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Happiness as a Driver of Risk-Avoiding Behavior

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Abstract
Most governments try to discourage their citizens from taking extreme risks with their health and lives. Yet, for reasons not understood, many people continue to do so. We suggest a new approach to this longstanding question. First, we show that expected-utility theory predicts that 'happier' people will be less attracted to risky behaviors. Second, using BRFSS data on seatbelt use in a sample of 300,000 Americans, we document evidence strongly consistent with that prediction. Our result is demonstrated with various methodological approaches, including Bayesian model-selection and instrumental-variable estimation (based on unhappiness caused by widowhood). Third, using data on road accidents from the Add Health data set, we find strongly corroborative longitudinal evidence. These results suggest that government policy may need to address the underlying happiness of individuals rather than focus on behavioural symptoms.

Keywords: subjective well-being, risky behaviors, effects of well-being, rational carelessness

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1 Introduction

In economics, and especially for the design of public policy, the reasons why individuals take risks, particularly avoidable risks, is an important open question (Barsky *et al.*, 1997; Dohmen *et al.*, 2011). Some researchers argue that in the industrialized world – where affluence has become the norm – the key question for policy-making has become that of how to understand risky health behaviors (Offer, 2006; Offer *et al.*, 2010). The scientific and public-policy issues addressed later in the paper are very general ones. To focus the argument, it treats the wearing and non-wearing of seatbelts as an iconic example.

Consider a standard expected-utility model. Assume that the individual chooses an action which carries with it both potential rewards and some risk of death. Let p be the probability of living and $1-p$ be the probability of death. Let a be the action, u be a fixed utility from life, v be a fixed utility from death, and $c(a)$ be a strictly convex cost function. Write expected utility, therefore, as

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

Assume that the probability of living, $p(a)$, increases with action a. Hence higher levels of a correspond here to greater safety (or safety-seeking). Then the optimal action is given by the usual turning-point condition

$$p'(a)\{u-v\} = c'(a)$$

and around the point of optimal action $a^{\star}$ we have that

$$\left\{p''(a^*)[u-v] - c''(a^*)\right\} da^* + p'(a^*)du = 0.$$

Crucially, by the requirement that the second-order condition holds, the derivative in curly parentheses can be unambiguously signed. It is negative (because EU must be strictly concave in a). Hence, as $p'(a) > 0$, it follows that da^*/du is unambiguously positive.

In this way, elementary algebra leads to a testable conclusion. Individuals with higher levels of utility, u, will invest more in a safety-seeking activity, a. Put informally, this is because humans who greatly enjoy life have a lot to lose (they have a large gap between u and v). By contrast, people who gain only a small utility premium from life have less to lose; thus, on an expected-utility calculation, they will rationally take greater risks (with their lives), in the sense that they are less willing to pay the costs associated with safety-seeking. The paper's analytical approach has much in common with the important early work on rational suicide by Hamermesh and Soss (1974).

We illustrate this simple, new idea within the specific setting of road safety. The key results are given later in the regression equations of Tables 4, 5, and 7 and in Tables 9 and 10. To the best of our knowledge, the principal finding is not known within the economics literature. Simple correlations consistent with the result have, however, been reported by the psychologist Adrian Furnham, as in Kirkcaldy and Furnham (2000).

Using U.S. data, this study establishes two main results. First, 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, even when a wide range of other factors are accounted for. Second, the less satisfied they are with life, the more likely they are to be involved in a motor vehicle accident later in life. After allowing for a range of covariates, 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.

Figure 1 shows that, in raw data, subjective well-being and seatbelt use are strongly associated. However, it is possible that 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 equations as well as methods rooted in Bayesian model selection. None of the confounders, either singly or jointly, are able to explain the observed connection between seatbelt use and subjective well-being (even after accounting for non-linear effects). By using widowhood as an instrument, the study also tests the hypothesis that life-satisfaction influences seatbelt use. It finds that the decreased level of subjective well-being induced by the loss of a spouse decreases the frequency with which individuals wear seat belts.

