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Happiness as a Driver of Risk-Avoiding Behavior

Abstract

Understanding the reasons why individuals take risks, particularly unnecessary risks, remains an important question in economics. We provide the first evidence of a powerful connection between happiness and risk-avoidance. Using data on 300,000 Americans, we demonstrate that happier individuals wear seatbelts more frequently. This result is obtained with five different methodological approaches, including Bayesian model-selection and an instrumented analysis based on unhappiness through widowhood. Independent longitudinal data corroborate the finding, showing that happiness is predictive of future motor vehicle accidents. Our results are consistent with a rational-choice explanation: happy people value life and thus act to preserve it.

JEL-Code: C300, D600, D810.

Keywords: risk preferences, seatbelt usage, vehicle accidents, subjective well-being, happiness.

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1 Introduction

Understanding the reasons why individuals take risks, particularly unnecessary risks, remains an important and open question in economics as well as the behavioral sciences. We argue in this paper that human beings are profoundly (if subconsciously) affected by how much they enjoy their own lives. Happiness leads them to protect themselves; unhappiness leads them to be rationally careless with life. We illustrate this simple, new idea within the specific setting of road safety. We show in U.S. data that the less satisfied people are with life, the less conscientious they are in taking action to preserve their life by the wearing of a seatbelt, and the more likely they are to be involved in a motor vehicle accident later in life. After correcting for a wide-range of covariates, we find that an increase of one level (out of four) in subjective well-being is associated with an increase by a factor of 1.383 in the odds ratio of wearing a seatbelt, and in longitudinal data, an increase of one level (out of five) in subjective well-being in 2001 is associated with a decrease by a factor of 0.9 in the odds ratio of experiencing a motor vehicle accident in 2008.

Decision processes involving risk are affected by a wide range of factors – including underlying risk preferences, perceptions, framing, level of involvement in the outcome-generating process, previous outcomes, and biological factors (Kahneman and Tversky, 1979; Zeckhauser and Viscusi, 1990; Thaler and Johnson, 1990; Fong and McCabe, 1999; Sapienza, Zingales, and

Maestripieri, 2009; Kimball, 1993). Utility theory remains the predominant framework for studies of risk, although questions about its assumptions have been raised (Kahneman and Tversky, 1979; Machina, 1987).

An increasing number of authors (e.g. Easterlin, 1974; Oswald, 1997; Frey and Stuzer, 2002) have argued for the importance of subjective well-being in the study of human behavior. A diverse literature is emerging on the determinants of human happiness (see Diener, 1984; Oswald, 1997; Radcliff, 2001; Clark, 2003; Easterlin, 2003; Layard, 2005; Luttmer, 2005; Fowler and Christakis, 2008; Stevenson and Wolfers, 2008; Pittau, Zelli, and Gelman, 2009), how they change over time (Blanchflower and Oswald, 2004, 2008), and its relationship to utility (Kimball and Willis, 2006; Benjamin, Heffetz, Kimball et al., 2010). There has been debate about the reliability of self-reported measures of well-being (Argyle, 2001; Bertand and Mullainathan, 2001), but much new evidence suggests that these measures are correlated with biological and other indicators (Urry, Nitschke, Dolski et al., 2004; Steptoe and Wardle, 2005; Fliessbach, Weber, Trautner et al., 2007), and thus do provide meaningful information. It has recently been demonstrated that across space there is a close match between U.S. life satisfaction scores and objective well-being indicators (Oswald and Wu, 2009).

Little is known, however, about the influence of people's well-being on their actions: that is, on what happiness 'does', rather than the factors that shape it. Here, investigating factors which influence individual proclivity for risk, we argue that well-being plays a key role.

Seatbelt use represents an attractive indicator of self-preserving behavior. In a modern industrialized nation, there are few widespread activities in which people are at risk of instantaneous death or serious injury. Driving is an activity which carries with it the risk of serious physical harm and the wearing of seatbelts is a demonstrably effective measure in reducing this risk (Wild, Kenwright, and Rastogi, 1985). As there is little cost associated with seatbelt usage, rationally the wearing of seatbelts should be universal. Yet seatbelt usage in the United States is far from universal. Only 83 percent of individuals in the data used in this study state they always use a seatbelt, a figure corroborated by the National Occupant Protection Use Survey by National Highway Traffic Safety Administration (Pickrell and Ye, 2008), which directly also observed that 83 percent of individuals actually used a seatbelt. Thus, there remain interesting and as yet unexplained patterns of variation in this key risk behavior.

Analyzing a large random sample of 313,354 individuals in the United States, we find striking evidence that an individual's life-satisfaction (subjective well-being) is an important determinant of their attitude to taking risks, even when a wide range of other factors are accounted for. Figure 1 shows – we believe this study is the first of its kind – that subjective well-being and seatbelt usage are associated across the sample used here.

A significant challenge is to probe causality and understand whether other factors might explain the observed association. To this end, we employ five complementary multivariate analyses to examine the influence of a range of plausible confounding factors (Tables 1 and 2). These include both standard regression-based approaches as well as methods rooted in Bayesian model selection. We find that none of the confounders, either singly or jointly, explain the observed connection between seatbelt usage and subjective well-being, even when non-linear effects are accounted for. We test the hypothesis that life-satisfaction influences seatbelt usage using widowhood as an instrument and find that the decreased level of subjective well-being caused by losing a spouse decreases the frequency with which individuals wear seat belts.

We replicate and extend this finding on an independent longitudinal sample of 13,027 Americans and find that lagged subjective well-being is predictive of later involvement in motor vehicle accidents. This result remains significant when other factors are controlled for, including the current level of well-being.

Taken together, our results are consistent with the idea that subjective well-being exerts a causal effect on seatbelt usage. A simple theoretical model provides an explanation for this finding, showing that, under mild assumptions, satisfied individuals should be more risk-averse.

The remainder of this paper is organized as follows. We first present details of the data and methods used in the study, including regression and model selection-based multivariate analyses and an instrumental variables regression. We then present our main results on seatbelt usage and motor vehicle accidents. Finally we discuss shortcomings and implications, as well as directions for further work.

