Unemployment: Where Does It Hurt?

Liliana Winkelmann and Rainer Winkelmann

Department of Economics

University of Canterbury

Christchurch, New Zealand

Abstract

We investigate how individual well-being is affected by unemployment. Analyzing German panel data on life-satisfaction, we find that unemployment has a large and negative effect for male individuals. The effect is large enough to increase the probability that a mid-aged male is dissatisfied by more than 10 percentage points. We decompose the total well-being costs of unemployment and find that for males at least two thirds are non-pecuniary while at most one third are pecuniary costs. One implication is that the benefits of employment generating policies exceed the benefits of policies that are designed to mitigate the effects of unemployment through income transfers.

[1] This research was supported by *The German Marshall Fund of the United States*. We thank Andrew Oswald, Art Goldsmith and two anonymous referees for helpful comments.

[2] Fax: (64 3) 364 2635, e-mail: r.winkelmann@econ.canterbury.ac.nz

1 Introduction

The growing concern about the extent of joblessness in advanced Western economies is fueled by the perception that the social costs of unemployment substantially exceed the costs of an economy operating below its potential. Rather, it is acknowledged that unemployment imposes an additional burden on the individual, a burden that might be referred to as the "psychological costs" of unemployment. Employment, by contrast, not only generates income but also provides non-pecuniary benefits, benefits that according to Sen (1975) stem from the "recognition aspect of employment". A lack of employment deprives individuals of this recognition effect.

If large non-pecuniary costs of unemployment exist, several well-established propositions need to be reconsidered. Firstly, the "natural" rate approach to unemployment clearly understates the usefulness of economic policies that are targeted at a reduction of unemployment. Darity and Goldsmith (1995) show how psychological cost can lead to hysteresis and changes in the "natural" rate itself. Secondly, critics of the welfare state might overestimate the extent to which generous unemployment assistance programs generate unemployment by increasing reservation wages. Thirdly, employment generating programs are clearly superior to unemployment assistance programs.

Whether or not non-pecuniary costs of unemployment exist, and how large they are, are mainly empirical questions. Previous empirical evidence is concentrated in the psychological literature with some scattered contributions in the economics literature. Researchers have studied the link between unemployment and mortality (Junankar 1987, 1991), unemployment and divorce rates (Sander 1992), unemployment and crime (Junankar, 1987), unemployment and mental illness (Björklund 1985), and unemployment and mental distress (Clark and Oswald 1994). Clark and Oswald (1994) use the first wave of the British Household Panel Survey (BHPS), which provides information on 'mental distress scores'. They find a strong positive effect of joblessness on mental distress and interpret this as evidence against the voluntariness postulate of unemployment. Buck et al. (1994) use the first two waves of the BHPS to provide descriptive evidence on the association between changes in labor market status and changes in happiness and mental distress. A positive link between unemployment and mental illness has also been found by Björklund (1985) who uses Swedish panel data. Björklund does not control for income effects while Clark and Oswald find no significant income effect.

The presence of life-satisfaction data in many recent household surveys suggests an alternative possibility for an operational measurement of the cost of unemployment. The use of such data in economic analyses, though still controversial, has been first advocated in Easterlin (1974, 1994). In his "Does economic growth improve the human lot?" Easterlin challenges the presumption that enhanced material welfare necessitates in enhanced social welfare. He measures the latter through individual statements on satisfaction levels. His data cover 19 countries with divergent levels and distributions of income during the period 1946-1970. Easterlin's work is as much a demonstration of the problems involved in handling such type of data, as it is an examination of the association between income and satisfaction.

We use similar data on individual life-satisfaction to assess the cost of unemployment. We are able to control for income and thereby isolate the non-pecuniary cost of unemployment. The data come from the *German Socio-Economic Panel*, a German longitudinal micro dataset for a representative sample of the working age population. We exploit the panel structure of the data to control for individual specific unobserved effects that are constant over time. The original responses are given on an ordinal scale between 0 and 10, suggesting the use of an ordered probit model. Since appropriate panel models for ordinal data are yet to be developed, we collapse the information into a satisfied-dissatisfied dichotomy. We estimate both a random effects probit model as suggested in Butler and Moffitt (1982) and a fixed effect logit model (Chamberlain, 1980). The results establish that the non-pecuniary costs are substantial and well above the pecuniary costs of unemployment. The effect of unemployment on satisfaction substantially differs between men and women.

2 Data

The paper uses data from the German Socio-Economic Panel. The empirical analysis on the determinants on individuals' subjective well-being is based on the response to the question

How satisfied are you at present with your life as a whole?

which is given on an ordinal scale from 0 to 10, where 0 means "completely dissatisfied" and 10 means "completely satisfied". We use these answers to
a) test whether unemployed individuals are satisfied or dissatisfied relative to individuals out of the labor force and employed individuals, and
b) establish the size of the non-pecuniary costs of unemployment relative to the pecuniary costs.

Easterlin (1974) gives an account of some of the measurement issues arising for such self-reported satisfaction data (see also Freeman (1978) who provides another early economic analysis of subjective response data). For instance, individuals might "anchor" their scale at different levels, making the inter-personal comparison of responses meaningless. This problem bears close resemblance to the issue of cardinal versus ordinal utility. Any statistic that is calculated from a cross-section of individuals, e.g. an average satisfaction, or an OLS regression coefficient, requires cardinality of the measurement scale. In contrast, using the information provided through variations in individual satisfaction over time avoids this assumption and only requires a time-invariant ordering scheme.

A second potential problem is that the observed negative correlation between, say, poor health, divorce, or unemployment, and satisfaction might arise since inherently dissatisfied individuals are more susceptible to health problems and are less desirable both as spouses and employees. In other words, the correlation might reflect an inverse causation. In fact, satisfaction variables have been repeatedly used as explanatory factors for variables such as turnover (Freeman, 1978, Akerloff, Rose, and Yellen, 1988) and worker absenteeism (Clegg, 1983).

