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Income Risk and Social Spending: Empirical Estimates

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Abstract

This paper uses panel data on developed countries to estimate simultaneous equations models of social spending. The methods take advantage of some recent innovations in the growth literature involving the treatment of country-level panel data. Another contribution is to treat income risk as an endogenous variable, as suggested by the recent theoretical work of Hans-Werner Sinn. The results indicate that social spending is moderately related to aggregate income variability, and strongly related to the share of elderly and unemployed.

Zusammenfassung

In diesem Beitrag werden – basierend auf Panel-Daten aus Industrieländern – mit Hilfe simultaner Modelle die Sozialausgaben geschätzt. Diese Methoden beruhen auf einigen neueren Erkenntnissen in der Wachstumstheorie, welche Panel-Daten auf Länderebene mit einbeziehen. Ein anderer Beitrag dieses Papiers besteht darin, das Einkommensrisiko als endogene Variable zu behandeln, wie dies in einer kürzlich von Hans-Werner Sinn veröffentlichten Arbeit vorgeschlagen wurde. Die Ergebnisse zeigen, dass die Höhe der Sozialausgaben in geringem Maße von den aggregierten Einkommensvariabilitäten abhängt und in starkem Maße mit der Höhe des Anteils von Älteren und Arbeitslosen korreliert.

JEL-Classification: H5, I3

1. What explains the level of social spending?

This paper uses a database of developed countries from 1960 to 1994 to assess the impact of a number of country-level variables on social spending. The two main contributions of the paper are 1) to apply practices recently developed in the growth literature to the question of social spending determination, and 2) to pay serious attention to the role of income risk as a causal factor in social spending.

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The literature on this subject, broadly speaking, is an effort to determine why the Welfare State is a more important thing in some countries than in others. The origins and causes of social spending (which most authors take as the best empirical proxy for "The Welfare State") are undoubtedly complex and there are many theories about them, some of them formal, many of them not. There is, however, no formal theory that is both general enough to encompass a significant number of different motivations, and that yields estimable equations, so a rigorous modeling and estimation strategy is not possible.

As a result, empirical research on the overall size of the Welfare State has adopted a different strategy. First, general concepts are laid out in order to identify the kinds of variables that ought to covary at the country level. Then basic regressions are estimated in order to test the predicted relationships. There are many such approaches in the literature; Esping-Anderson (1990), for example, traces the causes of the Welfare State to generalized historical 'worlds' or mind-sets involving the degree of conservatism, labor market institutions, and devotion to free-market capitalism. He then argues for this grouping on the basis of a large number of simply-specified OLS regressions on OECD cross-sections. Pampel and Williamson (1989) propose informal theories based on class, voting groups, institutions, politics, and macroeconomic indicators; their supporting evidence comes from a series of fairly basic GLS regressions. Similarly, Hicks and Swank (1992) assume that social spending is driven mostly by the structure of the political process and national institutions and run regressions of social spending on a series of political variables. Contributors in Flora and Heidenheimer (1981) also look for sources of the Welfare State in the intensity of left politics and general economic conditions.

This research is most successful in laying out general notions of Welfare State motivations.[1] Still, none of these papers make use of what is now a very large literature in public choice economics in which social spending is traced to the rational decisions of individual agents. Specifically, many have argued that income risk is an important determinant of the political demand for social insurance.[2] Hans-Werner Sinn (1996) has developed an empirically tractable formal theoretical version of this argument, which remains largely unexplored in multiple-equation empirical work (although see Bird, 2001; Katzenstein, 1985; Cameron, 1978).

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[1] See also: Uusitalo (1984), Hicks and Misra (1993), Huber, Ragin, and Stephens (1993), Baldwin (1990).

[2] The argument has been made in conceptual work (Barr, 1992; Esping-Andersen, 1990) and historical treatments (Rimlinger, 1971; Baldwin, 1990).

The empirical methods in this literature, moreover, suffer from serious problems: there is little attention paid to problems of causality, and the presence of unobserved fixed effects is ignored. As for the first issue, in most of these simple regression approaches, social spending is treated as the only endogenous variable, with everything else in society assumed to be an exogenous causal force. In reality, social spending is co-determined with other important social conditions, including the level of income, the degree of income risk, the amount of private investment, and possibly even the degree of inequality. When endogenous variables are treated as exogenous, coefficients reflect a simple correlation only; they indicate neither the size nor direction of causation from the RHS variable to the dependent variable.

As for the fixed effects problem, ignoring fixed effects in country-level data is effectively to ignore the existence of unobserved history: unobservable events, institutions, and forces that have an impact on the dependent variable. Ignoring them can lead to a misinterpretation of historical correlations as true causal forces. For example, the US has had historically higher levels of risk and historically lower levels of social spending than countries such as France and Sweden. Unless all of these historical differences are accounted for by some variable in the data set, a simple cross-country regression using contemporary data will lead one to conclude that the correlation between spending and risk is negative. It may be the case, however, that in all the countries and at all times within the current data set, an increase in social spending from its historical norm will lead to an increase in risk from *its* historical norm. Thus, the cross-country pattern endowed to the data set by history suggests a negative correlation, but the causal flow is actually positive. As a result, ignoring fixed effects can lead to biased conclusions about contemporary influences.

