Review of Income and Wealth
Series 41, Number 4, December 1995

AN EXPLORATORY COMPARISON OF INCOME RISK IN GERMANY AND THE UNITED STATES

BY EDWARD J. BIRD

University of Rochester

Using longitudinal data, I estimate the impact of redistribution on the welfare cost of income risk in Germany and the United States. The estimates account fully for behavior because individuals in each country have responded optimally to that country's policy. The results indicate that the welfare cost of income risk is 5.4 percent of disposable income in Germany, 8.5 percent in the U.S. Redistribution has reduced these risks from their pre-tax, pre-transfer levels by 43 percent in Germany, 21 percent in the U.S. The political importance of income security is evident in both countries, as risk relief often eliminates the net burden of redistributive taxes among middle-class households. The conclusions are robust across several models of income expectations.

I. INTRODUCTION

Economic theory suggests that redistribution policies should reduce income risk (Moffitt and Rothschild, 1987; Varian, 1980; Betson and Van Der Gaag, 1985). Policy commentators have argued that this effect is the primary service offered by the welfare state to middle-class voters, and hence is very important in explaining its political support (Lampman, 1984; Haveman, 1988). Nevertheless, few studies analyze income risk empirically, and those that do confront the difficult problem of estimating the response of risk to policy changes (Feldstein 1973; Gramlich and Wolkoff, 1979; Haveman and Wolfe, 1985). This paper improves on the empirical literature in two ways. First, it examines income risk in a comparative context, which eliminates the necessity of estimating counterfactual responses of risk to policy changes. Second, it employs rich longitudinal data, which allow more sophisticated models of individual expectations.

The results confirm previous suppositions about the political importance of income risk. In both Germany and the U.S., income risk is significantly reduced by the redistribution system. The benefits of this reduction fall in such great amounts to the middle quintiles of the income distribution that they may be sufficient to explain the continued political viability of redistribution programs. Further, were the U.S. to adopt a redistribution system similar to the German one, the income risk of a typical household would fall signifcantly, and that of a poor household would fall greatly. These results assume low risk aversion and are robust to several important modifications of methods.

The paper has the following structure. Section II discusses the core concept of the paper, income risk. Section III describes and justifies methods for measuring

Note: I thank Bob Haveman, Martin David, Jim Powell, Richard Hauser, and seminar participants at the Deutsches Institut für Wirtschaftsforschung and the Universities of Wisconsin, Frankfurt and Rochester, and two anonymous referees, for comments on earlier drafts. I thank the German Academic Exchange Service for research support.

income risk, its welfare cost, and the impact of policies upon it. Section IV describes the application of these methods to two comparable longitudinal data sets from the U.S. and Germany. Section V presents results. Section VI discusses broader conclusions of the research.

II. Income Risk

Rothschild and Stiglitz (1970) provide three equivalent definitions of income risk. A random income Y is *riskier* than X if and only if (a) Y is equal to X plus a random shock term, (b) the distribution of Y has the same mean as X but puts more weight in the tails, or (c) the expected utility of Y is less than that of X. All three definitions make income risk a function of the *ex ante* probability density function (pdf) of income.

Though Rothschild and Stiglitz (1970) do not discuss the origin of the income pdfs that they study, expected utility theory assumes that they reflect the subjective probabilities assigned by the agent to various states of the world. Thus, the pdf's shape and position is a function of the agent's expectations. For empirical research, it is necessary to assume that these expectations are formed through a stable *expectations model*, which specifies how agents use observable variables to calculate the pdf. Only two basic expectations models have been applied previously in empirical studies of income uncertainty. The *cross-section model of expectations* makes the income pdf a function of the cross-section inequality of current income, usually within a cell defined by socio-demographic characteristics. The *time series model of expectations* makes the pdf a function of the period-to-period variability of individual income. Haveman and Wolfe (1985) apply a cross-section model, using disability status to define the cross-section cells. Osberg, Erksoy and Phipps (1994) use a time series model, estimating the expected utility of income as the discounted average utility over the course of several years.

Both the cross-section and the time series models are reasonable approaches to expectations, and one cannot choose between them on the basis of past research; too little is known about the expectations models people actually use (however, see Dominitz and Manski, 1994, for an empirical study of income expectation formation). In this paper I will apply both, and I will also extend the cross-section model to generate new approaches. Roughly speaking, the new models still identify the income pdf with the inequality of income within a sample cell, but that cell is now defined by the agent's anticipation of income-change events, and by her current income. In examining several models, I hope to find broad patterns of risk effects that remain true regardless of the assumed expectations.

III. Overview of Methods

Redistribution policy refers to those laws at all levels of government that either impose direct taxes on individual income, or provide cash or near-cash payments directly to individuals. On the tax side, it includes income taxes and social insurance contributions. On the transfer side, it includes means-tested transfers, social insurance payments, and cash-equivalents, like the U.S. Food Stamp program.

The object of the paper is to estimate the effect of redistribution policy on income risk. This section describes a method for doing so. In essence, the method is to estimate individual-specific means and variance of incomes, and see how the variance reduces well-being. Then I measure the impact of redistribution policies on the variance of income, and, correspondingly, individual welfare. All of this is done at the level of the individual, using panel data from Germany and the U.S. This allows us to see how the welfare effects of income security vary among the rich, the poor, and the middle class.

In this section, part A presents a comparative approach to the question of policy impacts. Part B describes the risk-related outcomes that need to be compared. Part C provides a model of income determination that allows expectations to be easily described and analyzed. Part D discusses a new expectations model that generates two specific applications. Part E presents an econometric technique that can estimate risk within the most general framework of the income model. Part F discusses the utility function to be employed, while part G explains step-by-step how the methods are combined to produce estimates of income risk and other outcomes at the national level.

A. *Impact and Comparative Analysis*

Previous empirical studies of redistribution policy and income risk have focused on the redistribution policies of just one country. Most authors treat the U.S. case (Haveman and Wolfe, 1985; Feldstein, 1973; Gramlich and Wolkoff, 1979), though Jenkins and Millar (1989) and Osberg, Erksoy and Phipps (1994) analyze the U.K. and Canada, respectively. The focus on one country creates a problem, in that the effects of policies within a country can only be estimated by proposing some counterfactual set of policies and estimating how income risks would differ were that set of policies adopted.

In some cases, these estimates allow no behavioral reactions (Haveman and Wolfe, 1985; Bird, 1993). Studies such as these are *impact analyses*, which examine the current effect of policies. Impact analysis describes the status quo, but does not attempt to estimate the potential effect of a policy change.[1] While impact analysis is reasonable as an evaluation of outcomes under current policy parameters, it is not an effective tool of policy prediction.

In other cases, behavioral reactions are allowed through economic modeling (Feldstein, 1973; Jenkins and Millar, 1989; Gramlich and Wolkoff, 1979; Osberg, Erksoy and Phipps, 1994). These methods generate results that can be treated as predictions of potential policy effects, and their reliability depends on the realism and accuracy of the model. In the area of savings and risk, however, even simple theoretical notions are difficult to translate into workable empirical models.

Rather than pursue economic modeling, this paper develops its predictive power with a comparative approach. This requires comparable cross-national

[1] I draw this definition from the poverty literature. There, the impact analysis of redistribution programs estimates the number of people removed from poverty by government programs, under the status quo. The status quo assumes, obviously, that behavior and policies remain stable. Thus, the impact analysis does not indicate how many people would be poor if all redistribution policies were eliminated.

data, which can restrict the scope of the analysis, but has the advantage of being simple to implement. Two countries, A and B, have different policies, α and β respectively. It can be assumed that incomes in A already take into account the optimal behavioral response to policy α. Similarly, incomes in B will already include the optimal behavioral reaction of B's citizens to β. Then, the differences in income risk between the countries can be explained by two factors: original differences in the countries, and the difference between α and β. To the extent that two countries are similar in economy, population, and culture, differences in risk outcomes can be assigned with greater confidence to policy differences.