This finding is replicated and extended on an independent longitudinal sample of 13,027 Americans. It is shown that lagged subjective well-being is predictive of later involvement in motor vehicle accidents; specifically subjective well-being in the year 2001 predicts accidents in 2008. This association remains statistically significant when other factors are controlled for, including, importantly, subjective-well being in 2008.

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

2 Background

Decision processes involving risk are affected by a wide range of factors. These include 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; Kimball, 1993; Fong and McCabe, 1999; Sapienza *et al.*, 2009; Viscusi, 2009). The predominant framework for studies of risk remains utility theory, which we use here, although questions about its assumptions have been raised (Kahneman and Tversky, 1979; Machina, 1987).

The importance of subjective well-being in the study of human behavior has been argued for by an increasing number of authors (e.g. Easterlin, 1974; Oswald, 1997; Frey and Stuzer, 2002). A diverse literature is emerging on the determinants of human happiness (see Diener, 1984; Oswald, 1997; Radcliff, 2001; Clark, 2003; Easterlin, 2003; Di Tella and MacCulloch, 2005; Layard, 2005; Luttmer, 2005; Dolan and White, 2007; Dolan and Kahneman, 2008; Fowler and Christakis, 2008; Stevenson and Wolfers, 2008; Pittau *et al.*, 2009; Clark and Etilé, 2011), how they change over time (Blanchflower and Oswald, 2004, 2008b; Pischke, 2011), and its relationship to utility (Kimball and Willis, 2006; Benjamin *et al.*, 2010). There has been debate about self-reported measures of well-being (Argyle, 2001; Bertrand and Mullainathan, 2001), but much new evidence suggests that these measures are correlated with biological and other indicators (Urry *et al.*, 2004; Steptoe and Wardle, 2005; Fliessbach *et al.*, 2007; Blanchflower and Oswald, 2008a), and thus do provide meaningful information. It has also 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, 2010).

Less 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.

Seatbelt use represents an interesting 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 one 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 *et al.*, 1985). As there is little cost associated with seatbelt use, rationally the wearing of seatbelts should be universal. Yet seatbelt use 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. This figure is 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 as yet unexplained patterns of variation in this key risk behavior.

3 Materials and methods

This section describes the two data sources and briefly outlines Bayesian variable selection and joint confounding methods. Importantly, these Bayesian techniques allow a relaxation of the assumption of linearity.

3.1 Data

3.1.1 Behavioral Risk Factor Surveillance System Survey

The first data set we use is 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-use 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, 2010), 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 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.

3.1.2 Add Health

The second data set used is the National Longitudinal Study of Adolescent Health (Add Health). It measures the health-related behavior of adolescents (Harris *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 answer to a question “In the past 12 months, were you involved in a motor vehicle accident?”. The 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).

3.2 Bayesian Methods

3.2.1 Bayesian variable selection

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 *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 (Madigan and Raftery, 1994; Wasserman, 2000; Claeskens and Hjort, 2008).

The models M_S for seatbelt use that we consider are defined by subsets S of covariates, with $|S| \leq 9$ (Figure 2*A*). Suppose each of the p covariates has q_j levels, $1 \leq j \leq p$. For a model M_S, let $\mathscr{C}$ 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 $c \in \mathscr{C}$ of the covariates. This means the joint probability for vector of responses $\mathbf{y}$ 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, provides 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

$$P(\mathbf{y}|\mathbf{c},M_S) = \prod_{c\in\mathscr{C}} \frac{\Gamma(m_c+\alpha)\Gamma(n_c-m_c+\beta)\Gamma(\alpha+\beta)}{\Gamma(n_c+\alpha+\beta)\Gamma(\alpha)\Gamma(\beta)}, \tag{1}$$

where $\mathbf{c}$ is the vector of covariates with components c_i. Following previous authors (Heckerman *et al.*, 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.