Some papers do take account of these problems, and this paper will pick up where they leave off. Specifically, Peter Lindert uses methods that account for the endogeneity problem. He has two papers on the level of social spending, one using a remarkably extensive data set from 1880–1930 (Lindert 1994), and another with a more contemporary data set from 1960 to 1981 (Lindert, 1996). He successfully estimates models in which social spending is jointly determined with income growth. Focusing on a political pressure-group theory of social spending, Lindert finds that democracy, demography (i.e. age-group sizes), and the income distribution have the most influence. Surprisingly, the deadweight costs of social spending are found to have little impact on growth.[3]

[3] Some of the most intriguing Lindert results can be explained through the risk framework. The finding that the Welfare State does not reduce growth can be explained by the fact that the income insurance effect of the Welfare State encourages risk-taking and thereby growth (Bird, 2000). There is a result that spending falls as

This paper will adopt Lindert's multiple equations approach, and will add to it in three ways. First, the database here will be somewhat larger, in terms of years, countries, and variables. Second, this paper will consider income risk as an important, and endogenous, determinant of social spending. Third, this paper will account for fixed effects in the determination of social spending.

To summarize the literature, there has been broad interest in determining the empirical causes of social spending at the national level, but more work can be done on the details and rigor of the empirical modeling, as well as adding new concepts such as income risk. A strategy of formal modeling and testing still seems impractical, because the Welfare State has too many complex explanations to synthesize in a single testable model. Nevertheless, more rigorous analytical attention can be paid to the way that even broad and informal theories of social spending translate into specific empirical implications.

2. Conceptual underpinnings: risk and social spending

In any such exercise, it is necessary to discuss at least briefly the kinds of variables that are thought to have some kind of influence on the size of the Welfare State in a given country. Fortunately, the previous literature has suggested a number of possible determinants, including inequality and poverty, the population share of politically powerful and entitled groups, and political measures.[4] For example, even though it would be open to considerable debate, most authors assume that the best metric for the Welfare State is the share of social spending in GDP, and we will follow that convention here.

To focus attention on a relatively unexamined argument for social spending (at least in terms of formal empirics), consider Hans-Werner Sinn's (1995) argument for the importance of risk preferences in determining the size of the national budget. In essence, Sinn claims that a polity that enjoys investment and entrepreneurial activity may call on its government to increase social spending as a hedge against the risks that these activities entail. In Sinn's model, a country is using the Welfare State as a tool to help it

the gap between the middle income and lower incomes rises, which might be explained as follows: the middle class assesses its own risks of poverty by the distance between its incomes and those of the poor. As this gap widens, the perceived risk falls, so the demand for income-insuring social spending falls.

4 For a limited overview of some of the conceptual arguments for the Welfare State, see Trattner, 1999; Himmelfarb, 1992; Bird 1999; Hochman and Rogers (1969); Becker (1985); Kristov, Lindert and McClelland (1992); Meltzer and Richard (1981); Piven and Cloward (1971); Mead (1997).

choose its desired bundle of national risk and national income. There is some empirical evidence that the income insuring, anti-risk, effects of social spending can be substantial, even for middle class households (Bird, 1995, 2000). Other authors have pointed out that the middle class is often a strong supporter of the Welfare State (LeGrand, 1987; Pierson, 1996), and some argue that this is largely a self-insurance motivation (Atkinson, 1995). If indeed the Welfare State is a form of income insurance, it may actually promote economic growth. Sinn's ideas will be used as the basic framework for the empirical work.

3. Empirical methods

To implement Sinn's (1995) ideas about risk and social spending, consider the following simultaneous equation model of social spending, risk taking, and income generation. The unit of observation is a country-year; let y_{it} denote the income level in country i in year t, r_{it} the level of income risk (i.e. the variance), and s_{it} the level of social spending (empirical definitions of these variables in the data at hand will be given below). Each of these three variables is endogenous:

$$y_{it} = \alpha_{yi} + \beta_{yr} r_{it} + \beta_{ys} s_{it} + \beta_{y3} x_{yit} + \beta_{y4} k_{it} + \varepsilon_{yit}$$

$$r_{it} = \alpha_{ri} + \beta_{ry} y_{it} + \beta_{rs} s_{it} + \beta_{r3} x_{rit} + \varepsilon_{rit}$$

$$s_{it} = \alpha_{si} + \beta_{sy} y_{it} + \beta_{sr} r_{it} + \beta_{s3} x_{sit} + \varepsilon_{sit}$$

where the x_{*it} terms refer to exogenous variables, k is a measure of the (endogenous) capital stock or investment level, the α and β terms are parameters, and the ε terms are random errors. The intercepts are country-specific, which will call for a fixed-effects estimation strategy. The first equation is a fairly standard aggregate income equation, familiar from the growth literature (Temple, 1999). The important parameters are β_{yr} , which measures the presumably positive impact of risk-taking on the income level, and β_{ys} , which shows how social spending directly affects income. If deadweight costs are substantial, this should be negative. In the second equation, β_{ry} indicates the impact of higher incomes on the willingness to take risks; if r and y are defined in levels, declining absolute risk aversion would imply $\beta_{ry} > 0$. The other risk coefficient, β_{rs} measures the impact of social spending on risk – if the Welfare State encourages risk-taking, then $\beta_{rs} > 0$. Thus while β_{ys} shows the direct impact of the state on incomes, and presumably is dominated by deadweight costs, β_{rs} and β_{yr} show an indirect and presumably positive effect: the state encourages risk-taking, and risk-taking encourages growth. In the spending equation, β_{sy} measures the reaction of social spending to income; if the Welfare State is a normal good, $\beta_{sy} > 0$. Finally, β_{sr} shows how spending responds to the risk level. If voters facing higher risks are inclined to call for more income insurance (as the risk motive suggests they should), then $\beta_{sr} > 0$.

