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ABSTRACT

Chronic pain clearly lowers utility, but it is empirically challenging to estimate the monetary compensation needed to offset this utility reduction. We use the subjective well-being method to estimate the value of pain relief among individuals age 50 and older. We use a sample of 64,205 observations from 4 waves (2008-2014) of the Health and Retirement Study, a nationally representative individual-level survey data, permitting us to control for individual heterogeneity. Our models, which allow for nonlinear effects in income, show the value of avoiding pain ranging between 56 to 145 USD per day. These results are lower than previously reported, suggesting that the value of pain relief varies by income levels. Thus, previous estimates of the value of pain relief assuming constant monetary compensation for pain across income levels are heavily affected by the highest income level. Furthermore, we find that the value of pain relief increases with pain severity.

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Introduction

Chronic pain clearly lowers utility, but quantifying exactly how much people are willing to trade off pain and income is challenging empirically. We use rigorous econometric methods that avoid the problems of market-based valuation, stated-preference methods, and hedonic wage methods. Instead we use the subjective well-being method, which uses the statistical relationship between subjective well-being and health compared to the relationship between subjective well-being and income. The method has been used extensively in evaluating well-being, but relatively few published applications to health. However, with increased availability of individual longitudinal survey data on subjective well-being and health, it has the potential to improve previous values of health conditions derived from other methods.

The specific aim of this research is to estimate the monetary value of pain relief among individuals age 50 and older, using the subjective well-being method. The obvious aim of pain-relief treatment is to eliminate the welfare reductions associated with pain. Although there may be other benefits, such as productivity gains (Kapteyn, Smith, & van Soesta, 2008), the direct effect on quality-of-life is likely to be extensive and should thus not be overlooked. Monetizing this welfare reduction is needed to choose financing of the treatment with the largest net benefit or to choose between a new pain treatment and welfare-increasing policies in other sectors, for which benefits have been estimated. Pain prevalence is higher in samples of older individuals and chronic pain is associated with psychological distress, functional impairment and disability (Hardt, Jacobsen, Goldberg, Nickel, & Buchwald, 2008; Nahin, 2015).

We contribute to the literature in four ways: First, by analyzing a dataset that is exceptionally well suited for the research question and methods. Specifically, we study detailed, longitudinal individual-level data on a sample for which pain is prevalent and we can control for individual heterogeneity. Second, by exploring the methodology of the subjective well-being method from a new perspective — using models that are more flexible by allowing a piecewise-linear relationship in the income variable. Third, by addressing endogeneity, we also provide results where income is instrumented, because theory and previous research suggests a downward bias in the income variable without instrumentation. Finally, we test the sensitivity of results to the level of pain severity.

We find that the value of pain relief varies by income levels. Previous estimates that assume constant monetary compensation for pain across income levels are probably too high because those are heavily affected by the highest income levels. We thus highlight that the estimated value of pain is sensitive to the functional form of income in subjective well-being equations. In addition to allowing for nonlinear effects in income, including individual fixed effects in our models and instrumenting for income in some estimations allows us to infer that the value of pain relief is lower than previous research suggests. Our findings furthermore suggest that the value of pain relief increases with pain severity.

Conceptual framework

Because health care is generally partially or completely subsidized, the value of medical treatment cannot be inferred simply by observing the behaviors of buyers and sellers in the market. To overcome the lack of revealed preferences when valuing pain we estimate the change in well-being following a change in pain status using a monetary measure from welfare economics: An income-compensated money measure, often referred to as compensating variation (CV) (Hicks, 1939). In particular, CV is the amount of money received by or from an individual that leaves him at his original level of welfare following a welfare change. CVs are calculated under the assumption that the indifference curve represents the constant-utility trade-off between income (consumption) and the non-market good (pain).

The method used in this study relies on survey responses to a subjective well-being question that is taken as a proxy for utility. In line with this literature, we consider the concepts of subjective well-being, utility, happiness, life satisfaction, and welfare as interchangeable. Developments in subjective well-being research (happiness research) over the past four decades are reviewed in Frey and Stutzer (2002), Clark, Frijters and Shields (2008), DiTella and MacCulloch (2006), Becchetti and Pelloni (2013) and Frey, Luechinger, and Stutzer (2010).

Applications of the subjective well-being method to health using cross-sectional data include severe headache and migraine (Groot & van den Brink, 2004), cancer, cardiovascular disease, thyroid disease, arthritis and infectious disease (Rojas, 2009), cardiovascular disease (Groot & van den Brink, 2006, 2007; Groot, van den Brink, & Plug, 2004) and EQ5D conditions, pain and anxiety (Graham, Higuera, & Lora, 2011). Applications that use longitudinal data with fixed-effects (FE) models include chronic diseases (Ferrer-i-Carbonell & van Praag, 2002), 13 health conditions (Powdthavee & van den Berg, 2011), chronic pain (McNamee & Mendolia, 2014) cardiovascular disease (Latif, 2012) and general health status (Brown, 2015). Asgeirsdottir et al. (2017) and Howley (2017) use longitudinal data without FE-models to value 34 and 15 health conditions, the latter controlling for variables that proxy personality traits.

Other methods that have been used for non-market valuations are mainly either contingent valuation, the most widely used of stated preference methods, or the hedonic wage method, a revealed preference approach. The contingent-valuation method remains controversial (Carson, Flores, & Meade, 2001). It is more likely to capture attitudes rather than preferences whereof attitudes are more sensitive to situations, the focusing illusion and to the scale-of-reference bias (Kahneman & Sugden, 2005). Comparison of the hedonic method to the subjective well-being method has revealed that price differentials obtained from the hedonic method (or wage differentials in the case of health risks) may only partly represent the value being estimated (van Praag & Baarsma, 2005). Considering health risks, an example being if physical or emotional transaction costs of changing jobs are high, the value of health would not be reflected in wage differentials. Furthermore, those who take on risky jobs are likely to evaluate their health systematically lower than others. One of the main advantages of the subjective well-being method is that people are not aware that their responses will be used to derive their preferences for health and thus strategic responses are highly unlikely. Furthermore, this method puts less cognitive strain on individuals than the stated-preference method because they do not have to express their choices in imaginary situations, irrelevant of whether they have actually experienced the health condition under study or not.

It is beneficial to develop and use various methods of well-being evaluation so that they can serve as robustness checks to each other to validate results before they are implemented in policy. Comparison of estimates from subjective well-being measures to estimates from the widely used time-trade-off method (TTO) has, for example, revealed that policy implications can differ considerably between the two methods. Dolan and Metcalfe (2012) found that through TTO preferences, being confined to bed is worse than having extreme anxiety but using subjective well-being estimates, showed the opposite.

Although the subjective well-being method is a useful addition and even superior to hypothetical preferences in valuing health, it is not without limitations (Becchetti & Pelloni, 2013; Clark et al., 2008; Luechinger, 2009). Possible biases in the coefficients of interest, specifically income and pain, should be considered. This is due to a possible violation of the zero-conditional-mean assumption; $E(\varepsilon|x) = 0$, where ε is an error term in a regression model and the regressor(s), x thus are correlated with the error term because of a) simultaneous determination of the dependent variable and regressors (or reverse causality), b) omitted variables and c) measurement error in the regressors.

We address these potential biases in the following ways: First, individual fixed effects models are used to control for unobserved time-fixed characteristics. Previous research using

FE-models report a positive personality-traits bias of the income and health coefficient in life-satisfaction models without fixed effects (Ferrer-i-Carbonell & Frijters, 2004; McNamee & Mendolia, 2014). Powdthavee (2010) reviews literature that suggests that extroverts do better in the labor market and are happier. The same characteristics could also be associated with being healthy. Second, by using last year´s reported income to address the possibility of life satisfaction affecting income levels. Third, by analyzing a subsample of 65 years and older, we make use of the proposition that income is plausibly exogenous in retirement as a function of past values of the variables in the model. Finally, we report results from models where income is instrumented with mother´s education, further addressing the endogeneity of income that could cause a downward bias in the point estimate as well as to address possible measurement error. A measurement error in a covariate biases its´ coefficient towards zero, given that possible measurement errors on other regressors are independent (Cameron & Trivedi, 2005). However the use of lagged income to address endogeneity at time *t* is open to objections because of the adaptation argument that the current level of life satisfaction is not independent of income in the previous time periods (Di Tella, Haisken-De New, & MacCulloch, 2010).

We also note that the income coefficient could be biased downward if leisure (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) or other people´s income (aspirations) are not controlled for (Easterlin, 2005; Luttmer, 2005; McBride, 2001). This would result because of the negative correlation between income and leisure on one hand and the positive correlation between income and aspirations on the other hand, combined with the positive effect of leisure on life-satisfaction and the negative effect of aspirations on life-satisfaction. Ferreira and Moro (2010) experimented with including estimates of relative income (the difference between one´s own income and the average income of the local authority of residence) in their models when valuing air quality and warm climate but excluded the variable as it was not statistically significant. To summarize, it should be kept in mind that estimated welfare measures from models that cannot compensate well for violation of the zero-conditional-mean assumption may be an overestimate of the true compensation needed to make an individual indifferent between having and not having a sub-optimal health condition.