3.2.2 Joint confounding

An alternative to regression approaches, which models risk-taking behavior conditional on the observed covariates and life-satisfaction, is additionally to model life-satisfaction conditional on the observed covariates (Robins *et al.*, 1992; Senn *et al.*, 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 use, 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 use (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 use 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 *et al.*, 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 $\mathscr{C}$ 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 $\mathscr{D}$ the corresponding set including subjective well-being. We denote the number of observed individuals with confounding variables $c \in \mathscr{C}$ by $w_{\mathbf{c}}$, and number of these individuals who are 'very satisfied' by $v_{\mathbf{c}}$. Similarly defining n_d to be number of observed individuals with covariates $d \in \mathscr{D}$ and the number of these who always use a seatbelt by m_d, we have the following marginal likelihood for seatbelt use $\mathbf{y}$, subjective well-being $\mathbf{x}$, and confounders $\mathbf{c}$.

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

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.

4 Results

4.1 Seatbelt use and life satisfaction

The main idea of the paper is visible in the raw uncorrected data. Across the entire sample of $n = 313,354$ U.S. residents used here we find 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 $p < 2.2 \times 10^{-16}$.

4.1.1 Regression for seatbelt use

To try to investigate this more fully, and to understand the influence of other explanatory factors, we employed a range of analyses. First, we carried out a logistic regression that predicts whether an individual always wears a seatbelt. This regression includes 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 use after inclusion of a wide range of social, economic and demographic factors. The same conclusion, that subjective well-being is substantively important, is given when predicting the level of seatbelt use by OLS, as shown in Table 5.

4.1.2 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 Section 3 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 use, 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 find that, with probability 0.99, the subset of predictors that jointly best describe seatbelt use are state of residence, sex and life satisfaction (Figure 2*B*). Fitted posterior probabilities from this model are shown in Figure 4 by state, arranged into groups defined by seatbelt legislation. It can be seen in Figure 4 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 patterns are expected and fairly well-known, but it is the high rate of seatbelt use in very satisfied individuals that, to the best of our knowledge, is a new one in social science. This model estimates that the probability of an individual who is very satisfied always wearing their seatbelt is 0.067 higher.

4.1.3 Joint confounding

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

The best model (Figure 3*B*), in which the Bayesian posterior probability of the model is close to unity, retains the link from subjective well-being to seatbelt use. This model is preferred to the corresponding model – without such a 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, the probability of always wearing a seatbelt is estimated to be 0.053 higher in individuals who report themselves very satisfied with their life.

4.1.4 Instrumental-variable estimation

While our analysis shows an apparently strong relationship between seatbelt use 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 go beyond this, we exploit an instrumental-variable approach. 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. There are 5514 such individuals in the sample. The effect of widowhood on subjective well-being is demonstrably strong (Table 6), but it is arguably close to being independent of seat-belt use. That is, premature widowhood should exogenously cause dissatisfaction, but should not affect seatbelt use through any other channel. Unsurprisingly, widowhood has a large negative effect on happiness (Clark and Oswald, 2002; Easterlin, 2003), and this effect is fairly longlasting (Lucas *et al.*, 2003). Using this instrument, a standard two-stage least squares analysis provides the estimate that an exogenous increase of one class of subjective well-being category increases seatbelt use by 0.188 categories (Table 7). This implies that seatbelt use is indeed influenced by life-satisfaction, even when the possibility of unobserved confounding is considered.

4.2 Motor vehicle accidents and life satisfaction

The hypothesis that dissatisfied individuals are more 'careless' with their lives has an another, and potentially interesting and testable, implication. It suggests that these individuals should experience more motor vehicle accidents. That idea can be investigated by examining whether dissatisfaction is predictive of future motor vehicle accidents. To consider this, we exploit panel data.

The Add Health survey, an independent longitudinal data sample of 13,027 Americans, 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. Once again, a pattern is visible in raw data. 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 who 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 8). Table 9 reports a multivariate logistic regression that includes the same set of covariates as listed earlier. The probability of those individuals with higher earlier life satisfaction being involved in a later accident is significantly lower. The odds ratio is 0.90. Happiness may have an important stable component and so it is natural also to test this empirical model by including 2008 happiness levels. Table 10 does so. It shows that lagged life satisfaction is robust to this specification and produces an odds ratio of 0.92. This longitudinal analysis illustrates the predictive power that happiness has in estimating the likelihood of being involved in future motor vehicle accidents. As such, it complements and extends the prior findings on happiness and risky behavior as measured by seatbelt use.