The paper will include results of both impact and comparative analyses, to judge both the status quo effect of redistribution on risk, and the potential changes that may result should one country move closer to the other in its redistribution policies.

B. *Measuring Outcomes*

Though the welfare state and the redistribution policies that contribute to it have many goals, in this paper I single out one set of outcomes for analysis: *ex ante* well-being. The level of *ex ante* well-being provided by uncertain income is called the *certainty equivalent*: the certain amount of income that offers the same utility level as the expected utility provided by the uncertain income. The certainty equivalent solves the following equation:

$$U(C) = \int U(y) f(y)\, dy \tag{1}$$

where C is the certainty equivalent, y is income, with *ex ante* distribution $f(y)$, and $U(y)$ is a utility function. The *welfare cost of risk* is defined as the difference between the certainty equivalent and expected income. Thus, well-being can be decomposed into two effects, expected income and the welfare cost of risk:

$$C = M - R \tag{2}$$

where M is expected income and R is the welfare cost of risk. For risk averse agents, R is positive whenever income is uncertain, and increases in income risk, in the sense of Rothschild and Stiglitz (1970), elicit increases in R. With an assumed utility function, and estimates of the proper density functions of income, (1) and (2) allow the estimation of C, M, and R for pre- and post-redistribution income. Then, the impact of redistribution on risk is given by the difference between pre- and post-redistribution risk costs. Similarly, its impact on well-being is given by the difference between pre- and post-redistribution certainty equivalents.

C. *Model of Income Determination*

The shape of the income pdf in (1) depends on the process by which income evolves through time. The standard model makes income risk a function of permanent and transitory shock processes:

(3) $$y_{it+1}=y^p_{it+1}+\eta_{it+1}$$

with:

(4) $$y^p_{it+1}=\gamma+\alpha x_{1it}+\beta x_{2it}+v_{it+1}$$

where y^p_{it+1} is the permanent income of agent i in period $t+1$, determined by characteristics x_{1it} and x_{2it}, macroeconomic growth γ, and a random shock term v. The factors x_1 include items like education, which are observable by researchers. The factors x_2 include items like ability, which are unobservable. Both are known by the agent, however. Observed income, y_{it+1}, equals permanent income plus the random shock term η, which is independent of v. The model's structure indicates that the effects of the permanent shock v persist in the time series of observed income, while the effects of η are transitory. Both shock terms have zero means, and positive variances σ^2_v and σ^2_η, respectively.

According to the permanent-transitory model, the expectation of y_{it+1} is $\gamma+\alpha x_{1it}+\beta x_{2it}$, and its variance is $\sigma^2_v+\sigma^2_\eta$. In most applications, the goal is either to distinguish among observable and unobservable causes of income, or to trace changes in behavior to permanent and transitory shock effects. Here, however, the focus is less on the sources of income than on its level and variability. As a result, some of the structural distinctions of the model can be subsumed in a simpler framework as follows.

Ex ante income evolves as:

(5) $$y_{it+1}=E(y_{it+1}|Z=z_{it})+\varepsilon_{it+1}$$

with

(6) $$\varepsilon_{it+1}\sim f(\varepsilon|Z=z_{it})$$

where ε combines permanent and transitory shocks in an unspecified distribution $f(\cdot|\cdot)$. The *conditioning vector* Z defines the income model and the expectations within it. If Z contains x_1 and x_2, and if the density in (6) specified the distinction between permanent and transitory shocks as in (3) and (4), the permanent-transitory model would fall out from (5) and (6). Other variations are possible, however. If, as in Haveman and Wolfe (1985), the vector Z consists of the one dummy variable "Disability Status," then in (5) the expected income of a disabled person would be the average income of all disabled people. Further, in (6), individual i's *ex ante* distribution of deviations from mean income would be identical to the current cross-section distribution of deviations from mean income among all disabled people. Thus, Haveman and Wolfe's (1985) cross-section model is a special case of the model in (5) and (6). If, on the other hand, the vector Z contains only past realizations of income for the one individual i, then expected income fluctuates around a stationary mean. One could also give the mean a trend, or reproduce more complex time series specifications. All are special cases of the model in (5) and (6). The general model can apply the previous assumptions about expectations, but it also provides a framework in which new assumptions may be designed and evaluated.

D. *Four Expectations Models*

The structure of the model in (5) and (6) allows one to build new expectations models by manipulating the contents of the conditioning vector Z. For example, one can combine aspects of the time series and cross-section approaches by placing both past incomes and current characteristics in the conditioning vector Z. Though in principle one could combine any number of current characteristics with any number of past incomes, practical estimation concerns limit the number of variables in the conditioning vector.[2]

I develop four expectations models, intended to emulate existing models, and to exploit more sophisticated data. Model 1 takes the simple time series approach, calculating expected income as the mean income of the individual's time series, and income variance as its mean squared error. Thus, for individual i's income stream Y_{it}, $t=1, \ldots, T$, we have expected income as the average income over time:

$$E_i(Y)=\frac{1}{T}\sum_{t=1}^{T} Y_{it}$$

and the variance of income as the squared deviations from this average:

$$V_i(Y)=\frac{1}{T}\sum_{t=1}^{T} (Y_{it}-E_i(Y))^2$$

Here it is implicit that the Z vector, the contents of the individual's information, includes only information about that individual's income time series.

Model 2 creates a socio-demographic cell from information on the individual's income, age, sex, and ethnic group. Suppose there are K income groups, L age groups, and N ethnic groups. Let $m\in\{M, F\}$ denote sex, and let individual i be a member of group G_{klmn}. The group has N_{klmn} members. Let member j's income be Y_j. Then expected income is average income in i's group:

$$E_i(Y)=\frac{1}{N_{klmn}}\sum_{j\in G_{klmn}} Y_j$$

and the variance of income is the within-group squared deviations from this average:

$$V_i(Y)=\frac{1}{N_{klmn}}\sum_{j\in G_{klmn}} (Y_j-E_i(Y))^2$$

Here in model 2 it is implicit that the Z vector contains only the information that individual i is a member of a certain group.

[2]The difficulty here is in the curse of dimensionality. Very roughly speaking, adding conditioning variables radically reduces the sample sizes within cells, and greatly decreases the accuracy of measured income mean and variance.

Models 3 and 4 expand on Model 2. First, they make the role of information in Z explicit. In general, these models will produce expected income:

$$E_i(Y) = \sum_{q=1}^{Q} Y_q \hat{p}_i(Y_q, z_i)$$

where Y_q, $q=1, \ldots, Q$, are possible incomes that individual i might receive. (In this paper, the possible incomes take the form of a set of evenly-spaced points, such as {\$0, \$2,000, \$4,000, . . . , \$200,000}.) $\hat{p}_i(Y_q, z_i)$ is i's estimated probability of income Y_q. It is a nonparametric estimate, arrived at through a method explained in Part E below. For now it is sufficient to think of $\hat{p}_i(Y_q, z_i)$ as a conditional probability, expressing the likelihood that individual i will receive income Y_q, given z_i, i.e. the values that individual i observes in Z. Under this notion income variance will be

$$V_i(Y) = \sum_{q=1}^{Q} (Y_q - E_i(Y))^2 \hat{p}_i(Y_q)$$

New Assumptions About the Contents of Z. Models 1 and 2 assume that the only information people have about their income is either their own income time series, or their socio-demographic characteristics. A long line of research on income variability suggests, however, that critical events are better predictors of income change. Models 3 and 4 put this research to use.

