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# The Persistence of Unhappiness: Trapped into Despair?

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## Abstract

This paper investigates whether self-assessed states of unhappiness are persistent. To disentangle state dependence from unobserved heterogeneity in life satisfaction, it estimates a dynamic ordered Logit with correlated random effects on longitudinal data in France, in the UK, in Australia and in Germany. The persistence of life satisfaction is found to be heterogeneous: people already happy with their lives tend to remain happy while unhappiness sounds more transitory. Overall, there is no empirical evidence of unhappiness traps: rather, every individual faces the risk of experiencing some temporary spell of low subjective well-being in her life course.

**JEL Classification:** I31.

## 1 Introduction

The pursuit of happiness is sometimes viewed as one of governments' ultimate duties towards its citizens, remember the US Declaration of Independence in this regard. A more realistic, perhaps attainable, objective may rather consist in preventing people from falling into despair (Case and Deaton, 2017), or into a trap of unhappiness, i.e., from remaining persistently unhappy.<sup>1</sup> Even though such subjective concepts relate by nature to individual perceptions, it has been well documented that objective amenities including money, having a regular job or living in a safe environment contribute to life satisfaction. Public policies are therefore likely to impact people's well-being through the fight against poverty

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<sup>1</sup>Though this phenomenon looks specific to the US up to now, it is not guaranteed that other comparable countries will not soon be exposed to such problems.

and unemployment, or the guarantee of peaceful living conditions. From a welfare point of view, it is thus crucial to determine whether society is segmented in terms of subjective well-being, with some fraction of individuals being bound to, say, dissatisfaction, unhappiness and even despair -hence to test whether persistence in 'good' states is the same as persistence in 'bad' states. When seeking to minimize people's discontent, governments should rather do their best to prevent people from being trapped into despair than spend time or make effort to enhance already high levels of well-being for the concerned individuals.

In this paper, I investigate whether individuals, when asked about their subjective well-being in longitudinal surveys, tend to declare themselves persistently unhappy, or whether such dissatisfaction is more transitory. Indeed, subjective well-being is often proxied by life satisfaction, and self-assessed by individuals. Hence I study the persistence of overall satisfaction with life and its heterogeneity, focusing on the permanent or transitory natures of both 'happiness' and 'unhappiness'. To that aim, I provide first with some descriptive evidence on the types of trajectories of self-reported life satisfaction available in four OECD countries (France, the UK, Australia and Germany). All these countries dispose of longitudinal surveys which can be easily accessed to by researchers, and which include such measures of subjective well-being. The empirical evidence suggests that 'happiness' looks much more persistent than 'unhappiness'. Second, I disentangle the respective roles played by state dependence and by initial conditions. I estimate therefore a dynamic ordered Logit model with correlated random effects in order to quantify the persistence of life satisfaction. My empirical analysis is primarily based on a French panel dataset, SRCV, from 2013 to 2017, but I show that the results also hold in Australia, in Germany and in the UK. The main findings can be summarized as follows: (i) state dependence is significant at usual levels; (ii) its magnitude is strong when compared to usual determinants of happiness (income, having a partner, working regularly, etc.), and (iii) it is asymmetric: happier people tend to remain happy more than less happy people; put differently, happiness looks rather persistent while unhappiness is rather transitory. The magnitude of state dependence is such that top past happiness cushions by far the impact of unemployment, for instance.

These results are robust to parametric assumptions, to endogenous attrition concerns as well as to balancing issues. Moreover, in order to be sure that these

findings are specific neither to my dataset, nor to France, I resort to three other panels: (i) the Household, Income and Labour Dynamics in Australia (HILDA) survey, (ii) the UK Understanding Society (UKUS) survey that took over the British Household Panel Survey (BHPS), with 8 waves from 2009 to 2018, and (iii) the German Socio-Economic Panel (GSOEP) available from 1984 to 2017. Both descriptive transition matrices of subjective well-being at the individual level and estimations from the same econometric model as before concur to similar findings: life satisfaction is persistent at the top of the distribution, but low levels of life satisfaction look rather transitory, which is not consistent with happiness traps. These results strengthen previous empirical evidence and give some credit to the idea of unveiling some empirical regularity of individual behavior in the data. Importantly, and coming back to [Case and Deaton \(2017\)](#), the US are not considered here. Besides, the countries at stake meet rather high standards of social protection; remember that social insurance may be viewed as an insurance against the risk of being, or becoming, a high-risk with respect to unemployment or disease, for instance.