5 Conclusion

Economists and behavioral scientists currently lack a full understanding of why some people take extreme risks with their lives. Building on a prediction of standard expected-utility theory, this paper provides some of the first evidence of a powerful link between life-satisfaction and risk-avoiding behavior. The study finds that the less happy 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.

We have used seatbelt use as an indicator of individual propensity for risky behavior. Although relatively little-studied by economists and social scientists, driving is one of the few mainstream activities that even in developed countries remains potentially life-threatening. In contrast to behaviors like smoking and drug-taking, seatbelt use is probably habitual rather than addictive. For this reason, it is less likely that current seatbelt-wearing behavior is strongly affected by long-past attitudes to risk. In contrast, current smoking status, for example, may relate to decision-making processes of an individual some 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 use may reflect a more personal indication of propensity for risk than other measures. Seatbelt use has in addition been demonstrated to be associated with risk preference as elicited by a lottery choice experiment (Anderson and Mellor, 2008).

There remains work to be done. Some of the evidence in the paper is not definitive (because happiness cannot be randomly assigned by an experimenter). It will be necessary to explore the implications of the results presented here, both in terms of better characterizing the connection between life-satisfaction and risk-taking and in understanding, in a wider range of settings, how subjective well-being is correlated with human choices. The paper's conceptual account potentially has implications for science and policy. 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. This idea, for which the paper attempts to provide evidence, emerges from the expected-utility model of human behavior.

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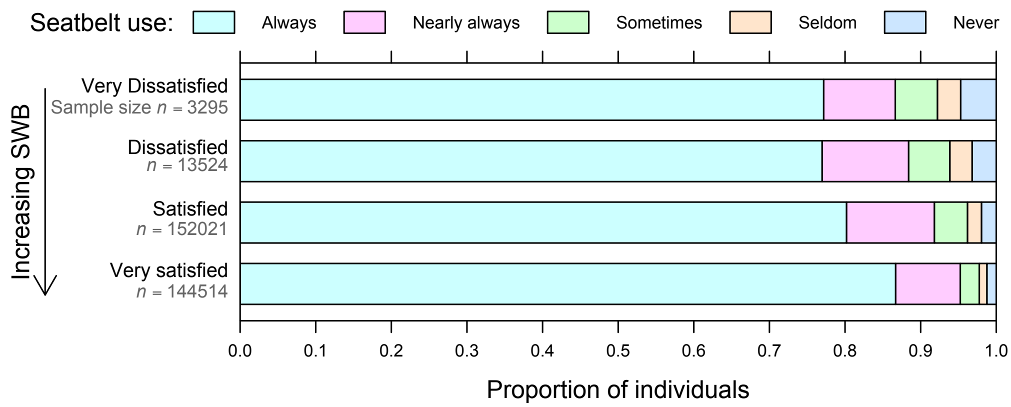

Figure 1: Frequency of seatbelt use cross-tabulated by subjective well-being (SWB). Each category contains at least 101 individuals. Pearson's chi-squared statistic is 3242 (p-value $p < 2.2 \times 10^{-16}$).

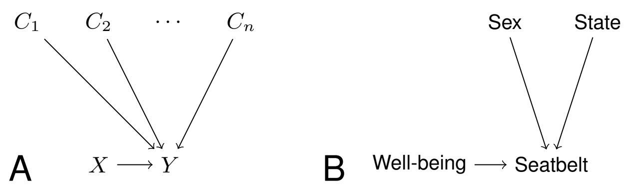

Figure 2: Variable selection for joint effects of multiple covariates. (A) The variable selection formulation explores subsets of $\{X, C_1, \ldots, C_n\}$ as joint explanatory factors for response Y. (B) The selected model, with selection occuring from 19 covariates, including subjective well-being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