Researchers have experimented with various instrumental variables (IVs) for income in the subjective well-being literature. Examples include father´s years of education and spouse´s years of education (Knight, Song, & Gunatilaka, 2009), and industry and occupation, Luttmer (2005). The IV income coefficient was four times larger than the one obtained in the baseline happiness estimation in the former study and instrumenting for income resulted in a threefold coefficient in the latter study. However, the income coefficients are likely upward biased by unobserved heterogeneity in both studies as the former use cross-sectional data and FE models are not used in the latter. Powdthavee (2010) used exogeneous over-time variation in the proportion of household members with payslip information for income instruments and reports a FE-IV income coefficient that is double the size of the OLS coefficient and ten times larger than the FE coefficient on income. Ambrey and Fleming (2014) used lottery winnings among other irregular sources of income as IVs for income and their results also suggest that OLS estimates lead to an overestimate of willingness to pay (WTP) for improved physical health. Howley (2017), being the first study to use IV estimates in a health application of the subjective well-being method, used parental education to instrument for income and found the income coefficient to more than triple in size between OLS and two-stage least squares (2SLS) models.

With the subjective well-being method, respondents are never asked to state a monetary value for pain. However, what is implicitly obtained is an answer to the question: "Considering your overall satisfaction with life without being troubled by pain, how much money must we pay you to make you just as happy even though you were often troubled by pain?" Or the other way around: "Consider your overall satisfaction with life being often troubled by pain, what would you be willing to pay to be just as happy but without pain?" Yet, the method does not require respondents to actually deal with this cognitively difficult question.

Data

To estimate the monetary value of pain using the subjective well-being method, we need person-level data with measures of life satisfaction, income, pain, and detailed controls for health status. In addition, we want a population for whom pain is prevalent and income is plausibly exogenous. Furthermore, to the extent that observations are missing person-level time-invariant health status, we want longitudinal data so that identification can come from within-person variation in income and pain, thus avoiding confounding by unobserved time-invariant variables.

The Health and Retirement Study (HRS) has all of these features. We use data from the four waves (2008, 2010, 2012 and 2014) of the HRS that include a question on life satisfaction. The HRS is a biannual nationally-representative panel survey that started in 1992, on the health and economic well-being of adults over 50 in the United States, including around 22,000 Americans per wave. The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and the Social Security Administration and is conducted by the University of Michigan´s Institute for Social Research.

All variables used in the analyses are data products of the RAND Center for the Study of Aging. Those variables were either cleaned and processed variables described in the RAND HRS DATA FILE (v.P) (Bugliari et al., 2016) with model-based imputations, or variables from the RAND Enhanced Fat Files (questions on life satisfaction and pain), with household data merged to the respondent level.

The original sample using four waves consisted of 78,553 observations on 24,967 individuals. Of those, we excluded individuals under 50 years old and those living in a nursing home. We also dropped observations that had missing values on the dependent and independent variables. Because income is highly skewed and potentially mis-reported, we used the condition DFbeta>1 to identify the overly influential observations on the income variable

(Long & Freese, 2014). We also used graphs to detect outliers in student´s and standardized residuals and STATA´s `lvr2plot` and `avplot` to identify observations with higher than average leverage and higher than average residuals (UCLA: Statistical Consulting Group). As a result of these tests, we dropped individuals with zero reported income, or the few observations with extraordinarily high reported income. The final sample consists of 64,205 observations on 21,104 individuals (see Table 1 for details) and did not differ significantly from the original data in terms of observable characteristics (results available on request). Dummies for health insurance and smoking had by far the most missing right-hand side observations (601 and 394).

The HRS sample is based on a multi-stage, area-clustered, stratified sample design. For 4 out of 7 recruitment cohorts, black and Hispanic respondents were oversampled at a rate of about 2 to 1 relative to their distribution in their respective age groups in the population. To achieve these oversamples, geographic areas with higher than average concentration of minority population were selected at higher sampling rates. In these areas, non-minority sample members were subsampled at a rate of about 50%. The original 1992 screen that generated the HRS, Aging and Health Dynamics (AHEAD) and War Baby cohorts contained an oversample of Florida residents. Sample weights are available in the data to account for the differential selection probabilities of individuals and are used in models that allow for time-varying sample weights. We refer to the HRS documentation report by Ofstedal et al. (2011) for a more detailed description of the sample design.

The dependent variable is a subjective measure of life satisfaction obtained with the question:

> “Please think about your life as a whole. How satisfied are you with it?”

Respondents could choose an answer on a scale from 1 (“completely satisfied”) to 5 (“not at all satisfied”). We reversed the scale so that 5 represents “completely satisfied”. Most people report high satisfaction with life (see Figure 1 for the full distribution by pain status).

The independent variables of interest are real household income (reported in wave *t* for wave *t*–1) and an indicator for whether the respondent is often troubled by pain. The question on pain used in our main models is:

“Are you often troubled with pain?”

Respondents answered either yes or no. For those who answered yes, the survey also includes a question on severity of pain with answer options: Mild, moderate, or severe. We use this variable to test whether the estimated CVs are sensitive to degree of pain severity.

The question on pain does not explicitly distinguish between acute pain and chronic pain. However, according to a study by Banks et al. (2009) we can assume that responses to the HRS pain question reflect pain that is recurrent and not completely relieved by medication (or alternative treatment). They compared two questions on pain that 2,000 respondents, 25 and older from the Dutch CentERpanel survey answered. One was the HRS pain question and another question asked whether they had experienced any pain in the last 30 days. 59% of the sample reported having “any pain in the last 30 days” but only 27% of the same sample reported being “often troubled by pain” (the HRS question). This suggests that those who reported being often troubled by pain are referring to recurrent pain, not short-term or acute pain that may be fully alleviated from pain. The type of pain that people are queried about with the HRS question is thus likely to be comparable to questions on chronic pain from other studies. As an example, McNamee and Mendolia (2014) used data from the Australian HILDA Survey in their estimation of the value of pain. They used responses from questions on whether individuals had any long-term health conditions, with chronic pain as one of the possible alternatives over a period of ten survey-waves.

The most common clinical definition of pain was introduced by the International Association for the Study of Pain in 1979 (IASP Subcommittee on Taxonomy, 1979) as “an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such damage”. The definition appreciates the multidimensional nature of pain as it takes into account both physiological processes and the subjectivity of pain experience. From a methodological perspective, the clinical definition of pain thus enforces the reasoning to control for individual heterogeneity as time-invariant personality traits are likely to simultaneously affect the subjective experience of both life satisfaction and pain.

The income variable is an all-inclusive sum of previous year´s wage and salary income, bonuses, business income, asset income, pensions, benefits, compensations, and inheritance. Total equivalised household income at the 2015 price level was calculated for each observation. We use the modified OECD scale to equivalise household income where the first adult has weight=1, the second adult in the household has weight=0.5 and children have weight=0.3. The total household income only includes income from the respondent and the spouse, not from other household members but a possible underestimation of household income is not considered a problem because of this, as intergenerational transfers generally do not flow from children to parents.

Other covariates are factors that are plausibly correlated with chronic pain and income and are listed in Table 2, for the whole sample and by pain status. Those include indicators for various health conditions as pain can be a consequence of those conditions. We chose conditions asked about in the survey in the following manner, thus validating the variables as much as possible: “Has a doctor ever told you that you have a ....?” querying about cancer, lung disease, heart disease, stroke, psychological condition, arthritis and high blood pressure. Other time-varying covariates included are: Age, marital status, labor-force status, health-insurance status, wave dummy (capturing period-specific effects), smoking dummy and number of children. Time-invariant covariates include gender, race, education, and census division. We include age in our models in 5-year ranges even though age effects would be captured by the time dummies if age was excluded. This is done because there is growing evidence from large cross-sectional studies as well as longitudinal analyses that life satisfaction is affected differently by age-groups, with a U-shaped relationship between well-being and age (Blanchflower & Oswald, 2008; Cheng, Powdthavee, & Oswald, 2017), although the exact form of the relationship is controversial. Studies have found well-being to decline after age 60 (Wunder, Wiencierz, Schwarze, & Kuchenhoff, 2013) and after age 75 (Frijters & Beatton, 2012) and some researchers report the reverse of a U-shape (Easterlin, 2006; Sutin et al., 2013). Furthermore, the age variable controls for deterioration in health capital (Grossman, 1972) that is not captured by the health condition dummies. We control for health-insurance status as health insurance is found to be welfare-increasing from mid-life (Pelgrin & St-Amour, 2016). The variable on marital status partly controls for relational goods, including companionship and emotional support (Becchetti & Pelloni, 2013).