The research shows that events such as family break-up and unemployment explain a large part of income change (Staines, 1982; Duncan and Hoffman, 1985; Burkhauser and Duncan, 1989; Burkhauser, Butler and Holden, 1991; Hauser, 1988; and Hauser and Berntsen, 1989). The most important events appear to be labor market events and family composition events. Though there are any number of ways of defining these events, I concentrate on three of them and give them definitions similar to those in the literature:

Event 1: A change in the number of adults in the family

Event 2: A decrease in gross family earnings of more than 50 percent

Event 3: An increase in gross family earnings of more than 50 percent

There are two strategies for placing these events in the conditioning vector. The first places the observed occurrence of the events in Z. The second estimates prior probabilities of the events and places these in Z. I use the second strategy as a base case.

The prior probabilities are estimated as follows. Let X be a vector of household characteristics, including age, race, sex, education, occupation, marital status, number of children, and size of household.[3] Suppose that for some events $E^r_{t,t+1}$ that may occur between time periods t and $t+1$, $r=1, \ldots, R$, the following relationship holds:

$$(7) \qquad \varepsilon_{it+1} \sim f[\varepsilon | y_{it}, Pr(E^1_{t,t+1}), Pr(E^2_{t,t+1}), \ldots, Pr(E^Q_{t,t+1})]$$

[3]In principle one could avoid much of this structure by putting the characteristics, X, in the Z vector rather than the three probabilities. Unfortunately, the curse of dimensionality cited above ensures that for reasonable sample sizes, the NCD estimator becomes inaccurate when the size of the Z vector expands beyond 5 or so variables.

with

$$Pr(E^r_{t,t+1}) = \Phi(-\gamma_r X) \tag{8}$$

where Φ is the cumulative standard normal. Then one can apply probit estimation to (8) and use the fitted values as the Z vector in (7). The density of ε remains a function of X, but the impact of X is summarized in a small number of event probabilities. Thus, this strategy allows a great deal of information from X to enter the conditioning vector indirectly. This is a useful property when the estimation environment puts strict limits on the amount of information that can go directly into the conditioning vector.

E. *Econometric Techniques*

Model 1 requires straightforward econometric techniques. Expected income for each individual is that individual's time series average, and income variance is the time series mean squared error. Model 2 also requires only the simplest methods: break the sample up into socio-demographic cells, and calculate the mean and variance of income within the cells. If income is assumed to be normally distributed, these two statistics will describe the entire income pdf for both models.

Models 3 and 4 require the construction of income probabilities conditional on discrete and continuous variables. One approach, similar to that of Model 2, would use Z to create groups, such as "individuals with high event probabilities" and "individuals with low event probabilities." Then one could find the probabilities of various incomes by looking at the distribution of income within these groups. The biggest problem with this method, however, is that it forces us to discrete-ize the continuous variables in Z. Moreover, like models 1 and 2, it would force us to impose normality if this within-group mean and variance are to describe the entire income pdf. Plenty of evidence suggests that income pdfs are not normally distributed, however (Bird, 1993).

The nonparametric conditional density (NCD) estimator will be used to solve both problems of discrete-izing continuous variables, and of imposing distributional form. A formal discussion of the NCD estimator can be found in the appendix. In essence, it operates as follows. Suppose we want to know $f(Y|X)$, i.e. the distribution of income, Y, conditional on some continuous variable X. To make the discussion concrete, let X be age, so that we are interested in estimating income risk for one person conditional on that person's age, and let us say the person is 44 years old. The empirical object of interest is $f(Y|X=44)$. The NCD estimator breaks up the range of income into a series of points, \$0, \$2,000, \$4,000, \$6,000, . . . , \$200,000. It then calculates the probability of each income point, given that age is 44. To do this, it assigns weights to each observation in the data, with the weight falling as the observation's age value differs from 44. All 44-year-old respondents receive a weight of 1; 40- and 48-year-olds receive weights less than 1 but greater than zero; 20- and 70-year-olds receive weights of zero. Within this weighted sample, it calculates the frequency of incomes near the income value whose probability is being estimated. Suppose we are looking for the probability of income of \$20,000. If, taking the weights into account, many observations have incomes at or near \$20,000, the NCD estimator assigns a high probability to this value. If the weighted sample shows no incomes at or near \$20,000, the NCD estimator assigns a probability of zero to this value. By repeating the weighted probability estimates for all the income values, the NCD estimator produces an income pdf that is the unique pdf faced by a 44-year-old. From this pdf, one can calculate a mean and variance of income that is also unique to a 44-year-old.

The NCD estimator is flexible and can produce a pdf for 44-year-olds or 25-year-olds. And it can produce pdfs on the basis of age and income together, which would take the form of a pdf unique for any 44-year-old with income of, for example, \$18,000. In models 3 and 4, the pdfs will be unique for individuals based on their current incomes, and the occurrence (model 3) or probabilities (model 4) of critical events.

There are several important reasons for using the NCD method. First, the continuous weighting scheme allows us to estimate distributions of income conditional on continuous as well as discrete variables. It is not necessary to "discrete-ize" a continuous variable to obtain cells within which to calculate income densities. Second, as a nonparametric method, the NCD estimator imposes no structure on the pdf of income, allowing unusual features to appear as the data dictate. Previous research has shown that individual income distributions can be highly skewed and have multiple modes (Bird, 1993). Third, as an extension of the cell-average technique, it relies on intuitions that should already be familiar. There are two principle disadvantages with the NCD method. First, in application the NCD method is cumbersome and time-consuming. Second, it requires a great deal of data, which places limits on the size of the Z vector that can be estimated with acceptable accuracy.

Whatever the econometric method, all four expectations models allow us to produce from longitudinal data a sample of individual-specific pdfs of income.

F. *Utility Function*

From equations (1) and (2), the pdf of income can be translated into welfare effects. Welfare effects will depend on assumptions about the utility function and the level of risk aversion. Following the literature on savings and income risk, I use the Constant Relative Risk Aversion (CRRA) function, which has the form $U(y) = (y^{1-e})/(1-e)$. It has a number of intuitive features. It implies that a rich person is more willing to wager \$1,000 than a poor person, but that both are equally willing to wager 10 percent of their income. Further, a ten percent risk of a \$1,000 gain has a smaller risk cost than a 10 percent risk of a \$1,000 loss (holding expected income constant). Thus, upside risk imposes less welfare cost than downside risk.

In the CRRA function, the one parameter e determines the degree of aversion to risk. Estimates of e range from 1.5 to 5.0 (Friend and Blume, 1975; Hall and Mishkin, 1982; Carroll, 1992; for a brief survey of estimates, see Bird, 1993). I will use the lower bound so as to avoid artificially overstating the importance of risk.[4]

[4]In other work (Bird, 1994), I show that doubling this parameter roughly doubles the risk costs. Thus, variations in risk aversion affect the magnitude of the results, but not the patterns.

G. *Combining Methods to Estimate Risk Costs*

Here is a step-by-step overview of the methods, showing how we proceed from data to risk cost estimates. Assume there is a sample of i.i.d. observations of incomes and conditioning variables, $\{y_i, z_i\}$, $i=1, \ldots, N$. In choosing the conditioning variables, we have established an expectations model (1, 2, 3, or 4). Using this expectations model, we want to estimate a sample of individual-specific pdfs for J individuals: $f(y|z_i)$, $j=1, \ldots, J$. Then we want to use these pdfs to calculate welfare effects of income variance. The process runs as follows.