2 Methodology

This section describes the two data sources and briefly outlines Bayesian variable selection and joint confounding methods. These Bayesian techniques complement the usual approaches of OLS and instrumented analyses, allowing a relaxation of the assumption of linearity and permitting principled comparison of a wide range of models representing competing explanations for the data.

2.1 Data

2.1.1 Behavioral Risk Factor Surveillance System Survey

The main data we use are from the publicly-available Behavioral Risk Factor Surveillance System Survey (BRFSS). This is a household-level random-digit telephone survey, collected by the U.S. Government's National Center for Chronic Disease Prevention and Health, that has been conducted throughout the United States since 1984. Seatbelt-usage statistics were collected in 2006 and 2008, but to avoid a discontinuous time-period, we use only 2008 data (results using 2006 data are similar). Following previous work (Oswald and Wu, 2009), we restrict our analyses to those between 18 and 85 years old, not residing in unincorporated U.S. territories, and exclude respondents who refused or were unsure of their response, or whose response is missing, for any of the 19 variables included in our analyses (Tables 1 and 2). The resulting sample size is 313,354.

Our measure of life satisfaction is the self-assessed response, on a 4-point scale ranging from 'Very satisfied' to 'Very dissatisfied', to the question, "In general, how satisfied are you with your life?". Seatbelt use is recorded as self-reported frequency of use when driving or riding in a car, on a 5-point scale. Respondents were also able to declare that they do not use a car. These questions were separated in the survey by at least 4 other questions. The questions from which the covariates are derived are listed in Table 3.

2.1.2 Add Health

Longitudinal data is from the National Longitudinal Study of Adolescent Health (Add Health) that explores health-related behavior of adolescents (Harris, Halpern, Whitsel et al., 2009), and is available from the Carolina Population Center at the University of North Carolina. Four waves (1995, 1996, 2001, 2008) of data collection have taken place and by 2008 participating individuals are around 30 years old. The Add Health measure of life satisfaction answers "How satisfied are you with your life as a whole?" on a 5-point scale ranging from 'Very dissatisfied' to 'Very satisfied'. Accident involvement is recorded as the self-reported answer to the question "In the past 12 months, were you involved in a motor vehicle accident?". Possible answers were 'no', 'yes', or 'don't know'. The latter category was discarded for the purpose of this study (less than 0.1 percent of interviewees gave such a response).

2.2 Bayesian Methods

2.2.1 Bayesian variable selection

While we fit standard regression models to the data, we additionally consider a less-constrained approach that accounts for the possibility of non-linearity and interactions. This provides a more rigorous test of the importance of a covariate because a larger number of possible alternative explanations are considered, including interaction effects that are sometimes key (e.g. in Gelman, Shor, Bafumi et al., 2007) and yet are often overlooked. We select effects by Bayesian variable selection (Smith and Kohn, 1996; Nott and Green, 2004), a convenient and widely-used framework that accounts for the trade-off between fit-to-data and model complexity in a principled manner. (Wasserman, 2000; Claeskens and Hjort, 2008; Madigan and Raftery, 1994)

The models M_S for seatbelt usage that we consider are defined by subsets S of covariates, with $|S| \leq 9$ (Figure 2A). Suppose each of the p covariates has q_j levels, $1 \leq j \leq p$. For a model M_S, let $\mathcal{C}$ be the set containing all $\prod_{j \in S} q_j$ combinations of values of the covariates included in the model. To control complexity in this setting, we simplify the data by reducing the levels of some variables with many categories, as shown in Tables 1 and 2, and binarize the response, enabling a simple contrast between those who always wear seatbelts with those who do not. For each of the n individuals, let y_i be the indicator of whether individual i always uses a seatbelt, and c_i be the corresponding vector of covariates. We use a Binomial model for the responses, with parameter θ_c dependent on the state $c \in \mathcal{C}$ of the covariates. This means the joint probability for vector of responses $\boldsymbol{y}$ depends on n_c, the number of observed individuals who have covariates c, and m_c, the number of these individuals who use a seatbelt.

The posterior distribution over models M_S, given the data, gives a measure of the fit of each model that incorporates a preference for simpler models of lower dimension. The posterior, up to proportionality, is given by the product of the model prior $P(M_S)$, and, using the standard assumption of independent Beta(α, β) parameter priors (Cooper and Herskovits, 1992), the closed-form marginal likelihood

$$P(\boldsymbol{y}|\boldsymbol{c}, M_S) = \prod_{c \in \mathcal{C}} \frac{\Gamma(m_c + \alpha)\Gamma(n_c - m_c + \beta)\Gamma(\alpha + \beta)}{\Gamma(n_c + \alpha + \beta)\Gamma(\alpha)\Gamma(\beta)},$$

where $\boldsymbol{c}$ is the vector of covariates with components c_i. Following previous authors (Heckerman, Geiger, and Chickering, 1995), we set the hyperparameters $\alpha = \beta = (\prod_{j \in S} q_j)^{-1}$ for each θ_c. We choose a flat prior $P(M_S) \propto 1$, but the large sample results in insensitivity to this choice. Penalized likelihood approaches offer an alternative to the Bayesian approach taken here: indeed, here were find that a BIC-based analysis (with $|S| \leq 5$, for computational reasons) in this setting selected the same model.

2.2.2 Joint confounding

An alternative to regression approaches, which model risk-taking behaviour conditional on the observed covariates and life-satisfaction, is additionally to model life-satisfaction conditional on the observed covariates (Robins, Mark, and Newey, 1992; Senn, Graf, and Caputo, 2007). This approach has the advantage of explicitly modelling the unbalanced distribution of subjective well-being among individuals, for which we must account to compare meaningfully how seatbelt-use varies with life-satisfaction. We can restore balance by identifying covariates that explain both subjective well-being and seatbelt usage, and examining the effect of life-satisfaction within particular values of these covariates.