Methodology

Define indirect utility (V) as a function of income (y), health (h), and a set of demographics and personal characteristics (x):

$$V(y, h, x) \tag{1}$$

Consider a reduction in health from h^1 to h^0, such that $h^1 > h^0$, with no changes to y or x. A change in utility because of a change in health is then defined as follows:

$$\Delta V = V(y, h^0|x) - V(y, h^1|x) \tag{2}$$

Then, the compensating variation (CV) is the amount of money that equalizes the individual´s utility before and after the change in health so that:

$$V(y + CV|h^0, x) = V(y|h^1, x) \tag{3}$$

The empirical well-being equation is as follows:

$$V_{it} = \beta_o + \beta_1 y_{it} + \beta_2 h_{it} + \sum_{k=1}^{K} \alpha_k X_{k,it} + \varepsilon_{it} \qquad (4)$$

where V_{it} in our case is reported life satisfaction of individual *i* at time *t*, and our health variable *h* is pain. The alphas and betas are coefficients and the *K* variables $X_{k,it}$ are demographics and personal characteristics. ε_{it} is a composite error term for individual time-invariant characteristics and time-varying characteristics for individual *i* at time *t*. We then use equation (4) and solve for CV in (3), which results in the negative ratio of the coefficients for pain and income:

$$CV = -\frac{\beta_2}{\beta_1} \qquad (5)$$

Estimation of the parameters in equation (4) and the corresponding CV in equation (5) involves several econometric issues. First, the correct functional form of the covariate income is not necessarily linear, as is assumed in equation (4). Therefore, we consider alternative, more flexible, functional forms that allow the CV to vary at different levels of income. Similarly, in some specifications we allow pain to have four values, including no pain, to indicate some measure of pain intensity instead of just the binary indicator for frequent pain or not. Second, repeated observations for each person allows the use of panel-data methods to control for time-invariant factors and to identify the two main coefficients using within-person variation. Third, because the data are collected from a survey, subjects are sampled with unequal weights. We explore whether weighted estimates differ from unweighted estimates. Fourth, we attempt to separate the life-satisfaction effects of pain itself from the underlying health conditions that might cause them with carefully selected health controls. Fifth, although we attempt to control for all possible confounders, including using person-level fixed effects, there is still the possibility that either income or pain (or both) are correlated with unmeasured factors that also affect happiness. An example of such a variable is unmeasured health status. Therefore, we also estimate models that use instrumental variables to control for endogeneity. Sixth, we test whether the results are sensitive to inclusion of additional covariates. Seven, we test for heterogeneous treatment effects by estimating the models on subsamples by age and gender. We explore each of these issues in more detail below.

We let the continuous variable income enter equation (4) in three different ways: linear, log-transformed and piecewise linear (PWL). Previous studies using the subjective well-being method use either linear income or more commonly its logarithmic transformation. The log transformation is used to model diminishing marginal utility of income citing Layard, Nickel and Mayraz (2008) but also to reduce effects of influential observations in the income distribution characterized by right skewness. We therefore highlight the empirical and theoretical reasons for those results, although we also report linear income results for reason of comparability between studies, as well as to compare results using different model specifications.

In models with the log transformation of income, the coefficient ratio compares marginal changes in pain to marginal changes in % income. Thus calculating CV calls for reverting the proportion of coefficients for pain and income from the logarithmic scale by using the exponential function. Thus, replacing income with ln(income) in (4) and solving for CV in (3) yields:

$$CV = \bar{y}\left(exp\left(\frac{-\beta_2}{\beta_1}\right) - 1\right) \qquad (6)$$

where $\bar{y}$ is average income in the sample. We report CVs as daily monetary amount and since the income variable is in 10,000 USD,

$$CV\ pr.day\ in\ USD = (CV * 10{,}000)/365 \qquad (7)$$

This amount is interpreted as the additional equivalised household income per day needed to compensate an individual who often suffers from pain for his/her loss in welfare (willingness to accept (WTA)) or as the equivalised income per day that he/she is willing to forgo to be relieved from pain (WTP).

Although using ln(income) generally provides a better fit than using linear income, it is not helpful for exploring differences in CV by income levels. Another option that does not impose the exact same tradeoff between income and pain across all income levels (as the linear case does) is to use a piecewise linear functional form for income. CVs from PWL models are calculated the same way as in the case of linear income for each income spline (see equation (5)).

We estimate CVs from individual FE models in addition to OLS and OLS-PWL models because previous research suggests that fixed effects play an important role in well-being equations (Ferrer-i-Carbonell & Frijters, 2004; McNamee & Mendolia, 2014). These models identify the parameters on income and pain through within-person variation in those variables, instead of cross-sectional variation. Models were weighted where possible, to account for the complex multistage probability survey design. This includes non-response, sample clustering, stratification and further post-stratification. Models with and without weights yielded quite similar results, relieving our concerns of not being able to include sampling weights in FE-models. For ease of comparison between models, we thus report unweighted results in the results tables but provide results from weighted regressions in an Appendix.

Using goodness-of-fit test statistics, the Akaike information criterion (AIC) and the Bayesian information Criterion (BIC), the piecewise linear (PWL) specifications consistently showed a better fit to the data than the transformation of income to logarithm scale. Nonlinear least-squares estimates were used to suggest a breakpoint combined with goodness of fit statistics, AIC and BIC, to choose from different sets of breakpoints. The choice of breakpoints was at 30,000 and 50,000 USD (annual income), corresponding to the 51st and 72nd percentiles of the income distribution. We report tests for differences in the spline coefficients between the first and second segments in the PWL-OLS model (see Table 3 of the results section). Figure 2 shows the relationship between income and life satisfaction using a non-parametric smoother and a fitted piecewise-linear function of income with the chosen knots marked by the horizontal lines. We include only income below 300,000 USD in the figure for better visibility of the difference in the slope of the function at income levels, where the marginal utility of income (non-adjusted) is proportionally large over the income distribution.

In addition to results from OLS, piecewise-linear and FE models, we provide results from 2SLS models with mother´s education as an instrument for income. The relevance of our control variables was confirmed by comparing results from unadjusted models, which include only pain and income on the right hand side of equation (1), to adjusted models that include all independent variables as feasible for each model estimator. As a robustness check of our CV estimates, we report results from analyses of a subsample of people age 65 and above because it is more plausible to think of income as an exogenous variable in a model with this age group. Previous research has reported gender differences in CVs (Groot & van den Brink, 2006; McNamee & Mendolia, 2014) and we provide results by gender for completeness. Further, estimates with pain severity instead of the pain dummy are included since the CVs are likely to be sensitive to whether pain is mild, moderate or severe.

Results

Results for the total sample are reported in Table 3, results by gender in Table 4 and results for the subgroup of 65 years and older in Table 5. Point estimates for pain and income by estimator and functional specification of income are reported along with corresponding CV estimates. Results are presented from models where income is used in a linear and piecewise-linear form in panels A. In panel B, we present results from models with log of income. As an example, looking at Table 3, the CV estimate in the first column, panel A is the negative ratio of the two reported coefficients (see equation (2)) and can be interpreted as the additional equivalised household income per day in USD that would be needed to compensate an individual for the welfare loss of often suffering from pain.

The results reported in column one, Table 3, assume that the CV is constant across all income levels, an assumption that is both restrictive and testable. In contrast, results in column 2 allow the CV to differ across three different income ranges. That result shows that the CV is much larger for those with income above $50,000. Furthermore, comparing panel A and B in column one, the calculated CV with ln(income) is 2.6 times larger than when income enters the model in linear form. This large difference calls for further exploration of the functional form of the income variable. By including income in the empirical model in linear splines, a CV estimate is directly observable for income splines that capture the part of the income distribution representing the majority of individuals in the population. That is, CV estimates from the first and second segments of the spline regression reflect the marginal rate of substitution between income (consumption) and pain at levels below the 72nd percentile of the income distribution. Thus, the value of pain differs by income levels. It ranges from 95 to 1,720 USD per day using OLS models. Even though the CIV for the third spline from the PWL-OLS model is statistically significant at the 1% level, the volatility in life-satisfaction predictions increases drastically at income levels above 300,000 USD (see Figures A1-A3 in Appendix). That is, the estimated CVs in columns one of Tables 3-5, are likely to be heavily affected by the trade-off between income and pain at the highest income levels.

Results from FE models confirm the positive personal traits bias in OLS models reported in previous research since the coefficients decrease in absolute value. However, the CV estimate is only statistically significant in the FE model in the case of linear income (panel A). The standard errors of the CV estimates are calculated by the delta method in STATA and in the FE model in panel B this results in proportionally large standard errors with this data. In column four (PWL-FE model), the estimated CV from the second segment is statistically significant and similar to the CV estimate from the PWL-OLS model. The reason for zero effect of income in the FE-spline regression is the lack of within-variation in the first and third income splines. However, as this estimator works well for the second spline of the income distribution, we include it for reasons outlined in the methodology section on preference for FE-models in the literature. Comparing CV estimates from PWL-OLS and PWL-FE models, the estimated CV from the second segment is statistically significant in both models (95 USD in PWL-OLS and 56 USD in PWL-FE model) suggesting a much smaller CV than estimates from models with ln(income) (Panel B) and from the third segment of the spline regressions.

We point out that precision in fixed-effects models is contingent on the within-variation in the variables used and we explored this in our data. 12,461 individuals change status in the life-satisfaction variable, 6,421 change status in the pain variable and 18,421 change status in the income variable during the observation period. This resulted in only 4,546 individuals changing status in all three variables. By using spline regression, this resulted in 3,238 individuals at the most changing status in life satisfaction, pain and first income spline (1,819 if conditional on change in third income spline). This explains the large standard errors in PWL-FE models for the first and third income splines.

Our results from fixed-effects models are similar to those from McNamee and Mendolia who used fixed effects models with log of income and found the daily CV for pain nine times the average income per day using Australian data. Our results suggest that an individual with average equivalised total household income of 125 USD per day would need extra USD of 1,040 per day to achieve the same level of life satisfaction as someone who is not often troubled with pain or eight times the average equivalised household income per day. Graham et al. (2011) found CV for extreme pain to be five times the income for the corresponding period using cross-sectional data. Results from piecewise-linear models however suggest a much smaller CV for pain than previous research or compensation of as low as 56 USD per day.