The structural coefficients in the model already provide useful information about the validity of the risk motive for the Welfare State. To provide information on the other motives, key exogenous variables will be added to the social spending equation (and the other equations where it seems theoretically appropriate). Anyone working with country-level data will be familiar with the difficulties that arise when making judgments as to which variables are exogenous and which are endogenous. Suffice it to say that this paper seeks primarily to extend previous research by adding risk as an endogenous variable. Making other variables endogenous (such as human capital and investment) would require still more identifying variables and thus put an even greater strain on the data. At a broader level, it will always be necessary to make some judgments as to which variables are endogenous and which are exogenous; otherwise, it is simply not be possible to say anything about causation. However, recall that most of the existing literature makes no effort at all to sort out causal effects. Single-equation OLS is the norm. This paper attempts to explore the causes of social spending by applying a structural model to the data, which requires making some assumptions about exogeneity; whether or not these are good assumptions, the fact remains that even making the effort here is an advance on the existing literature.

The exogenous variables are chosen based on conceptual arguments in prior literature, and will be limited to some extent by the data. They include:

- the gini coefficient (which will also be treated as an endogenous variable, and a mismeasured variable) and a measure of infant mortality;
- measures of the size of entitled voting-age populations, such as the aged and the unemployed, as well as a unionization score to account for the political power of labor;
- data on the number of strike days lost, the extent of military expenditures, the vote share of left parties, and the degree of voter turnout.

By altering how these variables are defined and used, it should be possible to get a sense of which relationships are robust in the data. There are some serious limitations in the kinds of variables that can be used, however, because of the difficulty of finding comparable cross-national data. These limitations and other aspects of the data will be discussed in the next section.

Assuming that the data come in the form of a panel of countries over several years, the data can be transformed by calculating the time average of the dependent variable, $\overline{y}$, and then subtract it from y_{it} for each observation. Applying the same process to the right-hand side of the regression equations sweeps out the fixed effect terms α_y , α_r , and α_s . In effect, this ensures that the parameter estimates will take account of (and be unbiased by) any country-specific factor that is constant throughout the time frame of the panel. This would include any historical forces, observable or not, whose effects occurred before 1960. Thus, historical differences in inequality, civil liberties, war experience, political culture, and religious traditions are all fully accounted for in these results. All of these forces have created historically normal levels for all of the variables, from which each variable in the data evolves from 1960 onward in the course of the panel. What is measured here is the effect of this contemporary evolution of independent variables on the contemporary evolution of the dependent variables. In fully accounting for history, then, these results provide the most accurate estimate of contemporary causality.[5]

With the transformed data, it is then possible to apply standard 2SLS techniques to the simultaneous equations. The coefficients will be identified if each of the endogenous variables (at a minimum y, r, s, and k) is instrumented by exogenous variables that do not appear in the other equations. As Temple (1999) has pointed out, with panel data on countries, each endogenous variable can be instrumented by its own lags. This seems to be an almost unavoidable choice, since the possibility of finding good instruments among contemporary variables – in other words, national aggregates that one is forced to assume do affect one thing currently but not some other thing currently – would seem to be slim. It is much more plausible that past values of a current variable do affect it strongly but do not have a strong affect on other current variables. In what follows, then, all endogenous variables are instrumented with three lag variables, in addition to other exogenous variables where exclusion seems plausible.

The subject of lagged variables brings up another methodological wrinkle: with national aggregate data, how does one account for the fact that years may pass before a shock to one variable has its causal influence on another? One approach is to apply and then explicitly analyze the pattern of lag effects, but this is needlessly complicated (especially so in a multiple-equation system with multiple lags). A simpler response is to define all the

[5] An alternative method for achieving the same results would be to assume that the historical norm effects a are not fixed parameters, like the α terms, but are unobserved random variables in the error term. This leads to random effects regression, which is mechanically not very different from fixed effects (Greene, 1993, pp. 466–71). Conceptually, the fixed effects assumption makes more sense here. The data here consist of a census of the available population (countries), each with a fixed history; this is not random sample from a large population where each observation has an unobservable individual shock term.

variables as averages within fixed time windows. Thus, effects are not interpreted as the instant effect of a shock to one variable upon another, but as the sustained effect on one variable of a sustained change in the other. For example, because of political bottlenecks and implementation problems, it is unlikely that an increase in income risk will immediately cause an increase in social insurance, even if the pressure for change is present. However, if the risk shock is sustained for, say, three years, spending has time to respond. To allow for these lagged effects, then, all variables are expressed as three-year averages.

In sum, we will estimate three equations of deviations-from-the-mean, where both the mean and the deviations are constructed from variables that are defined as averages over three-year time windows. Variables that are endogenous variables are instrumented by lagged values, and estimates are obtained using 2SLS. Because of the distinct possibility that the error terms in the equations might be correlated within countries, the reported standard errors are huber-white robust standard errors with clustering by country. As it turns out, taking account of clustering reveals that the usual standard errors are strongly biased downward.

4. Data

The study makes use of country-year panel data and is collected from two sources. The main source of data is the Comparative Welfare States (CWS) data set, compiled by Evelyne Huber, Charles Ragin, and John D. Stephens (Huber, Ragin, and Stephens 1997). The CWS contains comparable country time series from 1960 to 1994 for 19 developed countries (including Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, New Zealand, Sweden, Switzerland, the UK, and the US). Together these countries constitute virtually a census of the developed western world in the post-WWII period, including representatives from all of the major Welfare State 'models' (scandanavian, conservative-corporatist, laissez-faire), as well as other countries (Japan, Ireland) that do not fit these nice categories. The CWS provides a wealth of social spending categories as well as demographic data, macroeconomic data (including a subset of data from the Penn World Tables), and political data. The initial source for most of the series used in the paper is either the ILO or the OECD. The results also make use of some unionization data compiled by Jelle Visser (Visser, 1996).