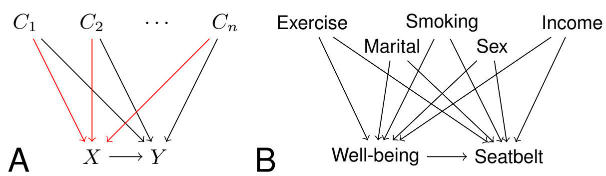

Figure 3: Model selection for joint confounding by multiple factors. (A) Graphical representation of family of models for considering the influence of conjectured explanatory variable X on response Y with potential observed confounders $C_1, \ldots, C_n$. A model selection approach is used to explore 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 Section 3 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 use, showing that well-being remains an important influence on seatbelt use even when all possible joint stratifications are considered in a fully general non-linear model.

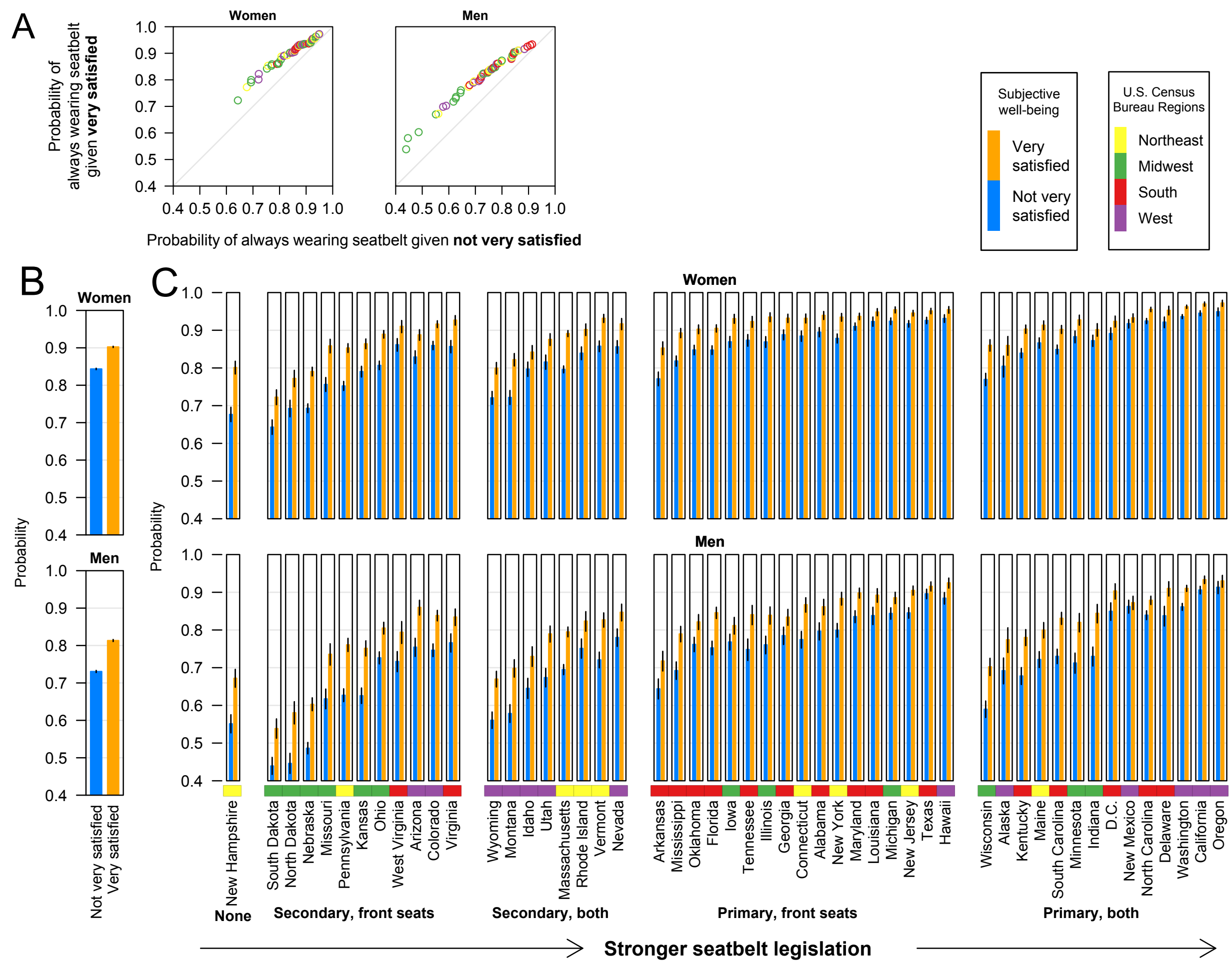

Figure 4: Fitted (posterior) probabilities of always wearing a seatbelt given subjective well-being. (A) For each state, the probability of always wearing a seatbelt for very satisfied residents against the probability of always wearing a seatbelt for residents who are not very satisfied. The colors 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 use 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 (‘Collapsed 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 ≤ 2 drinks/day	Not heavy drinker
	Women ≤ 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 equations for seatbelt use

Effect	Coefficient, β	Std. err.	p value	Odds ratio, $\exp(\beta)$
Subjective well-being	**0.324**	**0.008**	$< \mathbf{0.001}$	**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 use 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 have controlled for state of residence and interview month.

Table 5: Ordinary Least Squares (OLS) equations for seatbelt use

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 use from a panel of covariates (Table 1), including subjective well-being (shown in bold). We show the estimated coefficients 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 $p < 2\times10^{-16}$. All estimates have controlled for state of residence and interview month.

Table 6: First stage of instrumental variable (IV) regression equations.

Effect	Coefficient, β	Standard error	p value
Widowed	**-0.1692**	**0.0094**	< 0.001
Gender (baseline Male)			
Female	0.0287	0.0033	< 0.001
Race (baseline White)			