The advantage of longitudinal data is that they can provide insight into the direction of causation. If the same individual is observed over time, and if a discrete drop in satisfaction is observed during an unemployment episode, we interpret this as evidence that the causation runs from unemployment to satisfaction. The identifying assumption is that while individuals differ in their propensities to see themselves as satisfied, this inherent satisfaction does not vary over time. The beneficial aspects of longitudinal data on life-satisfaction have previously been recognized in the psychological literature (see Warr, Jackson and Banks, 1988, for a survey). Here, we use them to answer some economic questions. In addition, the number of observations available for our analysis exceeds the sample sizes of most of the earlier studies. As a result, the effects can be estimated with greater precision.

The data come from the first six waves (1984-1989) of the German Socio-Economic Panel. The dataset provides repeated measurements on various socio-economic and demographic characteristics for a pool of (initially) about 10.000 individuals. The subsample used in this analysis has the following structure. The period of analysis is 1985-1989. Data from 1984 are used to allow for dynamic effects. Since the focus is on changes in labor market status and satisfaction, individuals above the age of 65 are excluded. Some records are deleted due to missing values for one or more variables needed in the analysis, in most cases the income measure. Finally, the analysis uses a balanced panel, that is, only individuals with a complete survey presence are included.

The resulting sample has 24,055 observations. The average response to the satisfaction question in the final sample is 7.22 and coincides with the average response in the complete dataset. However, the final sample displays a lower incidence of unemployment (6.8 percent, based on 15,231 labor force observations) than does the complete dataset (8.7 percent, based on 33,138 observations). This difference may have been caused by a higher attrition among the unemployed in combination with the requirement for a balanced panel. No attempts have been made to correct for the attrition. One may suspect that individuals most adversely affected by unemployment are those least likely to be included in the sample, leading to a bias towards zero in the estimates of the negative effects of unemployment on satisfaction. In the following, the results have to be interpreted conditional on the sample selection.

Table 1 tabulates the relative frequencies of the answers to the satisfaction question for the year 1984. The frequency distribution is skewed to the right with a mean response of 7.4 and a modal response of 8. The middle response 5 exhibits a local mode, which might reflect a focal choice for those individuals who perceive themselves as neither particularly satisfied nor particularly dissatisfied. Accordingly, we classify individuals with responses 4 or below as having "low" satisfaction, or being "dissatisfied". The proportion of individuals with low satisfaction in the 1984 wave is 7.6 percent. The first two rows of Table 2 show that the average satisfaction slightly drops (from 7.4 to 7.1) during the five year period 1985-1989. Also, the proportion of individuals with low satisfaction increases by around one percentage point.

To approach the question of how changes in individual satisfaction are related to labor market status, we start with some cross tabulations. Table 2 gives the mean satisfaction and the proportion of individuals with low satisfaction by current labor market status for a given year. The states are *employment* (which is full-time employment excluding self-employment), *unemployment*, and *out of labor force*. The following pattern emerges: *employment* is associated with the highest (though falling) average satisfaction levels in all the years, closely followed by *out of labor force*. *Unemployment*, by contrast, is associated with much lower satisfaction levels varying around 6.1.

Comparing the percentage of individuals with low satisfaction for the various labor market states, we find that between 5 and 6 percent of the employed, 7 and 10 percent of the non-participants, but between 18 and 21 percent of the unemployed report a low satisfaction. In other words, a randomly selected unemployed person is much more likely to have a low satisfaction than a randomly selected employee or non-participant. The overall evidence suggests

a) that a persistent satisfaction gap for the unemployed exists, confirming the results from previous research using different data sources, and

b) that it is not 'joblessness' that lowers individuals' satisfaction, but unemployment rather than non-participation.

Next, we consider the argument of inverse causation: individuals experience unemployment because they are dissatisfied. In Table 2, we report satisfaction levels for those employed individuals that are unemployed in at least one of the other years. These employed individuals have a slightly lower satisfaction than the average employee. One explanation might be that these individuals have insecured jobs and their fear of potential job-losses reduces their satisfaction. Alternatively, they might have an intrinsically lower satisfaction. Whatever the cause, the effect is small compared to the drop that is experienced by those individuals who actually become unemployed. For instance, the average satisfaction of individuals who later will become unemployed is 7.0 in 1989, as compared to an average satisfaction of 7.2 of all the employed. The average satisfaction of the unemployed, however, is 6.1 . As a preliminary conclusion, unemployed individuals might be intrinsically dissatisfied to some extent but this effect is dominated by the drop in satisfaction that is caused by the actual experience of unemployment.

Table 3 gives corroborating evidence. It shows by how much the average satisfaction response changes as individuals change their labor force status. For males, changing from paid employment to unemployment causes a drop in satisfaction of -0.791. Conversely, the satisfaction of those, who were unemployed in the last period and become re-employed increases by 0.893. This evidence goes against the view that individuals who were already dissatisfied are those who become unemployed. Furthermore, Table 3 records little variation in satisfaction for those who do not change their labor force status. Dropping out of the labor force has adverse effects as well. However, the drop in satisfaction is of smaller magnitude (-0.469). For women, we again find an adverse effect of becoming unemployed. However, the distinction between "unemployment" and "out-of-labor force" is less clear. For instance, the satisfaction increases more for women who change from non-participation to paid work than for those who change from unemployment to paid work. The change from employment to unemployment is associated with a large drop (-0.820) in satisfaction.

We discern two main channels through which unemployment causes this drop in satisfaction. Firstly, unemployment is associated with an income loss, the size of which depends on various factors such as previous income, family status, unemployment duration and the like. For Germany, estimates of this income loss range from 40 to 50 percent of the pre-unemployment income. Secondly, unemployment creates non-pecuniary costs since it deprives the individual of the social rewards of employment.

To assess the relative magnitude of these two potential channels, we turn to a multiple regression analysis, where we control for the pecuniary aspects using a measure of (the log of) household income that includes all types of government transfers and is net of taxes, that is, disposable income. Our main interest is to test whether or not there is a specific negative effect of unemployment on well-being after controlling for the associated income loss as well as other effects.