In addition to the CWS, the paper makes use of the Deininger and Squire compilation of inequality estimates (Deininger and Squire, 1996). The Deininger and Squire data have recently been subjected to criticism

(Atkinson and Brandolini, 2001). Compared to more extensive and higher-quality data within specific developed countries, the DS series can differ in both magnitude and trend over several periods. Using fixed effects regressions or dummies for time period and country (as is done here) may not fully correct for the various institutional and historical factors that cause the data series to deviate. As a result, Atkinson and Brandolini caution against using the DS data mechanically; rather, the researcher should carefully adjust each series in the DS data according to some standardized requirements. At the same time, they note that any such choice of standards may affect the conclusions of the study. Adjusting the DS data according to these requirements is a weighty task; Atkinson and Brandolini's efforts occupy 29 pages in the *Journal of Economic Literature*. Rather than make a similar effort here, I will instead caution the reader that the inequality data have been criticized and may be extraordinarily inaccurate. At the same time, as Atkinson and Brandolini point out, we do not live in a world where such data sets are easy to find and assemble. The DS data are still the most comprehensive and accurate available; hopefully, since this paper focuses entirely on well-developed countries, any inaccuracies in their inequality data will be minimal.

Estimates of the gini coefficient in the DS data are much more extensive than of other inequality and poverty measures, so the gini will be taken as the most accurate available measure of inequality and poverty. The gini data is collected from many different data sources using different methods, so the comparability across countries and years is questionable. Also, there is no unified income concept behind it, so its role in a regression on social spending (which may mechanically affect it) may be problematic. It is important to have some measure of inequality in the model, so it is absolutely necessary to use the gini coefficient in some way. It seems prudent to handle it as an errors-in-variables problem, to be solved by instrumenting.

Table 1 presents a list of all the variables used in the study and a brief description of how they are defined. In the base case, income (y) is defined as the level of real per capita income in 1985 $US, in thousands, and social spending (s) is defined as the share of social spending (as identified by the OECD) in GDP, in percent. The variables have been defined so as to be about the same order of magnitude (10 – 100), to facilitate the assessment of substantive significance in the results.

Table 1

Variable Definitions

Variable	Mean	Min	Max	Description
Income	10.7	3.6	18.1	Income per capita, in $US 1985, in thousands
Risk	2.4	1.9	5.5	Standard deviation of log income (defined as above), divided by 100, as estimated by a GARCH(1,1) model on the income series of each country. See text for more detail.
Social Spending	13.8	3.7	28.8	Share of social spending in GDP (%)
Investment	26.5	14.2	44.7	Share of investment in GDP (%)
Inflation	6.0	-0.7	24.2	Annual percent change in country CPI
Unemployment	4.8	0.1	18.2	Unemployment rate
Aged	12.3	5.9	17.8	Percent of population over 65
Trade	63.9	9.1	211.9	Imports + Exports / GDP
Union	33.3	-0.1	77.1	Net union membership (gross minus retired and unemployed) relative to workforce (%), from Visser (1996)
Gini	33.8	19.9	58.2	Gini coefficient, from Deininger and Squire (1996)
Workers	65.0	57.6	70.5	Working age population as percent of total
Capital	29.0	5.3	76.7	Capital stock per worker (real 1985 $US, thousands)
Strikes	0.185	0	1.810	Working days lost to strikes per 1,000 workers
FLFPR	33.9	17.1	51.8	Female labor force participation rate
Kids	0.447	0.280	0.685	Ratio of children to females in the population
Mortality	13.6	4	42	Infant mortality rate
Turnout	80.7	33.0	95.8	Electoral turnout in all elections in given year (%)
Military	2.76	0.80	9.40	Military expenditure as percent of GDP
Left	39.0	10.3	61.1	Vote share of left parties in year

Source: Comparative Welfare States data set; Deininger and Squire inequality data.

The third dependent variable is risk (r), and it requires an extensive discussion here in the text because it is not generally observable in the usual data sets. Following a line of research into the welfare consequences of risky incomes (see Bird, 1995), let income risk be defined generally as the time variance of income. More specifically, suppose that income follows a standard permanent / transitory income process:

$$y_t = p_t + u_t$$

$$p_t = p_{t-1} + v_t$$

where y_t is income in period t, p_t is the expectation of income in period t (i.e. 'permanent income'), and u_t and v_t are error terms that are uncorrelated (both serially and with respect to one another), with zero means and variances σ_u^2 and σ_v^2 respectively. Rewriting expresses income as a function of its own lag and error terms:

$$y_t = y_{t-1} + (u_t - u_t - 1) + v_t$$

With y_{t-1} predetermined, the variance of income is $\sigma_y^2 = 2\sigma_u^2 + \sigma_v^2$. With this framework one could distinguish in principal between the variance of permanent (v) as opposed to transitory (u) shocks, but here we are interested in the overall risks to income as presented by σ_y^2. To ease interpretation, results will be discussed in terms of the standard error, σ_y.