We take a model selection approach to discovering such covariates (Robins and Greenland, 1986) that is similar to Bayesian variable selection, but as shown in Figure 3A we now mirror dependences between covariates C_i and seatbelt usage (Y) with corresponding direct dependences between C_i and subjective well-being (X). This can be thought of as exploring different stratifications for a model of the effect of X on Y. Any residual relationship after stratification between subjective well-being and seatbelt usage represents the controlled effect (Rosenbaum, 2002). The approach taken here can also be regarded as a special case of structural inference in Bayesian networks (Heckerman, Geiger, and Chickering, 1995; Madigan and York, 1995; Mukherjee and Speed, 2008).

Each model $M_{S,L}$ is defined by a set of confounders (a subset S of the covariates, excluding subjective well-being X, and with $|S| \leq 9$) and an indicator variable L for whether the direct dependence between X and Y is present. We redefine $\mathcal{C}$ to be the set containing all combinations of values of the confounders alone (i.e. excluding subjective well-being) in $M_{S,L}$, and denote by $\mathcal{D}$ the corresponding set including subjective well-being. We denote the number of observed individuals with confounding variables $c \in \mathcal{C}$ by $w_{\boldsymbol{c}}$, and number of these individuals who are 'very satisfied' by $v_{\boldsymbol{c}}$. Similarly defining n_d to be number of observed individuals with covariates $d \in \mathcal{D}$ and the number of these who always use a seatbelt by m_d, we have the following marginal likelihood for seatbelt usage $\boldsymbol{y}$, subjective well-being $\boldsymbol{x}$, and confounders $\boldsymbol{c}$.

$$
\begin{aligned}
P(\boldsymbol{y}, \boldsymbol{x} | \boldsymbol{c}, M_{S,L}) = & \prod_{d \in \mathcal{D}} \frac{\Gamma(m_d + \alpha)\Gamma(n_d - m_d + \beta)\Gamma(\alpha + \beta)}{\Gamma(n_d + \alpha + \beta)\Gamma(\alpha)\Gamma(\beta)} \\
& \times \prod_{c \in \mathcal{C}} \frac{\Gamma(v_c + \alpha)\Gamma(w_c - v_c + \beta)\Gamma(\alpha + \beta)}{\Gamma(w_c + \alpha + \beta)\Gamma(\alpha)\Gamma(\beta)}
\end{aligned}
$$

We again choose Beta priors for α, β, with $\alpha = \beta = (\prod_{j \in S} q_j)^{-1}$ for X, and $\alpha = \beta = (q_X \prod_{j \in S} q_j)^{-1}$ for Y, where q_X is the number of levels of X when $M_{S,L}$ includes direct dependence between X and Y, and 1 otherwise. Note that the result of adding extra dependencies is simply an additional term in the marginal likelihood, and so the computation time is identical to variable selection.

3 Results

3.1 Seatbelt usage and life satisfaction

Across the entire sample of $n = 313,354$ U.S. residents used here we found that, while 86.7 percent of individuals who are 'very satisfied' with their life report always using their seatbelt, only 77.2 percent of adults who are 'very dissatisfied' do so. Moreover, 4.7 percent of individuals who are 'very dissatisfied' with their life report never using their seatbelt, whereas only 1.2 percent of adults who are 'very satisfied' do so. The differences across all the levels in this large sample corresponds to a statistically highly significant association (Figure 1), yielding a Chi-squared p-value with $p < 2.2 \times 10^{-16}$.

3.1.1 Regression for seatbelt usage

To investigate the influence of other explanatory factors, we employed a range of complementary multivariate analyses. Firstly, we carried out a logistic regression that predicts whether an individual always wears a seatbelt, including sex, age, race, marital status, educational achievement, employment status, income, month of interview, and state of residence as independent variables. The resulting fitted odds ratio for always wearing a seatbelt in favor of very satisfied individuals is large at 1.383 (Table 4). This shows that subjective well-being remains a quantitatively important determinant of seatbelt usage after inclusion of a wide range of social, economic and demographic factors. The same conclusion that subjective well-being is important is given when predicting the level of seatbelt usage by OLS, as shown in Table 5.

3.1.2 Bayesian variable selection

A more rigorous test of the hypothesis can be performed by allowing non-linearity and interactions into the model, as detailed in Methodology above, to check that the result is robust to such deviations in the modelling assumptions. This approach addresses the possibility that in combination, and potentially through a non-linear relationship, other covariates may adequately describe seatbelt usage, without any dependence on subjective well-being. To consider this possibility, we use a variable selection framework to explore all possible subsets S of covariates (up to and including 9 covariates jointly) to quantify the joint explanatory ability of those subsets in terms of probability scores. We found that, with probability 0.99, the subset of predictors that jointly best describe seatbelt usage are state of residence, sex and life satisfaction (Figure $2B$). Fitted posterior probabilities from this model are shown in Figure 4 by state, arranged into groups defined by seatbelt legislation. We see that seatbelt-wearing rates vary widely across U.S. states and that differing legislation at the state-level explains some of this variation. Females are more likely to use a seatbelt than males. These results are expected and fairly well-known, but it is the high rate of seatbelt usage in very satisfied individuals that is new. This model estimates that the probability of an individual who is very satisfied always wearing their seatbelt is 0.067

higher.

3.1.3 Joint confounding

The regression approaches described above focus on factors affecting seatbelt usage. However, it is factors that explain, possibly in combination, both subjective well-being and seatbelt usage that may bias our result, through the unbalancing of the distribution of subjective well-being. We can consider this problem explicitly with models of form shown in Figure 3A, so that the covariates explain *both* subjective well-being and seatbelt usage. This allows us to isolate the fully controlled relationship between subjective well-being and seatbelt usage.

The best model (Figure 3B), selected with high confidence (Bayesian posterior probability of model was close to unity) retains the link from subjective well-being to seatbelt usage. This model is preferred to the corresponding model without this link with high confidence (Bayes factor $\approx 10^{33}$). Applying the back-door theorem (Pearl, 2000), which here implies taking the weighted average of the effect over the strata defined by the model, we estimate that the probability of always wearing a seatbelt is 0.053 higher in individuals exogenously very satisfied with their life.

