We know from the first order condition (2.9) that the low types' preferred policy will always set the insurance benefit higher than their after-tax earnings. This outcome is not implementable so their preferred policy will have to be a corner solution. When

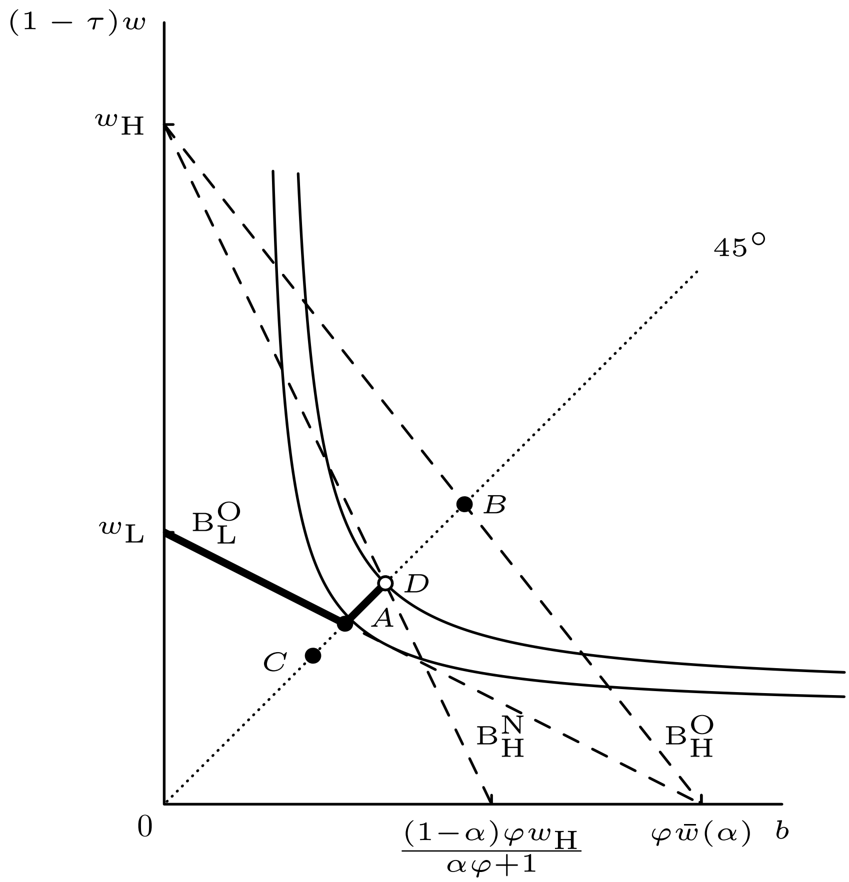

Figure 2.10: An Example of the Low Types Not Working

(2.25) is not true, the region described by (2.30) is non-empty so it is obviously best for the low types to set the benefit at the highest possible value which is just less than $(1-p)(1-\alpha)w_{\mathrm{H}}$. Doing so ensures that the high types work and alone finance the program, which Figure 2.10 depicts. When (2.25) is true and (2.30) is empty, there is no implementable region where the low types do not have to work. They still set the benefit as high as possible which is now just below $\frac{w_{\mathrm{L}}\bar{w}(\alpha)\varphi}{w_{\mathrm{L}}+\bar{w}(\alpha)\varphi}$, a situation we see in Figure 2.11.

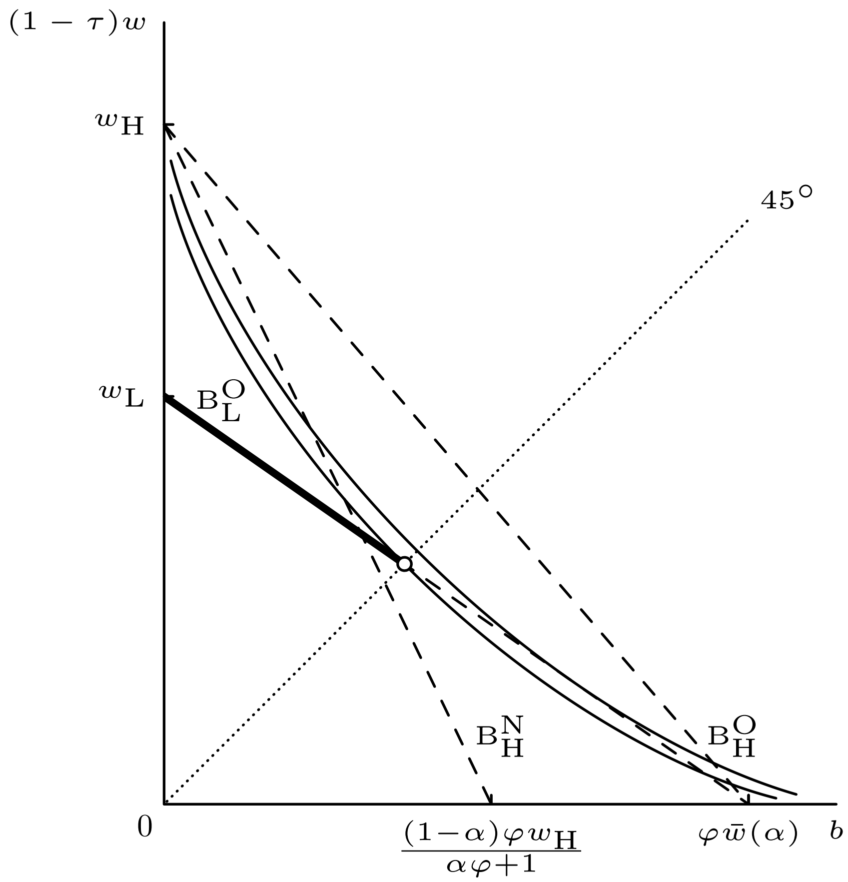

Figure 2.11: An Example of the Low Types Working

2.4.4 Implications of Changing Demographics

As before, when α is near 0, the high types will set their "healthy" and "sick" consumptions quite close to each other which ensures the low types will find it optimal not to work. As α grows, however, they will often either earn higher utility by making the low types work or be *forced* to make the low types work when (2.25) holds. If $\rho(x) < 1$, then it may be possible that the preferred observability solution will become implementable as was the case in Figure 2.4. With the "healthy" and "sick" consumption being substitutes the increasing relative price of "sick" consumption would become so costly for the high types that they would opt for a very small insurance benefit. The benefit may be driven so low so as to make the low types prefer to work when "healthy."

The low types will go through a similar process as α grows larger. For values of α that are close to $\frac{1}{2}$, it may be possible that they can set the benefit so that they do not have to work. As α grows, however, it will become less likely that this is the case and more likely that (2.25) will hold thereby forcing them to work. For no α will they be able to implement the program they would have preferred if observability were present because that benefit was always greater than their after-tax consumption.

Figure 2.12 and Figure 2.13 use the same parameter values as Figure 2.3 to contrast the path the government program can take as α changes, there is no observability, and $\rho(x) > 1$. The first thing to note is that the sharp vertical jumps are points where the program's generosity changes discontinuously. As noted before, this is one difference between the two cases. What it implies is that the lack of observability can lead to fundamental shifts in the nature of the insurance program. For example, Figure 2.12 displays quite a range of possibilities. When the low type population is relatively small, the high types find it best to allow them not to work. This point is confirmed by the fact that the benefit exceeds the low types' after-tax earnings were they to work. Starting at some point after 0.35, however, the preferred program changes. The high types slash both the tax and the benefit to such a point that the low types are just willing to work. That the two lines overlap confirms this claim.

When the low types take over the decision-making process, they immediately

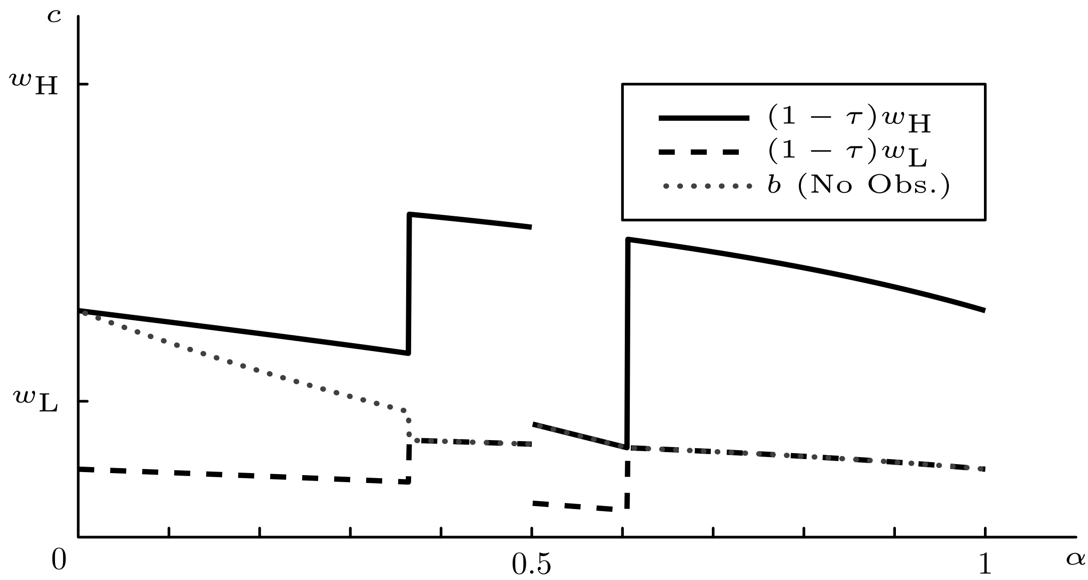

Figure 2.12: No Observability Case Program, $\rho > 1$

change the program again. Now they drive both the tax rate and the benefit back up until the point at which the high types are just willing to work. After 0.60 or so, equation (2.25) takes hold and there is no way for the low types to implement a policy where they do not have to work. Figure 2.13 compares the observability and no observability benefit using the same parameter values as in Figure 2.3. In addition to the sharp jumps, the no observability case benefit is always less generous than the observability case benefit.

Figure 2.14 and Figure 2.15 graph a simulation where $\rho < 1$ and confirms what we noticed in Figure 2.4,[5] that it may be possible to implement the preferred observability policy despite it being the no observability case. To the left of the point where the preferred observability solution becomes implementable, however, the high types change the program in the same way we saw in Figure 2.12. For low values of α the

[5]These three figures use the same parameter values.

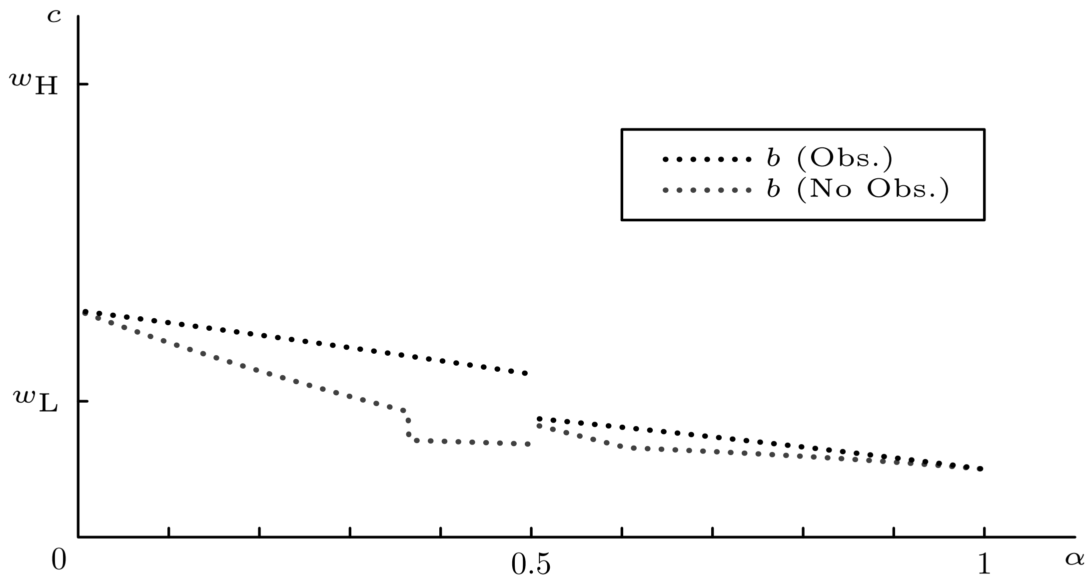

Figure 2.13: Observability Versus No Observability Benefit, $\rho > 1$

high types find it acceptable for the low types to masquerade and not have to work. As the low types grow in numbers, though, it becomes optimal to have them work. Starting around $\alpha = 0.40$, the observability case benefit becomes implementable so that is the program they choose. Finally, notice that for the low types, there is no region where they do not have to work when decisive over the decision-making process—(2.25) holds for $\forall\, \alpha \in (\frac{1}{2}\,, 1)$ in this simulation. Figure 2.15 compares the benefit chosen in the observability and no observability cases for these parameter values. This example also has the sharp jumps in the no observability case benefit, which is always greater than or equal to the observability case benefit.