3 Model Specification

3.1 Econometric Model

We consider the following specification of an underlying latent model.

$$S^*_{it} = x'_{it}\beta + \varepsilon_{it} \tag{1}$$

where

$$\varepsilon_{it} = v_i + u_{it} \qquad i = 1, \dots, N\,,\ t = 1, \dots, T$$

S^*_{it} is a continuous but unobserved index of satisfaction of individual i in period t. x_{it} is a vector of explanatory variables and v_i is an idiosyncratic unobserved error component which accounts for all the inter-individual differences in scaling and anchoring of the responses, as long as these differences are constant over time. In our applications, N will be between two and three thousands, while $T = 5$.

To estimate the above model using linear panel methods we would need to observe S^*_{it}. Instead, we only observe the ordered responses $S_{it} = 0, \dots, 10$, where we assume that

$$S_{it} = \begin{cases} 0 & \text{if} \quad S^*_{it} < 0 \\ 1 & \text{if} \quad 0 < S^*_{it} < \alpha_1 \\ \vdots & \qquad \vdots \\ 10 & \text{if} \quad S^*_{it} > \alpha_9 \end{cases}$$

If the $u'_{it}s$ in (1) are independently standard normal (logistic) distributed, and in the absence of individual specific effects v_i, we can estimate β using the standard ordered probit (logit) model. As we have argued above, this assumption is not realistic in the present context since we expect inter-individual differences in scaling of the satisfaction responses as well as other unobserved heterogeneity. If there are fixed individual specific effects v_i, we can estimate a conditional model by including $N-1$ indicator variables. However, if N is large and T is small, this approach will be computationally infeasible. Also, in contrast to the linear model, it will not be possible to eliminate the individual specific fixed effects through differencing. Alternative random effects estimators are currently under development (See Crouchley, 1995).

As a practical alternative we reduce the response scale to a satisfied–dissatisfied dichotomy. If individuals with a response of 5 or higher are classified as "satisfied" ($\mathcal{S}=1$), the relation between S^*_{it} and the observed outcome simplifies to

$$\mathcal{S}_{it} = \begin{cases} 0 & \text{if} \quad S^*_{it} - \alpha_4 < 0 \\ 1 & \text{else} \end{cases} \tag{2}$$

It can be shown that the resulting binary probit (or logit, if we assume that u_{it} is logistic distributed) estimator for β is consistent, a result that does not depend on the choice of the breaking point (Crouchley, 1995). We experimented with different breaking points ($\mathcal{S}_{it}=1$ if $S_{it}>4,..>5,\ldots$) and the results were remarkably robust. In the following we always refer to specification (2). While the binary variable approach does not use the available information efficiently, it enables us to make use of a relatively well developed class of limited dependent variable panel models. We will present estimation results under two alternative assumptions.

3.1.1 $u'_{it}s$ are independently logistic and v_i is a fixed effect.

In this case,

$$P(\mathcal{S}_{it}=1|x_{it},v_i) = \frac{\exp(x'_{it}\beta + v_i)}{1+\exp(x'_{it}\beta + v_i)} \tag{3}$$

Chamberlain (1980, 1984) shows that such a fixed effect logit model can be estimated by conditional maximum likelihood. In particular, the probability of a particular sequence

$(\mathcal{S}_{i1}, \ldots, \mathcal{S}_{iT})$ conditional on s_i where $s_i = \sum_{t=1}^{T} s_{it}$ is given by

$$P(\mathcal{S}_{it}, \ldots, \mathcal{S}_{iT} | x_{i1}, \ldots, x_{iT}, v_i, s_i) = \frac{\prod_{t=1}^{T} \exp(x_{it}' \beta \mathcal{S}_{it})}{\sum_{d \in D_i} \prod_{t=1}^{T} \exp(x_{it}' \beta d_t)} \tag{4}$$

D_i is the set of $\binom{T}{s_i}$ combinations of s_i ones and $T - s_i$ zeros. For instance, if $T = 3$ and $s_i = 1$, $D_i = \{(1,0,0), (0,1,0), (0,0,1)\}$. First, consider the unconditional probability $P(1,0,0)$. Assuming independence given v_i, we have

$$P(1,0,0|x_i) = \left(\frac{\exp(x_{i1}'\beta + v_i)}{1 + \exp(x_{i1}'\beta + v_i)} \right) \left(\frac{1}{1 + \exp(x_{i2}'\beta + v_i)} \right) \left(\frac{1}{1 + \exp(x_{i3}'\beta + v_i)} \right)$$

This probability clearly depends on the individual specific effects. However,

$$\begin{aligned} P(1,0,0|x_i, s_i = 1) &= \frac{P(1,0,0)}{P(1,0,0) + P(0,1,0) + P(0,0,1)} \\ &= \frac{\exp(x_{i1}'\beta)}{\exp(x_{i1}'\beta) + \exp(x_{i2}'\beta) + \exp(x_{i3}'\beta)} \end{aligned}$$

Thus, conditioning on the number of successes for individual i lets the individual fixed effects drop out. Note that $P(1,1,1|s) = P(0,0,0|s) = 1$. Hence, observations without variation in the satisfaction status over time will not contribute to the likelihood function.

There are two main drawbacks to the conditional maximum likelihood approach. First, it relies on the assumption that the $\mathcal{S}_{it}$ are independent conditional on x_{it} and v_i. Second, it does not allow for direct probability statements. The probability that an individual i is satisfied in period t is given in (3) and depends on v_i which is not estimated by the model. One possible interpretation is in terms of the log odds:

$$\log \frac{P(\mathcal{S}_{it} = 1 | x_{it}, v_i)}{P(\mathcal{S}_{it} = 0 | x_{it}, v_i)} = x_{it}'\beta + v_i \tag{5}$$

Hence, β measures the change in log-odds induced by a small change in x_{it}. A further disadvantage is that no time-invariant covariates can be included.