(1) Select a random sample of J individuals from the data.

(2) Using the values of Z for these individuals, estimate J pdfs.

(3) Using each individual's pdf, estimate expected income M_j.

(4) Using each individual's pdf, calculate expected utility $\int U(y) f(y)\, dy$. For models 1 and 2, this will involve using the normality assumption. For models 3 and 4, this will involve using the NCD estimates of each conditional income probability.

(5) Using equation 1, calculate each individual's certainty equivalent C_j. Using equation 2, calculate each individual's risk cost $R_j = M_j - C_j$.

(6) Analyze the sample of expected future incomes, certainty equivalents, and risk costs. For example, we can compare the risk costs of the rich to those of the poor. Or, we can repeat steps 1–5 for two income definitions, pre- and post-redistribution, and compare the median risk cost in the two samples. This provides an estimate of the impact of redistribution on risk. Exercises such as these form the basis for the empirical results below.

IV. Application of Methods to German and U.S. Data

A. *Comparative Panel Data*

Comparative analysis yields the richest information when the two countries compared are identical in all respects save policy. In the real world, of course, no two countries are identical, but a sufficient convergence in economy, population, and culture can allow robust conclusions to be drawn from sufficiently distinct policies. In the field of redistribution policy, comparisons between Western European countries and the U.S. offer the best hope for strong conclusions. As a general rule, Europe redistributes much more income than the U.S., while the contrasts in industrial development, population structure, and basic cultural attitudes are not as strong.

Primarily for reasons of data availability, I choose Germany as the country for comparison to the U.S.[5] The NCD estimator requires detailed panel data, and fortunately there exists a pair of roughly matched panel household surveys in the U.S. and Germany. The U.S. panel is the Michigan Panel Study of Income Dynamics (PSID), while the German panel is the German Socio-Economic Panel (SOEP). The design of the SOEP is derived largely from that of the PSID, and this allows extensive comparability of variables (Burkhauser and Wagner, 1994; Krupp and Hanefeld, 1987). The study will cover the four years from 1983 to

[5]The data are drawn from the former West Germany.

1986, in which both countries experienced similar macroeconomic conditions and little in the way of major policy innovation.[6] The data consist of 5,818 U.S. households and 4,827 German households that responded in all four of these years. The unit of observation is the household, though all welfare measures are reported in real per capita terms. Model 1, the time series expectations approach, uses the four-year balanced panel as it is. The other three models divide the four-year balanced panel into three two-year balanced panels (1983/84, 1984/85, and 1985/86), and then pool these to create data sets of 17,454 two-year household panels for the U.S., and 14,481 two-year household panels for Germany.

The key variables in the analysis are income and the conditioning variables. *Market income* is the pre-tax, pre-transfer equivalence income of the household.[7] It consists of labor market earnings of all household members, plus captial income and private pensions. *Disposable income* is post-tax, post-transfer equivalence income, consisting of market income, plus transfers from means-tested programs and social insurance, minus national-level taxes.[8] The two panels also include the standard measures of household socio-demographic characteristics, such as age, sex, ethnic group, and education, that will be used in various ways in the conditioning vector.

B. *Expectations Models*

The four expectations models correspond to four different definitions of the variables in Z.

1. The Individual Time Series Model. This model takes Z as the four years of income observations for each individual in the data. It assumes these are normally distributed, estimating expected income as the four-year average, and income variance as the four-year mean squared error.

2. The Cross-section Model. According to this model, current socio-demographic characteristics determine the *ex ante* distribution of income. The characteristics used here are ethnicity of head, age of head, sex of head, and income. "Ethnicity" refers to white/non-white differences in the U.S., and German citizen/non-German citizen differences in Germany. These conditioning variables are observed in the first year of each two-year panel, and are used to predict income in the second year.

3. The Pooled Model with Actual Events. This model takes first-year income as the first conditioning variable. The remaining conditioning variables consist of three dummy variables indicating the occurrence of an event for that household in the period between the observation of first-year income and second-year income. Thus, in predicting 1985 income, the Z vector includes 1984 income and the occurrence or non-occurrence of three events during the year 1985. Specifically, the first event dummy equals one if there is a difference in the number of adults present in the household between the year t interview and the year $t+1$ interview;

[6]In this period, average annual inflation was 2.0 percent in Germany, 3.3 percent in the U.S. Unemployment rates averaged 8.3 percent in Germany, 7.8 percent in the U.S. Real annual GDP growth was 2.4 percent in Germany, 4.1 percent in the U.S.

[7]"Equivalence income" is household income divided by the U.S. Census Bureau equivalence scale, which adjusts for returns to scale in the production of welfare out of a given income; see Bird (1993).

[8]In neither panel are measures of state-level taxes or indirect taxes available.

TABLE 1

MEDIAN RISK COSTS IN THE U.S. AND GERMANY
IMPACT ANALYSIS

Sample medians of:	U.S. ($)	Germany (DM)
Welfare cost of market income risk	1,456	2,002
Welfare cost of disposable income risk	1,150	1,135
Absolute difference	306	867
Relative difference (in %)	21	43
$N=994$ (U.S.), 995 (Germany)		

Sources: Author's calculations from the Michigan Panel Study of Income Dynamics, 1983–86 (column 1) and the German Socio-Economic Panel, 1983–86 (column 2).

Calculations are based on a sample of 1,000 market and disposable income densities in each country. These individual densities were estimated using the expectations model 4 and the NCD method. The U.S. and German density estimates are based on pooled two-year panels with 17,454 and 14,481 observations respectively.

Asymptotic consistency of the estimates requires that certain pdfs (those whose z values have zero probability) be dropped. There were six such densities in the U.S., five in Germany. See the appendix for more detail.

Risk costs were calculated for the remaining densities on the basis of equations (1) and (2) in the text. They assume constant relative risk aversion utility with a coefficient of relative risk aversion of 1.5. Currency figures are real 1986 values per equivalent person, where the equivalence scale is that implied by the U.S. Census Bureau's poverty line.

it equals 0 otherwise. The second event dummy equals one if the household's gross labor earnings in year $t+1$ exceed 1.5 times the household's gross labor earnings in year t, 0 otherwise. Household gross labor earnings are defined as the sum of all labor earnings of all household members, before taxes. The third event dummy equals one if the year $t+1$ gross labor earnings do not exceed 0.5 times the year t labor earnings, 0 otherwise.

4. The Pooled Model with Probabilities of Events. This model also takes observed first-year household income as the first conditioning variable. The remaining three conditioning variables are estimates of the probability of the events defined above. The probabilities are fitted values of probit regressions of the event variables on a large vector of socio-demographic characteristics. The probit results can be obtained from the author.

V. RESULTS

I apply the above methods to estimate risk costs for market and disposable income within random subsamples of $J=1{,}000$ households in each country. Impact analysis then compares the median risk cost of market income to that of disposable income in the same country. Comparative analysis compares risk costs in Germany to those in the U.S., for one income type. The results presented in Tables 1–4 assume expectations model 4, while Table 5 examines the other expectations models.

Table 1 presents impact analysis in each country, with median risk costs expressed in the respective national currencies.[9] Redistribution lowers median risk

[9]For reference purposes, the exchange rate at this time was about $1 = DM 2.5.