3.1.4 Instrumental variable

While our analysis shows a strong relationship between seatbelt usage and life satisfaction, we have so far assumed exogeneity, implying that biases in our analysis can be fully removed by adjusting for observed covariates, and thus overlooking the possibility of unobserved variables playing a key role. To explore this possibility, we consider an exogenous alteration to subjective well-being, which should result in a change in risk-aversion if subjective well-being determines risk-aversion.

We propose that widowhood at 60 years old or younger is such a suitable instrument, because its effect on subjective well-being is demonstrably strong, yet it is arguably close to being independent of seat-belt use. That is, we claim that premature widowhood should exogenously cause dissatisfaction, but should not affect seatbelt usage through any other channel. Widowhood has been shown to have a negative effect on happiness (Easterlin, 2003; Clark and Oswald, 2002), and this effect is long-lasting (Lucas, Clark, Georgellis et al., 2003). Using this instrument, a standard two-stage least squares analysis estimates that an exogenous increase of one class of subjective well-being category increases seatbelt usage by 0.188 categories (Table 6). This implies that seatbelt usage is indeed influenced by life-satisfaction, even when the possibility of unobserved confounding is considered.

3.2 Motor vehicle accidents and life satisfaction

Our hypothesis of dissatisfied individuals being more careless with their life suggests that these individuals should experience more motor vehicle accidents. This can be investigated by examining whether dissatisfaction is predictive of future motor vehicle accidents. To consider this, we exploit the

Add Health survey, an independent longitudinal data sample of 13,027 Americans that provides self-reported happiness levels in 2001 and 2008, as well as their involvement in a motor vehicle accident in the 12 months preceding the interview in 2008. We find that for individuals who were very dissatisfied with their lives in 2001, 14.7 percent reported being involved in an accident in 2008. In contrast, for individuals that earlier reported being very satisfied, 9.5 percent had had an accident in 2008. The differences across the levels of this sample produce a Chi-squared p-value with $p = 0.022$ (see Table 7). Table 8 reports on a multivariate logistic regression that includes the same set of covariates as listed earlier. The odds ratio for earlier life satisfaction on being involved in an accident is significant at 0.90. Happiness has an important stable component and so we also test this empirical model including 2008 happiness levels. Table 9 shows lagged life satisfaction is robust to this specification and produces an odds ratio of 0.92. This longitudinal analysis indicates the predictive power that happiness has in estimating the likelihood of being involved in future motor vehicle accidents. As such, it complements and extends our prior findings on happiness and risky behavior as measured by seatbelt usage.

These results show that across two large samples of the U.S. population life-satisfaction appears as a salient influence upon seatbelt usage and involvement in motor vehicle accidents, even when a range of other factors are accounted for.

4 Conclusion

Currently economists have little understanding of why some people take extreme risks with their lives. This paper provides new evidence for a link between life-satisfaction and risk-avoiding behavior. We show that the less satisfied an individual is with life, the less conscientious that person is in taking action to preserve their life by the wearing of a seatbelt, and the more likely they are to be involved in a motor vehicle accident later in life. A great deal of recent research has focused on identifying factors that influence life-satisfaction. In contrast, our work provides an example in which life satisfaction is an influential factor in a decision-making process.

Our empirical analysis suggests the following utility model. We assume expected utility is the following function, where p is the probability of living, a is seatbelt usage, u is the fixed utility from life, v is the fixed utility from death, and $c(a)$ is a strictly convex cost function.

$$E(U) = p(a)u + \{1 - p(a)\}\, v - c(a)$$

Naturally, we assume the probability of living $p(a)$ increases with seatbelt usage. We normalize the utility of death to zero. It is then clear that around the point of optimal action a^* we have that

$$\{p''(a^*)u - c''(a^*)\}\, da^* + p'(a^*)du = 0.$$

The derivative is unambiguously positive by the requirement that the second-order condition holds. This implies that da^*/du is positive, and thus increasing subjective well-being increases use of seatbelts. This theoretical model posits a simple explanation for our empirical findings in terms of utility theory.

We used seatbelt usage as an indicator of individual propensity for risky behavior. Seatbelt use is an interesting indicator for several reasons. Driving is one of the few mainstream activities that remains potentially life-threatening, even in developed countries. Seatbelt use is widely accepted as enhancing automotive safety, and indeed most countries, and nearly all the U.S. states that are the subject of our study, have some form of legislation that mandates the use of seatbelts. In contrast to behaviors like smoking and drug-taking, seatbelt usage is habitual rather than addictive. For this reason it is less likely that current seatbelt-wearing behavior is strongly affected by past attitudes to risk. In contrast, current smoking status, for example, may relate to decision-making processes decades previously. Additionally, the 'passive' effects on others brought about by the non-use of seatbelts are arguably smaller or at least less well appreciated than for smoking, and so seatbelt usage may reflect a more personal indication of propensity for risk than other measures. Seatbelt usage has in addition been demonstrated to be associated with risk preference as elicited by a lottery choice experiment (Anderson and Mellor, 2008).

We utilized a number of statistical analyses to investigate the relationship between life satisfaction and seatbelt usage. We employed Bayesian approaches to complement the well-established econometric tools of linear and logistic regression. The Bayesian approaches allowed us to explore the joint influence of multiple factors whilst taking account of both fit-to-data and model complexity in a principled way, although we note that the methods used here are not able to identify M-bias (Pearl, 2000). The longitudinal model demonstrated the predictive power of life-satisfaction in predicting future motor vehicle accidents. The fact that such a broad range of analyses, performed on a large sample of the population led to the same substantive conclusions gave us confidence in our findings.

There remains much to be done in exploring the implications of the work presented here, both in terms of better characterizing the connection between life-satisfaction and risk-taking and in understanding, in a wider sense, how subjective well-being impacts human activity. Our results suggest a number of specific directions for follow-up work. We showed how individuals suffering bereavement experience a reduction in life satisfaction which in turn led to a reduction in seatbelt usage. It would therefore be informative to study risky behaviors in further examples of subpopulations with lowered life-satisfaction.