In order to test for fixed individual effect one can perform a Hausman-type test based on the difference between the above conditional MLE and the usual logit MLE ignoring the individual effects (where the constant is dropped to compute the statistic). The logit MLE is consistent and efficient only under the null of no individual effect and inconsistent under the alternative. The conditional MLE is consistent whether H_0 is true or not, but it is inefficient under H_0 because it does not use all the data. The test-statistic

$$H = (\hat{\beta}_{\mathrm{CML}} - \hat{\beta}_{\mathrm{ML}})'[\hat{V}_{\mathrm{CML}} - \hat{V}_{\mathrm{ML}}]^{-1}(\hat{\beta}_{\mathrm{CML}} - \hat{\beta}_{\mathrm{ML}}) \tag{6}$$

is asymptotically χ^2 distributed with k degrees of freedom.

3.1.2 $u_{it}'s$ are independently normally distributed and v_i is a random effect.

The error in (1) consists of an individual specific random effect v_i and a contemporaneously and serially uncorrelated error u_{it}. Both v_i and u_{it} are normally distributed with $\mathrm{E}(u_{it}) = \mathrm{E}(v_i) = \mathrm{E}(\varepsilon_{it}) = 0$, $\mathrm{Var}(u_{it}) = \sigma_u^2$ and $\mathrm{Var}(v_i) = \sigma_v^2$. Further, it is assumed that v_i and x_{it} are uncorrelated.

Since $\mathrm{Var}(\varepsilon_{it}) = \sigma_u^2 + \sigma_v^2$, successive disturbances for the same individual are equicorrelated with $\rho = \sigma_v^2/(\sigma_v^2 + \sigma_u^2)$. The joint probability distribution for T observations for individual i is given by

$$P(\mathcal{S}_{it}, \ldots, \mathcal{S}_{iT} | x_{i1}, \ldots, x_{iT}) = \int_{a_{i1}}^{b_{i1}} \ldots \int \phi(\varepsilon_{i1}, \ldots, \varepsilon_{iT}) \mathrm{d}\varepsilon_{iT} \ldots \mathrm{d}\varepsilon_{i1} \tag{7}$$

where $a_{it} = -x_{it}'\beta$ and $b_{it} = \infty$ if $\mathcal{S}_{it} = 1$, and $a_{it} = -\infty$ and $b_{it} = -x_{it}'\beta$ if $\mathcal{S}_{it} = 0$, and ϕ is the standard normal density function.

This T-dimensional integral can be reduced to a single integral by conditioning on v_i. Buttler and Moffitt (1982) propose a computationally feasible approach to evaluate the resulting integral using Gaussian quadrature. Under the hypothesis of no random effect it hold that $\sigma_v^2 = \rho = 0$. Hence, the random effects model can be tested by a simple Wald or likelihood ratio test on ρ. The model is somewhat restrictive since it assumes a very simple covariance structure. Recent developments in simulation estimation that allow for more general covariance structures (See, for instance, Hajivassiliou and Ruud, 1994) are, however, beyond the scope of this analysis.

3.2 Explanatory Variables

In model (2), $P(\mathcal{S}_{it} = 1) = f(x'_{it}\beta)$. The set of explanatory variables x includes a set of dummy variables indicating current labor market status (UNEMP, NOPARTIC, SELFEMP, PARTTIME) with full-time employment as the omitted category. We further control for good health condition (OKHEALTH=1), AGE and AGESQUARED, post-secondary educational attainment (vocational degree (VOCATIONAL D. =1) or university degree (UNIVERSITY D. =1), family status (MARRIED=1), and logarithmic INCOME. The coefficient of log(INCOME) measures the approximate change in $x'_i\beta$ that is caused by a 100 percent increase in income.

For a correct interpretation of the effect of unemployment on satisfaction, several issues have to be addressed first. We will discuss the role of income as an intervening variable, interactive effects, dynamics, and the direction of causation and endogeneity.

3.2.1 Income as an intervening variable

Unemployment usually reduces income which in turn may reduce satisfaction. However, if income is included as a control, the unemployment coefficient in fact measures the specific effect of unemployment *ceteris paribus*, that is, keeping income constant.

This would occur, for instance, if the unemployment insurance replacement ratio was 100 percent. The regression will provide valid estimates despite an empirical negative correlation between unemployment and income, though the estimates will be less precise with increasing correlation.

Individual satisfaction may depend on individual and household income. Individuals are unlikely to be indifferent as to who earns income within the household. If distribution matters, unemployment may lead to a decrease in satisfaction despite the fact that an individuals reduced contribution to household income is made up by other members of the household. While we acknowledge this possibility, data limitations in the German Socio-Economic Panel preclude us from using individual income. In contrast to household income, which refers to the time of the interview, individual income is either restricted to wage income in the previous month or average total income in the previous year. Both measures are not suitable for the present analysis and hence we only use household income.

3.2.2 Interaction with other variables

Interactions allow us to single out differential effects of unemployment on individuals with specific attributes. Both economic theory and previous empirical evidence suggest that such differential effects are constituents of the complex phenomenon of "unemployment", and therefore have to be included to facilitate valid conclusions.

One of the interactions identified in the literature is between unemployment and age. Clark and Oswald (1994) find that there is a U-shaped relationship between the psychological damage of unemployment and age with a minimum mental well-being for those aged 30-49. As Clark and Oswald point out, young people may worry less about unemployment because they recognize that it happens more to people like them. Also, young people may perceive unemployment as a transitory experience associated with labor market entry. Another important interaction is between unemployment and the length of the current unemployment spell (UNEMPDUR). The importance of the duration of unemployment on the mental state of the individual is well documented in the psychological literature. For instance, Harrison (1976) distinguishes the sequential stages of shock–optimism–pessimism–fatalism during a period of unemployment. On the other hand Easterlin suggests that individuals get used to everything in the long run, so that unemployment should hurt more in the short run (See Easterlin, 1974, and the criticism in Veenhoven, 1990). The overall direction of the effect is an empirical matter. To allow for potential non-linearities, we also included the squared unemployment duration (UNEMPDURSQ).