The last column, displays estimates from 2SLS models. We explored the three possible instruments for income available, as suggested by previous research; mother´s education, father´s education and spouse´s education, (Howley, 2017; Knight et al., 2009). For an instrument to be relevant it has to be highly correlated with income and to be valid it must have no partial effect on life satisfaction, after conditioning on the other included variables (and individual fixed effects in the FE models). Spouse´s education did not pass the test of relevance in the first stage and was therefore discarded. Both father´s and mother´s education was relevant based on F-test of excluded instruments from the first stage. However, father´s education did not pass the test of weak-instrument robust inference (Anderson-Rubin Wald test), which can cause an IV estimate to exhibit greater bias than OLS estimate (Bound, Jaeger, & Baker, 1995). Furthermore, as correlation between father´s and mother´s education was high (ρ=0.68), adding the second instrument in this case would not add much information to produce the slope estimate as opposed to having only the one chosen. Thus, we instrument for income with mother´s education; the highest grade completed in school. This variable has a significant relationship of the expected sign with the income variable with F-test of the excluded instrument equal to 80 (a conventional minimum of this F-test is> 10) (Stock, Wright, & Yogo, 2002). The null hypothesis of B1 of the endogenous regressor in the structural equation being equal to zero was furthermore rejected (p=0.0009) (Anderson-Rubin Wald test, as described in Baum, Schaffer, & Stillman (2007)). The H0 of whether the endogenous variable can be treated as exogenous was rejected (p=0.0047 for the linear income model and p=0.0183 for the ln(income) model). The positive relationship between mother´s education and later achievements of her children, including their income as adults is well documented. Better educated mothers are likely to have greater resources when it comes to helping their children with homework and thereby facilitating educational achievement and higher income of their children later in life. Mother´s education may also assist her children in the labor market through social status and networks. We refer to Howley (2017) for a review of the literature supporting the relevance of our instrument. We assume that the variance in life satisfaction explained by variation in income is attributable solely to the variance in mother´s education (the exclusion restriction). In other words, the exclusion restriction asserts that mother´s education is only related to her child´s life satisfaction through child´s income as adult. Doubts on the legitimacy of this statement may be such that children of higher educated mothers are endowed with personal skills that are positively correlated with income, health, labor-market status and marital status, all of which are related to life satisfaction. However, as we control for such channels in our empirical model as well as individual time-fixed characteristics, we can reasonably oppose doubts based on such channels.

The downward bias of the income coefficient in models without instruments, as documented in previous research is likely explained by willingness to substitute leisure for working hours now as investment for future happiness, thereby increasing income at the expense of current happiness. Another explanation is that the 2SLS estimator corrects for an attenuation bias as a result of measurement error in the income variable. Furthermore, as reviewed by Powdthavee (2010), not being able to control for other people´s income or rate of adaptation and aspiration to income may cause this downward bias.

Compared to the OLS results, the income coefficient is 6.6 times larger in the model with instrumented income. This is a larger increase than in previous research. The calculated CV of 129 USD per day (Table 3, panel A) may however still be biased by unobserved individual heterogeneity as we could not estimate FE-IV models as mother´s education is time-invariable. Considering the proportional reduction of the coefficients for pain and income once individual fixed effects are controlled for (compare coefficients in first and third column) of 73% for the pain coefficient and 76% for the income coefficient and applying those to the coefficients from the 2SLS model in column five results in a CV estimate of 145 USD per day, an amount extremely close to the CV estimates of 129 in panel A and 152 in panel B.

Results by gender are reported in Table 4. We only display results by gender from OLS, FE and 2SLS models for reason of parsimony. Results from piecewise-linear models were similar by gender (results available upon request). The estimated CVs are similar for men and women in panel A but the CV estimate from the OLS model in panel B for women is larger than men´s by 1,067 USD per day. Results from 2SLS suggest a much larger CV for men than for women, explained by smaller marginal utility of income for men in column three of Table 4.

The results for the subsample of 65 years and older are shown in table 5. In general, the results are in line with the results for the full age sample in Table 3, in particular for OLS, PWL-OLS and OLS-IV models. Results from the PWL model reflect that the slope of the indifference curve between pain and income depends on income level. CV estimates from FE models have large standard errors and this may be due to less within-individual variation in income (and/or life satisfaction) in a restricted sample. This is in accordance with one or both of the following: (a) our proposition of income being fairly exogen for those 65 and older is not supported by those results, especially in light of the similar results from the models where we instrument for income or (b) income is generally fairly exogenous in life-satisfaction models, but the 2SLS estimations are mainly correcting biases due to other factors, such as measurement errors and omitted variable biases described above.

Finally, we explored the sensitivity of the estimated CVs to the severity of pain. As would be expected, the monetary amount needed to compensate for welfare losses due to pain suffering increases by level of pain severity (see Table 6).

We provide results tables in an Appendix that include all coefficients for OLS, FE and OLS-IV models (Table A1 and A2). Looking at results from the FE model, the coefficients are of the expected sign and in accordance with previous research. Unemployed are less satisfied with life than the employed or those out of the labor force. Retired are happier than the employed. Being married is preferred to being divorced, widowed or single. Number of resident children does not affect life satisfaction. Having ever reported cancer, heart problems, stroke, psychological problems or high blood pressure is negatively related to life satisfaction with psychological problems standing out as having the largest negative effect. It is preferred to have health insurance and surprisingly to smoke. However, life satisfaction is not affected over time ceteris paribus except for a small decrease in life satisfaction between 2008 and 2010. Life satisfaction increases with age at a diminishing rate with a decline in life satisfaction starting at age 70 (in accordance with U-shaped relationship between life-satisfaction and age in samples including all ages as our sample includes 50 years and older). Comparison of unadjusted and adjusted (all controls included) models revealed that as expected, the coefficients for chronic pain and income decrease when more control variables are added in the OLS models but stay mostly unchanged in the FE models, suggesting that the fixed effects capture an important part of the relationship between pain and life satisfaction on one hand and income and life satisfaction on the other (see Table 3A in Appendix). We note that results in Tables 3 to 6 are unweighted for ease of comparison as it was not possible to use weights in the FE models. Comparison of weighted and unweighted results yielded similar results for other models (see Table A4 in Appendix).

Discussion

The results in this paper add new information on the value of pain relief among people older than 50 years old. Using improved methods, our results suggest a lower CV for pain than previously reported. More importantly, we contribute to the literature in a novel way by using a PWL model as an alternative to OLS with ln(income), providing a more transparent method to express WTP/WTA across income ranges. The resulting CV-estimates are lower than those from models using the traditional log transformation of income. Results from IV-models also yield CVs that are considerably lower than previous research suggests.

We point out that even though the results show that higher monetary compensation is needed to offset the utility loss of often having pain for richer individuals than for lower-income individuals, it does not imply that society has to value the health of richer individuals more than that of poorer ones. It simply reflects the general assumption that the marginal utility of income is larger for low-income individuals than for high-income individuals. As expected, CVs are also found to be positively related to pain severity.

McNamee and Mendolia's (2014) CV estimate for chronic pain was 640 USD per day using ln(income) in FE models. We were not able to produce a reliable CV estimate from a comparable model but our CV estimate using FE model with linear income was 1,040 USD per day. Their sample differs from ours in a number of ways. They use data from 10 waves of the Household, Income, and Labor Dynamics of Australia Survey (HILDA) as opposed to 4 waves used in the current study, mean age in their sample is 45 as opposed to 68 in our sample and covariates are not identical. Their use of longer panel helps with identification and precision of point estimates but should not affect the size of the CV estimates. Prior studies (Graham et al., 2011; McNamee & Mendolia, 2014) do not report standard errors for estimates of CV, as we do, which makes comparison even more difficult. The large difference in CV estimates by income levels, clearly displayed with PWL-models with and without fixed effects, combined with results from 2SLS shed new light on the value of relief from chronic pain — being lower than previous results suggest or in the range of 56 to 145 USD per day (using CV estimates from panel A, column three and column four, with the latter adjusted for upward personality bias suggested by comparison of coefficients from OLS and FE models).

Our paper also has several methodological conclusions. Although a distinction is made between CV and EV in theory we can´t make a distinction between the two with the estimation method used. The same applies to differentiating between WTA and WTP. Therefore, we guide the reader on how to interpret the results acknowledging the limitations of the method in identifying exactly what is being measured according to price theory.

Comparing estimates from linear income and log income models, the CV-estimates should not be numerically the same but one cannot say a priori exactly how they should differ. Taking the log of income, applying the exponential function to the ratio of the coefficients and multiplying with mean income does not give the same results as using linear income. The linear splines allow for exploring explicitly different CVs by income levels. For that reason, along with a better model fit it is arguably better than taking log of income.

Our paper has several limitations. Pain can be a consequence of neurological diseases, diabetes, or of musculoskeletal origin, but we did not have controls for those conditions that we found validated by a doctor´s diagnosis. We acknowledge the possibility of a bias in the coefficient for pain because of not being able to isolate the true effect of pain on life satisfaction completely, but we assume that a possible omitted variable bias in the pain coefficient is captured by controlling for age as neurological disease and diabetes likelihood increases with age (referring to diabetes Type II). Furthermore, the other health controls included are likely to capture the effect of musculoskeletal conditions on pain and life satisfaction, in particular psychiatric problems, lung disease, cancer and arthritis.