Our conceptual account potentially has implications for science and policy across many domains of risky activity. If it wants to alter the dangerous actions chosen by citizens, a government may need to change its citizens' intrinsic happiness with their lives rather than, as at present, concentrate policy upon detailed behavioral symptoms themselves.

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Appendix

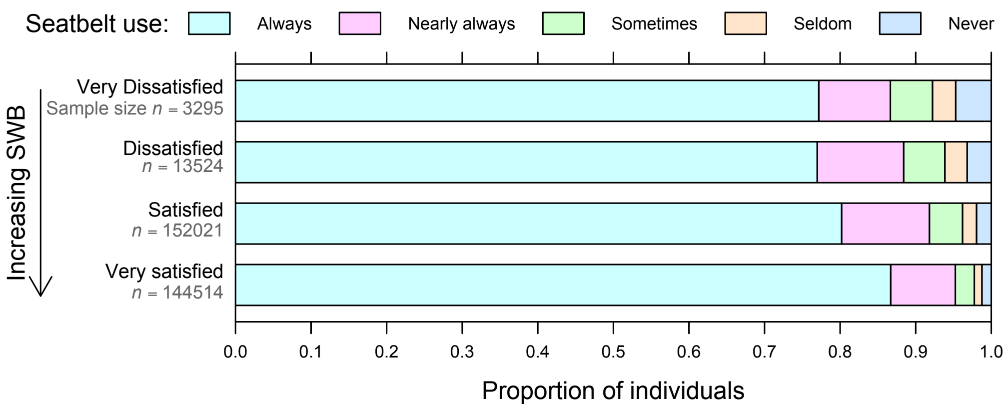

Figure 1: Frequency of seatbelt usage cross-tabulated by subjective well-being (SWB). Each category contains at least 101 individuals. Pearson's chi-squared statistic is 3242 (p-value $p < 2.2 \times 10^{-16}$).

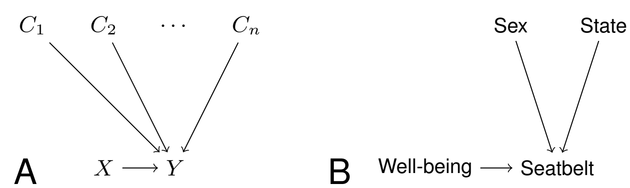

Figure 2: Variable selection for joint effects of multiple covariates. (A) The variable selection formulation explores subsets of $\{X, C_1, \ldots, C_n\}$ as joint explanatory factors for response Y. (B) The selected model, with selection occuring from 19 covariates, including subjective well-being (Tables 1 and 2). The approach accounts for interactions and non-linear effects, and so provides a more stringent test of the influence of subject well-being on seatbelt usage. The (posterior) probability of the model shown was close to unity: this shows that subjective well-being appears as a salient influence on seatbelt usage even when interactions and non-linear effects of other explanatory factors are allowed.

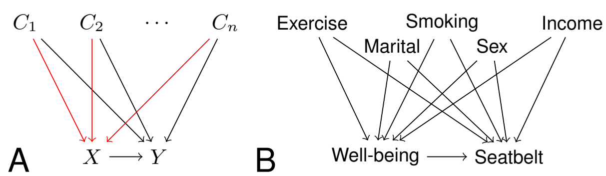

Figure 3: Model selection for joint confounding by multiple factors. (A) Graphical representation of family of models for considering the influence of conjectured explanatory variable X on response Y with potential observed confounders $C_1, \ldots, C_n$. A model selection approach is used to explore evidence in favor of a direct link from X to Y in light of subsets of $\{C_1, \ldots, C_n\}$ which may jointly explain both X and Y (see Methodology for details). (B) The selected model, treating seatbelt as Y, subjective well-being as X and selecting potential confounders C_i from Tables 1 and 2. The model shown was selected with high confidence (posterior probability of model was close to unity); it includes five factors, but retains the link from subjective well-being to seatbelt usage, showing that well-being remains an important influence on seatbelt usage even when all possible joint stratifications are considered in a fully general non-linear model.