So defined, risk can be estimated in many ways. In the base case of this paper, a GARCH(1,1) model is applied to the panel of real per capita income values y_{it}, with the one explanatory variable y_{it-1}. The GARCH model estimates the parameters of a variance model in which the variance is time-specific and has one autoregressive and one moving-average term. Even though the parametrization is thin, GARCH(1,1) has been shown to provide robust and accurate measures of the time-specific variance (Greene, 1993, p. 568). Applied in the panel data, it estimates time- and country-specific variances. The GARCH(1,1) method was used for most of the results in the paper, with risk being defined as the standard deviation of annual real per capita income (σ_y).

It can be shown that this aggregate income risk is directly related to the income risk facing the individual. In a country of N individuals, let Y_j be the income of individual j, so that aggregate per capita income $y = \Sigma_j Y_j/N$. Let the variance of each Y_j be σ_j^2 and let σ_{jk} be the covariance of Y_j and Y_k. The variance of aggregate income is $\sigma_y^2 = \mathrm{Var}(\Sigma_j Y_j)/N^2 = \Sigma_j \sigma_j^2/N^2$ $+2\Sigma_j \Sigma_{k>j} \sigma_{jk}/N^2$. This can be expressed approximately as $\sigma_y^2 \approx \bar{\sigma}^2/N + \bar{c}/N$, where $\bar{\sigma}^2$ is the average individual income risk in the sample, and $\bar{c}$ is the 'average' cross-sectional covariance in incomes (specifically, it is the sum of $(N-1)!$ values of σ_{jk} divided by $(N-1)!$). (Note that this expression makes use of the fact that $(N-1)!/N = (N-1)/2$ and that $(N-1)/N \approx 1$ for large N). If the 'average' cross-section correlation is zero, then we have $\sigma_y^2 \approx \bar{\sigma}^2/N$, i.e., aggregate risk is proportional to individual risk. In other words, if the cross-section correlation is assumed to be close to zero, then the aggregate risk measure used for the study (σ_y^2) is approximately equal to the population average of individual risk, divided by N. It seems fairly plausible to assume the cross-section covariance is, while not zero, nonetheless small.[6] If some significant cross-sectional income covariance exists, then an aggregate risk measure is a less accurate indicator of the risks facing individuals.

To test sensitivity to the GARCH(1,1) approach, variance is also estimated for one set of estimates in the simplest way possible, as squared deviations from the 34-year income trend.

In the base case, the GARCH model was executed on log income in order to express the resulting standard deviation in terms of annual relative income change. Recall that, under a normal distribution, there is about a 95 percent probability that the random variable will fall within a window of about two standard deviations from the mean in either direction. Thus, if income is log normal, the outcome $\sigma_y = .05$ (see table 1) indicates that there is approximately a 95 percent probability that income will rise or fall by ten percent or less in a given year.

A final aspect of the data worthy of attention is the fact that not all variables are available for all years. This, plus the reductions made necessary by the calculation of three-year averages, the use of three years of lagged variables as instruments, and the GARCH implementation on lagged income (for seven years of lost data in total), considerably reduce sample sizes from the 19*34 = 646 potential maximum. Typical sample sizes fall in the range from 300 to 400. Still, the results seem reasonably accurate in the sense that R^2 values are reasonably high and many coefficients pass standard statistical significance tests.[7]

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6 When one person experiences an income shock, its effect on others is diffused throughout the economy. My spending is a tiny element of the incomes of other people. Someone who wins a lottery does increase her spending, but the effect of this on any other person's income is minimal.

7 It is not entirely clear what 'statistical significance' means in a data set that consists of virtually every possible observation. A regression equation calculated on a census of observations is not an estimate of the conditional expectation function, it *is* the conditional expectation function. Still, the results will be discussed in the usual way.

5. Results

In general the results do not make a watertight case for the risk approach as opposed to any other candidate. Spending seems most strongly tied to the size of recipient groups, although, surprisingly, it does not seem to be induced by inequality as strongly as one might have thought.

These assessments are based on an overview of the coefficient signs, sizes, and statistical significance in Tables 2–6. Table 2 gives the results for a base case, and for the most part its results are representative of the other regressions. It reports coefficients for all three of the main equations in the model,

Table 2

Base case regression results

	Dependent Variables					
Independent Variables	1. Income		2. Risk		3. Social Spending	
	beta	s.e.	beta	s.e.	beta	s.e.
Income	–	–	-.130	*.050	.379	*.158
Risk	.113	.247	–	–	.666	.479
Social Spending	.139	*.080	.043	*.024	–	–
Investment	.107	*.042	–	–	–	–
Inflation	-.014	.018	.023	*.009	-.040	.039
Unemployment	-.041	.071	.001	.021	.372	*.108
Aged	–	–	–	–	.746	*.285
Trade	-.027	.030	2.26e-4	.004	.052	*.028
Union	2e-5	2e-5	-7.7e-7	6.6e-6	3e-5	4e-5
Gini	-.002	.017	.009	*.005	-.103	*.042
Workers	.229	*.079	–	–	–	–
Capital	.213	*.033	–	–	–	–
Strikes	-.838	*.445	-.141	.257	-.290	.879
FLFPR	–	–	.027	*.009	–	–
Kids	–	–	.030	1.131	–	–
Mortality	–	–	–	–	.093	.111
Turnout	–	–	–	–	-.051	.039
Military	–	–	–	–	.505	.514
Left	–	–	–	–	-.041	.029
R^2	.8506		.1721		.7516	
N	344		344		344	

Note: coefficients identified with a '*' are statistically significant at the 90 percent level, two-tailed test. Source: Comparative Welfare States data set; Deininger and Squire inequality data.