Responses to life-satisfaction questions may be liable to situational influences, such as the site of the interview, the weather, one´s mood and the interviewer, but those differences can be considered as random error (Veenhoven, 1993). Life-satisfaction scores have been found to correlate with variables that can be claimed to reflect utility, such as length of life and mental health. Furthermore, happiness scores are highest in countries with most material comfort, social equality, political freedom and access to knowledge (Veenhoven, 1993). Developments within the subjective well-being literature have resulted in the use of questions and terms that have been found to produce valid and reliable responses to measure utility, one being the satisfaction-with-life question framed in a way so that the question makes clear that life as a whole is to be considered. Life satisfaction is assumed to refer to a conscious global judgement of one´s life but life-satisfaction scores may also reflect current affect, adding noise to it as a measure of true experienced utility (Diener, 1984). Citing Ditella and MacCulloch (2006): “Ultimately, happiness research takes the view that happiness scores measure true internal utility with some noise, but that the signal-to-noise ratio in the available data is sufficiently high to make empirical research productive”. The validity of the assumption of interpersonal comparisons has been discussed thoroughly in the life-satisfaction literature with the consensus that the responses, although not without their problems, are meaningful and reasonably comparable among groups of individual (Easterlin, 2005).

We have learned that the value of pain is likely overestimated in previous research, with our best approximation to a WTP/WTA estimate being in the range of 56-145 USD per day. Furthermore, as expected, the data confirms that the value of pain relief is positively related to severity of pain. CVs calculated with linear income are likely to result in overestimates and PWL estimations are promising as they perform well econometrically in this context and allow for easier exploration of results across income groups than log transformations of income.

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Table 1: Origin of final sample size

Reasons for sample restriction	Obs	Obs dropped	Individuals	ID dropped
Original sample of 4 waves	78,553		24,967	
Drop if age< 50 or living in a nursing home		6,435		1,886
	72,118		23,081	
Drop if life satisfaction is missing		3,853		829
	68,265		22,252	
Drop if missing right-hand side variables		2,064		481
	66,201		21,771	
Drop if income is zero		1,981		663
	64,220		21,108	
Drop if influential outlier		15		4
Final sample used in analyses	64,205		21,104	
Total		14,348		3,863

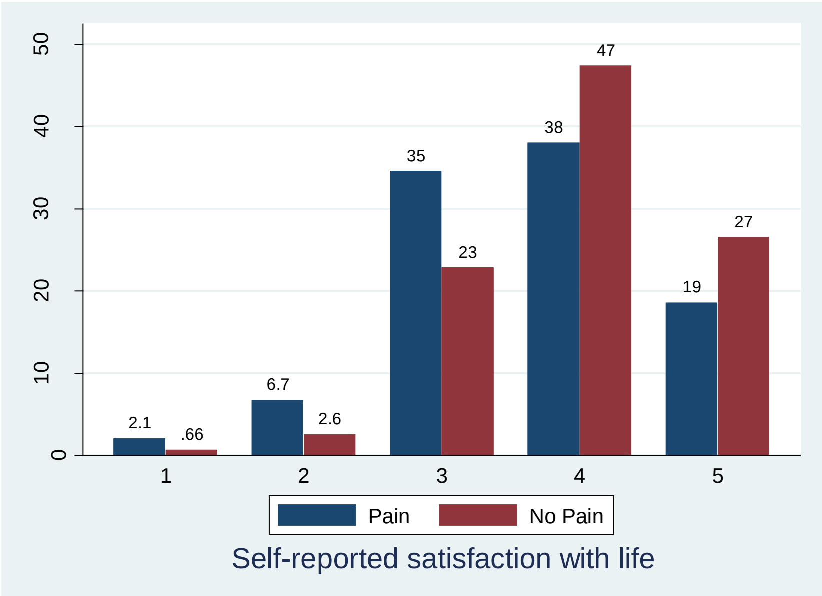

Figure 1. Self-reported satisfaction with life by pain status. 1=Not at all satisfied and 5=Completely satisfied. Figures above bars are percentages.

Table 2: Descriptive statistics by pain status (weighted)

Variable	All	No pain	Pain
Yearly household income (equivalised)[a]			
mean	5.69	6.30	4.58***
(SD)	(8.74)	(9.22)	(7.67)
Pain%	35.40		
Mild	64.79		
Moderate	10.43		
Severe	19.22		
Age			
mean	66.27	66.23	66.33
(SD)	(9.97)	(10.02)	(9.86)
Gender%			
Men	45.02	47.57	40.36***
Women	54.98	52.43	59.64***
Education %			
Less than high school (base)	13.01	11.14	16.42***
GED and high school graduate	32.73	30.85	36.17***
Some college	25.94	25.43	26.86***
College and above	28.32	32.58	20.54***
Marital status %			
Married or partnered (base)	65.38	67.22	62.04***
Divorced or separated	14.34	13.26	16.31***
Widowed	14.27	13.60	15.48***
Single	6.02	5.93	6.17
Race %			
White/Caucasian (base)	84.61	85.24	83.46***
Black/African American	9.68	9.43	10.14***
Other	5.71	5.33	6.40***
Indicator for Hispanic %	7.40	6.77	8.54***
Labor force status %			
Employed (base)	36.66	41.43	27.94***
Unemployed	2.62	2.70	2.47
Partly retired	8.53	9.32	7.09***
Retired	46.33	42.00	54.22***
Out of the labor force	5.86	4.54	8.28***
Health conditions %			
Cancer	14.28	13.20	16.26***
Lung disease	9.46	6.32	15.19***
Heart problems	22.39	18.58	29.33***
Stroke	6.98	5.65	9.41***
Psychiatric problems	18.36	12.13	29.72***
Arthritis	56.21	44.05	78.41***
High blood pressure	55.67	51.32	63.59***
Smoker	13.94	12.34	16.87***
Number of children in household	0.36	0.36	0.34

Health insurance %	80.56	79.61	82.29***

Note: Out of the labor force refers to disability or if none of the other options applied at the time of the survey. Census division (10 dummies) is left out of the table due to space limitations. *** is for difference in means (%) by pain status at the 1% significance level. [a]Yearly total equivalised household income is in 10,000 USD (2015 price level).

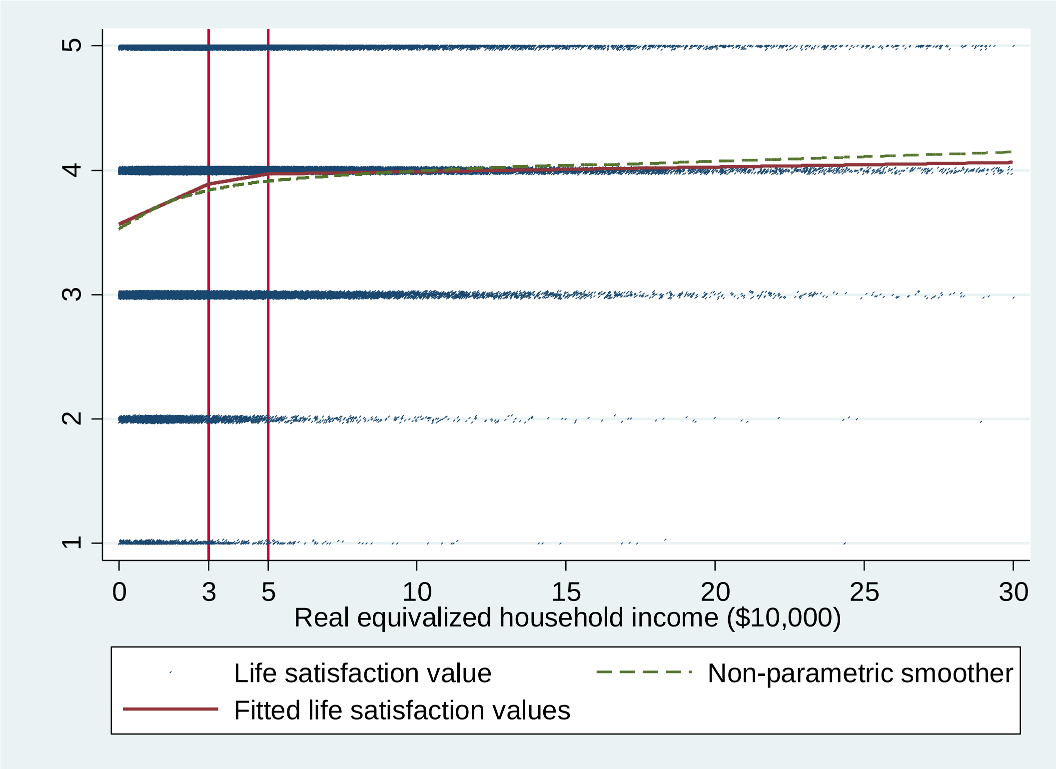

Figure 2. Scatterplot of life satisfaction by income values with plotted lowess (non-parametric smoother) and fitted life-satisfaction values from a PWL-OLS regression of three splines on life satisfaction, with knots at 30,000 and 50,000 USD (annual income). Note: Equivalised household income values in the figure are at the 2015 price level in 10,000 USD. Income is restricted to levels below 300,000 USD (99th percentile) in the figure for clear presentation of the difference in slope at lower income levels. See Appendix for a figure displaying the full income range (Figure A1).