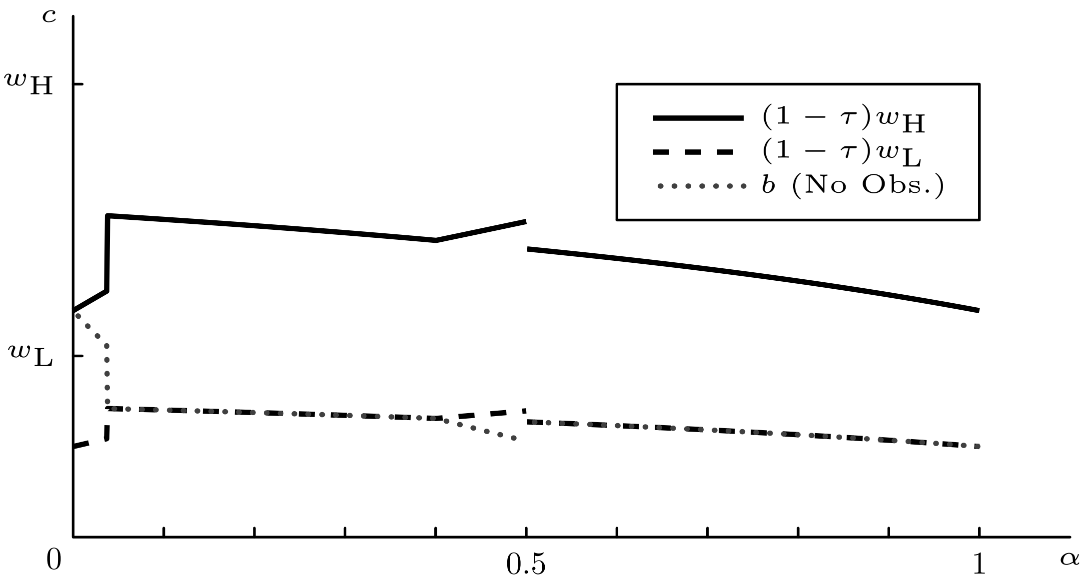

Figure 2.14: No Observability Case Program, $\rho < 1$

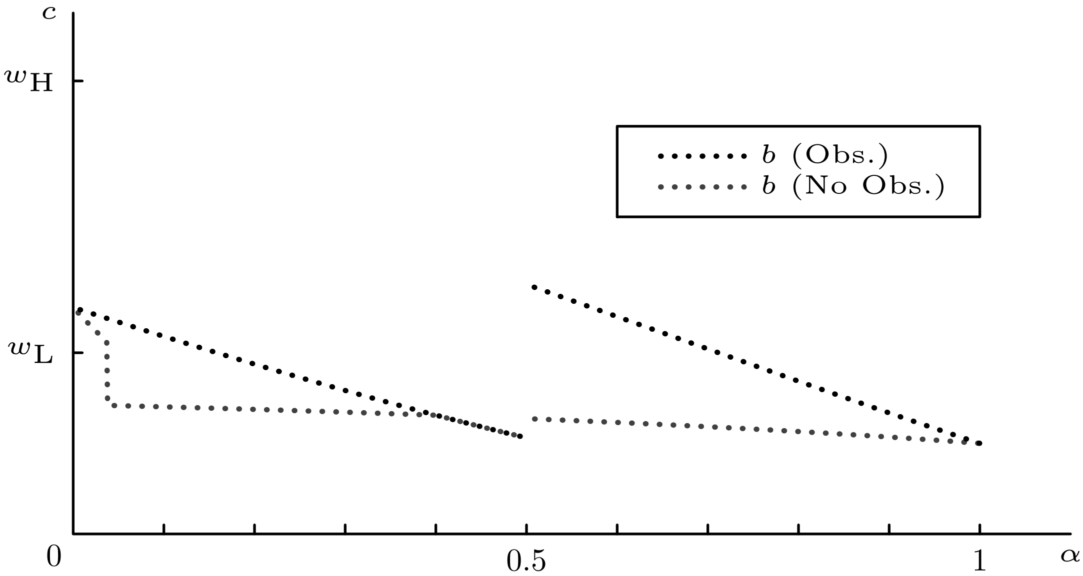

Figure 2.15: Observability Versus No Observability Benefit, $\rho < 1$

2.5 Discussion

The model in Chapter 2 incorporates some of the themes of the welfare reform story from Chapter 1.

1. **Political Process**—Voters choose the program's generosity. I argue implicitly in Chapter 1 that welfare reform was a voter-driven initiative.

2. **"Right" and "Wrong" Recipients**—Using the "sick" versus "healthy" construct gets at the issue of knowing who the intended recipient of a program is. The "healthy" person receiving the benefit is the "wrong" person because the program is meant to help the "sick" while the "healthy" should work. Chapter 1 argues that too many of the "wrong" people, unwidowed single parents, received welfare.

3. **Population Changes**—Exogenous changes within the population result in greater usage of a program by the "wrong" people. Chapter 1 provides evidence for the view that population changes exacerbated welfare's misclassification problem.

4. **Information Constraints**—The government is not able to identify the "wrong" people in order to screen them off. The *King vs Smith* (1968) Supreme Court decision is the analogous constraint in the welfare reform story.

5. **Social Insurance Preferences**—Voters like to smooth consumption and are willing to tax their more well-off selves to do so. Section 1.4 hypothesized that preferences for social insurance could have caused discontent over welfare's misclassification problem.

6. **Tolerance of Some Misallocation**—If the amount of waste is small, then voters will allow it because they like the more generous benefit that comes

with it. This implication is consistent with the view in Chapter 1 that welfare could be more generous when there were fewer unwidowed single parents in the population.

There are differences and simplifications that depart from the welfare reform story, though hopefully not in crucial ways.

1. **No Preferences for Morality**—Modeling just preferences for social insurance was a simplification so that voters would be purely self-interested. Although modeling morality probably would have hewed closer to reality, it would have required putting the behavior of others into an individual's utility function which struck me as unnecessarily complicating.

2. **Only Two Types**—Having more types in the model—or even a continuum of types—would have made the range of programs that resulted from the political process more realistic.

3. **Benefit Not Intertemporal**—This restriction means that voters' only lever over the program's design is the benefit level and not the duration of benefits. This is unfortunate considering that it is intertemporally that PRWORA reduced welfare's benefits.

2.6 Conclusion

To add rigor to the welfare reform story in Chapter 1, the two goals of this paper were to analyze 1) how lack of observability affects the design of a social insurance program, and 2) how it interacts with an increasing population who find going on social insurance attractive. We have seen that lack of observability reduces the program's generosity and alters its work incentives because what is preferred with observability often cannot be implemented without it. Finally, we saw that a rising population of the poor can induce voters to alter the program to force the poor to work because the high types subsidizing the program slash the benefit to reduce what they consider to be excessive redistribution.

Chapter 3

How Has Our Ability to Explain Welfare Usage Changed Since Reform?

3.1 Introduction

Chapter 1 hypothesized that problems with welfare as a social insurance program led to its reform while Chapter 2 modeled how that could have been the case. This chapter advances this analysis by examining how the ability of observable information to explain an individual's future welfare usage has changed since reform. The empirical strategy exploits the fact that social insurance exists to compensate for adverse, *probabilistic* events. An outside observer may know who in a population is more likely to use insurance in the future but will not know for sure who actually will. The reason is because a legitimate insurance claim depends on an event that has not happened and may not happen at all. An individual's usage of insurance for legitimate insurance reasons therefore should be probabilistic. The probabilistic nature of legitimate insurance usage stands in contrast to a social insurance program that is prone to accepting people that are only masquerading as qualifying for the insurance benefit. Those masquerading are more likely to be lower skilled because their work options are going to be less attractive to them in comparison to those more skilled. These descriptions highlight the difference between the two kinds of programs that I intend to exploit for the purpose of investigating the possibility that welfare operates more as insurance after reform than it did before. Though by no means is there a perfect ability to do so, I claim that observable information will do a better job of explaining low skilled people using a social insurance program inappropriately than it would anybody using a social insurance program appropriately.

The plan is to increment—a year at a time—estimates of a model that regresses an individual's decision to receive welfare on observable information lagged by more than a year.[1] For each of these estimated models we generate a measure of goodness-of-fit that tells us how well we are able to "explain" their welfare choice a variable number of years later. The argument I make is that a declining ability to explain a person's welfare decision could indicate a relatively increased role for insurance in what drives individuals to receive welfare. What I find is that the goodness-of-fit does decline over time and is consistent with the possibility that welfare functions relatively more

[1]There are three sets of these models where each set regresses the welfare choice on data lagged by two-year, three-year, and four-year lags.

as insurance after reform than before.

3.2 Literature Review

Moffitt (1992) in his review of the empirical literature on AFDC welfare identifies two strands that most relate to the methodology of this paper. In modeling the choice to receive welfare, researchers often adopt either a static or a dynamic approach. The static approach regresses an individual's binary welfare choice on contemporaneous explanatory variables while the dynamic approach models uses a hazard model to regress an individual's stay on welfare from entry to exit on information observed at the time of entry.[2] The approach I adopt in this chapter is a mixture of the two. As already indicated the model in this chapter regresses an individual's binary welfare choice not on contemporaneous observables but on lagged observables. Where these two strands diverge from this chapter's empirical strategy is on the issue of welfare's insurance properties which they do not consider and therefore limits their usefulness as a basis of comparison.

One exception is Gruber (2000), who investigates the effects that welfare benefits have on the ability of newly divorced women to smooth their consumption of food and housing. On the insurance qualities of AFDC he concludes that for the years 1968–1985, AFDC performed

> a very important consumption smoothing role for those becoming single

[2] To update the citations in Moffitt (1992), Connelly and Kimmel (2003) and Hu (1999) are examples of more recent static studies while Hoynes (2000) and Keng, Garasky, and Jensen (2002) are recent examples of the dynamic analysis approach.

> mothers [via divorce]. Moreover, the results suggest that there is not an important crowd out effect of AFDC on other sources of support (Gruber 2000, pg. 175).

Despite his findings on the insurance benefits of AFDC welfare, Gruber (2000) is not a paper concerned with how welfare's provision of insurance has changed over time. In this respect as well as in not modeling welfare participation, this chapter is a departure from Gruber (2000).

Beyond welfare there are a handful of papers that consider the insurance characteristics of other government programs and policies.[3] One notable example is Kniesner and Ziliak (2002). In addition to being one of the few papers to state that AFDC/TANF provides social insurance (Kniesner and Ziliak 2002, pg. 6), Kniesner and Ziliak take a comprehensive view of government-provided insurance and estimate the portion of insurance implicitly provided through progressive taxation and the portion explicitly provided by government programs like Unemployment Insurance and welfare. They find that "annual consumption variation is reduced by almost 20 percent due to explicit and implicit income smoothing."

3.3 Empirical Strategy

This paper's empirical strategy is to regress a model of welfare participation on a function of lagged observables. This model is estimated for successive years as well as for increasing amounts of time that separate the observed welfare choice from the

[3] See Blundell and Pistaferri (2003, pg. 1032–33) for citations.

information gathered about the individual. For each model estimated, a goodness-of-fit measure is calculated which is then compared across the years in order to draw conclusions about the relationship between welfare as social insurance since reform.

The model of welfare participation employed here is linear and relies on Ordinary Least Squares (OLS) for estimation. Using OLS provides an obvious candidate for goodness-of-fit, which is R^2. There are other goodness-of-fit measures but none with an interpretation quite as appropriate as R^2, which is that R^2 reflects the portion of the variation in the y_i's that can be explained by the explanatory variables. If R^2 falls, then the conclusion is that the observables are decreasing in their ability to explain the choices individuals make.

One issue worth discussing is why the model puts a wedge of time between the observed, explanatory information and the individual's welfare choice. The reason for this separation is because of the way social insurance works. The more time that separates the explanatory variables from the decision variable increases the role that unexpected events can play in the individual's decision to receive insurance. The choice I make in this paper is two, three, and four years of separation because it should permit plenty of time for the unexpected to manifest itself and drive some individuals to receive welfare for insurance reasons if that is in fact what people use it for.

Expressing this strategy in mathematical terms the equation to estimate is

$$y_{i,t+k} = \mathbf{x}_{i,t}\boldsymbol{\beta}_{t,k} + \nu_{i,t,k}. \tag{3.1}$$

In this equation $y_{i,t+k}$ is defined to be the binary variable indicating if individual i received welfare at any time in year $t+k$. $\mathbf{x}_{i,t}$ is the vector of observables for individual i observed at year t, $\boldsymbol{\beta}_{t,k}$ is the vector of coefficients to estimate in the statistical equation, and $\nu_{i,t,k}$ is the unexplained portion of the modeled relationship for the combination of t and k being estimated. The values that t takes on are from the set $\{1989, 1990, 1991, 1992, 1993, 1994, 1995, 1996\}$. The last year in this set is 1996 in order to have the modeling reflect the time at which welfare was reformed but not beyond. The values that k takes on are from the set $\{2, 3, 4\}$. In other words, we use observables from eight distinct years, all prior to or equal to the year of reform, to model the decision to go on welfare two, three, and four years hence. This gives us twenty-four (3×8) equations to estimate and twenty-four R^2's to compute. Of these twenty-four estimated equations, nine reflect regressions of post-reform welfare choices on information collected at the time of or before reform. The familiar OLS estimator for $\boldsymbol{\beta}$ is

$$\hat{\boldsymbol{\beta}} = \left(\mathbf{x}_t'\mathbf{x}_t\right)^{-1} \mathbf{x}_t'\mathbf{y}_{t+k} \tag{3.2}$$

where $\mathbf{x}_t$ and $\mathbf{y}_{t+k}$ are the matrix equivalents to $\mathbf{x}_{i,t}$ and $y_{i,t+k}$. Our measure of goodness-of-fit, R^2, is computed as

$$R^2 = \frac{\sum_{i=1}^{N} \left(\hat{y}_{i,t+k} - \bar{y}_{t+k}\right)^2}{\sum_{i=1}^{N} \left(y_{i,t+k} - \bar{y}_{t+k}\right)^2}, \tag{3.3}$$

which represents the ratio of the fitted values' variation to the actual values' variation.

Finally, a word about the composition of $\mathbf{x}_{i,t}$. It is important that all available and relevant information be included within $\mathbf{x}_{i,t}$. It is probable that there are attributes of individuals that are unobservable to the researcher that play an important role in determining who decides to receive benefits from a program of redistribution. The more of this kind of variation there is, the more likely we are to mistake this kind of variation for the variation that comes as a result of a properly functioning social insurance program.

3.4 Data

3.4.1 Data Source

The data source used in this analysis is the Panel Study of Income Dynamics (PSID), an ongoing panel of families and individuals begun in 1968. Collected annually until 1997, it has since become biennial. This fact would indicate that we would have two fewer years to use in our regressions, but they have conducted a supplemental survey to fill in the gaps for some of the data.[4] Fortunately, welfare usage and unemployment were two things they collected for the years in between surveys.

The primary reason for using the PSID over other sources is that it is a panel. This feature allows us to follow individuals from the time they enter the survey until they exit.[5] In our case we follow them for between two and four years, depending on the value of k. Most of the detailed information the PSID provides is for the head

[4]This supplemental survey is called the "T-2 Individual Income File" supplement, and it was administered with the 1999 and 2001 waves.

[5]Entries into the survey can come through birth, marriage, and expansion of the survey. Exits are due to death, divorce, and attrition.

and co-head (if present) of households. Though the PSID provides the composition of the entire household, most of the information one can obtain is only for the heads and co-heads, which is also the case with welfare participation. This fact prevents us from knowing who else in the household may be receiving welfare. This shortcoming is insurmountable if one wishes to obtain welfare recipiency at the individual level rather than at the level of the household.

The population of PSID individuals selected for this analysis is those women who headed or co-headed a family for year $t+k$ and who were in the sample in year t.[6] The other restriction is that these samples of women must belong to what the PSID classifies as the Sample Research Center (SRC) and Survey of Economic Opportunity (SEO) subsamples. The PSID actually consists of four distinct subsamples, two mentioned here and two others. Unfortunately, one of the two ended during the time-frame of this study while the other did not begin until after the start of this study. It is not possible to include them in the study.