even though most interest lies in the social spending equation (2.3). The income equation (2.1) has the pattern that growth theory predicts: investment, the size of the work force, and the amount of capital per worker all contribute significantly to the income level. Contrary to what one would expect, social spending does not have a negative impact on income. This is especially surprising since one of the main counterarguments, that spending encourages risk, which should raise incomes, has been accounted for specifically in the model. As a result, the positive and comparatively large coefficient on social spending reflects other ways that social spending encourages higher incomes. Whatever these forces are, they seem to dominate the deadweight costs of the Welfare State. This finding is consistent with Lindert's (1996) results. In general, there seems to be no evidence in the country-level historical record that increases in the size of the Welfare State cause declines in income levels. Another finding of interest in the income equation is the weak negative effect of the gini coefficient; a large literature exists to explore the impact of inequality on income, but there seems to be little evidence here that inequality has a significant impact on the income level. Perhaps the gini effect is small simply because it is such a noisy variable (but see Table 6 below).

The income equation contains the first piece of evidence against the insurance motive of social spending. That theory requires that society can increase the income level by increasing the risk level, but the risk coefficient in the income equation, while positive and reasonably large, is not statistically significant. It will be seen in later tables that the size and sign of the coefficient is not stable; one could not conclude that the evidence supports the idea that risk raises incomes. On the other hand, the risk equation itself (2.2) provides some evidence in support of the insurance motivation, in that social spending does seem to encourage risk taking (beta = .043). It will be seen that the sign is reasonably robust to variations in method, but the size and statistical significance is not. Again, the evidence is only weak. The fact that income has a negative, large, and statistically significant effect on risk taking indicates an increasing relative risk aversion, since the risk variable is defined relative to the income level (see the preceding section). Overall, however, there is more instability in the risk equation than in the others ($R^2 = 0.1721$), evidence that none of the various approaches to estimating risk produce a particularly noise-free estimate. The variance of aggregate income time series seems to be intangible. In the spending equation (2.3), the insurance motive again receives weak support. Risk leads to an increase in social spending, and the effect is large (beta = 0.666). Still, the coefficient is not statistically significant and not particularly robust to variations.

The social spending equation allows a number of motives to be tested. Most theories of the Welfare State predict that income will raise spending, and it does seem to have a powerful positive effect (beta = 0.379). The demographics of recipient populations, such as the aged and unemployed, should increase spending, and this is the case. These two coefficients are universally large, positive, and statistically significant throughout. Conversely, indicators of social stress such as strikes (beta = -0.290) and turnout (beta = -0.051), as well as left vote shares (beta = -0.041) are small and have unintuitive signs. The signs vary, but the coefficients only rarely appear to be large or statistically significant.[8]

As for anti-poverty motives for total social spending, the evidence seems to argue against it: the coefficient on the gini is large, negative, and statistically significant throughout virtually all the results. This runs directly counter to the view that social spending is mainly driven by a desire to help the poor. Infant mortality has a positive but not large or statistically significant impact, and is not robust. As already mentioned, left voting has a negative impact. While some of this evidence could be considered only inconclusive, the general trend seems to argue against compassion for the poor as a main motive for social spending.

Table 3 repeats the estimation using the income growth rate in place of the income level in the income equation. From a welfarist perspective, it would seem that the income level, which determines utility, would be of greater interest than the growth rate, which has only indirect implications for well-being. Still, most of the literature focuses on income growth rather than levels, so this table is included to allow comparison to the literature. Most of the patterns from Table 2 are repeated, in particular those of greatest interest here, in the social spending equation. One difference there is that growth has a negative impact on spending. This is consistent with a convergence theory of growth: the smaller the country, the higher the growth rate. Hence if social spending is lower in poorer countries (see Table 2), then it should be lower where growth rates are highest. Another difference worth noting is in the growth equation, where now social spending apparently deters growth (beta = -0.188). This is again conceivable through a convergence theory: social spending makes countries richer (Table 2) but richer countries do not grow as quickly. Setting aside the convergence idea, however, the question of whether or not the Welfare State imposes a significant drag on the economy depends on one's object of interest: well-being or development. It seems to raise well-being but slow the rate of development. (The result is robust across multiple variations in methods, not shown.) Note, however, that the gini coefficient has no noticeable impact on growth or the income level, and in both tables the gini reduces social spending as well. This pat-

[8] The political literature (Flora and Heidenheimer, 1981; Hicks and Misra, 1993) actually has not been able to establish clearly that left governments have a larger effect on social spending.

Table 3

Growth regression results

	Dependent Variables					
Independent Variables	1. Income		2. Risk		3. Social Spending	
	beta	s.e.	beta	s.e.	beta	s.e.
Growth	–	–	.028	.022	-.453	*.066
Risk	.096	.329	–	–	.545	.472
Social Spending	-.188	*.070	.024	.033	–	–
Investment	.150	*.078	–	–	–	–
Inflation	-.294	*.038	.035	*.013	-.162	*.044
Unemployment	.007	.128	.023	.026	.291	*.085
Aged	–	–	–	–	.871	*.189
Trade	.064	*.020	-9.3e-4	.004	.070	*.020
Union	.089	*.017	-.003	.007	.044	.034
Gini	.002	.017	.008	.006	-.089	*.037
Workers	.077	.082	–	–	–	–
Capital	-.151	*.036	–	–	–	–
Strikes	-.025	.641	-.074	.249	-.255	.874
FLFPR	–	–	.010	.009	–	–
Kids	–	–	1.949	*1.038	–	–
Mortality	–	–	–	–	.069	.094
Turnout	–	–	–	–	-.028	.039
Military	–	–	–	–	.108	.440
Left	–	–	–	–	-.051	*.024
R^2	.4531		.1225		.7882	
N	344		344		344	