Table 3: Point estimates and corresponding CVs by model estimator and functional form of income

Panel A	OLS		PWL-OLS		FE		PWL-FE		OLS-IV	
	Coeff.	CV	Coeff.	CV	Coeff.	CV	Coeff.	CV	Coeff.	CV
Pain	-0.2123***		-0.2081***		-0.0563***		-0.0562***		-0.1999***	
	(0.0089)	910***	(0.0088)		(0.0093)	1,040**	(0.0093)		(0.0103)	129***
Income	0.0064***	(115)			0.0015***	(422)			0.0426***	(42)
	(0.0008)				(0.0006)				(0.0131)	
Income										
1. spline			0.0312***	183***			0.0017	NV		
			(0.0068)	(40)			(0.0073)			
2. spline[1]			0.0598***	95***			0.0276***	56***		
			(0.0062)	(11)			(0.0065)	(16)		
3. spline			0.0033***	1,720***			0.0005	NV		
			(0.0006)	(301)			(0.0005)			
Panel B	**OLS**				**FE**				**OLS-IV**	
	Coeff.	CV			Coeff.	CV			Coeff.	CV
Pain	-0.2089***				-0.0561***				-0.1922***	
	(0.0089)	2,377***			(0.0093)	3,983			(0.0107)	152**
ln(income)	0.0704***	(611)			0.0162***	(5,224)			0.2529***	(72)
	(0.0049)				(0.0053)				(0.0753)	

N=64,205 person-years observations. N=58,588 in OLS-IV models. PWL: Piecewise linear. *p<0.10, ** p<0.05, *** p<0.01. Models include age, age squared, number of children in household, year dummies, dummies for comorbidities, marital status, census division, labor-force status, gender, education, race, Hispanic and health insurance. FE models include age, age squared, year dummies, dummies for comorbidities, marital status, labor-force status, children in household and health insurance as covariates in addition to pain and income. Knots are at income values 3 and 5 in PWL-OLS and PWL-FE models and the income variable is in 10,000 USD. CVs are reported in USD per day, 2015 price level and are calculated with coefficients from adjusted models. [1]t-value for difference in slope between 1. and 2. segment in PWL-OLS model is -2.54. Results are unweighted. Weighted results are in Appendix. NV=no CV value as the income coefficient was not different from zero. Mean income in CV formula in Panel B=47,088. Standard errors (in parentheses) are clustered on individuals.

Table 4: Point estimates and corresponding CVs by model estimator and functional form of income

	Men			Women		
Panel A	OLS	FE	OLS-IV	OLS	FE	OLS-IV
Pain	-0.2129***	-0.0738***	-0.2058***	-0.2094***	-0.0450***	-0.1904***
	(0.0140)	(0.0149)	(0.0151)	(0.0115)	(0.0120)	(0.0138)
Income	0.0056***	0.0021**	0.0204	0.0072***	0.0010	0.0630***
	(0.0010)	(0.0009)	(0.0172)	(0.0011)	(0.0007)	(0.0192)
CV	1,035***	950**	276	796***	1,197	83***
	(197)	(431)	(236)	(126)	(858)	(28)
Panel B	OLS	FE	OLS-IV	OLS	FE	OLS-IV
Pain	-0.2092***	-0.0734***	-0.2010***	-0.2068***	-0.0449***	-0.1827***
	(0.0139)	(0.0150)	(0.0158)	(0.0115)	(0.0120)	(0.0146)
ln(income)	0.0797***	0.0244***	0.1310	0.0635***	0.0104	0.3562***
	(0.0074)	(0.0083)	(0.1085)	(0.0065)	(0.0068)	(0.1063)
CV	1,865***	2,790	551	2,932**	8,792	81**
	(608)	(3,539)	(930)	(1,167)	(27,396)	(36)

Men: N=26,876 person-years observations. N=24,342 in OLS-IV models. Women: N=37,329 person-years observations. N=34,246 in OLS-IV models.*p<0.10, ** p<0.05, *** p<0.01. Models include age, age squared, number of children in household, year dummies, dummies for comorbidities, marital status, census division, labor-force status, gender, education, race, Hispanic and health insurance. FE models include age, age squared, year dummies, dummies for comorbidities, marital status, labor force status, children in household and health insurance as covariates in addition to pain and income (income variable is in 10,000 USD). CVs are reported in USD per day, 2015 price level. Results are unweighted. Weighted results are in Appendix. Mean income in CV formula in Panel B=53,088 for men and 42,769 for women. Standard errors (in parentheses) are clustered on individuals.

Table 5: Point estimates and corresponding CVs by model estimator and functional form of income. 65 years and older

Panel A	OLS		PWL-OLS		FE		PWL-FE		OLS-IV	
	Coeff.	CV	Coeff.	CV	Coeff.	CV	Coeff.	CV	Coeff.	CV
Pain	-0.1965***		-0.1943***		-0.0340***		-0.0339***		-0.1903***	
	(0.0113)	1,256***	(0.0112)		(0.0123)	2,703	(0.0123)		(0.0127)	116**
Income	0.0043***	(259)			0.0003	(5,224)			0.0451**	(47)
	(0.0008)				(0.0007)				(0.0180)	
Income										
1. spline			0.0286***	186***			0.0026	NV		
			(0.0089)	(59)			(0.0103)			
2. spline			0.0431***	123***			0.0138	67		
			(0.0078)	(23)			(0.0084)	(47)		
3. spline			0.0019***	2,776***			-0.0002	NV		
			(0.0007)	(954)			(0.0007)			

Panel B	OLS		FE		OLS-IV	
	Coeff.	CV	Coeff.	CV	Coeff.	CV
Pain	-0.1946***		-0.0339***		-0.1820***	
	(0.0112)	2,777**	(0.0123)	NV	(0.0123)	112**
ln(income)	0.0602***	(1,185)	0.0058		0.2735***	(63)
	(0.0068)		(0.0080)		(0.1058)	

N=38,010 person-years observations. N=34,656 in OLS-IV models. PWL: Piecewise linear.*p<0.10, ** p<0.05, *** p<0.01. Models include age, age squared, number of children in household, year dummies, dummies for comorbidities, marital status, census division, labor force status, gender, education, race, Hispanic, and health insurance. FE models include age, age squared, year dummies, dummies for comorbidities, marital status, labor-force status, children in household and health insurance as covariates in addition to pain and income. Knots are at income values 3 and 5 in PWL-OLS and PWL-FE models and the income variable is in 10,000 USD. CVs are reported in USD per day, 2015 price level and are calculated with coefficients from adjusted models. Results are unweighted. Weighted results are in Appendix. NV=no CV value as the income coefficient was not different from zero. Mean income in CV formula in Panel B= 47,097. Standard errors (in parentheses) are clustered on individuals.

Table 6 CV estimates by pain severity

Panel A: linear income	(1)	(2)	(3)
	OLS	FE	OLS-IV
Pain			
Mild	434***	639**	65***
	(72)	(639)	(23)
Moderate	1,008***	1,023**	144***
	(128)	(428)	(47)
Severe	1,547***	2,500**	225***
	(203)	(996)	(75)

Panel B: ln(income)	(1)	(2)	(3)
	OLS	FE	OLS-IV
Pain			
Mild	409***	948	63**
	(106)	(1,067)	(27)
Moderate	3,510***	3,766	180**
	(1,029)	(5,059)	(88)
Severe	20,658**	543,290	357
	(9,682)	(1,612,647)	(219)

*p<0.10, ** p<0.05, *** p<0.01

Appendix. Valuing pain using the subjective well-being method

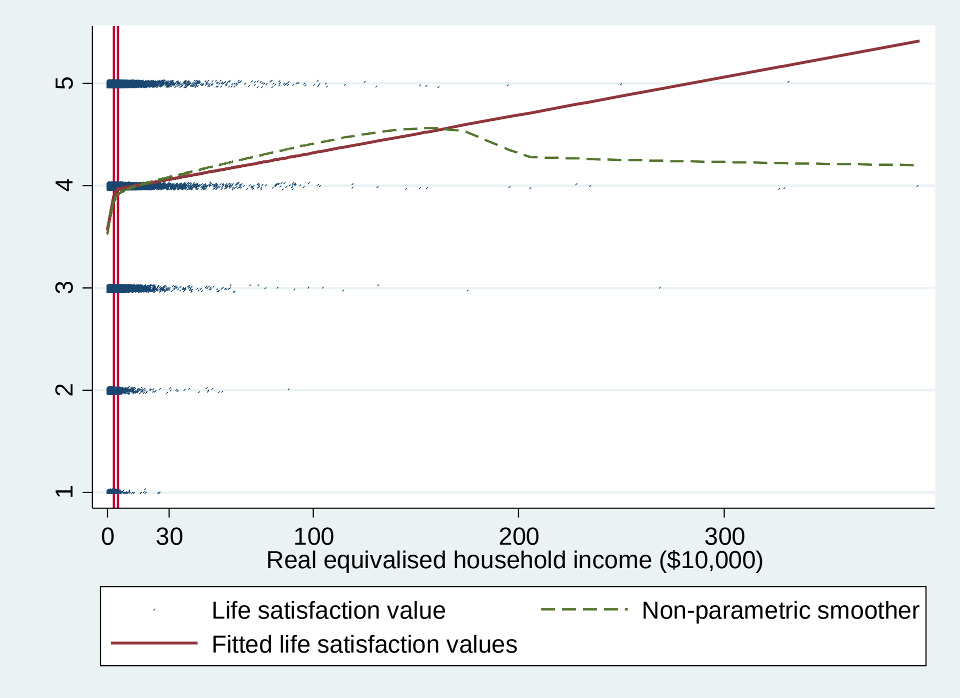

Figure A1. Scatterplot of life satisfaction by income values with plotted lowess (non-parametric smoother) and fitted life satisfaction values from piece-wise-linear OLS regression of life satisfaction on three income splines, with knots at 30,000 and 50,000 USD (annual income). Note: Equivalised household income values in the figure are at price level 2015 in 10,000 USD.