A further interesting interaction is between unemployment and the local unemployment rate. The higher the local unemployment rate, the lower the chances of becoming re-employed. On the other hand, the stigmatizing effect of unemployment may in fact be lower in high unemployment regions, increasing individual well being. Unfortunately, we cannot test for this effect since all regional information has been deleted from the public usage version of the German Socio Economic Panel.

A final important differential effect is gender. We run separate regressions split by gender and thereby allow all slope coefficients to differ between females and males. Traditionally, women in the German labor market have had a much weaker attachment to the labor force than men. The participation rate is lower and movements in and out of the labor force are more common. The differences result from the traditional gender specific role where the man is the primary income provider. In particular, the social position of a man is determined to a much higher degree by his employment status, than is the case for a woman. We expect that these differences in social conditioning are reflected in gender differentials in the perception of, and reaction to, unemployment.

3.2.3 Dynamics

The longitudinal structure of the data allows for the inclusion of dynamic elements. While we expect persistence in the individual satisfaction responses over time, we do not include lagged satisfaction as a regressor. It can be shown that the resulting estimator is inconsistent if the errors are serially correlated. In our approach, persistence is incorporated through the individual specific error component. As mentioned above, we include the length of the current unemployment spell. We use retrospective information on the cumulative duration of previous unemployment episodes during the ten-year period 1974-1984 (PREVDUR) to test whether or not unemployment leaves persisting "scars" on individual well-being

As a final dynamic element, we use the relative change in monthly household income from the previous year (CHANGEINC) as an explanatory variable. Since Easterlin's (1974) seminal work, it has been a matter of some controversy whether satisfaction is determined by income levels or income changes. The analysis disentangles these two propositions.

3.2.4 Endogeneity and Inverse Causation

The inverse causation argument says that (intrinsically) less satisfied individuals are more likely to become unemployed. If this is true, unemployment is correlated with the individual specific error in the random effects model and the maximum likelihood estimator is inconsistent. However, the same problem does not arise in the fixed effect model, where we condition on the individual specific effect (See Hsiao, 1986). Since we present results using both specifications, we can assess the robustness of the results with respect to this potential endogeneity.

4 Results

Table 4 shows the results for the ordered probit equations where the dependent variable is the ordered response to the satisfaction question. These regressions do not take into account the panel structure of the data. The data are pooled over the different years and the regressions include time effects. We report results both separately for men and women and for a pooled sample. These regressions are directly comparable to those described in Clark and Oswald (1994) and in Blanchflower, Oswald, and Warr (1993), the latter using a set of independent cross-sections over time. Table 5 gives the result for the random effects probit and fixed effects logit models where the dependent variable is a binary variable indicating whether the individual is satisfied or dissatisfied.

The results confirm our previous findings in the cross tabulations in Section 2, and are consistent with previous evidence based on different data sets and different countries. In particular, the effect of unemployment is negative and well determined. This holds true both for the ordered probit models and for the panel regressions. But is this effect of quantitative significance as well? In non-linear models, the estimated coefficients do not represent marginal effects. Moreover, coefficients are not directly comparable across different specifications. We will use two ways to assess and compare the magnitude of the impact of unemployment on satisfaction.

Firstly, we compute the change in probability of being dissatisfied that is caused by unemployment for an individual with otherwise unchanged average characteristics. In the ordered probit model the predicted probability of dissatisfaction is given by

$$P(\widehat{\mathcal{S}_{it} = 0}) = \Phi(\hat{\alpha}_4 - x'_{it}\hat{\beta}) \tag{8}$$

whereas in the random effects probit model it is given by

$$P(\widehat{\mathcal{S}_{it} = 0}) = 1 - \Phi(x'_{it}\hat{\beta}) \tag{9}$$

(This probability cannot be computed for the fixed effects logit model). Secondly, we compute "compensating income variations", that is, the relative increase in income that is needed to compensate an individual for the drop in satisfaction due to unemployment. Since log(income) and unemployment interact linearly this variation is easy to calculate and independent of other characteristics: if a 100 percent increase of income raises happiness by β_{inc} and unemployment decreases satisfaction by β_{ue}, then the compensating variation is simply given by β_{ue}/β_{inc}. The situation is somewhat complicated by the fact that we include several interactions and the growth rate of income. Typically, we will report the compensating variation for an individual aged 30 to 49 at the start of the unemployment spell (UEDUR=0). Furthermore, we will sum the level and the change effects of income to derive the overall improvement in satisfaction caused by an increased income. Other means of interpreting the coefficients exist. In the order probit case, slope coefficients can be compared to the threshold values. For instance, one may ask whether an effect is strong enough to move the individual from response 6, say, to response 7 or 8. In the conditional logit case, the coefficients can be interpreted as measuring changes in the log-odds caused by changes in x.

Initially, we discuss the results from the ordered probit regressions. The pooled regression can be rejected in favor of the unrestricted regressions that allow for differential slopes for men and women. The test statistic is $\chi^2 = 131.8$. Nevertheless, we discuss the pooled results, since they are directly comparable to the regressions reported in Clark and Oswald. As in Clark and Oswald, the negative effect of unemployment on satisfaction is U-shaped in age. Unemployment is worst for people in the middle of their careers. For this group, the negative effect is larger than the negative effect of bad health. Income has a significantly positive effect when measured in levels, but no effect in changes. In contrast, Clark and Oswald find no significant effect of income, which may be due to the fact that they use a mental distress score as the dependent variable whereas we consider satisfaction.

The income effect is small relative to the unemployment effect. The compensating income variation is 2.15, that is, income would need to increase by more that 200 percent to offset the negative effect of unemployment. Given the problems of the income measure that were discussed above, we take this number only as an indicator of the magnitude of the unemployment effect rather than a point estimate of the actual income compensation needed. The substantial size of the unemployment effect is also evident when alternative metrics are used: unemployment in the middle age group is sufficient to cross threshold values and cause responses to drop by one. The probability of dissatisfaction increases from 6 percent for an employed individual to 15 percent for an otherwise identical unemployed individual. At the same time we find that non-participation has a minor negative impact on satisfaction. Hence, it appears that it is not "non-employment" that matters but unemployment rather than non-participation.