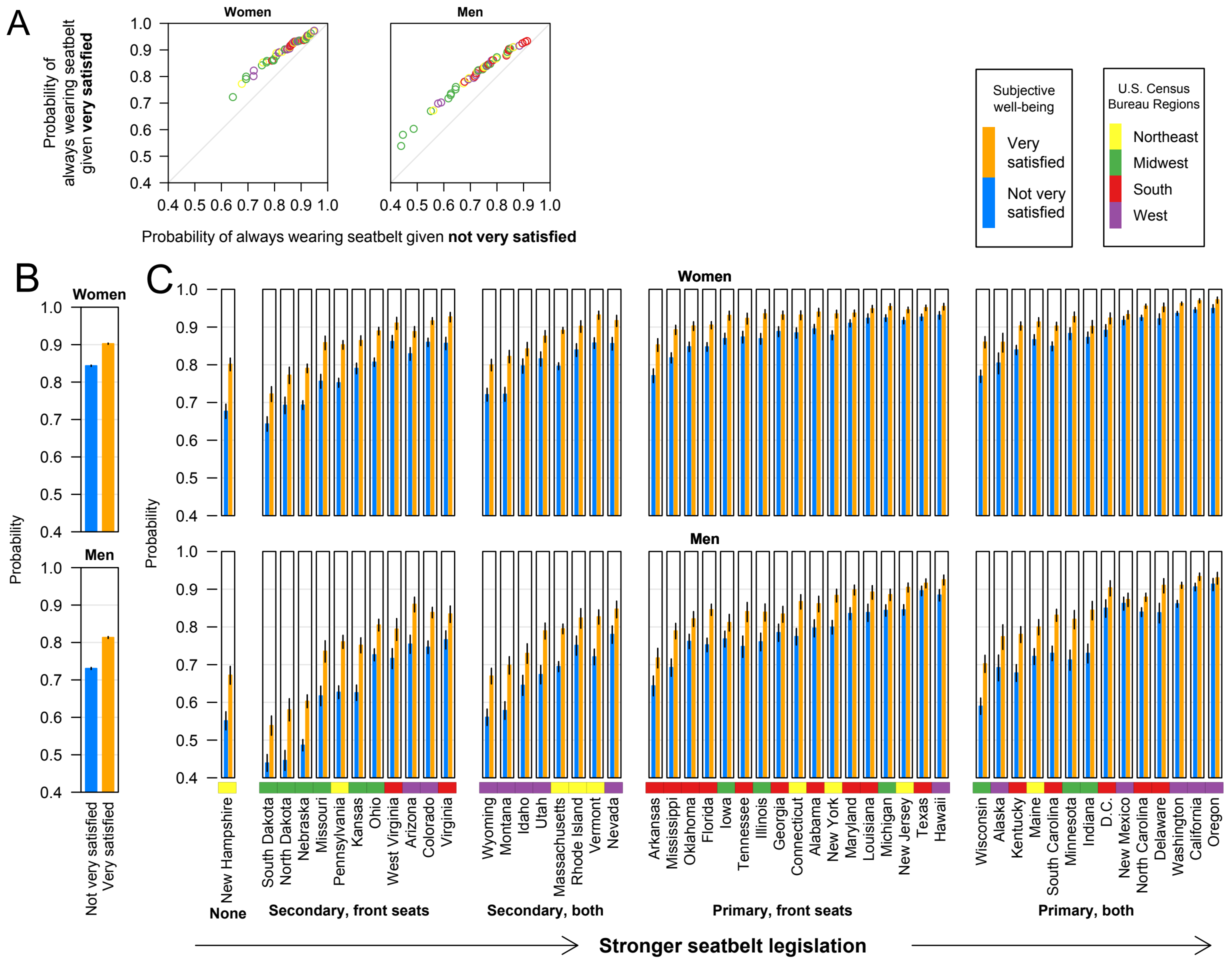

Figure 4: Fitted (posterior) probabilities of always wearing a seatbelt given subjective well-being. (A) For each state, the probability of always wearing a seatbelt for very satisfied residents against the probability of always wearing a seatbelt for residents who are not very satisfied. The colors denote U.S. Census Bureau Regions. (B) Probability of always wearing a seatbelt (Bayesian posterior probabilities, with bars indicating 95 percent highest probability density region), given subjective well-being, stratified by gender. (C) As (A), but stratified by state of residence and gender (these covariates were identified as influential by a variable selection approach; see the main text for details and Figure 2). States are grouped by legislation type, and the adjacent colors denote U.S. Census Bureau Regions. Both state/legislation and gender effects are important, but the association between subjective well-being and seatbelt usage remains clear under stratification.

Table 1: The main covariates used from BRFSS.

Variable	Levels	Collapsed levels
Seatbelt	Always (coded 5)	Always
	Nearly always (4)	Not always
	Sometimes (3)	
	Seldom (2)	
	Never (1)	
Subjective well-being	Very satisfied (4)	Very satisfied
	Satisfied (3)	Not very satisfied
	Dissatisfied (2)	
	Very dissatisfied (1)	
Gender	Male	Male
	Female	Female
Race	White only, non-Hispanic	White only, non-Hispanic
	Black only, non-Hispanic	Black only, non-Hispanic
	Asian only, non-Hispanic	Asian only, non-Hispanic
	Other/Multiracial, non-Hispanic	Other/Multiracial, non-Hispanic
	Hispanic	Hispanic
Age	(Age in years)	Young (18—34 years)
		Middle-aged (35–64 years)
		Old (65 years or older)
Marital Status	Never Married	Never Married
	Married	In couple
	Divorced	Formerly in couple
	Separated	Formerly in couple
	Widowed	Widowed
	Unmarried couple	In couple
Education	No high school	Not a high school graduate
	Some high school	
	High school graduate	High school graduate
	Some college/technical school	
	College graduate	College graduate
Employment	Employed for wages	Employed
	Self-employed	
	Unemployed	Unemployed
	Homemaker	Not in workforce
	Student	
	Retired	
	Unable to work	
Annual Income	$10,000 or less	Low income
	$10,000 – $15,000	
	$15,000 – $20,000	
	$20,000 – $25,000	Medium income
	$25,000 – $35,000	
	$35,000 – $50,000	
	$50,000 – $75,000	High income
	$75,000 or more	
State of residence	(State of residence)	
Month of interview	(Month of interview)	
Number of children	(Number of children in household)	No children
		1 child
		2 or more children

Note: The discretisation in Column 2 ('Levels') is used in our linear analyses, while our analyses based upon model selection use the discretisation in Column 3 ('Reduced Levels'). (The additional covariates used in our model selection analyses are detailed in Table 2.)

Table 2: Additional covariates from BRFSS used in model selection analyses

Variable	Raw levels	Collapsed levels
Body Mass Index (BMI)	(Height and weight)	
	BMI $<$ 2500	Neither overweight or obese
	2500 $<$ BMI $<$ 3000	Overweight
	BMI $>$ 3000	Obese
Heavy alcohol	(Number drinks of drinks/month)	
	Men $>$ 2 drinks/day	Heavy drinker
	Women $>$ 1 drinks/day	Heavy drinker
	Men $\leq$ 2 drinks/day	Not heavy drinker
	Women $\leq$ 1 drinks/day	Not heavy drinker
Physical Activity	Do exercise	Do exercise
	Don't exercise	Don't exercise
Diabetes	Have diabetes	Have diabetes
	Had diabetes when pregnant	Had diabetes when pregnant
	No diabetes	No diabetes
	Only pre- or borderline	Only pre- or borderline
Heart Attack	Had heart attack	Had heart attack
	Not had heart attack	Not had heart attack
Special Equipment	Use special equipment	Use special equipment
	Don't use special equipment	Don't use special equipment
Current Smoker	Current smoker	Current smoker
	Not current smoker	Not current smoker
Asthma	Currently have asthma	Currently have asthma
	Do not currently have asthma	Do not currently have asthma