Those familiar with the PSID know that there are issues of timing with respect to some of the variables collected. While the data collectors interview individuals in year t, some of their questions ask for information current at the time of interview while other questions ask for information from year $t-1$. The analysis performed in this chapter takes this issue seriously and has corrected it. So while an individual's receipt of welfare in 1991 is recorded in the 1992 PSID, the data fed into (3.2) records the receipt of welfare as occurring so that $t+k=1991$ not $t+k=1992$.

[6]The population of female heads or co-heads of household are the set of women who were single heading a household, cohabitating with a boyfriend who is a head of household, or married to a head of household.

3.4.2 Dependent Variable

Earlier sections of this chapter identified the dependent variable as an indicator for the receipt of welfare in year $t+k$. Two other decision variables arose as possibilities during the course of this research. One was to model the monetary amount of welfare benefits received by the individual in year $t+k$, and the other was to model the number of months an individual received welfare during a given period of time. In a sense, both of these other values provide richer information to model. In both cases, however, there were limitations in the PSID that rendered both of them unusable. In the case of the monetary benefits, the more recent years of PSID data simply do not permit this annual calculation to be made. With respect to the number of months of welfare received by the individual, there was another problem entirely. The PSID asks individuals to report the months during the previous year that they received welfare. This data ought to be straightforward, but upon inspection it proves to be suspicious. What one finds is that for those individuals who report positive months of welfare receipt, an overwhelming number of them say they were on welfare exactly six or twelve months. If one inspects what individuals report over a longer span of time, one finds similarly suspicious results—of those individuals who report positive amounts of welfare receipt, there are spikes in the data at six, twelve, eighteen, twenty-four, thirty-two, and thirty-six months. It is difficult to think of anything besides the fallibility of human recollection to explain this data.

Because of the problems with these other candidates, I use the binary welfare choice as the dependent variable. This variable is defined to be equal to 1 if an individual reports having received welfare in any month during year $t+k$, otherwise, it equals 0. Obviously, this definition assumes that while the individuals surveyed for the PSID may imperfectly recall the number of months they received welfare, they accurately report whether they received welfare at all.

Figure 3.1 shows the welfare participation rate among the PSID sample that satisfies the above criteria while Figure 3.2 graphs the government's official caseload data as a comparison. In Figure 3.1 the reader should note the different participation rates for a given year but different values of k. The mechanical reason for this disparity is due to the restriction that an individual be in the PSID for both years t and $t+k$. The consequence is that for any single year, the sample will not be the same for different values of k. While there is a satisfactory explanation for there to be discrepancies in participation rates, it is worth noting that there appears to be a correlation between k and the welfare participation rate in year $t+k$. For larger k welfare participation decreases. Table 3.1 demonstrates that this result comes from greater attrition in the sample as k increases. Otherwise, the most interesting piece of information to come from Figure 3.1 is that welfare participation fell sharply in the years after the 1996 reform. In fact, the largest fall was in 1996 to 1997, the first year after reform, and it further declined for the three years after reform as well.

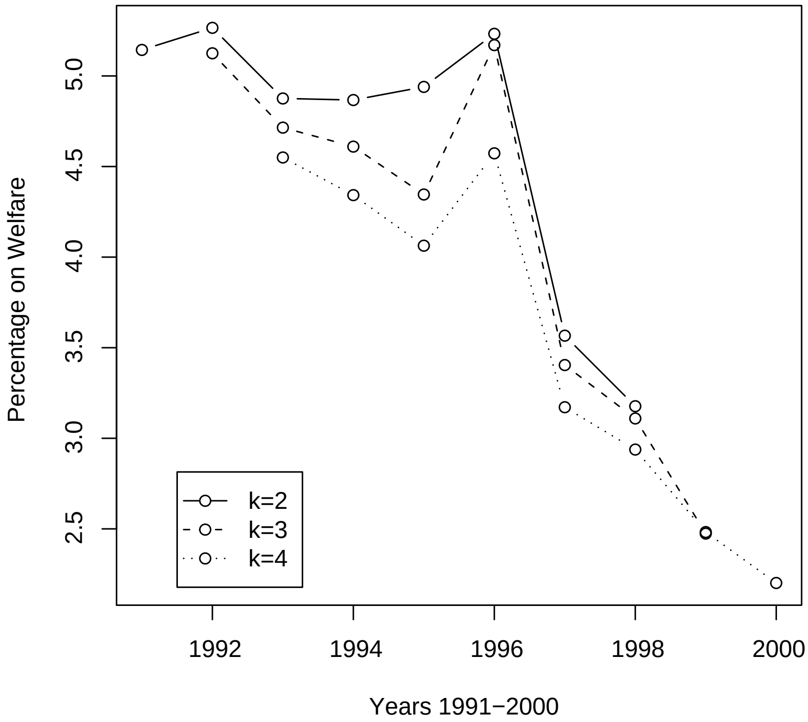

Figure 3.1: Welfare Participation Among PSID Subsample

Table 3.1: Number of Observations

YEAR $(t+k)$	$k=2$	$k=3$	$k=4$
1991	4,316	–	–
1992	4,235	4,078	–
1993	4,184	4,051	3,912
1994	4,212	4,013	3,892
1995	4,474	4,050	3,864
1996	3,784	3,288	2,974
1997	3,673	3,613	3,153
1998	3,777	3,634	3,574
1999	–	3,678	3,545
2000	–	–	3,634

Figure 3.2: Welfare Recipients as Percentage of Population, 1991–2000

3.4.3 Explanatory Variables

The explanatory variables in the regressions are a dummy for whether married in January of year t, a dummy for welfare receipt in year t, age in January of year t, number of children under the age of 18 in January of year t, racial dummies, education dummies, regional dummies for year t, industry dummies for year t, and occupation dummies for year t. These variables capture as much relevant information as the PSID can reasonably provide about the employability, family status, and individual characteristics of those individuals in the study.[7] Past wage information would be

[7] See Appendix B for additional information on the explanatory variables.

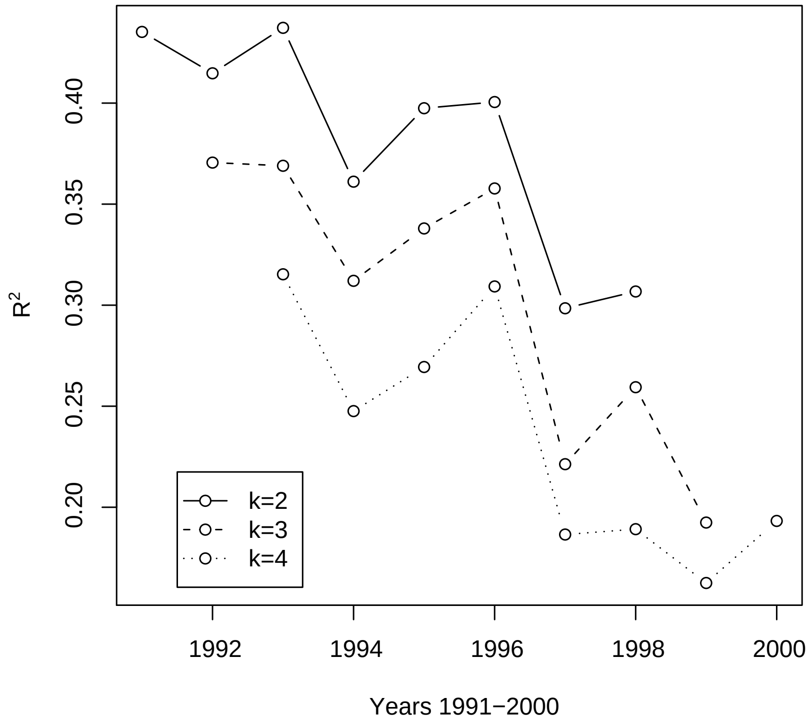

Figure 3.3: R^2 for Regressions on Observables Lagged k Years

nice to include, but the PSID's wage data is not reliable enough. There are too many instances where the PSID reports that individuals are working with a zero wage or not working but having a positive wage.

3.5 Results

3.5.1 Goodness-of-Fit

Figure 3.3 displays the R^2's computed from the twenty-four regressions. The figure shows that R^2 fell overall during the time-frame of the study for all values of k with the largest drop coming in the year immediately after reform. The premise of this paper is that a fall in R^2 is consistent with welfare being used more as social insurance so these results support the view that welfare usage became more unpredictable. On the other hand, we cannot discount that the results are due to other factors such as an increase in unobservable variation at play in the welfare decision.

3.5.2 Estimates of Coefficients

Because of the sheer number of estimated coefficients, they are reported in their entirety in Appendix C. This section highlights and summarizes some of the more interesting estimates that are always or nearly always statistically significant. Many of the estimated coefficients display a similar pattern: with the passage of time the estimated coefficients tend toward zero. With positive coefficients there is a tendency to fall while for negative coefficients there is a tendency to increase. In Figure 3.4, for example, the coefficient estimates for age in year t share this latter pattern. Despite being statistically significant, however, the estimates are so close to zero that one can conclude that they are not economically meaningful.

By contrast Figure 3.5 presents a set of estimated coefficients that are both statistically and economically significant in a sense. This figure graphs the estimated coefficients for the dummy variable indicating welfare receipt in year t. Though one should be cautious about doing so, the traditional interpretation of the coefficients in this case is that, *ceteris paribus*, receipt of welfare for the three years from 1989 to

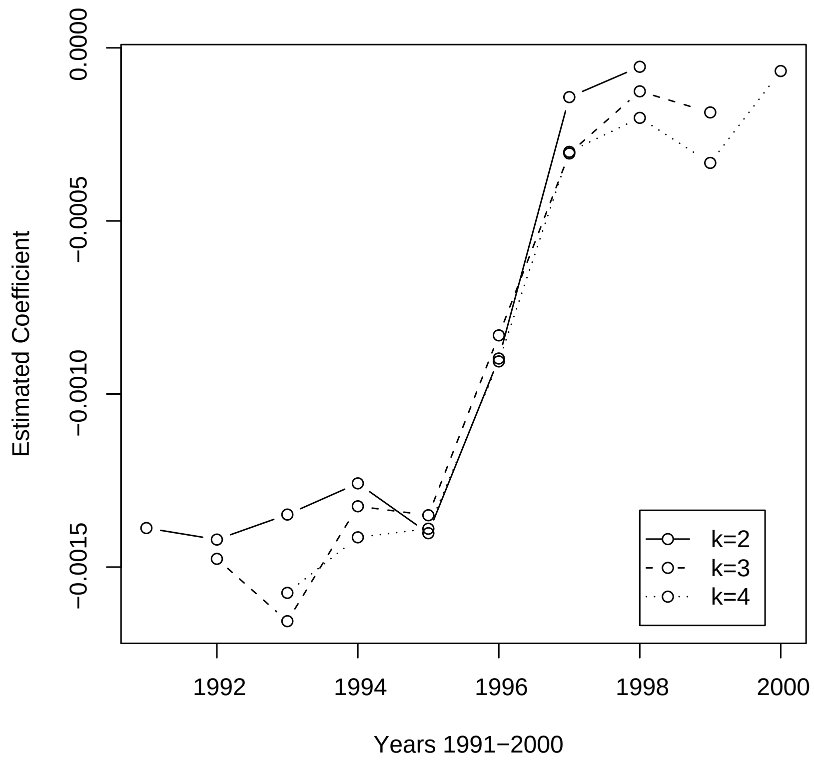

Figure 3.4: Estimate of Coefficient on Age in Year t

1991 increased the probability of receiving welfare two years hence ($k = 2$) in 1991 to 1993, respectively, by over 50%. For $k = 2$ this declines to a little under 40% by 1998. Similarly, for $k = 4$ this estimate declines from a little over 40% in 1993 to a little over 20% in 2000. While a causal interpretation is likely to be an inaccurate one with this model, these coefficients certainly indicate a high degree of correlation between the receipt of welfare across two, three, and four years of time.

The final two estimated coefficients presented in this section are two of the dummy variables representing information on educational attainment. There are five educational dummies included in the regression with no high school diploma as the reference

Figure 3.5: Estimate of Coefficient on Receipt of Welfare in Year t

variable and the one withheld from the regression. In Figure 3.6 and Figure 3.7, we see the estimated coefficients for having received a college degree and having received a high school diploma, respectively. These two graphs indicate a pattern distinct from the one depicted earlier. Instead of a tendency towards zero as time progressed, we see both a rise and a fall in the estimated coefficient.

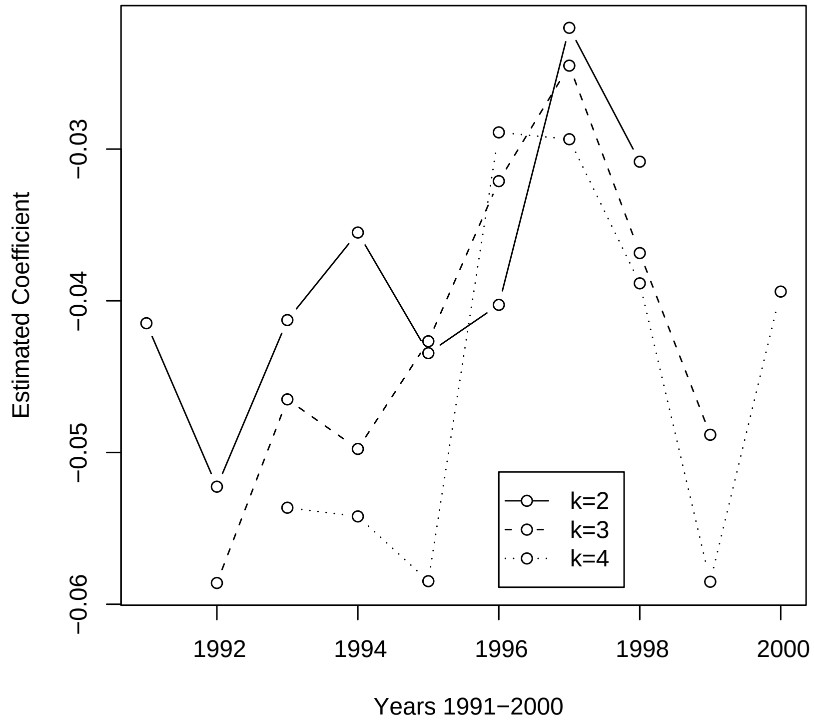

Figure 3.6: Estimate of Coefficient on Whether Received College Degree

3.6 Conclusion

The fall in R^2 that we see in Figure 3.3 indicates that our ability to explain welfare usage 2–4 years in the future has declined in the period of time following welfare reform. I have argued that this is consistent with the social insurance function of AFDC/TANF being more important than it was before reform. It is also consistent, however, with a rise in the importance of unexplained variation. While more research is needed to understand what is going on, the results in this chapter make a tentative case for an increasing role for social insurance in welfare participation because our

Figure 3.7: Estimate of Coefficient on Whether Received High School Diploma

ability to explain it has gone down.