A further results is that satisfaction of the unemployed is U-shaped in the unemployment duration with a minimum at 42 month. Taken at face value, this result complies neither with the shock-optimism-pessimism sequence suggested in Harrison (1976) nor with the Easterlin hypothesis. However, the effect is not statistically significant. The insignificance may be caused by measurement error in this variable since it is based on retrospective calendar information for the previous year. As in Clark and Oswald (1994) we find that satisfaction is U-shaped in age. This effect is well determined and robust across specifications (except for the fixed effect logit, where the effect cannot be picked up properly). The minimum is around the age of 40. We take this as an empirical regularity without attempting to offer an economic explanation. We find that both marriage and post-graduate degrees contribute to increased satisfaction levels, though the magnitude of these effects is a fraction of the unemployment effects. Finally, we notice that satisfaction is subject to a negative trend over the five year period. This trend, which has been apparent in the raw tabulations in Table 2, thus persists after controlling for various socio-economic characteristics.

Splitting up the sample by sex, we find evidence for large differential effects of labor market status. Reporting only pooled results like in Clark and Oswald (1994) may be quite misleading. The main difference is that men are much more affected by unemployment. For instance, for a mid-aged male, the effect of unemployment is -0.65, as compared to -0.29 for a mid-aged female. This translates to an increase in the probability of dissatisfaction of 12 percentage points for male, but only 4 percentage points for female. In fact, for females aged 50 or over, unemployment has no significant negative effect at all. In addition, males are negatively affected by non-participation, whereas women are not, and women have a larger estimated increase in satisfaction from a given increase in income. The other coefficients are quite similar across gender. Overall, we conclude from the ordered probit regressions that there is substantial evidence for a detrimental effect of unemployment on satisfaction, in particular for men.

We obtain the same result when we allow for individual specific effects and employ panel techniques. The regression results are given in Table 5. We report results for the random effects probit and the fixed effects logit separated by sex. Note that in the fixed effect logit, all time invariant regressors are excluded. Also, the number of individuals is reduced since only cases with variation in the binary satisfaction response over the five years can be included. For both specifications, the homogeneity restriction of no individual specific effects is rejected. In the random effects probit model, the t-value under the hypothesis of no intra-individual correlations of the errors ($\rho = 0$) is 9.6 for males and 10.5 for females. Thus, H_0 is rejected. For the fixed effect logit model, we report the Hausman statistic for a test against the pooled logit model. The test-statistics of 59.6 for males and 63.7 for females are significantly greater than χ^2-critical values at any significance level. As expected, we find evidence for individual specific unobserved heterogeneity in the satisfaction responses.

However, allowing for such effect does not substantially alter the conclusions. For the ordered probit estimations, unemployment is the single most important source of dissatisfaction. Based on the random effect probit model, unemployment increases the probability of dissatisfaction for a middle aged male by 10 percentage points. The coefficient is twice as large as the coefficient for good health, and the compensating income variation is 2.9 . Based on the conditional logit model, the compensating income variation is 1.2 . Thus, there is considerable variation in the point estimates of the effects. However, in no case does the required offsetting relative increase in income fall below 100 percent. The main difference between the ordered probit and the panel results for male is that the interaction between age and unemployment is insignificant in the latter. In contrast, family status and health have quite similar effects. Overall, the panel estimates have larger estimated standard errors than the pooled ordered probit coefficients. This is due to several factors: the ordered probit model can use more variation in the dependent variable, the individual specific effects take out variation previously attributed to the regressors, and the number of observations is substantially lower in the conditional logit model.

For women, we find the same similarities in the results for the different specifications. Again, the standard errors are larger. Unemployment only hurts women in the 30-49 age group, and non-participation has no detrimental effect at all. Good health is an important and significant contributor to satisfaction, as is marriage and income.

5 Conclusions

Using data on life-satisfaction for 1984 to 1989 from the German Socio-Economic Panel, we perform a multivariate analysis of the determinants of satisfaction. We find that, after controlling for various observed individual characteristics and after exploiting the panel structure of the data to allow for individual specific effects, unemployment has a significant and substantial negative impact on satisfaction. By including income in the regressions, we can decompose the overall cost of unemployment to the individual into a pecuniary and a non-pecuniary part. The pecuniary cost of unemployment depend on the associated reduction in household income. To find an upper bound, assume that the only component of household income is the wage income of the individual. Then, unemployment will reduce income by around 40 percent, or one minus the replacement ratio. On the other hand, the compensating income variation required for men is at least a 100 percent increase in income. If we take this as an estimated lower bound for the non-pecuniary cost of unemployment, we find that at least 100/(40+100)= 71 percent of the total cost of unemployment are non-pecuniary. The pure non-pecuniary effect of unemployment is large enough to increase the probability that a mid-aged male is dissatisfied by more than 10 percentage points.

These costs are expected to be subject to social conditioning and the data exhibit the patterns pointing that out: the non-pecuniary costs are higher for men than for women. One implication of our study is to call for employment generating policies *and for them* rather than for alternative redistributive mechanisms designed to mitigate the (insufficient) income effects of unemployment exclusively.

References

Akerlof, G.A., A.K. Rose, and J.L. Yellen 1988 Job Switching and Job Satisfaction in the U.S. Labor Market, *Brookings Papers on Economic Activity* 2, 495-582.

Blanchflower, D.G., A.J. Oswald and P.B. Warr 1993 Well-Being Over Time in Britain and the USA, Paper presented at the November 1993 Happiness and Fairness Conference. London School of Economics.

Björklund, A. 1985 Unemployment and Mental Health: Some Evidence From Panel Data, *Journal of Human Resources* 10, 469-483.