Black	-0.0232	0.0079	0.003
Asian	-0.0713	0.0106	< 0.001
Hispanic	0.0250	0.0072	0.001
Other race	-0.0384	0.0091	< 0.001
Age	-0.0246	0.0015	< 0.001
Age^2	0.0003	< 0.001	< 0.001
Educational achievement (baseline No High School)			
Attended High School	-0.0178	0.0167	0.287
Graduated High School	0.0168	0.0149	0.259
Attended College	0.0158	0.0150	0.294
Graduated college	0.0746	0.0150	< 0.001
Employment status (baseline Employed)			
Self-employed	0.0324	0.0047	< 0.001
Unemployed	-0.2234	0.0099	< 0.001
Homemaker	0.0403	0.0054	< 0.001
Student	-0.0174	0.0167	0.296
Retired	0.0768	0.0085	< 0.001
Unable to work	-0.3649	0.0109	< 0.001
Income (baseline Less than $10,000)			
$10,000 – $15,000	0.0256	0.0221	0.247
$15,000 – $20,000	0.0592	0.0198	0.003
$20,000 – $25,000	0.0848	0.0188	< 0.001
$25,000 – $35,000	0.1229	0.0182	< 0.001
$35,000 – $50,000	0.1848	0.0179	< 0.001
$50,000 – $75,000	0.2499	0.0179	< 0.001
More than $75,000	0.3553	0.0178	< 0.001
Children			
Number of children	0.0050	0.0015	0.001
Constant			
Constant	3.7483	0.0400	< 0.001

Note: First stage model estimates predicting satisfaction using widowhood, 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 use. All estimates have controlled for state of residence and interview month.

Table 7: Instrumental variable (IV) regression equations for seatbelt use

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 use (please see Main Text for details). Subjective well-being is significant at the 0.005 level. All estimates have controlled for state of residence and interview month.

Table 8: Cross-tabulation of accidents in 2008 by life-satisfaction in 2001

	Accident (2008)		
Life satisfaction (2001)	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 9: Logistic regression equations for involvement in an accident in 2008

Effect	Odds ratio, $\exp(\beta)$	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
Marital 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 $\exp(\beta)$, 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).

Table 10: Logistic regression equations 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
Marital 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).

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