Table 3: Questions used in the study from BRFSS

Variable	Question
Seatbelt	How often do you use seat belts when you drive or ride in a car?
Life Satisfaction	In general, how satisfied are you with your life?
Gender	(Noted by interviewer)
Race	Are you Hispanic or Latino? Which one or more of the following would you say is your race? [Mark all that apply.] (from White, Black or African American, Asian, Native Hawaiian or Other Pacific Islander, American Indian or Alaska Native, Other.)
Age	What is your age?
Marital Status	Are you: Married, Divorced, Widowed, Separated, Never married, A member of an unmarried couple?
Education	What is the highest grade or year of school you completed?
Employment	Are you currently: Employed for wages, Self-employed, Out of work for more than 1 year, Out of work for less that 1 year, A homemaker, A student, Retired, Unable to work
Income	Is your annual household income from all sources: (from Less than $25,000, $10,000 – $15,000, $15,000 – $20,000, $20,000 – $25,000, $25,000 – $35,000, $35,000 – $50,000, $50,000 – $75,000, $75,000 or more)
Number of children	How many children less than 18 years of age live in your household?
Body Mass Index	About how much do you weigh without shoes? About how tall are you without shoes?
Heavy alcohol	One drink is equivalent to a 12-ounce beer, a 5-ounce glass of wine, or a drink with one shot of liquor. During the past 30 days, on the days when you drank, about how many drinks did you drink on the average? [A 40 ounce beer would count as 3 drinks, or a cocktail drink with 2 shots would count as 2 drinks.]
Physical Activity	During the past month, other than your regular job, did you participate in a activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?
Diabetes	Have you ever been told by a doctor that you have diabetes?
Heart Attack	Has a doctor, nurse, or other health professional ever told you that you had a heart attack, also called a myocardial infarction?
Special Equipment	Do you now have any health problem that requires you to use special equipment, such as a cane, a wheelchair, a special bed, or a special telephone? (Include occasional use or use in certain circumstances.)
Current Smoker	Do you now smoke cigarettes every day, some days, or not at all?
Current Asthma	Have you ever been told by a doctor, nurse, or other health professional that you had asthma? Do you still have asthma?

Table 4: Logistic regression for seatbelt usage

Effect	Coefficient, β	Std. err.	p value	Odds ratio, $\exp(\beta)$
Subjective well-being	**0.324**	**0.008**	**< 0.001**	**1.383**
Gender (baseline Male)				
Female	0.716	0.011	< 0.001	2.047
Race (baseline White)				
Black	-0.009	0.021	0.668	0.991
Asian	0.593	0.060	< 0.001	1.809
Hispanic	-0.038	0.026	0.149	0.963
Other race	0.353	0.026	< 0.001	1.424
Age	0.032	0.002	< 0.001	1.032
Age^2	0.000	0.000	< 0.001	1.000
Marital Status (baseline Never Married)				
Married	0.230	0.018	< 0.001	1.259
Divorced	0.110	0.020	< 0.001	1.116
Widowed	0.182	0.025	< 0.001	1.200
Separated	0.159	0.037	< 0.001	1.173
Unmarried couple	0.006	0.034	0.855	1.006
Educational achievement (baseline No High School)				
Attended High School	-0.090	0.038	0.017	0.914
Graduated High School	-0.033	0.034	0.325	0.967
Attended College	0.100	0.034	0.004	1.105
Graduated college	0.410	0.035	< 0.001	1.506
Employment status (baseline Employed)				
Self-employed	-0.477	0.016	< 0.001	0.620
Unemployed	0.023	0.025	0.374	1.023
Homemaker	0.219	0.025	< 0.001	1.245
Student	0.172	0.042	< 0.001	1.187
Retired	0.198	0.019	< 0.001	1.219
Unable to work	0.177	0.023	< 0.001	1.193
Income (baseline Less than $10,000)				
$10,000 – $15,000	-0.047	0.031	0.125	0.954
$15,000 – $20,000	-0.022	0.029	0.460	0.978
$20,000 – $25,000	0.007	0.029	0.795	1.007
$25,000 – $35,000	-0.054	0.028	0.054	0.947
$35,000 – $50,000	-0.064	0.028	0.022	0.938
$50,000 – $75,000	-0.004	0.029	0.895	0.996
More than $75,000	0.158	0.029	< 0.001	1.171
Number of children	0.001	0.001	0.262	1.001
Constant	-0.873	0.086	< 0.001	0.418

Logistic regression was used to predict seatbelt usage from a panel of covariates (Table 1), including subjective well-being. We show the estimated coefficients β, and their standard errors and p-values, and the odds ratios (OR), for the model as fitted to data from $n = 313,354$ individuals from the BRFSS in 2008. Subjective well-being has p-value $p < 2 \times 10^{-16}$. All estimates are controlled for state of residence and interview month.

Table 5: Ordinary Least Squares (OLS) for seatbelt usage

Effect	Coefficient, β	Standard error	p value
Subjective well-being	**0.081**	**0.002**	$<$ **0.001**
Gender (baseline Male)			
Female	0.196	0.003	< 0.001
Race (baseline White)			
Black	0.016	0.005	0.003
Asian	0.059	0.008	< 0.001
Hispanic	-0.032	0.008	< 0.001
Other race	0.084	0.006	< 0.001
Age			
Age	0.007	0.001	< 0.001
Age^2	-4.4×10^{-5}	<0.001	< 0.001
Marital Status (baseline Never married)			
Married	0.086	0.005	< 0.001
Divorced	0.028	0.006	< 0.001
Widowed	0.064	0.007	< 0.001
Separated	0.050	0.011	< 0.001
Unmarried couple	0.025	0.010	0.015
Educational achievement (baseline No High School)			
Attended High School	-0.016	0.012	0.193
Graduated High School	0.016	0.011	0.138
Attended College	0.077	0.011	< 0.001
Graduated college	0.160	0.011	< 0.001
Employment status (baseline Employed)			
Self-employed	-0.144	0.005	< 0.001
Unemployed	-0.008	0.008	0.276
Homemaker	0.024	0.005	< 0.001
Student	0.070	0.011	< 0.001
Retired	0.023	0.004	< 0.001
Unable to work	0.003	0.007	0.670
Income (baseline Less than $10,000)			
$10,000 – $15,000	-0.002	0.010	0.871
$15,000 – $20,000	0.007	0.009	0.473
$20,000 – $25,000	0.019	0.009	0.034
$25,000 – $35,000	0.005	0.009	0.538
$35,000 – $50,000	0.010	0.009	0.239
$50,000 – $75,000	0.026	0.009	0.004
More than $75,000	0.051	0.009	< 0.001
Children			
Number of children	-0.001	0.000	0.016
Constant			
Constant	3.997	0.023	< 0.001