Appendix A

Source Descriptions for Figures

Figure 1.1
U.S. Department of Health and Human Services (1995, pg. 63).

Figure 1.2
U.S. Department of Health and Human Services (1995, pg. 63) and
U.S. Department of Health and Human Services, Administration for Children and Families (`http://www.acf.hhs.gov/news/stats/3697.htm`)

Figure 1.3
U.S. Department of Health and Human Services, Administration for Children and Families (`http://www.acf.hhs.gov/news/stats/3697.htm`).

Figure 1.4
U.S. Department of Health and Human Services, Administration for Children and Families (`http://www.acf.hhs.gov/news/stats/3697.htm`).

Figure 1.5
Caseload data from U.S. Department of Health and Human Services, Administration for Children and Families (`http://www.acf.hhs.gov/news/stats/3697.htm`). U.S. population data from U.S. Department of Commerce, Bureau of the Census (1976), U.S. Department of Commerce, Bureau of the Census (2001), and U.S. Department

of Commerce, Bureau of the Census (2004).

Figure 1.6
U.S. Department of Commerce, Bureau of the Census
(`http://www.census.gov/population/socdemo/hh-fam/tabFM-1.pdf`).

Figure 1.7
U.S. Department of Commerce, Bureau of the Census
(`http://www.census.gov/population/socdemo/hh-fam/tabFM-1.pdf`).

Figure 1.8
U.S. Department of Commerce, Bureau of the Census
(`http://www.census.gov/population/socdemo/hh-fam/tabFM-1.pdf`) and
U.S. Department of Health and Human Services, Administration for Children and Families (`http://www.acf.hhs.gov/news/stats/3697.htm`).

Figure 1.9
U.S. Department of Health and Human Services (2001) and U.S. Department of Commerce, Bureau of the Census (2004).

Figure 3.2
Caseload data from U.S. Department of Health and Human Services, Administration for Children and Families (`http://www.acf.hhs.gov/news/stats/3697.htm`). U.S. population data from U.S. Department of Commerce, Bureau of the Census (1976), U.S. Department of Commerce, Bureau of the Census (2001), and U.S. Department of Commerce, Bureau of the Census (2004).

Appendix B

Chapter 3 Explanatory Variables

Table B.1 lists the variables used in the regressions and provides descriptions of them. All of the industry and occupation dummies represent employment status in year t. Educational status does not change from year to year for individuals in the PSID.

The regressions consist of a number of dummy variables as well as an intercept. In order for the regression to satisfy the rank condition, a number of variables have to be suppressed. The withheld category for the racial/ethnic dummy variables was for whites. For education status the category withheld was for no high school diploma and no GED. The withheld regional category was for Alaska/Hawaii. The withheld category for industry of employment was the not working category. Finally, there are two categories withheld from the occupational dummies. One is for clerical workers. The other was for the not working category. I edited the data to insure that it reflected that if the individual was not working, then both of the dummy variables for industry and occupation would be set to 1, otherwise 0. Therefore, the not working category cannot function as the withheld variable category alone for the occupation dummies.

Table B.1: Variable Definitions

Variable Name	Definition
begMarried	Whether married in year t dummy
begWelfInd	Whether received welfare in year t dummy
begAge	Age in January of year t
begChildU18	Number of children in January of year t
begRace1C_ASIAN_PI	Asian/Pacific Islander dummy
begRace1C_BLACK	Black dummy
begRace1C_LATINO	Latino dummy
begRace1C_NATIVE_AMN	Native American dummy
begRace1C_OTHER	Other race/ethnicity dummy
EducStatus_COLL_DEG	Received college degree dummy
EducStatus_GED_GRAD	Received GED dummy
EducStatus_HS_GRAD	Received HS diploma dummy
EducStatus_SOME_COLL	Attended but not completed college dummy
begRegionC_NORTH CENTRAL	Regional dummy
begRegionC_NORTHEAST	Regional dummy
begRegionC_SOUTH	Regional dummy
begRegionC_WEST	Regional dummy
indusC_AGRICU	Agriculture, forestry, and fisheries industry dummy
indusC_BUSIN	Business and repair services industry dummy
indusC_CONSTR	Construction industry dummy
indusC_ENTERT	Entertainment and recreation industry dummy
indusC_FINANC	Finance industry dummy
indusC_MANUF	Manufacturing industry dummy
indusC_MINING	Mining industry dummy
indusC_PA	Public administration industry dummy
indusC_PERSON	Personal services industry dummy
indusC_PROFES	Professional services industry dummy

Table B.1: Variable Definitions (cont.)

VARIABLE NAME	DEFINITION
indusC_PUC	Public utilities industry dummy
indusC_TRADE	Wholesale and retail trade industry dummy
occupC_CRAFTS	Craftsmen and kindred workers occupation dummy
occupC_FARM	Farmers and farm managers occupation dummy
occupC_FARM_LA	Farm laborers and farm foremen occupation dummy
occupC_LABOR	Laborers occupation dummy
occupC_MGMT	Managers and administrators occupation dummy
occupC_OPERAT	Operatives occupation dummy
occupC_PROFESH	Professional and technical workers occupation dummy
occupC_PVT_HOU	Private household workers occupation dummy
occupC_SALES	Sales workers occupation dummy
occupC_SERVIC	Service workers occupation dummy
occupC_TRANSP	Transport equipment operatives occupation dummy

Appendix C

Chapter 3 Estimated Coefficients

Tables C.1–C.24 are the coefficient estimates of the regressions described in Chapter 3.

Table C.1: Coefficient Estimates for $t = 1989$, $k = 2$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.12	0.07	1.66	0.10
begMarried	−0.03	0.01	−5.60	0.00
begWelfInd	0.53	0.01	42.99	0.00
begAge	−0.00	0.00	−4.89	0.00
begChildU18	0.01	0.00	2.74	0.01
begRace1C_ASIAN_PI	0.00	0.04	0.02	0.99
begRace1C_BLACK	0.03	0.01	4.83	0.00
begRace1C_NATIVE_AMN	0.06	0.03	1.75	0.08
begRace1C_OTHER	0.09	0.03	2.71	0.01
EducStatus_COLL_DEG	−0.04	0.01	−4.13	0.00
EducStatus_GED_GRAD	−0.03	0.01	−2.28	0.02
EducStatus_HS_GRAD	−0.04	0.01	−4.53	0.00
EducStatus_SOME_COLL	−0.05	0.01	−4.92	0.00
begRegionC_NORTH CENTRAL	0.02	0.07	0.28	0.78
begRegionC_NORTHEAST	0.01	0.07	0.18	0.86
begRegionC_SOUTH	0.02	0.07	0.22	0.83
begRegionC_WEST	0.03	0.07	0.43	0.67
indusC_AGRICU	−0.04	0.05	−0.79	0.43
indusC_BUSIN	−0.04	0.02	−2.04	0.04
indusC_CONSTR	−0.03	0.03	−1.17	0.24
indusC_ENTERT	−0.04	0.04	−1.08	0.28
indusC_FINANC	−0.04	0.01	−3.04	0.00
indusC_MANUF	−0.03	0.01	−2.42	0.02
indusC_MINING	−0.04	0.06	−0.68	0.50
indusC_PA	−0.04	0.01	−3.10	0.00
indusC_PERSON	−0.02	0.02	−1.45	0.15
indusC_PROFES	−0.04	0.01	−3.97	0.00
indusC_PUC	−0.03	0.02	−1.63	0.10
indusC_TRADE	−0.03	0.01	−2.71	0.01
occupC_CRAFTS	0.01	0.02	0.49	0.63
occupC_FARM	0.03	0.18	0.19	0.85

Table C.1: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM_LA	0.15	0.09	1.70	0.09
occupC_LABOR	0.04	0.04	1.10	0.27
occupC_MGMT	0.01	0.01	0.51	0.61
occupC_OPERAT	−0.00	0.01	−0.08	0.93
occupC_PROFESH	0.01	0.01	0.73	0.47
occupC_PVT_HOU	−0.01	0.03	−0.43	0.67
occupC_SALES	−0.01	0.02	−0.71	0.48
occupC_SERVIC	−0.00	0.01	−0.24	0.81
occupC_TRANSP	−0.01	0.04	−0.18	0.86

Table C.2: Coefficient Estimates for $t = 1990$, $k = 2$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.12	0.06	2.19	0.03
begMarried	−0.03	0.01	−5.16	0.00
begWelfInd	0.54	0.01	40.47	0.00
begAge	−0.00	0.00	−4.74	0.00
begChildU18	0.01	0.00	4.15	0.00
begRace1C_ASIAN_PI	0.00	0.04	0.07	0.94
begRace1C_BLACK	0.02	0.01	3.41	0.00
begRace1C_LATINO	0.08	0.04	1.93	0.05
begRace1C_NATIVE_AMN	0.11	0.04	2.91	0.00
begRace1C_OTHER	0.07	0.08	0.85	0.40
EducStatus_COLL_DEG	−0.05	0.01	−4.92	0.00
EducStatus_GED_GRAD	0.01	0.02	0.92	0.36
EducStatus_HS_GRAD	−0.04	0.01	−4.55	0.00
EducStatus_SOME_COLL	−0.05	0.01	−5.58	0.00
begRegionC_NORTH CENTRAL	0.02	0.05	0.45	0.65
begRegionC_NORTHEAST	0.02	0.06	0.31	0.76
begRegionC_SOUTH	0.01	0.05	0.27	0.79
begRegionC_WEST	0.03	0.05	0.62	0.53
indusC_AGRICU	0.07	0.06	1.24	0.21
indusC_BUSIN	−0.05	0.02	−2.78	0.01
indusC_CONSTR	−0.05	0.03	−1.64	0.10
indusC_ENTERT	−0.05	0.04	−1.19	0.23
indusC_FINANC	−0.04	0.01	−3.02	0.00
indusC_MANUF	−0.05	0.01	−4.10	0.00
indusC_MINING	−0.05	0.07	−0.77	0.44
indusC_PA	−0.04	0.01	−2.88	0.00
indusC_PERSON	−0.02	0.02	−1.55	0.12
indusC_PROFES	−0.03	0.01	−3.51	0.00
indusC_PUC	−0.03	0.02	−1.66	0.10
indusC_TRADE	−0.04	0.01	−3.35	0.00
occupC_CRAFTS	0.01	0.02	0.62	0.53

Table C.2: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.09	0.13	−0.65	0.52
occupC_FARM_LA	−0.12	0.08	−1.39	0.17
occupC_LABOR	−0.04	0.03	−1.13	0.26
occupC_MGMT	0.01	0.01	0.56	0.57
occupC_OPERAT	0.01	0.02	0.50	0.62
occupC_PROFESH	0.00	0.01	0.43	0.66
occupC_PVT_HOU	−0.02	0.03	−0.77	0.44
occupC_SALES	0.00	0.02	0.20	0.84
occupC_SERVIC	−0.00	0.01	−0.43	0.67
occupC_TRANSP	−0.03	0.04	−0.79	0.43

Table C.3: Coefficient Estimates for $t = 1991$, $k = 2$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.10	0.05	1.87	0.06
begMarried	−0.01	0.01	−2.08	0.04
begWelfInd	0.58	0.01	45.22	0.00
begAge	−0.00	0.00	−4.69	0.00
begChildU18	0.00	0.00	1.50	0.13
begRace1C_ASIAN_PI	0.00	0.04	0.06	0.95
begRace1C_BLACK	0.02	0.01	3.12	0.00
begRace1C_LATINO	−0.06	0.16	−0.38	0.70
begRace1C_NATIVE_AMN	−0.03	0.03	−0.92	0.36
begRace1C_OTHER	0.00	0.04	0.13	0.89
EducStatus_COLL_DEG	−0.04	0.01	−4.12	0.00
EducStatus_GED_GRAD	0.01	0.01	0.66	0.51
EducStatus_HS_GRAD	−0.03	0.01	−3.78	0.00
EducStatus_SOME_COLL	−0.04	0.01	−4.48	0.00
begRegionC_NORTH CENTRAL	0.03	0.05	0.64	0.52
begRegionC_NORTHEAST	0.01	0.05	0.20	0.84
begRegionC_SOUTH	0.01	0.05	0.22	0.83
begRegionC_WEST	0.03	0.05	0.69	0.49
indusC_AGRICU	−0.03	0.04	−0.68	0.49
indusC_BUSIN	−0.01	0.02	−0.83	0.40
indusC_CONSTR	−0.03	0.03	−1.17	0.24
indusC_ENTERT	−0.04	0.04	−0.96	0.34
indusC_FINANC	−0.03	0.01	−2.20	0.03
indusC_MANUF	−0.02	0.01	−1.83	0.07
indusC_MINING	−0.03	0.07	−0.48	0.63
indusC_PA	−0.02	0.01	−1.58	0.11
indusC_PERSON	−0.03	0.01	−1.75	0.08
indusC_PROFES	−0.02	0.01	−2.61	0.01
indusC_PUC	−0.02	0.02	−1.28	0.20
indusC_TRADE	−0.01	0.01	−1.38	0.17
occupC_CRAFTS	−0.01	0.02	−0.44	0.66

Table C.3: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.00	0.08	−0.02	0.99
occupC_FARM_LA	0.09	0.09	0.98	0.33
occupC_LABOR	−0.03	0.03	−0.84	0.40
occupC_MGMT	0.00	0.01	0.20	0.84
occupC_OPERAT	−0.02	0.01	−1.09	0.28
occupC_PROFESH	0.00	0.01	0.37	0.71
occupC_PVT_HOU	−0.04	0.03	−1.67	0.09
occupC_SALES	−0.02	0.02	−1.19	0.23
occupC_SERVIC	0.01	0.01	0.53	0.59
occupC_TRANSP	−0.05	0.03	−1.34	0.18