Buck, N., J. Gershuny, D. Rose and J. Scott 1994 *Changing Households: The BHPS 1990 to 1992* ESCR Research Centre on Micro-Social Change, Essex.

Butler, J.S. and R. Moffitt 1982 A Computationally Efficient Quadrature Procedure for the One Factor Multinomial Probit Model, *Econometrica* 50, 761-764.

Chamberlain, G. 1980 Analysis of Covariance with Qualitative Data, *Review of Economic Studies* 47, 225-238.

Chamberlain, G. 1984 Panel Data in: Z. Griliches and M.D. Intriligator (eds.) *Handbook of Econometrics Vol. II*, Amsterdam: North-Holland.

Clark, A.E. and A.J. Oswald 1994 Unhappiness and Unemployment, *Economic Journal* 104, 648-659.

Clegg, C.W. 1983 Psychology of Employee Lateness, Absence, and Turnover: a Methodological Critique and an Empirical Study. *Journal of Applied Psychology* 68, 88-101.

Crouchley, R. 1995 A Random-Effects Model for Ordered Categorical Data, *Journal of the American Statistical Association* 90, 489-498.

Darity, W. Jr. and A.H. Goldsmith 1995 Social Psychology, Unemployment, and Macroeconomics, forthcoming in: *Journal of Economic Perspectives*.

Easterlin, R.A. 1974 Does Economic Growth Improve the Human Lot? Some Empirical Evidence, in: P.A. David and M.W. Reder (eds.) *Nations and Households in Economic Growth - Essays in Honor of Moses Abramovitz*, Academic Press: New York and London.

Easterlin, R.A. 1994 Will Raising the Income of all Increase the Happiness of All? forthcoming in: *Journal of Economic Behavior and Organization*

Freeman, R.B. 1978 Job Satisfaction as an Economic Variable *American Economic Review* 58 (May), 135-141.

Hajivassiliou, V.A. and P.A. Ruud 1994 Classical Estimation Methods for LDV Models Using Simulation, in: R. F. Engle and D.L.McFadden (eds.) *Handbook of Econometrics Vol. IV*, Amsterdam: North-Holland.

Harrison, R. 1976 The Demoralising Experience of Prolonged Unemployment, *D E Gazette*, 339-348.

Hsiao, C. 1986 *Analysis of Panel Data*, Cambridge University Press, Cambridge.

Junankar, P.N. 1987 *Social Costs of Unemployment* Commission of the European Communities, Luxembourg.

Junankar, P.N. 1991 Unemployment and Mortality in England and Wales: a Preliminary Analysis, *Oxford Economic Papers* 43, 305-320.

Oswald, A.J. 1994 Four Pieces of the Unemployment Puzzle, Paper presented at the annual meeting of the European Association of Labour Economists, Warsaw, 1994.

Sander, W. 1992 Unemployment and Marital Status in Great Britain, *Social Biology* 39, 299-305.

Sen, A. 1975 Employment, Institutions and Technology: Some Policy Issues, *International Labour Review* 112, 45-73.

Warr, P.B., P.R. Jackson, and M. Banks 1988 Unemployment and Mental Health: Some British Studies, *Journal of Social Issues* 44, 47-68.

Table 1. Satisfaction 1984[1]

Value	0	1	2	3	4	5	6	7	8	9	10
N	110	56	107	188	268	1138	784	1467	2390	1233	1832
percent	0.012	0.006	0.011	0.020	0.028	0.119	0.082	0.153	0.250	0.129	0.191

Notes:

[1] 0: completely dissatisfied; 10: completely satisfied.

Table 2. **Average Satisfaction and Proportion of Individuals with Low Satisfaction**[1]

	1985	1986	1987	1988	1989
All					
Average satisfaction	7.362	7.343	7.197	7.133	7.096
Low satisfaction (in %)	0.066	0.062	0.069	0.079	0.080
N	4811	4811	4811	4811	4811
Employed					
Average satisfaction	7.445	7.461	7.305	7.225	7.218
Low satisfaction (in %)	0.053	0.046	0.056	0.063	0.063
N	2919	2892	2855	2778	2748
Unemployed					
Average satisfaction	6.102	6.199	6.096	6.159	6.143
Low satisfaction (in %)	0.212	0.184	0.212	0.195	0.202
N	236	201	208	226	168
Employed with Unemployment Experience					
Average satisfaction	7.367	7.135	7.066	7.145	7.132
Low satisfaction (in %)	0.070	0.068	0.057	0.070	0.061
N	256	266	229	200	212
Out of labor force					
Average satisfaction	7.350	7.251	7.160	7.120	6.981
Low satisfaction (in %)	0.072	0.081	0.080	0.092	0.098
N	1164	1196	1224	1256	1351

[1]Individuals with low satisfaction are those reporting a satisfaction level of 4 or below on the 0-10 scale.

Table 3. Change in labour force status and change in satisfaction

a) MALE (N=10084)

	Labor Force Status in t		
	Employed	Unemployed	No Participation
Labor Force Status in $t-1$			
Employed	-0.063	-0.791	-0.469
	(7880)	(177)	(147)
Unemployed	0.893	0.013	0.369
	(178)	(228)	(65)
No Participation	0.532	-0.800	0.015
	(62)	(25)	(660)

b) FEMALE (N=9160)

	Labor Force Status in t		
	Employed	Unemployed	No Participation
Labor Force Status in $t-1$			
Employed	-0.032	-0.820	-0.122
	(2789)	(100)	(148)
Unemployed	0.183	0.036	0.269
	(60)	(168)	(130)
No Participation	0.292	-0.324	-0.088
	(96)	(68)	(3762)

Notes:

Cell sizes in parentheses.

Data are pooled for the years 1985-1989.