TABLE 2

THE AGGREGATE EFFECT OF REDISTRIBUTION ON WELL-BEING IN THE U.S. AND GERMANY
IMPACT ANALYSIS

Country and Quintile($)	Aggregate Impact: Total Social Difference in Welfare Outcomes Between Pre- and Post-Redistribution Income Billions of 1986 Currency		
	Aggregate Expected Transfer (M)	Aggregate Value of Increased Economic Security (R)	Aggregate Welfare Change (C)
U.S. ($)			
Lowest 20%	+31.2	+4.6	+35.8
Middle 60%	−29.9	+22.2	−7.7
Upper 20%	−159.5	+7.4	−152.1
Germany (DM)			
Lowest 20%	+49.9	+7.5	+57.4
Middle 60%	−40.6	+41.5	+0.9
Upper 20%	−149.9	+10.7	−139.2

Sources: Author's calculations from the Michigan Panel Study of Income Dynamics, 1983–86, and the German Socio-Economic Panel, 1983–86. Aggregation based on subsamples of approximately 1,000 households in each country; see Table 1. Aggregation also based on populations of about 61 million individuals in Germany and 238 million individuals in the U.S. in the mid-1980s. Quintiles determined by *ex post* disposable equivalent income.

costs by $306 in the United States, from $1,456 to $1,150, and by DM 867 in Germany, from DM 2,002 to DM 1,135. These figures represent declines of 21 percent and 43 percent, respectively. Redistribution programs evidently have a significant impact on risk in both countries, and the impact in Germany is greater. This is not surprising given that social spending is 17 percent of the GDP in Germany, and only 8 percent in the U.S. (Ringen, 1987, p. 260). Germany reduces risks by $(43/17)=2.53$ percentage points per percentage-point of social spending, while the U.S. reduces risks by $(21/8)=2.63$ percentage points. Relative to spending levels, then, the U.S. and Germany appear to be equally cost effective against risk.

Table 2 explores the distributional implications of Table 1. It divides the sample into quintiles by expected disposable income levels, and then aggregates the outcomes within the quintiles. Three outcomes are examined. First, the aggregate difference between expected pre- and post-redistribution income measures the expected total cash transfer to or from the quintile's membership. Second, the aggregate difference between pre- and post-redistribution risk costs measures the total value of increased economic security, produced for that quintile by the redistribution system. Third, the difference between pre- and post-redistribution certainty equivalents, which is the sum of the first and second outcomes, measures the overall impact of redistribution on the well-being of the quintile's membership. For ease of exposition, I combine the middle three quintiles into one group.

In the U.S., the redistribution system reduces expected incomes in the upper 20 percent of the income distribution by $159.5 billion, and in the middle 60 percent by $29.9 billion. Of these funds, $31.2 billion are transferred to the lowest quintile, the rest going for government purchases of real goods (and whose incidence is unknown). In Germany, the redistribution system removes DM 149.9

billion and DM 40.6 billion from upper and middle class households, respectively, and gives DM 49.9 billion to lower class households. Evidently, both countries substantially redistribute expected incomes.

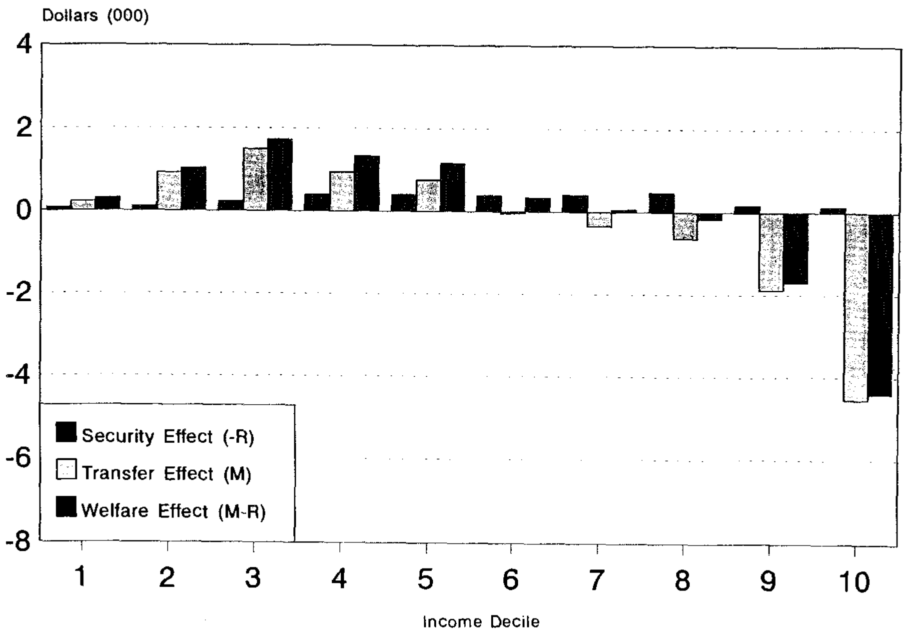
These transfers increase income security for all quintiles in both countries. Two patterns stand out. First, aggregate security benefits are higher for the upper quintile than the lower. In Germany, the richest 20 percent of households enjoy DM 10.7 billion in enhanced security, while the poorest 20 percent enjoy only DM 7.5 billion. In the U.S., the rich get \$7.4 billion, while the poor get only \$4.6 billion. This pattern reflects the fact that the rich have more income at risk than the poor.[10] Second, the aggregate security effect is so large in the middle quintiles that it practically erases the tax burden of redistribution. In Germany, the middle quintile pays taxes of DM 40.6 billion but receives reductions in risk costs of DM 41.5 billion. In the U.S., the net benefit of redistribution is negative but still close to zero. Thus, the redistribution system offers significant returns on the taxes it imposes on the middle class. These returns may explain the continued political viability of redistribution programs, even given low risk aversion. At higher levels of risk aversion, redistribution programs may pay for themselves many times over.

We get a more specific view of these effects in Figures 1 and 2. Here I have broken the sample into deciles and produced security effects ($-R$), transfer effects (M), and total well-being effects ($C=M-R$) per capita within the decile. Figure 1 shows results for the U.S. We see that the security effects are positive for all deciles and are comparable in magnitude to transfer effects for all of the middle-income deciles. Importantly, security effects result in net gains in well-being for deciles 6 and 7. Looking at the transfer effects alone, deciles 6 through 10 are net losers from redistribution. Due to the security effects, however, only deciles 8 through 10 are net losers, and decile 8 bears only a small net burden. The U.S. redistribution system makes a large fraction of the population net winners.

The story in Germany is similar. For comparability, the German effects have been translated into U.S. dollar terms at a rate such that the mean disposable income in both countries is the same. We see that security effects are positive for all deciles, and are a substantively important part of total well-being for the middle deciles (4 through 7). Looking at transfer effects alone, deciles 5 through 10 are net losers from redistribution. Unlike the U.S., however, when security effects are considered, deciles 5 through 10 are still net losers. The security effects do, however, cut the net burden of redistribution by more than 50 percent in deciles 5 and 6.

The figures show that the U.S. system does a better job of spreading the benefits of redistribution through the middle-middle class and even into the upper-middle class, an effect that is consistent with the particular political pressures of U.S. social policy formation (Bird, forthcoming 1995). In both countries, however, we see strong evidence that security benefits greatly enhance the attractiveness of redistribution policy for middle-class voters.

[10]The positive relationship between income and income risk appears regardless of how one analyzes the data (Bird, forthcoming 1995). This finding results from the fact that the *ex ante* standard deviation of income is lower among families with low incomes.