Table C.4: Coefficient Estimates for $t = 1992$, $k = 2$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.10	0.06	1.74	0.08
begMarried	−0.03	0.01	−3.97	0.00
begWelfInd	0.48	0.01	36.49	0.00
begAge	−0.00	0.00	−4.09	0.00
begChildU18	0.01	0.00	2.28	0.02
begRace1C_ASIAN_PI	0.00	0.04	0.12	0.91
begRace1C_BLACK	0.02	0.01	3.66	0.00
begRace1C_LATINO	0.03	0.06	0.49	0.62
begRace1C_NATIVE_AMN	−0.03	0.03	−0.85	0.39
begRace1C_OTHER	−0.07	0.04	−1.84	0.07
EducStatus_COLL_DEG	−0.04	0.01	−3.31	0.00
EducStatus_GED_GRAD	−0.03	0.02	−2.12	0.03
EducStatus_HS_GRAD	−0.02	0.01	−2.55	0.01
EducStatus_SOME_COLL	−0.03	0.01	−2.83	0.00
begRegionC_NORTH CENTRAL	0.03	0.06	0.45	0.65
begRegionC_NORTHEAST	0.01	0.06	0.22	0.82
begRegionC_SOUTH	0.01	0.06	0.24	0.81
begRegionC_WEST	0.02	0.06	0.35	0.73
indusC_AGRICU	−0.07	0.05	−1.34	0.18
indusC_BUSIN	−0.05	0.02	−2.48	0.01
indusC_CONSTR	−0.04	0.03	−1.48	0.14
indusC_ENTERT	−0.04	0.04	−1.09	0.27
indusC_FINANC	−0.04	0.01	−2.87	0.00
indusC_MANUF	−0.04	0.01	−2.61	0.01
indusC_MINING	−0.05	0.07	−0.73	0.47
indusC_PA	−0.04	0.01	−2.78	0.01
indusC_PERSON	−0.03	0.02	−1.68	0.09
indusC_PROFES	−0.04	0.01	−4.08	0.00
indusC_PUC	−0.03	0.02	−1.50	0.13
indusC_TRADE	−0.03	0.01	−2.88	0.00
occupC_CRAFTS	−0.02	0.02	−0.92	0.36

Table C.4: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.03	0.10	0.30	0.77
occupC_FARM_LA	0.02	0.09	0.21	0.84
occupC_LABOR	0.02	0.03	0.77	0.44
occupC_MGMT	0.00	0.01	0.32	0.75
occupC_OPERAT	−0.01	0.02	−0.71	0.48
occupC_PROFESH	0.01	0.01	0.81	0.42
occupC_PVT_HOU	0.00	0.03	0.11	0.91
occupC_SALES	0.00	0.02	0.26	0.79
occupC_SERVIC	0.00	0.01	0.06	0.95
occupC_TRANSP	−0.04	0.04	−1.05	0.30

Table C.5: Coefficient Estimates for $t = 1993$, $k = 2$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.11	0.05	2.24	0.03
begMarried	−0.03	0.01	−4.55	0.00
begWelfInd	0.49	0.01	40.30	0.00
begAge	−0.00	0.00	−4.80	0.00
begChildU18	0.01	0.00	3.92	0.00
begRace1C_ASIAN_PI	0.01	0.04	0.26	0.80
begRace1C_BLACK	0.03	0.01	4.53	0.00
begRace1C_LATINO	0.08	0.05	1.76	0.08
begRace1C_NATIVE_AMN	0.01	0.03	0.22	0.83
begRace1C_OTHER	−0.04	0.03	−1.27	0.20
EducStatus_COLL_DEG	−0.04	0.01	−4.29	0.00
EducStatus_GED_GRAD	−0.01	0.01	−0.79	0.43
EducStatus_HS_GRAD	−0.03	0.01	−2.99	0.00
EducStatus_SOME_COLL	−0.04	0.01	−4.03	0.00
begRegionC_NORTH CENTRAL	0.03	0.05	0.51	0.61
begRegionC_NORTHEAST	0.01	0.05	0.29	0.77
begRegionC_SOUTH	0.01	0.05	0.16	0.88
begRegionC_WEST	0.03	0.05	0.59	0.56
indusC_AGRICU	−0.06	0.06	−1.04	0.30
indusC_BUSIN	−0.05	0.02	−2.88	0.00
indusC_CONSTR	−0.05	0.03	−1.88	0.06
indusC_ENTERT	−0.08	0.03	−2.62	0.01
indusC_FINANC	−0.04	0.01	−2.95	0.00
indusC_MANUF	−0.03	0.01	−2.48	0.01
indusC_MINING	−0.05	0.06	−0.86	0.39
indusC_PA	−0.05	0.01	−3.71	0.00
indusC_PERSON	−0.06	0.02	−3.47	0.00
indusC_PROFES	−0.05	0.01	−5.19	0.00
indusC_PUC	−0.04	0.02	−2.49	0.01
indusC_TRADE	−0.05	0.01	−4.33	0.00
occupC_CRAFTS	0.00	0.02	0.18	0.85

Table C.5: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.02	0.09	0.23	0.82
occupC_FARM_LA	−0.12	0.09	−1.28	0.20
occupC_LABOR	0.03	0.03	1.02	0.31
occupC_MGMT	0.01	0.01	0.92	0.36
occupC_OPERAT	−0.03	0.02	−1.94	0.05
occupC_PROFESH	0.02	0.01	1.78	0.07
occupC_PVT_HOU	−0.00	0.03	−0.05	0.96
occupC_SALES	0.03	0.02	1.74	0.08
occupC_SERVIC	−0.00	0.01	−0.13	0.90
occupC_TRANSP	−0.03	0.03	−0.95	0.34

Table C.6: Coefficient Estimates for $t = 1994$, $k = 2$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.11	0.05	2.44	0.01
begMarried	−0.04	0.01	−5.23	0.00
begWelfInd	0.50	0.01	37.61	0.00
begAge	−0.00	0.00	−2.74	0.01
begChildU18	0.01	0.00	3.96	0.00
begRace1C_ASIAN_PI	−0.01	0.05	−0.16	0.87
begRace1C_BLACK	0.03	0.01	3.51	0.00
begRace1C_LATINO	−0.03	0.06	−0.46	0.65
begRace1C_NATIVE_AMN	−0.03	0.04	−0.80	0.42
begRace1C_OTHER	0.01	0.03	0.36	0.72
EducStatus_COLL_DEG	−0.04	0.01	−3.47	0.00
EducStatus_GED_GRAD	−0.03	0.02	−1.69	0.09
EducStatus_HS_GRAD	−0.02	0.01	−2.42	0.02
EducStatus_SOME_COLL	−0.03	0.01	−3.13	0.00
begRegionC_NORTH CENTRAL	0.01	0.04	0.26	0.79
begRegionC_NORTHEAST	−0.01	0.04	−0.13	0.90
begRegionC_SOUTH	−0.01	0.04	−0.18	0.86
begRegionC_WEST	0.02	0.04	0.36	0.72
indusC_AGRICU	−0.10	0.06	−1.76	0.08
indusC_BUSIN	−0.04	0.02	−2.38	0.02
indusC_CONSTR	−0.05	0.03	−1.60	0.11
indusC_ENTERT	−0.08	0.04	−2.09	0.04
indusC_FINANC	−0.02	0.01	−1.86	0.06
indusC_MANUF	−0.05	0.01	−3.63	0.00
indusC_MINING	−0.05	0.08	−0.68	0.50
indusC_PA	−0.05	0.02	−3.22	0.00
indusC_PERSON	−0.05	0.02	−2.72	0.01
indusC_PROFES	−0.04	0.01	−4.26	0.00
indusC_PUC	−0.03	0.02	−1.64	0.10
indusC_TRADE	−0.04	0.01	−3.27	0.00
occupC_CRAFTS	0.00	0.02	0.05	0.96

Table C.6: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.07	0.09	0.78	0.44
occupC_FARM_LA	0.03	0.10	0.26	0.79
occupC_LABOR	0.03	0.04	0.86	0.39
occupC_MGMT	0.02	0.01	1.27	0.20
occupC_OPERAT	0.00	0.02	0.13	0.90
occupC_PROFESH	0.02	0.01	1.53	0.13
occupC_PVT_HOU	0.05	0.03	1.56	0.12
occupC_SALES	0.00	0.02	0.10	0.92
occupC_SERVIC	0.01	0.01	0.97	0.33
occupC_TRANSP	0.03	0.04	0.75	0.45

Table C.7: Coefficient Estimates for $t = 1995$, $k = 2$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.13	0.05	2.77	0.01
begMarried	−0.02	0.01	−3.33	0.00
begWelfInd	0.39	0.01	30.60	0.00
begAge	−0.00	0.00	−0.48	0.63
begChildU18	0.00	0.00	1.28	0.20
begRace1C_ASIAN_PI	−0.00	0.04	−0.02	0.98
begRace1C_BLACK	0.02	0.01	3.11	0.00
begRace1C_LATINO	0.05	0.06	0.88	0.38
begRace1C_NATIVE_AMN	−0.01	0.03	−0.33	0.74
begRace1C_OTHER	0.03	0.03	1.05	0.30
EducStatus_COLL_DEG	−0.02	0.01	−2.09	0.04
EducStatus_GED_GRAD	−0.01	0.02	−0.72	0.47
EducStatus_HS_GRAD	−0.01	0.01	−1.62	0.11
EducStatus_SOME_COLL	−0.03	0.01	−2.78	0.01
begRegionC_NORTH CENTRAL	−0.07	0.04	−1.50	0.13
begRegionC_NORTHEAST	−0.07	0.04	−1.56	0.12
begRegionC_SOUTH	−0.08	0.04	−1.86	0.06
begRegionC_WEST	−0.07	0.04	−1.52	0.13
indusC_AGRICU	−0.02	0.05	−0.32	0.75
indusC_BUSIN	−0.02	0.02	−1.10	0.27
indusC_CONSTR	−0.02	0.03	−0.94	0.35
indusC_ENTERT	−0.03	0.03	−0.92	0.36
indusC_FINANC	−0.02	0.01	−1.45	0.15
indusC_MANUF	−0.02	0.01	−1.76	0.08
indusC_MINING	−0.02	0.09	−0.27	0.79
indusC_PA	−0.03	0.01	−2.04	0.04
indusC_PERSON	−0.02	0.02	−1.55	0.12
indusC_PROFES	−0.02	0.01	−2.63	0.01
indusC_PUC	−0.03	0.02	−1.55	0.12
indusC_TRADE	−0.02	0.01	−1.89	0.06
occupC_CRAFTS	−0.00	0.02	−0.16	0.88

Table C.7: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.00	0.09	−0.03	0.97
occupC_FARM_LA	−0.01	0.07	−0.18	0.86
occupC_LABOR	−0.00	0.03	−0.12	0.91
occupC_MGMT	0.00	0.01	0.38	0.70
occupC_OPERAT	−0.02	0.02	−0.97	0.33
occupC_PROFESH	0.01	0.01	0.78	0.44
occupC_PVT_HOU	0.08	0.03	2.58	0.01
occupC_SALES	−0.00	0.02	−0.26	0.79
occupC_SERVIC	0.01	0.01	1.48	0.14
occupC_TRANSP	0.05	0.03	1.74	0.08

Table C.8: Coefficient Estimates for $t = 1996$, $k = 2$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.12	0.04	2.87	0.00
begMarried	−0.02	0.01	−3.44	0.00
begWelfInd	0.37	0.01	31.41	0.00
begAge	−0.00	0.00	−0.20	0.84
begChildU18	0.00	0.00	1.29	0.20
begRace1C_ASIAN_PI	−0.01	0.04	−0.26	0.80
begRace1C_BLACK	0.02	0.01	3.58	0.00
begRace1C_LATINO	0.05	0.05	0.98	0.33
begRace1C_NATIVE_AMN	−0.01	0.03	−0.24	0.81
begRace1C_OTHER	0.06	0.03	2.35	0.02
EducStatus_COLL_DEG	−0.03	0.01	−3.15	0.00
EducStatus_GED_GRAD	−0.02	0.01	−1.52	0.13
EducStatus_HS_GRAD	−0.02	0.01	−2.58	0.01
EducStatus_SOME_COLL	−0.04	0.01	−3.84	0.00
begRegionC_NORTH CENTRAL	−0.06	0.04	−1.48	0.14
begRegionC_NORTHEAST	−0.05	0.04	−1.40	0.16
begRegionC_SOUTH	−0.07	0.04	−1.89	0.06
begRegionC_WEST	−0.04	0.04	−1.08	0.28
indusC_AGRICU	−0.02	0.04	−0.45	0.65
indusC_BUSIN	−0.03	0.02	−1.74	0.08
indusC_CONSTR	0.00	0.03	0.02	0.98
indusC_ENTERT	−0.02	0.03	−0.63	0.53
indusC_FINANC	−0.03	0.01	−2.50	0.01
indusC_MANUF	−0.03	0.01	−2.60	0.01
indusC_MINING	−0.04	0.15	−0.28	0.78
indusC_PA	−0.02	0.01	−1.97	0.05
indusC_PERSON	−0.02	0.02	−1.61	0.11
indusC_PROFES	−0.02	0.01	−2.59	0.01
indusC_PUC	−0.03	0.02	−2.16	0.03
indusC_TRADE	−0.03	0.01	−2.67	0.01
occupC_CRAFTS	−0.00	0.02	−0.11	0.91

Table C.8: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.02	0.15	−0.11	0.91
occupC_FARM_LA	−0.00	0.07	−0.02	0.99
occupC_LABOR	−0.01	0.03	−0.35	0.72
occupC_MGMT	0.01	0.01	1.08	0.28
occupC_OPERAT	0.00	0.01	0.08	0.93
occupC_PROFESH	0.01	0.01	1.11	0.27
occupC_PVT_HOU	0.07	0.03	2.55	0.01
occupC_SALES	0.01	0.01	0.94	0.35
occupC_SERVIC	−0.00	0.01	−0.07	0.94
occupC_TRANSP	0.02	0.03	0.72	0.47