Where does state dependence in self-assessed life satisfaction come from? Persistence might arise from people not changing their mind every year about their subjective well-being ([Krueger and Schkade, 2008](#)). A possible explanation could lie in individuals evaluating once-and-for-all their average, permanent satisfaction with life, from which they would rarely deviate across different waves of longitudinal surveys, but depart from it when they experience good or bad shocks. Such a behavior would resemble to anchoring effects according to which agents would stick to initial or past self-evaluation. Interestingly, the revealed heterogeneity in the persistence of well-being, namely the asymmetry between satisfaction and dissatisfaction, does not favor the hypothesis of unhappiness traps in all the countries considered, while it is consistent with, say, psychological costs incurred when revising one's subjective well-being downwards.

The rest of the paper is organized as follows. Next section is devoted to a literature review. [Section 3](#) describes the French SRCV data. The econometric model is presented in [Section 4](#). Results are discussed in [Section 5](#) and [Section 6](#) investigates some robustness checks, including the estimation on data from other countries. [Section 7](#) concludes.

## 2 Literature

Key determinants of subjective well-being, often proxied by life satisfaction, have been widely documented by the literature: see, for instance, the excellent survey by [Layard et al. \(2015\)](#). The main types of determinants of life satisfaction are: (i) individual determinants (income: [Easterlin \(1974\)](#), [Clark et al. \(1996\)](#), [Clark et al. \(2005\)](#), [Senik \(2005\)](#), [Clark and Senik \(2010\)](#), age: [Clark et al. \(1996\)](#), labor force status,<sup>2</sup> family status, education, gender, occupation are seldom significant, but can be invoked depending on the country); (ii) macroeconomic determinants (GDP growth, unemployment rate, inflation, inequality, environmental issues, government and unions, not pretending to be exhaustive; their identification requires variation across countries, hence they are often absent in a one-country econometric analysis): see, e.g., [Tella et al. \(2003\)](#) on that topic; (iii) spatial determinants (rural versus urban areas: [Easterlin et al. \(2011\)](#), regional effects: [Oswald and Wu \(2010\)](#), the price of gasoline: [Boyd-Swan and Herbst \(2012\)](#), among others).

From a methodological perspective, subjective well-being is specific in the sense that individuals are asked to report their life satisfaction on an ordered, discrete scale ranging from 0 to 10 (a Cantril scale). To deal with ordinality, researchers have estimated ordered polytomous models which rely on a latent, unobserved but cardinal propensity to happiness. In practice though, estimating linear models does not affect the sign of the covariates,<sup>3</sup> and yields qualitatively similar results.

Moreover, many studies on subjective well-being relied first on cross-sectional data, which limits the ability of the researcher to control for unobserved heterogeneity. As soon as panel data have been available on that topic, econometric specifications have included individual effects, which do a better job at controlling for unobserved heterogeneity, and hence limit omitted variable biases (see [Ferrer-i Carbonell and Frijters \(2004\)](#) on that topic). For instance, the problem of optimism (or pessimism) arises as soon as one seeks to explain the level of subjective well-being from a cross-sectional analysis: two individuals may well report very different answers as regards their life satisfaction, though they look close in the sense that their observed characteristics are similar. To take unobserved heterogeneity into account, but also to avoid the problem of incidental parameters, the

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<sup>2</sup>Being unemployed causes significant, persistent losses ([Clark and Oswald, 1994](#)). Interestingly, [Clark et al. \(2008\)](#) show that the recovery after such unfortunate career shocks is much slower than it is after personal events like widowhood.

<sup>3</sup>That sign is identified non-parametrically.

literature has estimated conditional ordered Logit models with fixed effects, see, e.g., [Frijters et al. \(2004\)](#). Though such models are powerful tools to capture unobserved heterogeneity, their identification relies on a subset of movers; empirically, this restriction induces likely a dramatic selection.