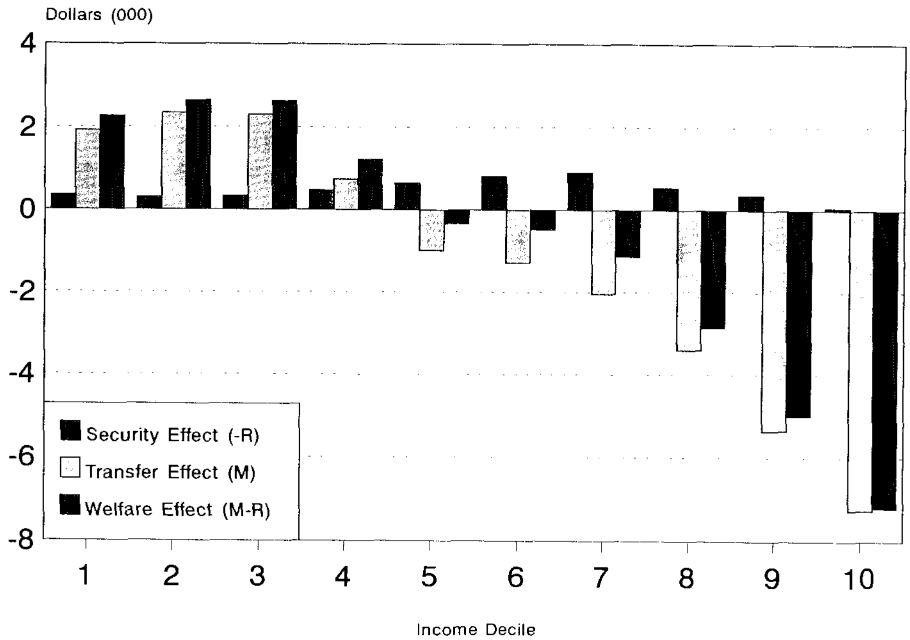
Source: Michigan Panel Study of Income Dynamics, 1983–86

Figure 1. U.S. per Capita Welfare Effects (by deciles)

These results should be treated with some caution, however, because they ignore two important considerations. First, as impact analyses, they hold behavior constant and do not indicate what aggregate income risks would be if redistribution policies were actually changed. Second, the figures take no account of efficiency costs. Table 2 shows only that redistribution currently produces substantial gross benefits; it does not demonstrate that the net benefits of redistribution are positive at any level of society.

Table 3 presents a comparative analysis, which can be treated as an estimate of the potential effects of policy change. To allow comparison, risk costs are expressed relative to expected incomes. In the U.S., for disposable income, the median risk cost is 8.5 percent of the median expected income, while in Germany it is only 5.4 percent. For market income, the difference is 10.8 percent vs. 8.2 percent. Thus, though pre-redistribution income risks are lower in Germany than the U.S., post-redistribution income risks are lower still. By switching to a German policy system, the U.S. could cut its risk costs by more than one-third. The caveat to this conclusion is that the U.S. and Germany differ in many more respects than social policy. One would not expect that a wholesale adoption of German policies in the U.S. would elicit exactly the same effects. Nevertheless, to the extent that the two countries are comparable, these figures suggest that movement toward the German system by the U.S. would result in lower risk costs, even after accounting for reactions to the changes.

Table 4 presents comparative analysis of the distribution of risk costs by quintile. In the bottom quintile, income risks are lower in Germany than the U.S.



Source: German Socio-Economic Panel, 1983–86

Figure 2. German per Capita Welfare Effects (expressed in U.S. $, by deciles)

In the upper quintile, they are higher. Thus, the distribution of income risk is more equal in the U.S. The difference is especially evident in the disposable income risk costs of the poor. In Germany, risk costs make up only 10 percent of disposable income in the lowest quintile, while in the U.S. they make up 24.3 percent. A U.S. shift in the direction of the German redistribution system would greatly increase the income security of the U.S. poor.

Finally, Table 5 presents evidence on the robustness of the conclusions to differences in the expectations model.[11] Results for the event probability model, the base case in the preceding four tables, are reproduced in the bottom panel. The other expectations models produce substantially different levels of risk cost in both countries. The simplest cross-section model, Model 2, produces risk costs as much as ten times higher than the time series approach of Model 1. The more intricate cross-section models, Models 3 and 4, produce risk costs that lie between the first two models. Given that low risk costs imply low uncertainty in *ex ante* income, one can interpret these patterns as follows. Individuals who pay attention only to their own *ex post* incomes (Model 1) will generally not perceive much uncertainty in their *ex ante* incomes, and will feel economically secure. Those who compare themselves to others who share similar current characteristics (Model

[11]The results have been tested for sensitivity to a number of other choices, such as the risk aversion parameter, the choice of kernel function, the bandwidth, and the income determination model (Bird, 1993). As with the expectations models, variations in assumptions can powerfully affect the level of risk costs, but does not affect their pattern. Thus, the basic relative relationships are unaffected by changes in these parameters.

TABLE 3

RELATIVE RISK COSTS IN THE U.S. AND GERMANY
COMPARATIVE ANALYSIS

	Welfare Cost of Risk in the Respective Income, Relative to the Individual's Expected Income, in %	
Ratio of medians in:	Market Income	Disposable Income
United States	10.8	8.5
Germany	8.2	5.4
Absolute difference	2.6	3.1
Relative difference (in %)	24	36
$N=994$ (U.S.), 995 (Germany)		

Sources: Author's calculations from the Michigan Panel Study of Income Dynamics, 1983–86 (line 1) and the German Socio-Economic Panel, 1983–86 (line 2).

Calculations are based on a sample of 1,000 market and disposable income densities in each country. These individual densities were estimated using the expectations model 4 and the NCD method. The U.S. and German density estimates are based on pooled two-year panels with 17,454 and 14,481 observations respectively.

Asymptotic consistency of the estimates requires that certain pdfs (those whose z values have zero probability) be dropped. There were six such densities in the U.S., five in Germany. See the appendix for more detail.

Risk costs were calculated for the remaining densities on the basis of equations (1) and (2) in the text. They assume constant relative risk aversion utility with a coefficient of relative risk aversion of 1.5. Currency figures are real 1986 values per equivalent person, where the equivalence scale is that implied by the U.S. Census Bureau's poverty line.

TABLE 4

THE DISTRIBUTION OF RISK COSTS IN THE U.S. AND GERMANY
COMPARATIVE ANALYSIS BY QUINTILE

Ratio of medians within disposable income quintiles	Welfare Cost of Risk in the Respective Income, Relative to the Individual's Expected Income, in Percent	
	Market Income	Disposable Income
Lowest 20%		
United States	29.8	24.3
Germany	25.6	10.0
Absolute difference	4.2	14.3
Relative difference (%)	14	59
Middle 60%		
United States	13.2	9.7
Germany	11.4	6.7
Absolute difference	1.8	3.0
Relative difference (%)	14	31
Highest 20%		
United States	6.3	5.4
Germany	8.4	5.9
Absolute difference	−2.1	−0.5
Relative difference (%)	−33	−9

N per quintile: 199 (U.S.), 199 (Germany).

Sources: Author's calculations from the Michigan Panel Study of Income Dynamics, 1983–86 (column 1) and the German Socio-Economic Panel, 1983–86 (column 2).

Notes: Membership in income quintiles is determined by the disposable equivalent income of the individual's household in year t.