Table C.9: Coefficient Estimates for $t = 1989$, $k = 3$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.12	0.07	1.63	0.10
begMarried	−0.03	0.01	−3.95	0.00
begWelfInd	0.49	0.01	35.66	0.00
begAge	−0.00	0.00	−4.68	0.00
begChildU18	0.01	0.00	4.16	0.00
begRace1C_ASIAN_PI	0.00	0.04	0.09	0.93
begRace1C_BLACK	0.03	0.01	3.74	0.00
begRace1C_NATIVE_AMN	0.11	0.04	2.81	0.00
begRace1C_OTHER	0.10	0.04	2.68	0.01
EducStatus_COLL_DEG	−0.06	0.01	−5.34	0.00
EducStatus_GED_GRAD	−0.01	0.02	−0.80	0.43
EducStatus_HS_GRAD	−0.05	0.01	−5.75	0.00
EducStatus_SOME_COLL	−0.06	0.01	−5.67	0.00
begRegionC_NORTH CENTRAL	0.02	0.07	0.26	0.79
begRegionC_NORTHEAST	0.01	0.07	0.17	0.87
begRegionC_SOUTH	0.01	0.07	0.18	0.85
begRegionC_WEST	0.04	0.07	0.48	0.63
indusC_AGRICU	−0.04	0.06	−0.76	0.45
indusC_BUSIN	−0.03	0.02	−1.77	0.08
indusC_CONSTR	−0.04	0.03	−1.13	0.26
indusC_ENTERT	−0.04	0.04	−1.00	0.32
indusC_FINANC	−0.03	0.01	−2.63	0.01
indusC_MANUF	−0.04	0.01	−2.70	0.01
indusC_MINING	−0.04	0.07	−0.59	0.55
indusC_PA	−0.03	0.02	−2.01	0.04
indusC_PERSON	−0.05	0.02	−2.69	0.01
indusC_PROFES	−0.03	0.01	−3.14	0.00
indusC_PUC	−0.02	0.02	−0.93	0.35
indusC_TRADE	−0.02	0.01	−2.13	0.03
occupC_CRAFTS	0.05	0.03	1.81	0.07
occupC_FARM	0.03	0.18	0.17	0.86

Table C.9: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM_LA	0.19	0.10	1.98	0.05
occupC_LABOR	0.05	0.04	1.20	0.23
occupC_MGMT	0.00	0.01	0.12	0.90
occupC_OPERAT	−0.00	0.02	−0.16	0.87
occupC_PROFESH	0.01	0.01	0.75	0.46
occupC_PVT_HOU	−0.01	0.03	−0.45	0.65
occupC_SALES	−0.01	0.02	−0.73	0.47
occupC_SERVIC	0.02	0.01	1.58	0.11
occupC_TRANSP	−0.01	0.04	−0.28	0.78

Table C.10: Coefficient Estimates for $t = 1990$, $k = 3$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.10	0.06	1.87	0.06
begMarried	−0.01	0.01	−2.18	0.03
begWelfInd	0.53	0.01	37.82	0.00
begAge	−0.00	0.00	−5.31	0.00
begChildU18	0.00	0.00	1.39	0.16
begRace1C_ASIAN_PI	−0.00	0.04	−0.06	0.95
begRace1C_BLACK	0.02	0.01	3.72	0.00
begRace1C_LATINO	0.04	0.04	1.03	0.30
begRace1C_NATIVE_AMN	0.00	0.04	0.00	1.00
begRace1C_OTHER	0.08	0.08	1.00	0.32
EducStatus_COLL_DEG	−0.05	0.01	−4.32	0.00
EducStatus_GED_GRAD	0.01	0.02	0.33	0.74
EducStatus_HS_GRAD	−0.04	0.01	−4.04	0.00
EducStatus_SOME_COLL	−0.05	0.01	−4.83	0.00
begRegionC_NORTH CENTRAL	0.03	0.05	0.56	0.57
begRegionC_NORTHEAST	0.02	0.05	0.34	0.73
begRegionC_SOUTH	0.01	0.05	0.26	0.80
begRegionC_WEST	0.04	0.05	0.75	0.45
indusC_AGRICU	−0.02	0.06	−0.35	0.73
indusC_BUSIN	0.00	0.02	0.03	0.98
indusC_CONSTR	−0.03	0.03	−1.17	0.24
indusC_ENTERT	−0.04	0.04	−0.90	0.37
indusC_FINANC	−0.03	0.01	−2.15	0.03
indusC_MANUF	−0.02	0.01	−1.29	0.20
indusC_MINING	−0.04	0.07	−0.55	0.58
indusC_PA	−0.02	0.01	−1.51	0.13
indusC_PERSON	0.01	0.02	0.51	0.61
indusC_PROFES	−0.02	0.01	−1.88	0.06
indusC_PUC	−0.03	0.02	−1.46	0.14
indusC_TRADE	−0.02	0.01	−1.70	0.09
occupC_CRAFTS	−0.01	0.02	−0.46	0.64

Table C.10: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.00	0.13	0.02	0.98
occupC_FARM_LA	−0.02	0.08	−0.27	0.78
occupC_LABOR	−0.03	0.03	−0.93	0.35
occupC_MGMT	0.00	0.01	0.28	0.78
occupC_OPERAT	−0.01	0.02	−0.67	0.50
occupC_PROFESH	0.00	0.01	0.01	0.99
occupC_PVT_HOU	−0.02	0.03	−0.65	0.52
occupC_SALES	0.00	0.02	0.27	0.79
occupC_SERVIC	−0.00	0.01	−0.02	0.99
occupC_TRANSP	−0.02	0.04	−0.56	0.57

Table C.11: Coefficient Estimates for $t = 1991$, $k = 3$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.10	0.05	1.83	0.07
begMarried	−0.02	0.01	−3.43	0.00
begWelfInd	0.44	0.01	31.44	0.00
begAge	−0.00	0.00	−4.09	0.00
begChildU18	0.01	0.00	3.21	0.00
begRace1C_ASIAN_PI	0.00	0.04	0.10	0.92
begRace1C_BLACK	0.03	0.01	3.67	0.00
begRace1C_LATINO	−0.07	0.18	−0.38	0.70
begRace1C_NATIVE_AMN	−0.02	0.04	−0.42	0.67
begRace1C_OTHER	−0.08	0.04	−2.08	0.04
EducStatus_COLL_DEG	−0.05	0.01	−4.50	0.00
EducStatus_GED_GRAD	−0.03	0.02	−2.01	0.04
EducStatus_HS_GRAD	−0.03	0.01	−3.66	0.00
EducStatus_SOME_COLL	−0.04	0.01	−4.13	0.00
begRegionC_NORTH CENTRAL	0.04	0.05	0.67	0.50
begRegionC_NORTHEAST	0.02	0.05	0.34	0.74
begRegionC_SOUTH	0.01	0.05	0.25	0.80
begRegionC_WEST	0.03	0.05	0.58	0.56
indusC_AGRICU	−0.02	0.05	−0.43	0.67
indusC_BUSIN	−0.03	0.02	−1.49	0.14
indusC_CONSTR	−0.03	0.03	−1.09	0.27
indusC_ENTERT	−0.03	0.04	−0.73	0.47
indusC_FINANC	−0.03	0.01	−2.08	0.04
indusC_MANUF	−0.03	0.01	−1.82	0.07
indusC_MINING	−0.05	0.07	−0.65	0.51
indusC_PA	−0.03	0.02	−2.29	0.02
indusC_PERSON	−0.02	0.02	−1.06	0.29
indusC_PROFES	−0.03	0.01	−2.52	0.01
indusC_PUC	0.00	0.02	0.13	0.89
indusC_TRADE	−0.02	0.01	−1.32	0.19
occupC_CRAFTS	−0.02	0.02	−0.87	0.39

Table C.11: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.01	0.09	−0.08	0.93
occupC_FARM_LA	0.11	0.10	1.08	0.28
occupC_LABOR	−0.06	0.03	−1.71	0.09
occupC_MGMT	−0.00	0.01	−0.07	0.95
occupC_OPERAT	−0.00	0.02	−0.09	0.93
occupC_PROFESH	0.01	0.01	0.68	0.50
occupC_PVT_HOU	−0.07	0.03	−2.42	0.02
occupC_SALES	−0.01	0.02	−0.39	0.70
occupC_SERVIC	−0.00	0.01	−0.09	0.93
occupC_TRANSP	−0.07	0.04	−1.71	0.09

Table C.12: Coefficient Estimates for $t = 1992$, $k = 3$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.11	0.06	1.83	0.07
begMarried	−0.02	0.01	−3.07	0.00
begWelfInd	0.43	0.01	33.02	0.00
begAge	−0.00	0.00	−4.36	0.00
begChildU18	0.01	0.00	2.40	0.02
begRace1C_ASIAN_PI	0.00	0.04	0.07	0.94
begRace1C_BLACK	0.03	0.01	4.46	0.00
begRace1C_LATINO	−0.10	0.06	−1.63	0.10
begRace1C_NATIVE_AMN	−0.02	0.03	−0.70	0.48
begRace1C_OTHER	−0.07	0.04	−1.85	0.06
EducStatus_COLL_DEG	−0.04	0.01	−4.01	0.00
EducStatus_GED_GRAD	−0.01	0.02	−0.42	0.68
EducStatus_HS_GRAD	−0.03	0.01	−3.08	0.00
EducStatus_SOME_COLL	−0.04	0.01	−3.66	0.00
begRegionC_NORTH CENTRAL	0.03	0.06	0.48	0.63
begRegionC_NORTHEAST	0.01	0.06	0.16	0.88
begRegionC_SOUTH	0.00	0.06	0.08	0.93
begRegionC_WEST	0.03	0.06	0.56	0.58
indusC_AGRICU	−0.08	0.05	−1.48	0.14
indusC_BUSIN	−0.05	0.02	−2.81	0.00
indusC_CONSTR	−0.04	0.03	−1.66	0.10
indusC_ENTERT	−0.04	0.03	−1.13	0.26
indusC_FINANC	−0.03	0.01	−2.68	0.01
indusC_MANUF	−0.03	0.01	−2.34	0.02
indusC_MINING	−0.05	0.07	−0.71	0.48
indusC_PA	−0.04	0.01	−2.88	0.00
indusC_PERSON	−0.01	0.02	−0.75	0.46
indusC_PROFES	−0.04	0.01	−3.91	0.00
indusC_PUC	−0.04	0.02	−2.10	0.04
indusC_TRADE	−0.04	0.01	−3.49	0.00
occupC_CRAFTS	−0.02	0.02	−0.82	0.41

Table C.12: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.04	0.10	0.40	0.69
occupC_FARM_LA	0.03	0.09	0.30	0.77
occupC_LABOR	0.05	0.03	1.53	0.13
occupC_MGMT	0.01	0.01	1.11	0.27
occupC_OPERAT	−0.02	0.02	−1.41	0.16
occupC_PROFESH	0.01	0.01	1.36	0.17
occupC_PVT_HOU	0.01	0.03	0.50	0.62
occupC_SALES	0.01	0.02	0.83	0.41
occupC_SERVIC	−0.01	0.01	−1.36	0.17
occupC_TRANSP	−0.03	0.04	−0.82	0.41

Table C.13: Coefficient Estimates for $t = 1993$, $k = 3$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.09	0.06	1.52	0.13
begMarried	−0.04	0.01	−4.81	0.00
begWelfInd	0.45	0.01	30.64	0.00
begAge	−0.00	0.00	−2.25	0.02
begChildU18	0.01	0.00	3.30	0.00
begRace1C_ASIAN_PI	−0.00	0.06	−0.02	0.99
begRace1C_BLACK	0.03	0.01	4.19	0.00
begRace1C_LATINO	0.12	0.09	1.29	0.20
begRace1C_NATIVE_AMN	−0.01	0.04	−0.21	0.83
begRace1C_OTHER	0.01	0.04	0.25	0.80
EducStatus_COLL_DEG	−0.03	0.01	−2.50	0.01
EducStatus_GED_GRAD	−0.03	0.02	−1.31	0.19
EducStatus_HS_GRAD	−0.02	0.01	−1.59	0.11
EducStatus_SOME_COLL	−0.02	0.01	−2.02	0.04
begRegionC_NORTH CENTRAL	0.02	0.06	0.41	0.68
begRegionC_NORTHEAST	0.01	0.06	0.18	0.86
begRegionC_SOUTH	0.00	0.06	0.07	0.95
begRegionC_WEST	0.02	0.06	0.35	0.73
indusC_AGRICU	−0.05	0.07	−0.79	0.43
indusC_BUSIN	−0.05	0.02	−2.46	0.01
indusC_CONSTR	−0.04	0.03	−1.33	0.18
indusC_ENTERT	−0.09	0.04	−2.14	0.03
indusC_FINANC	−0.03	0.02	−1.87	0.06
indusC_MANUF	−0.04	0.02	−2.20	0.03
indusC_MINING	−0.05	0.06	−0.79	0.43
indusC_PA	−0.04	0.02	−2.28	0.02
indusC_PERSON	−0.04	0.02	−2.22	0.03
indusC_PROFES	−0.04	0.01	−3.26	0.00
indusC_PUC	−0.04	0.02	−1.90	0.06
indusC_TRADE	−0.02	0.01	−1.20	0.23
occupC_CRAFTS	−0.01	0.03	−0.30	0.76

Table C.13: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.02	0.11	0.20	0.84
occupC_FARM_LA	−0.11	0.11	−1.07	0.28
occupC_LABOR	0.06	0.04	1.43	0.15
occupC_MGMT	−0.00	0.01	−0.01	0.99
occupC_OPERAT	−0.01	0.02	−0.35	0.73
occupC_PROFESH	0.01	0.01	0.61	0.54
occupC_PVT_HOU	0.03	0.04	0.85	0.40
occupC_SALES	−0.01	0.02	−0.38	0.70
occupC_SERVIC	−0.01	0.01	−0.40	0.69
occupC_TRANSP	0.04	0.04	0.99	0.32

Table C.14: Coefficient Estimates for $t = 1994$, $k = 3$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.13	0.04	2.95	0.00
begMarried	−0.02	0.01	−3.67	0.00
begWelfInd	0.28	0.01	22.41	0.00
begAge	−0.00	0.00	−0.96	0.34
begChildU18	0.00	0.00	1.95	0.05
begRace1C_ASIAN_PI	−0.01	0.04	−0.21	0.83
begRace1C_BLACK	0.03	0.01	3.73	0.00
begRace1C_LATINO	0.03	0.06	0.57	0.57
begRace1C_NATIVE_AMN	−0.02	0.03	−0.48	0.63
begRace1C_OTHER	0.03	0.03	1.10	0.27
EducStatus_COLL_DEG	−0.02	0.01	−2.22	0.03
EducStatus_GED_GRAD	0.00	0.02	0.13	0.90
EducStatus_HS_GRAD	−0.02	0.01	−1.70	0.09
EducStatus_SOME_COLL	−0.03	0.01	−2.62	0.01
begRegionC_NORTH CENTRAL	−0.06	0.04	−1.36	0.17
begRegionC_NORTHEAST	−0.06	0.04	−1.51	0.13
begRegionC_SOUTH	−0.08	0.04	−1.86	0.06
begRegionC_WEST	−0.05	0.04	−1.22	0.22
indusC_AGRICU	−0.04	0.05	−0.76	0.45
indusC_BUSIN	−0.03	0.02	−1.63	0.10
indusC_CONSTR	−0.03	0.03	−1.13	0.26
indusC_ENTERT	−0.05	0.03	−1.52	0.13
indusC_FINANC	−0.02	0.01	−1.96	0.05
indusC_MANUF	−0.04	0.01	−2.83	0.00
indusC_MINING	−0.05	0.08	−0.57	0.57
indusC_PA	−0.04	0.01	−2.49	0.01
indusC_PERSON	−0.02	0.02	−1.12	0.26
indusC_PROFES	−0.03	0.01	−3.19	0.00
indusC_PUC	−0.03	0.02	−1.49	0.14
indusC_TRADE	−0.03	0.01	−2.96	0.00
occupC_CRAFTS	0.00	0.02	0.14	0.89