Note: Ordinary Least Squares was used to predict seatbelt usage from a panel of covariates (Table 1), including subjective well-being (shown in bold). We show the estimated coefficents β, the standard error and the p-value for the model as fitted to data from n=313,354 individuals from the 2008 Behavioral Risk Factor Surveillance System Survey (BRFSS). Subjective well-being has p-value $p < 2 \times 10^{-16}$. All estimates are controlled for state of residence and interview month.

Table 6: Instrumental variable (IV) regression for seatbelt usage

Effect	Coefficient, β	Standard error	p value
Subjective well-being	**0.1881**	**0.0656**	**0.004**
Gender (baseline Male)			
Female	0.1954	0.0045	< 0.001
Race (baseline White)			
Black	0.0259	0.0088	0.003
Asian	0.0607	0.0115	< 0.001
Hispanic	0.0961	0.0083	< 0.001
Other race	-0.0343	0.0125	0.006
Age	0.0103	0.0025	< 0.001
Age^2	-0.0001	0.0000	0.003
Educational achievement (baseline No High School)			
Attended High School	-0.0206	0.0218	0.344
Graduated High School	0.0018	0.0191	0.924
Attended College	0.0709	0.0191	< 0.001
Graduated college	0.1582	0.0196	< 0.001
Employment status (baseline Employed)			
Self-employed	-0.1362	0.0072	< 0.001
Unemployed	0.0190	0.0184	0.302
Homemaker	0.0237	0.0062	< 0.001
Student	0.0460	0.0177	0.009
Retired	0.0171	0.0104	0.101
Unable to work	0.0371	0.0274	0.176
Income (baseline Less than $10,000)			
$10,000 – $15,000	0.0105	0.0273	0.699
$15,000 – $20,000	0.0344	0.0250	0.169
$20,000 – $25,000	0.0362	0.0242	0.134
$25,000 – $35,000	0.0061	0.0247	0.804
$35,000 – $50,000	0.0041	0.0265	0.877
$50,000 – $75,000	0.0178	0.0293	0.543
More than $75,000	0.0397	0.0344	0.249
Children			
Number of children	-0.0014	0.0020	0.483
Constant			
Constant	3.6252	0.2487	< 0.001

Note: Estimates are shown for an IV regression in which widowhood at 60 years old or younger was used as an instrument to probe the potential link between subjective well-being and seatbelt usage (please see Main Text for details). Subjective well-being is significant at the 0.005 level. All estimates are controlled for state of residence and interview month.

Table 7: Cross-tabulation of accidents in 2008 by life-satisfaction in 2001

Life satisfaction (2001)	Accident (2008) 0	1	Total
Very dissatisfied	64	11	75
	85.3%	*14.7%*	*100%*
Dissatisfied	397	60	457
	86.9%	*13.1%*	*100%*
Neither	1,438	185	1,623
	88.6%	*11.4%*	*100%*
Satisfied	5,481	619	6,100
	89.8%	*10.2%*	*100%*
Very satisfied	4,321	451	4,772
	90.5%	*9.5%*	*100%*
Total	11,701	1,326	13,027
	89.8%	*10.2%*	*100%*

Note: The table shows the individuals who had experienced an accident in 2008 cross-tabulated by life satisfaction in 2001. The data are from n = 13,027 individuals from the National Longitudinal Study of Adolescent Health (Add Health). Pearson's χ^2 statistic is 11.4 (p-value $p = 0.022$)

Table 8: Logistic regression for involvement in an accident in 2008

Effect	Odds ratio, exp(β)	Std. err.	p-value
Life satisfaction (2001)	**0.90**	**0.04**	0.007
Gender			
Male	1.14	0.08	0.056
Race			
Black	1.25	0.10	0.005
Hispanic	0.78	0.12	0.107
Asian	0.73	0.12	0.058
Native	2.21	0.79	0.027
Age			
Age	0.94	0.02	0.003
Martial status			
Married	0.89	0.06	0.085
Others			
Education	1.02	0.02	0.209
Job	0.99	0.08	0.872
Income	1.00	0.00	0.020
Interview month	0.96	0.01	0.004
Constant			
Constant	0.92	0.58	0.892

Note: We show the estimated odds ratio exp(β), and their standard errors and p-values, for the model as fitted to data from n = 13,027 individuals from the National Longitudinal Study of Adolescent Health (Add Health).

Table 9: Logistic regression for involvement in an accident in 2008, including 2008 happiness

Effect	Odds ratio, $\exp(\beta)$	Standard error	p-value
Life satisfaction (2001)	**0.92**	**0.04**	0.039
Happiness (2008)	0.96	0.02	0.011
Gender			
Male	1.15	0.08	0.042
Race			
Black	1.25	0.10	0.005
Hispanic	0.78	0.12	0.097
Asian	0.72	0.12	0.097
Native	2.24	0.80	0.025
Age			
Age	0.94	0.02	0.003
Martial status			
Married	0.90	0.06	0.125
Others			
Education	1.02	0.02	0.126
Job	1.00	0.09	0.966
Income	1.00	0.00	0.019
Interview month	0.96	0.01	0.004
Constant			
Constant	1.09	0.59	0.887

Note: We show the estimated odds ratio $\exp\beta$, and their standard errors and p-values, for the model as fitted to data from n = 13,027 individuals from the National Longitudinal Study of Adolescent Health (Add Health).