TABLE 5

RISK COSTS IN THE U.S. AND GERMANY UNDER ALTERNATIVE EXPECTATION MODELS
IMPACT ANALYSIS

		Medians of Risk Costs			
Models	Country	Market Income	Disposable Income	Absolute Difference	Difference in Percent
1. Time series	U.S. ($)	749	534	215	29
	Germany (DM)	632	384	248	39
2. Cross-section	U.S. ($)	5,470	5,597	1,493	27
	Germany (DM)	3,977	2,433	3,164	57
3. Actual occurrence of events	U.S. ($)	2,298	1,562	384	17
	Germany (DM)	1,914	1,123	439	28
4. Probabilities of events	U.S. ($)	1,456	2,002	306	21
	Germany (DM)	1,150	1,135	867	43

N: Model 1: U.S. market 994, U.S. disposable 994, German market 995, German disposable 995. Model 2: U.S. market 1,000, U.S. disposable 1,000, German market 998, German disposable 999. Model 3: U.S. market 1,000, U.S. disposable 1,000, German market 997, German disposable 997. Model 4: U.S. market 994, U.S. disposable 994, German market 995, German disposable 995.

Sources: Author's calculations from the Michigan Panel Study of Income Dynamics, 1983-86 (U.S.) and the German Socio-Economic Panel, 1983-86 (Germany).

2), however, will perceive a great deal of uncertainty, which is consistent with the finding in the inequality literature that within-cell inequality tends to be more important than between-cell inequality. Those who focus attention on good predictors of income change (Models 3 and 4) perceive only a moderate level of income uncertainty. Overall, the expectations model has a powerful effect on the perceived level of economic risk.

Nonetheless, these differences do not greatly affect the patterns of income risk within countries. Across the various models, redistribution reduces risk costs by between 15 and 30 percent in the U.S., and by between 30 and 60 percent in Germany. Regardless of expectations, the tax-transfer system significantly reduces risks, and the German system has the stronger effect.

VI. DISCUSSION

Any conclusions drawn from these figures are subject to a number of cautions. First, the results rely on a large number of methodological assumptions, not all of which have been varied for sensitivity analysis. As a result, the patterns are not conclusive; their character is more exploratory than final. Second, the two analytical approaches are both subject to important reservations about reliability. The first, impact analysis, holds behavior constant in attempting to estimate the impact of redistribution programs. Clearly, however, behavior would change were redistribution programs changed, hence the generality of any patterns revealed by impact analysis is very limited. The results should be treated as an analysis of the current state of affairs, with no implications for hypothetical counterfactual worlds in which policies change. The second approach, comparative analysis, can be treated as a meaningful analysis of policy counterfactuals, *if* the two countries are identical. Germany and the U.S. are not identical, however, and the reliability of any patterns observed here depends on the degree of similarity between them at relevant points.

Nevertheless, the results support several broad conclusions. First, in both the U.S. and Germany, the redistribution system has an important impact on income risk. The benefits of risk reduction may be so large among the middle class that they explain the political support for redistribution programs, even given a low level of risk aversion. At higher aversion levels, redistribution programs may generate economic security in such amounts that even the deadweight costs of the programs are more than offset. If this is not the case, the security effects may still bring the net material costs of redistribution programs close enough to zero that the altruistic impulses of the voters are sufficient to give redistribution a winning measure of political support. Indeed, despite the sense of hostility that has surrounded them in recent years, transfer programs in both Germany and the U.S. have largely avoided dramatic cuts (as of this writing). Income security effects help explain why.

Second, a move by the U.S. toward a German redistribution system would be accompanied, in all likelihood, by a decrease in the welfare cost of income risk, even after accounting for behavioral reactions. The decline would be especially dramatic among the poor. Whether such a shift would be worth the added efficiency cost is unknown. The social value of risk reduction depends on risk aversion, and to some extent also on the altruistic impulses of the voters. Nevertheless, the German case demonstrates that real material gains are available for the U.S.

Third, the patterns show that the social benefits of redistribution policies cannot be reduced to their effects on poverty. Anti-poverty effects are important and should not be ignored, but the anti-risk effects are large enough to deserve attention as well. Further, they are important largely in the middle of the income distribution, to people who may never receive a cash benefit from any welfare program. Benefits for the middle class play an important role in the political economy of the welfare state (Goodin and LeGrand, 1987).

Appendix

A. *Nonparametric Conditional Density Estimator*

The nonparametric conditional density (NCD) estimator applies kernel estimation techniques and Bayes' Rule to estimate a density function $g(u|Z=z_i)$ on a sample of observations u_i and z_i, $i=1, \ldots, N$. Bayes' Rule implies:

$$g(u|Z=z_i)=\frac{g_1(u, z_i)}{g_2(z_i)} \tag{A1}$$

The denominator is the marginal density of one point, z_i. The numerator is the joint density of this z value and a one-dimensional random variable u. If g_2 is not zero at z_i, a consistent estimator of the numerator, divided by a consistent estimator of the denominator, will itself be consistent. Thus, the problem has two steps. First one estimates the single point density in the denominator and checks that it is not zero. (If it is zero, no estimate is made.) Then one estimates the one-dimensional density in the numerator, and divides.

While one could apply any density estimation method to these two problems, I take a kernel approach. A kernel estimator can be applied to any joint density problem, and has the feature that each point in the joint density is estimated individually. Thus, the estimate of g_2 is a joint density estimate conducted for the point z_i. The estimate of g_1 is a sequence of joint density estimates for points $\{u_1, z_i\}$, $\{u_2, z_i\}$, . . . , $\{u_Q, z_i\}$, where u_j, $j=1, \ldots, Q$ are a set of chosen values from the support of u. Each of these point estimates is made individually via the kernel method.

The general formula for the kernel method is as follows. Let X be a d-dimensional i.i.d. random variable with pdf $g(\cdot)$, and let there be observations x_i, $i=1, \ldots, N$, from X. Let a be a point on the support of X. The kernel estimate of $g(a)$ is:

$$\hat{g}(a)=\frac{1}{Nh^d}\sum_{i=1}^{N} K\left[\frac{a-x_i}{h}\right] \tag{A2}$$

where h is a small number called the bandwidth and $K(\cdot)$ is a function which integrates to 1. Both bandwidth and kernel function may be chosen by the researcher. The estimates in this paper use an Epanechnikov kernel and a bandwidth of $h=2.83$. The Epanechnikov is an error-minimizing kernel formula (see Silverman, 1986, p. 43), and it has the following form:

$$K(\underset{\sim}{x})=\{\tfrac{1}{2}c_d^{-1}(d+2)(1-\tfrac{1}{5}\underset{\sim}{x}'\underset{\sim}{x})/\sqrt{5}\}\{I(\underset{\sim}{x}'\underset{\sim}{x}<5)\} \tag{A3}$$

where d is the dimension of the point being estimated, c_d is the volume of the d-dimensional unit sphere, and $I(\cdot)$ is the indicator function ($I=1$ if the logical statement within is true, $I=0$ otherwise).

The bandwidth is chosen visually, by comparing pdf estimates produced by different bandwidths and choosing the bandwidth that provides a smooth pdf but does not completely smooth out important features. The visual selection process is common in the literature and is necessary since there is no way of determining the proper bandwidth without knowing beforehand the exact density being estimated. Sensitivity analysis shows that welfare analysis similar to that done here is invariant to the bandwidth choice over a large range of values centered at 2.83 (Bird, 1993). The data are pre-whitened so as to have a unit variance–covariance matrix (i.e. to cause the shape of the "box" drawn around an estimated point to conform to the shape of the data); the process is known as the Fukunaga transformation of the kernel estimator. The Fukunaga estimator is (Silverman, 1986, p. 78):

$$\hat{g}(a)=\frac{(|S|)^{-1/2}}{nh^d}\sum_{i=1}^{n} k\{h^{-2}(x-X_i)'S^{-1}(x-X_i)\} \tag{A4}$$

where S is the covariance matrix of $\underset{\sim}{x}$, d is the dimension, and the function $k(\cdot)$ is related to the kernel function by $k(\underset{\sim}{x}'\underset{\sim}{x})=K(\underset{\sim}{x})$.