Table C.14: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.02	0.09	0.20	0.84
occupC_FARM_LA	−0.01	0.10	−0.07	0.95
occupC_LABOR	−0.03	0.04	−0.92	0.36
occupC_MGMT	0.01	0.01	0.69	0.49
occupC_OPERAT	0.02	0.02	0.98	0.33
occupC_PROFESH	0.01	0.01	0.90	0.37
occupC_PVT_HOU	0.09	0.03	2.65	0.01
occupC_SALES	−0.01	0.02	−0.89	0.37
occupC_SERVIC	0.01	0.01	1.14	0.25
occupC_TRANSP	0.05	0.03	1.47	0.14

Table C.15: Coefficient Estimates for $t = 1995$, $k = 3$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.13	0.04	2.87	0.00
begMarried	−0.01	0.01	−2.19	0.03
begWelfInd	0.34	0.01	27.47	0.00
begAge	−0.00	0.00	−0.43	0.67
begChildU18	0.00	0.00	0.57	0.57
begRace1C_ASIAN_PI	−0.00	0.04	−0.03	0.98
begRace1C_BLACK	0.02	0.01	3.58	0.00
begRace1C_LATINO	0.06	0.05	1.09	0.27
begRace1C_NATIVE_AMN	−0.01	0.03	−0.23	0.82
begRace1C_OTHER	0.03	0.03	1.22	0.22
EducStatus_COLL_DEG	−0.04	0.01	−3.60	0.00
EducStatus_GED_GRAD	−0.03	0.01	−1.95	0.05
EducStatus_HS_GRAD	−0.02	0.01	−2.79	0.01
EducStatus_SOME_COLL	−0.05	0.01	−4.80	0.00
begRegionC_NORTH CENTRAL	−0.07	0.04	−1.70	0.09
begRegionC_NORTHEAST	−0.07	0.04	−1.55	0.12
begRegionC_SOUTH	−0.09	0.04	−2.07	0.04
begRegionC_WEST	−0.06	0.04	−1.39	0.16
indusC_AGRICU	−0.00	0.05	−0.08	0.94
indusC_BUSIN	−0.00	0.02	−0.19	0.85
indusC_CONSTR	0.01	0.03	0.44	0.66
indusC_ENTERT	−0.02	0.03	−0.58	0.56
indusC_FINANC	−0.01	0.01	−0.54	0.59
indusC_MANUF	−0.02	0.01	−1.56	0.12
indusC_MINING	−0.02	0.09	−0.24	0.81
indusC_PA	−0.01	0.01	−0.66	0.51
indusC_PERSON	0.01	0.02	0.74	0.46
indusC_PROFES	−0.01	0.01	−1.13	0.26
indusC_PUC	−0.01	0.02	−0.72	0.47
indusC_TRADE	−0.01	0.01	−1.19	0.24
occupC_CRAFTS	−0.01	0.02	−0.24	0.81

Table C.15: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.00	0.08	0.01	0.99
occupC_FARM_LA	−0.02	0.07	−0.27	0.79
occupC_LABOR	−0.00	0.03	−0.14	0.89
occupC_MGMT	0.01	0.01	0.54	0.59
occupC_OPERAT	0.00	0.01	0.12	0.91
occupC_PROFESH	0.01	0.01	0.62	0.54
occupC_PVT_HOU	0.05	0.03	1.80	0.07
occupC_SALES	−0.00	0.02	−0.11	0.91
occupC_SERVIC	−0.00	0.01	−0.16	0.87
occupC_TRANSP	0.05	0.03	1.69	0.09

Table C.16: Coefficient Estimates for $t = 1996$, $k = 3$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.06	0.04	1.56	0.12
begMarried	−0.01	0.01	−2.31	0.02
begWelfInd	0.23	0.01	20.58	0.00
begAge	−0.00	0.00	−0.69	0.49
begChildU18	0.00	0.00	0.75	0.45
begRace1C_ASIAN_PI	−0.00	0.04	−0.02	0.98
begRace1C_BLACK	0.02	0.01	4.06	0.00
begRace1C_LATINO	−0.04	0.04	−0.84	0.40
begRace1C_NATIVE_AMN	−0.01	0.03	−0.18	0.86
begRace1C_OTHER	0.01	0.03	0.32	0.75
EducStatus_COLL_DEG	−0.05	0.01	−5.12	0.00
EducStatus_GED_GRAD	−0.03	0.01	−2.42	0.02
EducStatus_HS_GRAD	−0.05	0.01	−5.60	0.00
EducStatus_SOME_COLL	−0.05	0.01	−5.48	0.00
begRegionC_NORTH CENTRAL	0.02	0.04	0.41	0.68
begRegionC_NORTHEAST	0.01	0.04	0.32	0.75
begRegionC_SOUTH	−0.00	0.04	−0.02	0.98
begRegionC_WEST	0.02	0.04	0.39	0.70
indusC_AGRICU	−0.03	0.04	−0.62	0.54
indusC_BUSIN	−0.03	0.02	−1.65	0.10
indusC_CONSTR	−0.02	0.03	−0.79	0.43
indusC_ENTERT	−0.01	0.03	−0.19	0.85
indusC_FINANC	−0.01	0.01	−0.52	0.60
indusC_MANUF	−0.03	0.01	−2.13	0.03
indusC_MINING	−0.03	0.14	−0.19	0.85
indusC_PA	−0.02	0.01	−1.99	0.05
indusC_PERSON	−0.02	0.01	−1.35	0.18
indusC_PROFES	−0.02	0.01	−2.45	0.01
indusC_PUC	−0.03	0.02	−1.89	0.06
indusC_TRADE	−0.02	0.01	−1.99	0.05
occupC_CRAFTS	−0.00	0.02	−0.24	0.81

Table C.16: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.00	0.15	0.02	0.99
occupC_FARM_LA	0.00	0.07	0.03	0.97
occupC_LABOR	0.02	0.03	0.80	0.43
occupC_MGMT	0.00	0.01	0.24	0.81
occupC_OPERAT	−0.00	0.01	−0.10	0.92
occupC_PROFESH	0.01	0.01	0.65	0.52
occupC_PVT_HOU	0.05	0.03	1.71	0.09
occupC_SALES	0.00	0.01	0.32	0.75
occupC_SERVIC	0.01	0.01	0.59	0.56
occupC_TRANSP	−0.01	0.03	−0.40	0.69

Table C.17: Coefficient Estimates for $t = 1989$, $k = 4$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.12	0.07	1.59	0.11
begMarried	−0.01	0.01	−2.04	0.04
begWelfInd	0.43	0.01	30.64	0.00
begAge	−0.00	0.00	−4.80	0.00
begChildU18	0.01	0.00	2.29	0.02
begRace1C_ASIAN_PI	−0.00	0.04	−0.11	0.91
begRace1C_BLACK	0.03	0.01	4.36	0.00
begRace1C_NATIVE_AMN	0.00	0.04	0.05	0.96
begRace1C_OTHER	0.07	0.04	1.97	0.05
EducStatus_COLL_DEG	−0.05	0.01	−4.84	0.00
EducStatus_GED_GRAD	−0.01	0.02	−0.92	0.36
EducStatus_HS_GRAD	−0.04	0.01	−4.94	0.00
EducStatus_SOME_COLL	−0.05	0.01	−5.16	0.00
begRegionC_NORTH CENTRAL	0.03	0.07	0.43	0.67
begRegionC_NORTHEAST	0.02	0.07	0.23	0.82
begRegionC_SOUTH	0.01	0.07	0.18	0.86
begRegionC_WEST	0.04	0.07	0.55	0.58
indusC_AGRICU	−0.05	0.06	−0.96	0.34
indusC_BUSIN	−0.02	0.02	−1.25	0.21
indusC_CONSTR	−0.04	0.03	−1.34	0.18
indusC_ENTERT	−0.05	0.04	−1.19	0.23
indusC_FINANC	−0.04	0.01	−3.17	0.00
indusC_MANUF	−0.04	0.01	−2.49	0.01
indusC_MINING	−0.04	0.07	−0.60	0.55
indusC_PA	−0.03	0.01	−1.95	0.05
indusC_PERSON	−0.02	0.02	−1.10	0.27
indusC_PROFES	−0.04	0.01	−3.88	0.00
indusC_PUC	−0.03	0.02	−1.59	0.11
indusC_TRADE	−0.04	0.01	−3.43	0.00
occupC_CRAFTS	−0.01	0.02	−0.28	0.78
occupC_FARM	0.03	0.18	0.15	0.88

Table C.17: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM_LA	−0.00	0.10	−0.02	0.98
occupC_LABOR	0.06	0.04	1.49	0.14
occupC_MGMT	0.01	0.01	0.52	0.60
occupC_OPERAT	−0.02	0.02	−0.99	0.32
occupC_PROFESH	0.01	0.01	0.96	0.34
occupC_PVT_HOU	−0.00	0.03	−0.00	1.00
occupC_SALES	0.00	0.02	0.09	0.93
occupC_SERVIC	0.00	0.01	0.17	0.87
occupC_TRANSP	0.00	0.04	0.00	1.00

Table C.18: Coefficient Estimates for $t = 1990$, $k = 4$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.10	0.06	1.76	0.08
begMarried	−0.03	0.01	−3.69	0.00
begWelfInd	0.37	0.01	24.83	0.00
begAge	−0.00	0.00	−4.13	0.00
begChildU18	0.01	0.00	3.78	0.00
begRace1C_ASIAN_PI	0.00	0.04	0.00	1.00
begRace1C_BLACK	0.03	0.01	3.98	0.00
begRace1C_LATINO	−0.01	0.04	−0.25	0.80
begRace1C_NATIVE_AMN	0.01	0.04	0.20	0.84
begRace1C_OTHER	−0.10	0.08	−1.23	0.22
EducStatus_COLL_DEG	−0.05	0.01	−4.69	0.00
EducStatus_GED_GRAD	−0.03	0.02	−1.67	0.10
EducStatus_HS_GRAD	−0.04	0.01	−4.08	0.00
EducStatus_SOME_COLL	−0.05	0.01	−4.32	0.00
begRegionC_NORTH CENTRAL	0.03	0.06	0.56	0.57
begRegionC_NORTHEAST	0.02	0.06	0.35	0.72
begRegionC_SOUTH	0.01	0.06	0.25	0.80
begRegionC_WEST	0.04	0.06	0.61	0.54
indusC_AGRICU	−0.03	0.06	−0.40	0.69
indusC_BUSIN	−0.05	0.02	−2.69	0.01
indusC_CONSTR	−0.04	0.03	−1.39	0.17
indusC_ENTERT	−0.04	0.04	−0.84	0.40
indusC_FINANC	−0.03	0.01	−1.90	0.06
indusC_MANUF	−0.03	0.01	−2.13	0.03
indusC_MINING	−0.05	0.07	−0.62	0.53
indusC_PA	−0.03	0.01	−2.36	0.02
indusC_PERSON	0.01	0.02	0.87	0.38
indusC_PROFES	−0.03	0.01	−2.50	0.01
indusC_PUC	−0.00	0.02	−0.11	0.91
indusC_TRADE	−0.03	0.01	−2.23	0.03
occupC_CRAFTS	0.03	0.02	1.34	0.18

Table C.18: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.01	0.14	0.08	0.94
occupC_FARM_LA	−0.02	0.09	−0.26	0.79
occupC_LABOR	−0.05	0.04	−1.53	0.13
occupC_MGMT	0.02	0.01	1.76	0.08
occupC_OPERAT	−0.00	0.02	−0.22	0.82
occupC_PROFESH	0.01	0.01	0.88	0.38
occupC_PVT_HOU	−0.04	0.03	−1.42	0.16
occupC_SALES	0.01	0.02	0.36	0.72
occupC_SERVIC	0.01	0.01	0.56	0.57
occupC_TRANSP	−0.04	0.04	−1.00	0.32

Table C.19: Coefficient Estimates for $t = 1991$, $k = 4$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.11	0.05	2.13	0.03
begMarried	−0.02	0.01	−2.77	0.01
begWelfInd	0.35	0.01	25.63	0.00
begAge	−0.00	0.00	−4.23	0.00
begChildU18	0.01	0.00	2.86	0.00
begRace1C_ASIAN_PI	0.01	0.04	0.13	0.90
begRace1C_BLACK	0.03	0.01	5.05	0.00
begRace1C_LATINO	−0.08	0.17	−0.46	0.65
begRace1C_NATIVE_AMN	−0.01	0.04	−0.22	0.83
begRace1C_OTHER	−0.08	0.04	−1.97	0.05
EducStatus_COLL_DEG	−0.06	0.01	−5.30	0.00
EducStatus_GED_GRAD	−0.02	0.02	−1.47	0.14
EducStatus_HS_GRAD	−0.04	0.01	−4.52	0.00
EducStatus_SOME_COLL	−0.05	0.01	−5.12	0.00
begRegionC_NORTH CENTRAL	0.03	0.05	0.67	0.50
begRegionC_NORTHEAST	0.01	0.05	0.21	0.83
begRegionC_SOUTH	0.00	0.05	0.09	0.93
begRegionC_WEST	0.04	0.05	0.76	0.44
indusC_AGRICU	−0.03	0.05	−0.64	0.53
indusC_BUSIN	−0.00	0.02	−0.07	0.94
indusC_CONSTR	−0.04	0.03	−1.31	0.19
indusC_ENTERT	−0.04	0.04	−0.94	0.35
indusC_FINANC	−0.03	0.01	−2.51	0.01
indusC_MANUF	−0.03	0.01	−1.92	0.05
indusC_MINING	−0.04	0.07	−0.62	0.53
indusC_PA	−0.04	0.01	−2.94	0.00
indusC_PERSON	−0.02	0.02	−1.55	0.12
indusC_PROFES	−0.04	0.01	−3.52	0.00
indusC_PUC	−0.02	0.02	−1.20	0.23
indusC_TRADE	−0.03	0.01	−2.40	0.02
occupC_CRAFTS	−0.03	0.02	−1.46	0.14