Note: coefficients identified with a '*' are statistically significant at the 90 percent level, two-tailed test. *Source:* Comparative Welfare States data set; Deininger and Squire inequality data.

tern runs counter to that predicted by a set of recent theories on the role of inequality in growth, which argue that inequality discourages growth because it causes social spending, which is a growth deterrent (Persson and Tabellini, 1994, Aghion, Caroli, and Garcia-Penalosa, 1999).[9]

[9] That literature (see Persson and Tabellini, 1994; Aghion, Caroli, and Garcia-Penalosa, 1999) uses a slightly different method, regressing subsequent growth rates on some initial inequality measure in a reduced-form model. That is, the procedure is not to regress social spending on inequality and then growth on social spending, as is done here. Instead, growth is directly regressed on inequality, with the results that inequality at the start of some time period causes lower growth in later years. Here the finding is slightly different: contemporary innovations in inequality have no apparent effect on contemporary innovations in growth, either directly or through the mechanism of social transfer. The difference in methods is probably dictated mostly by a difference in data; the Comparative Welfare States data base allows examination of social spending, but is limited to developed countries, while the Heston-Summers Penn World Tables do not have social spending but allow examination of developing countries.

Tables 4 – 6 return to income in levels and focuses on the social spending equation, with other relevent coefficients included as an addendum at the bottom of the table. Table 4 presents results based on a different approach to estimating risk. In the base case, risk is estimated from a GARCH model on log income, in regression 4.1, it is estimated from a GARCH model on the

Table 4

Variations in risk and income definitions

	Dependent Variable: Social Spending					
Independent Variables	1. Risk calculated from income levels, not logs		2. Permanent income (from GARCH) replaces observed income; risk based on levels, not logs		3. Income in logs, not levels; risk based on log income	
	beta	s.e.	beta	s.e.	beta	s.e.
Income	.174	.150	.400	*.155	5.676	*1.402
Risk	-.662	.453	-.500	.439	.793	.486
Inflation	-.022	.041	-.029	.041	-.039	.042
Unemployment	.377	*.103	.384	*.101	.370	*.103
Aged	.870	*.247	.675	*.265	.702	*.223
Trade	.049	*.029	.053	*.027	.050	*.029
Union	.030	.038	.038	.037	.028	.035
Gini	-.096	*.042	-.089	*.040	-.102	*.041
Strikes	-.624	.882	-.558	.845	-.365	.828
Mortality	.103	.114	.133	.108	.141	.116
Turnout	-.053	.042	-.046	.042	-.057	.039
Military	.369	.505	.362	.505	.305	.486
Left	-.040	.032	-.039	.031	-.034	.029
R^2	0.7534		0.7597		0.7590	
N	344		344		344	
Addendum: Coefficient on risk in income equation	-.668	*.341	-.470	.316	-.016	.027
Coefficient on social spending in income equation	.122	*.074	.161	*.064	.017	*.008
Coefficient on social spending in risk equation	.021	.018	.028	.022	.041	.026

Note: coefficients identified with a '*' are statistically significant at the 90 percent level, two-tailed test. *Source:* Comparative Welfare States data set; Deininger and Squire inequality data.

Table 5

Variations in risk and social spending definitions

	Dependent Variable: Social Spending					
Independent Variables	1. Risk defined as squared deviations from trend of log income (no GARCH)		2. Social spending defined as spending per capita (not relative to GDP), in 000		3. Social spending defined as non-health social spending relative to GDP	
	beta	s.e.	beta	s.e.	beta	s.e.
Income	.310	*.162	.218	*.047	.453	.305
Risk	.152	.198	.142	*.046	.515	.349
Inflation	-.032	.042	-.011	.009	-.041	.048
Unemployment	.339	*.110	.052	*.002	.497	*.160
Aged	.728	*.247	.171	*.062	.983	*.416
Trade	.056	*.027	.007	.004	.066	*.035
Union	.007	.045	.011	*.007	.094	*.051
Gini	-.102	*.040	-.023	*.007	-.159	*.049
Strikes	-.200	.824	.343	*.122	2.000	*.756
Mortality	.039	.110	.026	.022	.223	*.133
Turnout	-.052	.047	-.003	.010	-.036	.048
Military	.492	.496	-.041	.069	.233	.452
Left	-.043	.032	.004	.008	-.023	.063
R^2	0.7391		0.8345		0.6787	
N	319		311		311	
Addendum: Coefficient on risk in income equation	.030	.106	.118	.184	.317	.291
Coefficient on social spending in income equation	.168	*.092	1.2e-3	*3.9e-4	10.415	6.981
Coefficient on social spending in risk equation	.047	.066	1.9e-3	*8.4e-4	1.36	1.30

Note: coefficients identified with a '*' are statistically significant at the 90 percent level, two-tailed test. *Source:* Comparative Welfare States data set; Deininger and Squire inequality data.

income level, and then expressed as a fraction of income. There is no substantial change in the social spending pattern, but risk now has a large, negative, and statistically significant impact on income, a direct contradiction of the insurance motive. In regression 4.2, the GARCH model is used to predict a level of permanent income and this is used as the income measure (i.e. p_t instead of y_t). Again there is no major impact on the patterns. In