According to [Hsiao \(2003\)](#), state dependence and individual heterogeneity offer 'diametrically opposite' explanations of persistence in life satisfaction outcome.<sup>4</sup> Few dynamic models have been considered so far: the role of state dependence has rarely been explored *per se*, though recommended by [Clark \(2018\)](#). Exceptions include [Frijters et al. \(2011\)](#) who considered the dynamics of covariates and assessed how current life satisfaction depends on past events like getting married or divorced, becoming unemployed, widowhood, etc. [Bottan and Truglia \(2011\)](#) tries to disentangle a 'specific habituation' channel, namely the causal effect of lagged covariates, from a 'general habituation' channel, which has trait to the persistent nature of subjective well-being *per se*. According to [Wunder \(2012\)](#) who exhibits an 'adaptation' channel, individuals update their expectations as a response to changing circumstances. Few of these papers address the ordinal nature of the data, at the notable exception of [Pudney \(2008\)](#). In this paper, I estimate a non-linear, ordered polytomous model that helps me investigate the heterogeneity of persistence across reported levels of life satisfaction: to the best of my knowledge, this has not been the object of any attention up to now.

### 3 Data

Many papers in happiness economics have used data from Germany, from the UK or from Australia since all these countries dispose of longitudinal surveys (resp. GSOEP, BHPS and HILDA) that enable researchers to follow individuals over time and to learn about changes in their subjective well-being. Following the recommendation of the [Stiglitz et al. \(2009\)](#) commission, France has also started to ask individuals directly how they felt about their lives. The Insee produces the SRCV survey (*enquête Statistique sur les Ressources et Conditions de Vie*) targeting about 10,000 households every year. From 2010 onwards, it has included several questions related to individual life satisfaction, job satisfaction, and satisfaction with family and friends. On top of these measures of subjective well-being, it of-

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<sup>4</sup>Serial correlation in life satisfaction has been studied in [Krueger and Schkade \(2008\)](#).

fers usual information at the individual level: gender, age, education, occupation, family status and labor force status. Income is measured at the household level; in what follows, I consider the logarithm of the CPI-deflated annual household income, i.e., the sum of real incomes from all members in the household divided by the number of units of consumption as defined by the OECD scale.<sup>5</sup>

The unit in charge of SRCV at Insee indicates that, though the survey has started in 2010, its reliability casts doubts before 2013. The questionnaire has been modified in 2013: questions relative to life satisfaction have been placed after those relative to income. *De facto*, a break in the time series of life satisfaction can be observed from that date. Hence I assume that the first reliable wave, common to all individuals, is 2013.

Table 1 shows some descriptive statistics relative to the working sample, an unbalanced panel of 13,574 individuals followed from 2013 to 2017 with at least three observations including two consecutive ones, which is necessary to the identification of the role played by state dependence. By construction, the annual income of these individuals exceeds €1. Subjective well-being is measured on a Cantril scale ranging from 0 to 10. It has an average score of 7.18, it is rather concentrated around levels 7 and 8 (see Figure 1), it nevertheless uses the whole support of the distribution and it has a cross-sectional coefficient of variation as small as .23. Women and elders are slightly over-represented (60% of the sample aged 55 on average), which is usual in French household surveys. The average income amounts to nearly €26,000 per year. Income exhibits sizeable dispersion: its coefficient of variation is roughly 1.5 and the top 1% earns more than €83,800 a year. As regards education, 32% of individuals in the sample have a vocational degree, 29% graduated from high-school, 16% from college while 23% don't have any degree. As far as labor force status is concerned, about 47% of the sample is employed while 39% is retired. The remaining part of the sample is either unemployed or inactive. One half of the sample is made up of current or former clerks (28%) or individuals with an intermediate occupation (23%); the others are (or were) mainly blue collars (17%) or white collars (14%). Regarding family status, singles account for one quarter of the sample, while nearly 40% of individuals are living with a partner; then come parents of two children (11%), one child (9%),

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<sup>5</sup>According to this scale, the first adult in the household has weight 1, the other adults or children aged at least 14 have a weight equal to .5, and children aged less than 14 have a weight equal to .3.

three children at least (5%) and single parents (4%).