Table C.19: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.00	0.08	−0.06	0.95
occupC_FARM_LA	0.13	0.10	1.35	0.18
occupC_LABOR	−0.05	0.03	−1.49	0.14
occupC_MGMT	0.01	0.01	0.51	0.61
occupC_OPERAT	−0.03	0.02	−1.57	0.12
occupC_PROFESH	0.01	0.01	1.03	0.30
occupC_PVT_HOU	−0.04	0.03	−1.53	0.13
occupC_SALES	0.00	0.02	0.18	0.86
occupC_SERVIC	−0.01	0.01	−1.32	0.19
occupC_TRANSP	−0.05	0.04	−1.34	0.18

Table C.20: Coefficient Estimates for $t = 1992$, $k = 4$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.10	0.07	1.45	0.15
begMarried	−0.04	0.01	−4.92	0.00
begWelfInd	0.39	0.02	24.52	0.00
begAge	−0.00	0.00	−2.32	0.02
begChildU18	0.01	0.00	2.86	0.00
begRace1C_ASIAN_PI	0.01	0.06	0.13	0.90
begRace1C_BLACK	0.03	0.01	4.00	0.00
begRace1C_LATINO	−0.16	0.10	−1.62	0.11
begRace1C_NATIVE_AMN	−0.06	0.04	−1.31	0.19
begRace1C_OTHER	−0.02	0.06	−0.27	0.79
EducStatus_COLL_DEG	−0.03	0.01	−2.14	0.03
EducStatus_GED_GRAD	−0.02	0.02	−0.94	0.35
EducStatus_HS_GRAD	−0.01	0.01	−1.13	0.26
EducStatus_SOME_COLL	−0.02	0.01	−1.56	0.12
begRegionC_NORTH CENTRAL	0.02	0.07	0.33	0.74
begRegionC_NORTHEAST	0.00	0.07	0.05	0.96
begRegionC_SOUTH	0.00	0.07	0.02	0.99
begRegionC_WEST	0.02	0.07	0.25	0.80
indusC_AGRICU	−0.08	0.06	−1.25	0.21
indusC_BUSIN	−0.04	0.02	−1.88	0.06
indusC_CONSTR	−0.04	0.03	−1.40	0.16
indusC_ENTERT	−0.05	0.04	−1.08	0.28
indusC_FINANC	−0.04	0.02	−2.74	0.01
indusC_MANUF	−0.05	0.02	−2.99	0.00
indusC_MINING	−0.06	0.08	−0.73	0.46
indusC_PA	−0.04	0.02	−2.08	0.04
indusC_PERSON	−0.01	0.02	−0.34	0.73
indusC_PROFES	−0.04	0.01	−3.07	0.00
indusC_PUC	−0.05	0.02	−2.16	0.03
indusC_TRADE	−0.05	0.01	−3.43	0.00
occupC_CRAFTS	−0.02	0.03	−0.77	0.44

Table C.20: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.03	0.14	0.25	0.80
occupC_FARM_LA	0.00	0.11	0.04	0.97
occupC_LABOR	0.06	0.04	1.48	0.14
occupC_MGMT	0.01	0.01	0.46	0.64
occupC_OPERAT	0.01	0.02	0.41	0.68
occupC_PROFESH	0.00	0.01	0.13	0.89
occupC_PVT_HOU	0.01	0.04	0.36	0.72
occupC_SALES	0.03	0.02	1.39	0.17
occupC_SERVIC	−0.02	0.01	−1.57	0.12
occupC_TRANSP	0.02	0.04	0.51	0.61

Table C.21: Coefficient Estimates for $t = 1993$, $k = 4$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.06	0.06	1.05	0.29
begMarried	−0.02	0.01	−2.92	0.00
begWelfInd	0.25	0.01	18.30	0.00
begAge	−0.00	0.00	−0.87	0.38
begChildU18	0.00	0.00	1.71	0.09
begRace1C_ASIAN_PI	−0.00	0.05	−0.02	0.99
begRace1C_BLACK	0.02	0.01	3.40	0.00
begRace1C_LATINO	0.16	0.08	2.05	0.04
begRace1C_NATIVE_AMN	−0.01	0.04	−0.24	0.81
begRace1C_OTHER	0.02	0.04	0.68	0.50
EducStatus_COLL_DEG	−0.03	0.01	−2.51	0.01
EducStatus_GED_GRAD	−0.01	0.02	−0.67	0.50
EducStatus_HS_GRAD	−0.02	0.01	−2.14	0.03
EducStatus_SOME_COLL	−0.03	0.01	−2.84	0.00
begRegionC_NORTH CENTRAL	0.01	0.06	0.20	0.84
begRegionC_NORTHEAST	0.00	0.06	0.02	0.98
begRegionC_SOUTH	−0.01	0.06	−0.11	0.91
begRegionC_WEST	0.02	0.06	0.29	0.77
indusC_AGRICU	−0.02	0.07	−0.27	0.78
indusC_BUSIN	−0.01	0.02	−0.71	0.47
indusC_CONSTR	−0.03	0.03	−0.98	0.33
indusC_ENTERT	−0.06	0.04	−1.61	0.11
indusC_FINANC	−0.02	0.01	−1.38	0.17
indusC_MANUF	−0.03	0.01	−1.82	0.07
indusC_MINING	−0.03	0.06	−0.56	0.58
indusC_PA	−0.03	0.02	−2.10	0.04
indusC_PERSON	−0.02	0.02	−1.36	0.17
indusC_PROFES	−0.02	0.01	−2.20	0.03
indusC_PUC	−0.01	0.02	−0.65	0.52
indusC_TRADE	−0.02	0.01	−1.90	0.06
occupC_CRAFTS	0.00	0.02	0.07	0.95

Table C.21: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.00	0.10	−0.03	0.98
occupC_FARM_LA	−0.08	0.10	−0.80	0.42
occupC_LABOR	−0.02	0.04	−0.57	0.57
occupC_MGMT	0.01	0.01	0.45	0.65
occupC_OPERAT	−0.00	0.02	−0.20	0.84
occupC_PROFESH	0.01	0.01	0.48	0.63
occupC_PVT_HOU	0.06	0.03	1.76	0.08
occupC_SALES	0.01	0.02	0.62	0.54
occupC_SERVIC	0.01	0.01	0.85	0.39
occupC_TRANSP	0.01	0.04	0.17	0.86

Table C.22: Coefficient Estimates for $t = 1994$, $k = 4$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.13	0.04	3.04	0.00
begMarried	−0.02	0.01	−2.74	0.01
begWelfInd	0.24	0.01	19.82	0.00
begAge	−0.00	0.00	−0.65	0.51
begChildU18	0.00	0.00	1.49	0.14
begRace1C_ASIAN_PI	−0.01	0.04	−0.25	0.81
begRace1C_BLACK	0.02	0.01	3.55	0.00
begRace1C_LATINO	0.04	0.05	0.82	0.41
begRace1C_NATIVE_AMN	−0.01	0.03	−0.42	0.67
begRace1C_OTHER	0.04	0.03	1.30	0.20
EducStatus_COLL_DEG	−0.04	0.01	−3.67	0.00
EducStatus_GED_GRAD	−0.02	0.02	−1.27	0.20
EducStatus_HS_GRAD	−0.03	0.01	−2.85	0.00
EducStatus_SOME_COLL	−0.04	0.01	−4.37	0.00
begRegionC_NORTH CENTRAL	−0.06	0.04	−1.54	0.12
begRegionC_NORTHEAST	−0.06	0.04	−1.43	0.15
begRegionC_SOUTH	−0.08	0.04	−1.93	0.05
begRegionC_WEST	−0.04	0.04	−1.08	0.28
indusC_AGRICU	−0.03	0.05	−0.57	0.57
indusC_BUSIN	−0.03	0.02	−1.74	0.08
indusC_CONSTR	−0.03	0.03	−0.99	0.32
indusC_ENTERT	−0.04	0.03	−1.20	0.23
indusC_FINANC	−0.02	0.01	−1.72	0.09
indusC_MANUF	−0.04	0.01	−2.94	0.00
indusC_MINING	−0.04	0.08	−0.46	0.64
indusC_PA	−0.01	0.01	−1.10	0.27
indusC_PERSON	−0.01	0.02	−0.68	0.50
indusC_PROFES	−0.02	0.01	−2.23	0.03
indusC_PUC	−0.02	0.02	−1.34	0.18
indusC_TRADE	−0.02	0.01	−2.12	0.03
occupC_CRAFTS	−0.00	0.02	−0.01	0.99

Table C.22: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	0.02	0.09	0.21	0.84
occupC_FARM_LA	−0.01	0.09	−0.09	0.93
occupC_LABOR	−0.03	0.04	−0.87	0.38
occupC_MGMT	0.01	0.01	0.57	0.57
occupC_OPERAT	0.01	0.02	0.94	0.35
occupC_PROFESH	0.01	0.01	0.98	0.33
occupC_PVT_HOU	0.09	0.03	2.97	0.00
occupC_SALES	−0.01	0.02	−0.83	0.41
occupC_SERVIC	0.01	0.01	0.71	0.47
occupC_TRANSP	0.02	0.03	0.54	0.59

Table C.23: Coefficient Estimates for $t = 1995$, $k = 4$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.08	0.04	1.81	0.07
begMarried	−0.01	0.01	−1.83	0.07
begWelfInd	0.20	0.01	17.01	0.00
begAge	−0.00	0.00	−1.16	0.25
begChildU18	0.00	0.00	0.59	0.56
begRace1C_ASIAN_PI	−0.00	0.04	−0.00	1.00
begRace1C_BLACK	0.03	0.01	4.15	0.00
begRace1C_LATINO	−0.05	0.05	−1.02	0.31
begRace1C_NATIVE_AMN	−0.01	0.03	−0.28	0.78
begRace1C_OTHER	0.01	0.03	0.36	0.72
EducStatus_COLL_DEG	−0.06	0.01	−5.89	0.00
EducStatus_GED_GRAD	−0.05	0.01	−3.59	0.00
EducStatus_HS_GRAD	−0.05	0.01	−6.06	0.00
EducStatus_SOME_COLL	−0.06	0.01	−6.26	0.00
begRegionC_NORTH CENTRAL	0.02	0.04	0.37	0.71
begRegionC_NORTHEAST	0.01	0.04	0.24	0.81
begRegionC_SOUTH	−0.00	0.04	−0.08	0.94
begRegionC_WEST	0.01	0.04	0.32	0.75
indusC_AGRICU	−0.01	0.05	−0.17	0.86
indusC_BUSIN	0.01	0.02	0.51	0.61
indusC_CONSTR	−0.02	0.02	−0.64	0.52
indusC_ENTERT	−0.02	0.03	−0.69	0.49
indusC_FINANC	0.00	0.01	0.01	0.99
indusC_MANUF	−0.02	0.01	−1.97	0.05
indusC_MINING	−0.02	0.10	−0.18	0.85
indusC_PA	−0.01	0.01	−0.66	0.51
indusC_PERSON	−0.00	0.01	−0.20	0.84
indusC_PROFES	−0.02	0.01	−1.74	0.08
indusC_PUC	−0.03	0.02	−1.78	0.07
indusC_TRADE	−0.03	0.01	−2.57	0.01
occupC_CRAFTS	−0.01	0.02	−0.43	0.67

Table C.23: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.00	0.08	−0.06	0.96
occupC_FARM_LA	−0.04	0.07	−0.53	0.60
occupC_LABOR	−0.00	0.03	−0.13	0.90
occupC_MGMT	−0.00	0.01	−0.10	0.92
occupC_OPERAT	−0.01	0.01	−0.53	0.60
occupC_PROFESH	−0.00	0.01	−0.07	0.94
occupC_PVT_HOU	0.02	0.03	0.73	0.47
occupC_SALES	0.01	0.01	0.57	0.57
occupC_SERVIC	−0.00	0.01	−0.52	0.60
occupC_TRANSP	−0.02	0.03	−0.53	0.60

Table C.24: Coefficient Estimates for $t = 1996$, $k = 4$

Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.05	0.04	1.26	0.21
begMarried	−0.02	0.01	−3.39	0.00
begWelfInd	0.23	0.01	21.47	0.00
begAge	−0.00	0.00	−0.26	0.80
begChildU18	0.00	0.00	1.15	0.25
begRace1C_ASIAN_PI	0.00	0.04	0.02	0.98
begRace1C_BLACK	0.01	0.01	1.42	0.16
begRace1C_LATINO	−0.04	0.04	−0.90	0.37
begRace1C_NATIVE_AMN	0.03	0.03	1.15	0.25
begRace1C_OTHER	0.01	0.02	0.25	0.80
EducStatus_COLL_DEG	−0.04	0.01	−4.32	0.00
EducStatus_GED_GRAD	−0.02	0.01	−1.47	0.14
EducStatus_HS_GRAD	−0.03	0.01	−3.89	0.00
EducStatus_SOME_COLL	−0.04	0.01	−4.86	0.00
begRegionC_NORTH CENTRAL	0.01	0.04	0.37	0.71
begRegionC_NORTHEAST	0.01	0.04	0.22	0.83
begRegionC_SOUTH	0.01	0.04	0.21	0.83
begRegionC_WEST	0.02	0.04	0.54	0.59
indusC_AGRICU	−0.01	0.04	−0.23	0.82
indusC_BUSIN	−0.02	0.01	−1.31	0.19
indusC_CONSTR	−0.02	0.03	−0.79	0.43
indusC_ENTERT	0.03	0.02	1.28	0.20
indusC_FINANC	−0.01	0.01	−0.96	0.34
indusC_MANUF	−0.02	0.01	−1.72	0.09
indusC_MINING	−0.02	0.13	−0.18	0.86
indusC_PA	−0.01	0.01	−1.15	0.25
indusC_PERSON	−0.02	0.01	−1.21	0.23
indusC_PROFES	−0.01	0.01	−1.72	0.08
indusC_PUC	−0.02	0.01	−1.45	0.15
indusC_TRADE	−0.02	0.01	−2.07	0.04
occupC_CRAFTS	−0.01	0.02	−0.37	0.71

Table C.24: Coefficient Estimates (cont.)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
occupC_FARM	−0.01	0.14	−0.09	0.93
occupC_FARM_LA	−0.01	0.07	−0.08	0.94
occupC_LABOR	−0.01	0.02	−0.49	0.63
occupC_MGMT	0.00	0.01	0.44	0.66
occupC_OPERAT	0.00	0.01	0.12	0.90
occupC_PROFESH	0.00	0.01	0.31	0.76
occupC_PVT_HOU	0.05	0.03	1.86	0.06
occupC_SALES	0.00	0.01	0.09	0.93
occupC_SERVIC	−0.00	0.01	−0.31	0.76
occupC_TRANSP	−0.01	0.03	−0.43	0.67

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