Table 6

Variations in regression structure

	Dependent Variable: Social Spending					
Independent Variables	1. Gini endogenous and instrumented		2. No fixed effects		3. No fixed effects, no instruments, no endogeneity	
	beta	s.e.	beta	s.e.	beta	s.e.
Income	.304	*.157	.359	*.189	.265	*.077
Risk	.571	.501	-.751	.851	-.066	.348
Inflation	-.018	.038	.016	.050	.006	.035
Unemployment	.386	*.109	.303	*.122	.292	*.051
Aged	.936	*.282	.718	*.315	.927	*.074
Trade	.042	.035	.101	*.035	.084	*.007
Union	.020	.038	-.129	*.047	-.131	*.012
Gini	-.124	*.047	-.006	.059	.024	.022
Strikes	-.618	.819	-.596	1.312	-.626	.611
Mortality	.126	.107	-.008	.117	-.022	.044
Turnout	-.056	.039	.055	.052	.065	*.016
Military	.420	.499	-.544	.358	-.414	*.117
Left	-.050	.030	.142	*.041	.087	*.019
R^2	0.7477		0.7388		0.7123	
N	320		378		461	
Addendum: Coefficient on risk in income equation	.170	.283	.063	.556	-.424	*.195
Coefficient on social spending in income equation	.147	*.076	.127	*.071	.061	*.022
Coefficient on social spending in risk equation	.037	.022	-.019	.015	-.013	*.006

Note: coefficients identified with a '*' are statistically significant at the 90 percent level, two-tailed test. *Source:* Comparative Welfare States data set; Deininger and Squire inequality data.

regression 4.3, $\log(y_t)$ replaces y_t as the income variable, again without major effects. In results not shown, regressions were run with various measures of income growth as the dependent variable in the income equation, again without any significant impact on the basic patterns. The results do not seem sensitive to the treatment of income.

Table 5 shows some variations on the definition of risk and social spending. Regression 5.1 abandons the GARCH model and estimates risk simply as squared deviations of log income around its time trend. This preserves the positive and statistically insignificant impact of risk on income in the income equation, but has little impact on the social spending equation. Regression 5.2 expresses social spending as a per capita figure, in thousands of real $US. Risk and strikes have a statistically significant and positive impact on spending under this definition, while the other effects are the same. Regression 5.3 expresses social spending as the share of non-health social spending in GDP. In this definition, strikes again have a positive impact and it is very large. Oddly, focusing on non-health social spending also makes infant mortality a positive motive for the Welfare State.

Table 6 presents the results of more radical changes in the regression structure. First, one might argue that the level of inequality should be treated as endogenous. Also, the gini used here is derived from multiple studies using many methods, and is probably distorted by measurement error (although this would only affect the size, not the sign). Both problems require that the gini be instrumented. Regression 6.1 shows, however, that instrumenting the gini variable has no significant effect on its sign or magnitude, and it remains statistically significant. The negative impact of inequality on social spending seems to be both robust and causal in these data.

Regression 6.2 explores the impact of ignoring the presence of fixed effects, and regression 6.3 also ignores the endogeneity of any variables (except the dependent variable) and abandons instrumenting. Here risk actually has a negative impact on social spending, although the effect is not statistically significant. Openness of the economy (Trade) seems to increase social spending while unionization decreases it. Interestingly, left voting here does increase social spending, which suggests that the common assumption that left parties support the Welfare State has its basis in the historical record prior to 1960 (i.e. the pattern of historical cross-country norms). The results in other tables suggest that this historical pattern is no longer valid. Other than this, the results are largely the same as in the other regressions.

Considering all the regressions as a whole (and others not shown), the most robust findings are:

- Social spending rises with income
- Social spending rises with size of the aged and unemployed populations
- Social spending falls with level of inequality

Weaker results include:

- Social spending increases risk taking
- Risk increases social spending

- Left voting, strikes, military spending, turnout, and infant mortality have little apparent effect
- There is no consistent effect of risk-taking on the income level, and only a small, statistically insignificant effect of social spending on risk-taking.

6. Conclusion

The most robust results thus support the idea that demographics, more than anything, drive social spending. Sinn's insurance motive receives some support but it is only weak, while inequality, per se, does not have a strong influence.

Future research could focus on two aspects of these results. First, the fact that social spending seems unrelated to poverty and inequality is itself surprising. Certainly, better data and better theories are needed to explain this counterintuitive, yet robust, outcome. Second, it is surprising that the results offer only weak support for the insurance motive. That may lie at the hands of the risk estimates, which seem to be noisy. Still, many different approaches were taken to measuring the variance of the income process, and none yielded tight estimates or robust regression coefficients. It would be ideal to develop a country panel data set with individual-level risk estimates.

From a broader perspective, we might need to rethink what people view as "income risk." As researchers we tend to focus on risk as an observable component of the income process, the second moment of income. It is not clear that average people view their risks in such a manner, however, and it is their perceptions, and not our estimates, which affect behavior. To what extent does the second moment of income in a well-specified rational agent model of income determination accurately reflect the perceptions of income variability among real people? Since all estimates of income variance begin with the problematic expected utility model, we might not be surprised to find that our estimates of individually-perceived risk are unrealistic. These issues are similar to those that confront policy analysts attempting to design policies for handling environmental and workplace risk. It is not clear where risk perceptions come from, but they do not seem to come from a rational-actor expected utility model. The implication here is that large populations of aged and unemployed people, instead of the variance of income, might be the effective indicator of perceived income risk in the population. Whatever the true variance of his income, the citizen sees bread lines and imagines himself in them, and then votes for increases in social spending. This may or may not be a rational way to estimate the risk of poverty, but it may be the way real people do it. If so (and this would be a good avenue for more work), the results here could be said to support the insurance theory as much as any other.

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