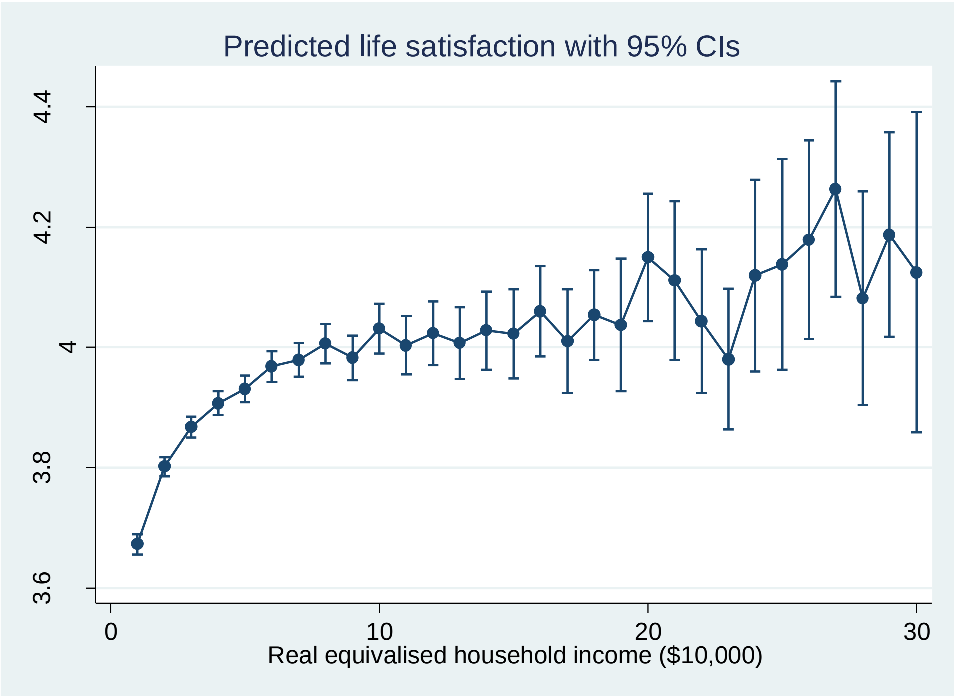

Figure A2. The connected points on the figure are predicted life-satisfaction values (margins) up to income of 300,000 USD from a regression of life satisfaction on 30 income dummies with income rounded to nearest integer.

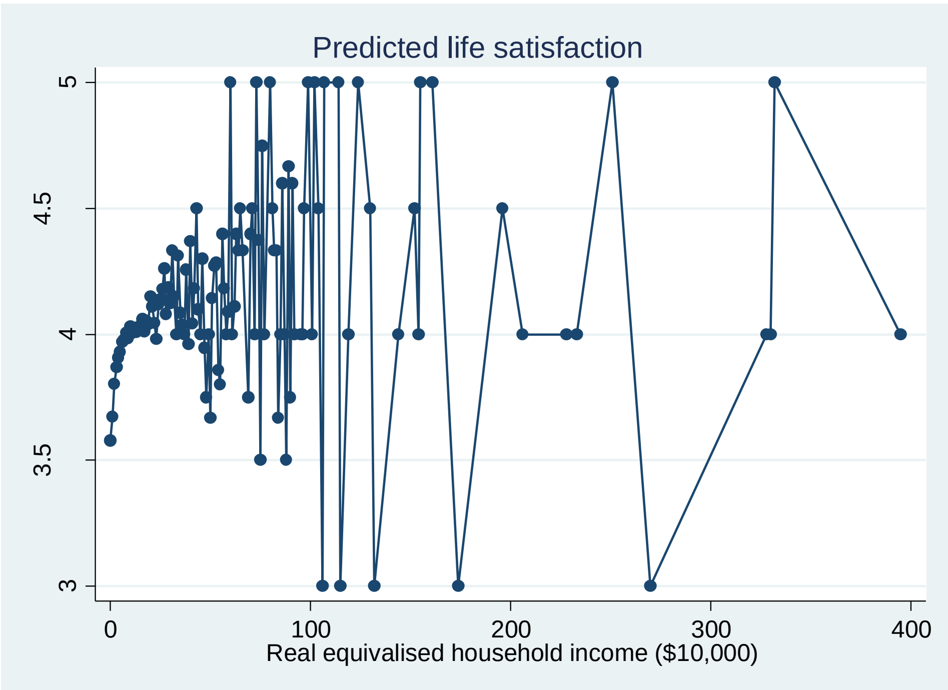

Figure A3. Same as Figure A2 but here over the full income range (highest value is 3,950,000 USD). The figure displays the volatility in the life satisfaction predictions at higher income levels. Note income above 300,000 USD at price level 2015 is top 1% of the income distribution.

Table A1: Point estimates from OLS, FE and OLS-IV models with linear income

Dependent variable: Life satisfaction	OLS	FE	OLS-IV	
			First-stage	IV
Real equivalised household income	0.0064***	0.0015***		0.0426***
	(0.0008)	(0.0006)		(0.0131)
Mother´s education			0.1245***	
			(0.0136)	
Pain	-0.2123***	-0.0563***	-0.2349***	-0.1999***
	(0.0089)	(0.0093)	(0.0886)	(0.0103)
Age	0.0510***	0.0501***	0.0614	0.0494***
	(0.0098)	(0.0152)	(0.1051)	(0.0108)
Age squared	-0.0014	-0.0050***	-0.0239**	-0.0004
	(0.0009)	(0.0014)	(0.0094)	(0.0011)
Second wave	-0.0133*	-0.0156*	-0.2715***	-0.0025
	(0.0076)	(0.0086)	(0.0740)	(0.0091)
Third wave	-0.0263***	-0.0180	-0.2735***	-0.0173*
	(0.0080)	(0.0112)	(0.0748)	(0.0093)
Fourth wave	-0.0050	0.0063	-0.0488	-0.0038
	(0.0085)	(0.0148)	(0.0833)	(0.0094)
Ever reported cancer	-0.0358***	-0.1050***	-0.0076	-0.0278**
	(0.0124)	(0.0261)	(0.1018)	(0.0132)
Ever reported lung disease	-0.1128***	-0.0053	-0.3710***	-0.1053***
	(0.0159)	(0.0308)	(0.0867)	(0.0176)
Ever reported heart problems	-0.0775***	-0.0537***	-0.0023	-0.0731***
	(0.0108)	(0.0203)	(0.0987)	(0.0117)
Ever reported stroke	-0.0831***	-0.0603*	-0.3187***	-0.0796***
	(0.0178)	(0.0327)	(0.1093)	(0.0197)
Ever reported psychological problems	-0.3542***	-0.1766***	-0.3744***	-0.3306***
	(0.0133)	(0.0305)	(0.0885)	(0.0148)
Ever reported arthritis	-0.0203**	-0.0023	-0.1936**	-0.0136
	(0.0096)	(0.0185)	(0.0934)	(0.0108)
Ever reported high blood pressure	0.0086	-0.0415**	-0.4048***	0.0244**
	(0.0092)	(0.0183)	(0.0972)	(0.0115)
Do you smoke cigarettes now?	-0.1488***	0.0412*	-0.7781***	-0.1261***
	(0.0139)	(0.0229)	(0.0895)	(0.0178)
Divorced or separated	-0.3151***	-0.1152***	-1.6364***	-0.2625***
	(0.0142)	(0.0308)	(0.1072)	(0.0260)
Widowed	-0.2425***	-0.2195***	-0.6860***	-0.2203***
	(0.0131)	(0.0242)	(0.1085)	(0.0170)
Single	-0.2484***	-0.1812***	-1.8204***	-0.1843***
	(0.0229)	(0.0652)	(0.3917)	(0.0368)
Unemployed	-0.2507***	-0.1361***	-2.4110***	-0.1735***
	(0.0261)	(0.0241)	(0.1486)	(0.0415)
Partly retired	0.0973***	0.0396**	-1.3083***	0.1412***
	(0.0148)	(0.0163)	(0.1848)	(0.0239)
Retired	0.0635***	0.0060	-2.5102***	0.1516***
	(0.0122)	(0.0152)	(0.1402)	(0.0357)
Out of the labor force	-0.0151	-0.0638***	-1.8077***	0.0512*