Turning to the persistence of subjective well-being, the main insight from Figure 1 which depicts the evolution of aggregate subjective well-being from 2013 to 2017 in France is that the distribution of answers is rather stable from year to year.

Focusing now at the individual level, about 1/8 of surveyed individuals report systematically the same level of life satisfaction over the five waves (Table 2). For slightly more than 1/3 of them, the difference between the highest and the lowest self-assessed level of life satisfaction is equal to one, while for about 1/4 of them, this difference is equal to two. That difference exceeds three for a last 1/4 of individuals, which suggests that subjective well-being is persistent over time at the individual level. It is therefore consistent with the hypothesis that individuals have some anchor in mind, from which they depart in case of favorable or less favorable shocks.

Table 3 provides with the transition matrix of individual levels of life satisfaction, and confirms that persistence of subjective well-being over time is strong. Its diagonal is heavy, which means that the probability of reporting the same level of life satisfaction as the year before is high. The most plausible past level of life satisfaction, given any current, self-assessed level of life satisfaction, is often that very same level. Static models of subjective well-being ignore state dependence in that they do not include any lagged variable as an explanatory variable: hence they implicitly assume that each destination state has the same probability, regardless of the initial state. The main lesson from this descriptive analysis is that this assumption is rejected on the data: this transition matrix suggests that happiness is almost an absorbing state.

Interestingly, this persistence looks asymmetric: happiest individuals tend to stay happy, while unhappiness tends to be more transitory. As one gets higher in the distribution of reported levels of life satisfaction, the annual probabilities of reporting the same level of subjective well-being as before increase: the coefficients on the diagonal may be as high as 52.2% (level 8), and do not fall below 35.3% (level 9). By contrast, they are comprised between 11.4% (level 2) and 24.5% (level 0) at the bottom of that distribution. Even though upward mobility is mechanically more frequent at the bottom, it is striking to see that individuals reporting a level less than 4 have at least nearly 3/4 chance to see their life satisfaction increase



next year. Intermediate levels 5 and 6 exhibit a slightly upward-biased trend, too: their annual persistence ranges from 26% to 32%, with a probability of having a higher subjective well-being higher than 1/2. From levels 0 to 6, upward mobility is hence more likely while inertia is more plausible from level 7 onwards.

Defining now 'happiness' as the fact of reporting level 7 or more, the transition matrix of happiness would be symmetric with 3/4 on its diagonal and equally distributed states among the population. Doing the same with 'unhappiness', defined as the fact of reporting level 4 or less, would yield a 40% chance of remaining unhappy for the 5% concerned individuals. Such a contrast is also apparent on Figure 2 which depicts the fraction of their surveyed time individuals spend being happy, conditional on being happy once. From Figure 2a it looks quite clear that happiness is an absorbing state, while Figure 2b suggests that unhappiness looks by far more transitory. To illustrate, nearly 80% (resp. 57%) of individuals declaring themselves happy once also report being happy more than one half of (resp. all) their surveyed time. Meanwhile, only 25% (resp. less than 8%) of individuals once unhappy remain unhappy this very same fraction of (resp. all the) time. To sum up, this descriptive evidence suggests that dissatisfaction with life resembles more to some transitory state, rather than to a persistent state.

To confirm previous eyeball impressions and to check that they are not the mere consequence of both observed and unobserved heterogeneity, an econometric model that disentangles carefully state dependence from heterogeneity is however needed.