Table 4: Satisfaction Equation; Ordered Probit Model

	Pooled		Male		Female	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Constant	1.661	(0.168)	2.273	(0.246)	1.259	(0.234)
MALE	-0.059	(0.015)				
UNEMP	-0.265	(0.050)	-0.402	(0.063)	-0.118	(0.089)
UNEMP$*$AGE<29	-0.164	(0.078)	-0.321	(0.105)	-0.064	(0.126)
UNEMP$*$AGE30-49	-0.221	(0.065)	-0.245	(0.085)	-0.175	(0.109)
UNEMPDUR	-0.011	(0.007)	-0.003	(0.010)	-0.010	(0.018)
UNEMPDURSQ$*10^{-2}$	0.013	(0.020)	-0.013	(0.028)	0.042	(0.064)
PREVDUR	-0.009	(0.001)	-0.010	(0.001)	-0.008	(0.001)
NOPARTIC	-0.042	(0.018)	-0.273	(0.035)	0.056	(0.024)
SELFEMP	-0.107	(0.033)	-0.087	(0.038)	-0.155	(0.069)
PARTTIME	-0.060	(0.028)	-0.180	(0.129)	-0.001	(0.031)
MARRIED	0.140	(0.017)	0.133	(0.024)	0.110	(0.026)
OKHEALTH	0.428	(0.014)	0.409	(0.021)	0.426	(0.021)
AGE	-0.050	(0.004)	-0.063	(0.006)	-0.049	(0.006)
AGESQ$*10^{-2}$	0.062	(0.005)	0.078	(0.007)	0.062	(0.007)
VOCATIONAL D.	0.083	(0.013)	0.066	(0.019)	0.093	(0.019)
UNIVERSITY D.	0.106	(0.033)	0.086	(0.040)	0.174	(0.059)
LOGINCOME	0.208	(0.017)	0.165	(0.024)	0.253	(0.025)
CHANGEINC	0.018	(0.022)	0.014	(0.030)	0.015	(0.031)
1986	-0.027	(0.020)	-0.018	(0.028)	-0.037	(0.029)
1987	-0.127	(0.020)	-0.104	(0.028)	-0.152	(0.030)
1988	-0.191	(0.020)	-0.175	(0.028)	-0.206	(0.030)
1989	-0.219	(0.021)	-0.178	(0.029)	-0.258	(0.030)
α_1	0.208	(0.021)	0.200	(0.028)	0.220	(0.031)
α_2	0.502	(0.027)	0.499	(0.037)	0.513	(0.040)
α_3	0.865	(0.030)	0.857	(0.041)	0.887	(0.044)
α_4	1.152	(0.031)	1.137	(0.043)	1.183	(0.045)
α_5	1.777	(0.031)	1.759	(0.044)	1.816	(0.047)
α_6	2.111	(0.032)	2.102	(0.044)	2.142	(0.047)
α_7	2.643	(0.032)	2.662	(0.045)	2.648	(0.047)
α_8	3.445	(0.032)	3.496	(0.045)	3.416	(0.048)
α_9	4.000	(0.033)	4.041	(0.046)	3.983	(0.049)
Log-Likelihood	-45803.8		-23747.2		-21990.7	
Log-Likelihood H_0	-46669.2		-24252.8		-22397.4	
Observations	24055		12605		11450	

Table 5: Panel Regressions for Life-Satisfaction[1]

	MALE				FEMALE			
	Random Effects		Fixed Effects		Random Effects		Fixed Effects	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Constant	1.849	(0.682)			-0.160	(0.639)		
UNEMP	-0.849	(0.145)	-1.257	(0.358)	0.003	(0.209)	-0.192	(0.484)
UNEMP∗AGE<29	-0.089	(0.225)	0.115	(0.518)	-0.255	(0.299)	-0.069	(0.641)
UNEMP∗AGE30-49	-0.013	(0.187)	0.368	(0.419)	-0.550	(0.240)	-0.821	(0.548)
UNEMPDUR	-0.026	(0.025)	-0.030	(0.047)	-0.017	(0.039)	0.014	(0.074)
UNEMPDURSQ$*10^{-2}$	0.027	(0.072)	0.109	(0.145)	0.047	(0.144)	-0.022	(0.270)
PREVDUR	-0.011	(0.004)			-0.009	(0.003)		
NOPARTIC	-0.511	(0.084)	-0.287	(0.243)	0.007	(0.069)	-0.180	(0.225)
SELFEMP	-0.185	(0.107)	0.643	(0.418)	-0.057	(0.191)	-0.268	(0.497)
PARTTIME	-0.274	(0.274)	-0.162	(0.554)	0.022	(0.087)	-0.206	(0.241)
MARRIED	0.294	(0.068)	0.575	(0.254)	0.220	(0.074)	0.561	(0.261)
OKHEALTH	0.448	(0.052)	0.409	(0.128)	0.529	(0.053)	0.620	(0.126)
AGE	-0.073	(0.019)	0.009	(0.114)	-0.035	(0.019)	-0.179	(0.108)
AGESQ$*10^{-2}$	0.086	(0.023)	-0.112	(0.131)	0.042	(0.023)	0.066	(0.125)
VOCATIONAL D.	0.098	(0.060)			0.149	(0.063)		
UNIVERSITY D.	0.057	(0.115)			0.280	(0.185)		
LOGINCOME	0.135	(0.068)	0.676	(0.245)	0.278	(0.068)	0.356	(0.233)
CHANGEINC	0.158	(0.072)	0.086	(0.174)	0.159	(0.073)	0.265	(0.160)
ρ	0.382	(0.040)			0.411	(0.039)		
No. of individuals	2521		556		2290		538	
Log-Likelihood	-2751.4		968.8		-2684.6		-944.4	
Log-Likelihood H_0 [2]	-2896.5				-2856.5			
Hausman test			59.6				63.7	

Notes:

[1]Dependent variable is 1 if the individual reports a satisfaction level between 5 and 10 ("satisfied"), and 0 if the individual reports a satisfaction level between 0 and 4 ("dissatisfied").

[2] $H_0 : \beta_1 = \ldots = \beta_k = 0$; This restrictions cannot be imposed in the panel logit model which has no intercept.