The estimation makes use of the sampling weights provided in the PSID and SOEP to account for differential sampling probabilities in both surveys.

B. *Construction of Variables; Probit Regressions*

The source of uncertainty in the paper's income model is the shock term ε, estimated in each period by the change income $y_{t+1} - y_t$. Four years of annual data from both panels, for the years 1983–86, yield three two-year panels, 1983–84, 1984–85, and 1985–86. These are pooled. For the PSID, each year has 5,818 observations and the pooled data has 17,454 observations. For the SOEP, a year has 4,827 observations and the pooled data has 14,481 observations. An observation consists of an ε and a z, where z is an information vector. For any ε defined as income change from t to $t+1$, the corresponding z observation is taken from period t. One element of the z vector is always period-t income, y_t. The other three elements are the event probabilities as described in Section III of the text. These are estimated with the probit method on the pooled data, and tables reporting the probits are available from the author.

Pooling assumes that all the years were similar, a reasonable assumption given that macroeconomic conditions and economic policy did not change greatly in either country between 1983 and 1986. Significant effects of TRA 86 in the U.S. were probably felt by 1987, which limits the length of the panel. Pooling also overstates accuracy. A pooled sample of N observations implies less accuracy than a random sample of N observations. Fortunately, the accuracy of individual density estimates is not a serious issue, given that what we report in Tables 1–4 are not density estimates themselves but rather medians of functions of densities. That is, we create a large sample of densities and then calculate a characteristic of each (the risk cost); then we report the sample median of this characteristic. The accuracy of the risk cost estimate is determined solely by the sample size in this step (1,000), not the sample size of NCD estimates. Put another way, whatever error is present in the NCD estimator will appear as part of the standard deviation of the risk cost. Hence pooling at the NCD stage is not critical. In any case, even at the NCD stage, we have far more observations than would appear necessary; simulation evidence in Silverman (1986) suggests that only 4,000–5,000 observations achieve reasonable accuracy for this type of problem, and we have over 14,000 observations in both samples.

References

Betson, D and Van der Gaag, J., Measuring the Benefits of Income Maintenance Programs, in David, M. H. and Smeeding, T. M. (eds.), *Horizontal Equity, Uncertainty, and Economic Well Being*, NBER Studies in Income and Wealth, No. 50, University of Chicago Press, Chicago, 1985.

Bird, E. J., *The Welfare Cost of Income Uncertainty*, Westview Press, Boulder, 1993.

———, Repairing the Safety Net: Is the EITC the Right Patch? *Journal of Policy Analysis and Management*, forthcoming, 1995.

Burkhauser, R. V., Butler, J. S. and Holden, K., How Death of a Spouse Affects Economic Well-Being After Retirement: A Hazard Model Approach, *Social Science Quarterly*, Vol. 72, 504–519, September 1991.

——— and Duncan, G. J., Economic Risks of Gender Roles: Income Loss and Life Events Over the Life Course, *Social Science Quarterly*, Vol. 70, 3–23, 1989.

——— and Wagner, G. G. (eds.), *Proceedings of the 1993 International Conference of German Socio-Economic Panel Study Users*, Duncker and Humblot, Berlin 1994.

Carroll, C. D., The Buffer-Stock Theory of Saving: Some Macroeconomic Evidence, *Brookings Papers on Economic Activity*, Vol. 2, 61–156, 1992.

Dominitz, J. and Manski, C. F., Using Expectations Data to Study Subjective Income Expectations, *Institute for Research on Poverty*, Discussion Paper No. 1050-94, December, 1994.
Duncan, G. J. and Hoffman, S. D., A Reconsideration of the Economic Consequences of Marital Dissolution, *Demography*, Vol. 22, 485-497, 1985.
Feldstein, M., The Welfare Loss of Excess Health Insurance," *Journal of Political Economy*, Vol. 81, 251-280, 1973.
Friend, I. and Blume, M. E., The Demand for Risky Assets, *American Economic Review*, 65(5), 900-922, 1975.
Goodin, R. and Le Grand, J., *Not Only the Poor*, Allen and Unwin, London 1987.
Gramlich, E. M. and Wolkoff, M. J., A Procedure for Evaluating Income Distribution Policies, *Journal of Human Resources*, Vol. 14, 319-350, 1979.
Hall, R. E. and Mishkin, F. S., The Sensitivity of Consumption to Transitory Income: Estimates from Panel Data on Households, *Econometrica*, Vol. 50, 461-481, 1982.
Hauser, R., Zum Problem der Staatlichen Produktion von Verläßlichkeit bei langen Zeiträumen–Möglichkeiten und Grenzen der Gewährleistung sozialer Sicherheit bei Schwankendem Wirtschafts- und Bevölkerungswachstum, in Rolf, G. *et al.* (eds.), *Sozialvertrag und Sicherung*, 147-194, Campus Verlag, Frankfurt, 1988.
——— and Bernstsen, R., Einkommens- und Wohlstandsmobilität von Haushalten und Personen unter dem Einfluß demographischer Ereignisse, University of Frankfurt, mimeo, 1989.
Haveman, R. H., *Starting Even*, Simon and Schuster, New York, 1988.
——— and Wolfe, B. L., Income, Inequality, and Uncertainty: Differences Between the Disabled and the Nondisabled, in David, M. H. and Smeedings, T. M. (eds.), *Horizontal Equity, Uncertainty, and Economic Well-Being*, University of Chicago Press, Chicago, 1985.
Jenkins, S. and Millar, J., Income Risk and Income Maintenance: Implications for Incentives to Work, in Dilnot, A. and Walker, I. (eds.), *The Economics of Social Security*, Oxford University Press, Oxford, 1989.
Krupp, H.-J. and Hanefeld, U., *Lebenslagen im Wandel—Analysen 1987*, Campus Verlag, Frankfurt, 1987.
Lampman, R. J., *Social Welfare Spending: Accounting For Changes From 1950 to 1978*, Academic Press, New York, 1984.
Moffitt, R. and Rothschild, M., Variable Earnings and Nonlinear Taxation, *Journal of Human Resources*, 22(3), 405-421, 1987.
Osberg, L., Erksoy, S. and Phipps, S., Behavioral Response, Sociodemographic Change and the Distribution of Income: How to Value the Poorer Prospects of the Young? presented at the 23rd General Conference of the International Association for Research on Income and Wealth, St. Andrews, New Brunswick, Canada, 1994.
Ringen, S., *The Possibility of Politics*, Clarendon Press, Oxford, 1987.
Rothschild, M. and Stiglitz, J. E., Increasing Risk I: A Definition, *Journal of Economic Theory*, Vol. 2, 225-243, 1970.
Silverman, B. W., *Density Estimation for Statistics and Data Analysis*, Chapman and Hall, London, 1986.
Staines, V. S., *Seven Events' Effects On Families' Earnings, Transfer Incomes, and Economic Well-Being*, Ph.D. dissertation, University of Wisconsin-Madison, 1982.
Varian, H. R., Redistributive Taxation As Social Insurance, *Journal of Public Economics*, 14(1), 49-68, 1980.