	(0.0188)	(0.0223)	(0.1523)	(0.0310)
Number of resident children	-0.0155**	-0.0004	-0.8023***	0.0085
	(0.0068)	(0.0106)	(0.0525)	(0.0129)
Female	0.0631***		-0.2982***	0.0727***
	(0.0096)		(0.0958)	(0.0112)
GED and high school graduate	-0.0087		0.2146***	-0.0171
	(0.0145)		(0.0704)	(0.0170)
Some college	-0.0513***		1.0231***	-0.1000***
	(0.0155)		(0.0904)	(0.0245)
College and above	-0.0071		3.8386***	-0.1612***
	(0.0161)		(0.1394)	(0.0580)
Black/African American	-0.0589***		-1.3026***	-0.0085
	(0.0134)		(0.0817)	(0.0237)
Other	0.0222		-0.4982***	0.0584**
	(0.0208)		(0.1803)	(0.0246)
Hispanic==1	-0.0220		-1.2094***	0.0410
	(0.0184)		(0.1451)	(0.0301)
Health insurance	0.0795***	0.0601***	0.1828*	0.0763***
	(0.0121)	(0.0140)	(0.1102)	(0.0132)
Constant	3.7789***	3.8713***	7.0925***	3.4849***
	(0.0359)	(0.0457)	(0.4303)	(0.1163)
Observations	64,205	64,205	58,588	58,588
Adjusted R-squared	0.1259	0.0096	0.1407	0.0368
F-statistic of excluding instrument				83.95
Anderson-Rubin F-test (p-value)				0.0008

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Reference groups are married or partnered, employed, less than high school and white.

Table A2: point estimates from OLS, FE and OLS-IV models with ln(income)

Dependent variable: Life satisfaction	OLS	FE	OLS-IV	
			First-stage	IV
Real equivalised household income(ln)	0.0704***	0.0162***		0.2529***
	(0.0049)	(0.0053)		(0.0753)
Mother´s education			0.0210***	
			(0.0017)	
Pain	-0.2089***	-0.0561***	-0.0702***	-0.1922***
	(0.0089)	(0.0093)	(0.0092)	(0.0107)
Age	0.0487***	0.0500***	0.0358***	0.0429***
	(0.0097)	(0.0152)	(0.0106)	(0.0105)
Age squared	-0.0011	-0.0051***	-0.0052***	-0.0001
	(0.0009)	(0.0014)	(0.0010)	(0.0011)
Second wave	-0.0135*	-0.0153*	-0.0247***	-0.0079
	(0.0076)	(0.0086)	(0.0076)	(0.0082)
Third wave	-0.0245***	-0.0172	-0.0485***	-0.0167*
	(0.0079)	(0.0112)	(0.0078)	(0.0089)
Fourth wave	-0.0033	0.0072	-0.0286***	0.0013
	(0.0085)	(0.0148)	(0.0087)	(0.0090)
Ever reported cancer	-0.0380***	-0.1052***	0.0303**	-0.0358***
	(0.0124)	(0.0261)	(0.0126)	(0.0131)
Ever reported lung disease	-0.1083***	-0.0053	-0.0916***	-0.0979***
	(0.0159)	(0.0308)	(0.0158)	(0.0183)
Ever reported heart problems	-0.0764***	-0.0534***	-0.0186*	-0.0685***
	(0.0108)	(0.0203)	(0.0111)	(0.0115)
Ever reported stroke	-0.0784***	-0.0596*	-0.0978***	-0.0684***
	(0.0178)	(0.0327)	(0.0168)	(0.0205)
Ever reported psychological problems	-0.3510***	-0.1760***	-0.0798***	-0.3264***
	(0.0132)	(0.0305)	(0.0134)	(0.0151)
Ever reported arthritis	-0.0213**	-0.0023	-0.0030	-0.0211**
	(0.0095)	(0.0185)	(0.0106)	(0.0101)
Ever reported high blood pressure	0.0096	-0.0415**	-0.0524***	0.0204*
	(0.0092)	(0.0183)	(0.0103)	(0.0106)
Do you smoke cigarettes now?	-0.1421***	0.0413*	-0.1618***	-0.1184***
	(0.0138)	(0.0229)	(0.0151)	(0.0189)
Divorced or separated	-0.2887***	-0.1101***	-0.5252***	-0.1994***
	(0.0143)	(0.0308)	(0.0161)	(0.0422)
Widowed	-0.2235***	-0.2162***	-0.3312***	-0.1658***
	(0.0132)	(0.0242)	(0.0137)	(0.0286)
Single	-0.2149***	-0.1757***	-0.6358***	-0.1011*
	(0.0229)	(0.0652)	(0.0288)	(0.0532)
Unemployed	-0.2253***	-0.1340***	-0.5725***	-0.1315***
	(0.0261)	(0.0241)	(0.0305)	(0.0510)
Partly retired	0.1105***	0.0414**	-0.3085***	0.1635***
	(0.0147)	(0.0163)	(0.0175)	(0.0279)
Retired	0.0885***	0.0092	-0.5728***	0.1895***
	(0.0124)	(0.0152)	(0.0141)	(0.0452)
Out of the labor force	0.0151	-0.0605***	-0.5720***	0.1188**

	(0.0189)	(0.0223)	(0.0230)	(0.0474)
Number of resident children	-0.0043	0.0015	-0.2234***	0.0308*
	(0.0068)	(0.0106)	(0.0077)	(0.0185)
Female	0.0647***		-0.0478***	0.0721***
	(0.0096)		(0.0106)	(0.0107)
GED and high school graduate	-0.0272*		0.2661***	-0.0753***
	(0.0146)		(0.0148)	(0.0278)
Some college	-0.0775***		0.4336***	-0.1661***
	(0.0157)		(0.0166)	(0.0406)
College and above	-0.0409**		0.7874***	-0.1967***
	(0.0164)		(0.0182)	(0.0669)
Black/African American	-0.0427***		-0.3346***	0.0206
	(0.0135)		(0.0150)	(0.0306)
Other	0.0282		-0.1089***	0.0647***
	(0.0208)		(0.0256)	(0.0246)
Hispanic==1	-0.0001		-0.3913***	0.0884**
	(0.0184)		(0.0213)	(0.0408)
Health insurance	0.0723***	0.0593***	0.1190***	0.0540***
	(0.0120)	(0.0140)	(0.0153)	(0.0156)
Constant	3.7258***	3.8572***	1.3094***	3.4560***
	(0.0361)	(0.0462)	(0.0440)	(0.1202)
Observations	64,205	64,205	58,588	58,588
Adjusted R-squared	0.1277	0.0097	0.3731	0.1003
F-statistic of excluding instrument				160.07
Anderson-Rubin F-test (p-value)				0.0008

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Reference groups are married or partnered, employed, less than high school and white.

Table A3: CV estimates from unadjusted and adjusted models

Panel A	OLS		FE	
	Unadjusted	Adjusted	Unadjusted	Adjusted
Pain	-0.3113***	-0.2123***	-0.0575***	-0.0563***
	(0.0092)	(0.0089)	(0.0093)	(0.0093)
Income	0.0091***	0.0064***	0.0017***	0.0015***
	(0.0009)	(0.0008)	(0.0006)	(0.0006)
CV		910***		1,040**
		(115)		(422)

Panel B	OLS		FE	
	Unadjusted	Adjusted	Unadjusted	Adjusted
Pain	-0.2926***	-0.2089***	-0.0570***	-0.0561***
	(0.0091)	(0.0089)	(0.0094)	(0.0093)
ln(income)	0.1057***	0.0704***	0.0236***	0.0162***
	(0.0043)	(0.0049)	(0.0052)	(0.0053)
CV		2,377***		3,983
		(611)		(5,224)

*p<0.10, ** p<0.05, *** p<0.01. Unadjusted models include pain and real equivalized household income in panel A and ln (real equivalized household income) in panel B. Adjusted models also include age, age squared, number of children in household, year dummies, dummies for comorbidities, marital status, census division, labor-force status, gender, education, race, Hispanic and health insurance. FE models include age, age squared, year dummies, dummies for comorbidities, marital status, labor force status, children in household and health insurance as covariates in addition to pain and income. CVs are reported in USD per day, 2015 price level. Unweighted results. Standard errors (in parentheses) are clustered on individuals.

Table A4: CV estimates with and without weights

Models with linear income	OLS		PWL-OLS		OLS-IV	
	No weights	With weights	No weights	With weights	No weights	With weights
	910***	893***			129***	144***
	(115)	(121)			(42)	(52)
Income						
1. spline			183***	185***		
			(40)	(56)		
2. spline[1]			95***	76***		
			(11)	(9)		
3. spline			1,720***	1,533***		
			(301)	(274)		
Models with ln(income)	OLS				OLS-IV	
	No weights	With weights			No weights	With weights
	2,377***	1,513***			152**	137**
	(611)	(427)			(72)	(68)

*p<0.10, ** p<0.05, *** p<0.01. Compensating variation (CV) is calculated from models including age, age squared, number of children in household, year dummies, dummies for comorbidities, marital status, census division, labor-force status, gender, education, race, Hispanic and health insurance. Knots are at income values 30,000 and 50,000 in PWL-OLS model. CVs are reported in USD per day at 2015 price level. Standard errors (in parentheses) are clustered on individuals.