## 4 Model

To take both state dependence and unobserved heterogeneity into account, I consider an econometric specification that relies on a dynamic ordered Logit with correlated random effects and unknown thresholds. Let  $y_{it}$  be the dependent variable, i.e., subjective well-being, ranging from  $j = 0$  to  $j = J \equiv 10$ .<sup>6</sup> To deal with ordinal preferences, the ordered polytomous model assumes the existence of an explicit relationship between the observed variable  $y_{it}$  and some unobserved,

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<sup>6</sup>It is possible to consider a model with a smaller number of groups, say 7, to mimic the UK case after grouping 0-2, 3-4 and 5-6 levels for instance. The corresponding estimates are available upon request: the results are robust to such an aggregation choice.

latent variable  $y_{it}^*$  such that  $\forall j \in \llbracket 0, J \rrbracket$ ,

$$y_{it} = j \iff y_{it}^* \in [s_j, s_{j+1}[$$

or equivalently,

$$y_{it} = \sum_{j=0}^J j \mathbb{1}\{s_j \leq y_{it}^* < s_{j+1}\}.$$

$\{s_j\}_{j=1}^J$  are the unknown thresholds with  $s_0 = -\infty$  and  $s_{J+1} = +\infty$ .

I consider a dynamic model on the latent variable of the form:

$$y_{it}^* = \sum_j \rho_j \mathbb{1}[y_{i,t-1} = j] + x'_{it} \beta + \alpha_i + \varepsilon_{it}, \quad (1)$$

where idiosyncratic shocks  $\varepsilon_{it}$  follow the logistic distribution with mean 0 and variance  $\frac{\pi^2}{3}$ . As in [Wooldridge \(2005\)](#), state dependence is allowed to be nonlinear, too – namely specific to every value of past subjective well-being: the  $\rho_j$  coefficient is related to lagged  $j$ -value of life satisfaction.

At this stage, a first option could be to posit individual fixed effects, i.e., in making no parametric assumption on the distribution of  $\alpha_i$ . This solution requires however to overcome the incidental parameter problem ([Neyman et al., 1948](#); [Lancaster, 2000](#)). When the model is linear, differencing enables the econometrician to get rid of individual fixed effects. By contrast, in nonlinear models, the maximum likelihood estimator (MLE) is generally not consistent and asymptotically normal (CAN) due to the presence of numerous incidental parameters. In the Logit case, a well-known trick consists in conditioning the likelihood of an observed sequence  $(y_{i1}, \dots, y_{iT})$  by a sufficient statistics in order to make the fixed effects disappear of the likelihood. This so-called conditional likelihood estimation (CLE) has been used by [Rasch \(1960\)](#); [Andersen \(1973\)](#); [Chamberlain \(1980\)](#); [Honoré and Kyriazidou \(2000\)](#); [Magnac \(2000\)](#); [Frijters et al. \(2004\)](#). In the case of a dynamic Logit model with fixed effects, a sufficient statistics corresponds to the number of occurrences of each state in the observed sequence of outcomes, initial and terminal conditions aside; in the binary case, [Bartolucci and Nigro \(2010, 2012\)](#) refer to total scores. This method is the analog, in spirit, to first-differencing in linear models. However, its cost is rather high since it requires to compute the denominator of the conditional likelihood which is composed of numerous terms.

Moreover, the identification of the model relies on a subset of individuals only, the 'movers', i.e., individuals whose sequence is not constant over time; these supplementary exclusion restrictions may be problematic in practice since they often constrain the estimation to rely on small sub-samples. On top of that, and to the best of my knowledge, there is no obvious extension of such a method to deal with ordinal variables.<sup>7</sup>

Another option consists in assuming some parametric form for the individual effects  $\alpha_i$ , typically a normal distribution: this solution corresponds namely to the random effect approach. To enrich the latter, I consider rather the correlated random effects (CRE) solution *à la* Chamberlain (1982). Its main advantages are (i) to approximate fixed effects as much as possible by allowing for an explicit relationship between the individual effect and the covariates; (ii) to solve the initial condition problem that arises in dynamic models. Once again, two options are possible. As put by Arulampalam and Stewart (2009), 'the Heckman (1981) estimator approximates the joint probability of the full observed  $y$  sequence  $(y_0, y_1, \dots, y_T)$ . Wooldridge (2005) on the other hand, has proposed an alternative conditional maximum likelihood estimator that considers the distribution of  $(y_1, y_2, \dots, y_T)$  conditional on the initial period value  $y_0$  (and exogenous variables)'. I follow the latter approach and assume that

$$\alpha_i | y_{i0}, x_{i0}, \bar{x}_i \sim \mathcal{N} \left( \sum_{j=0}^J \rho_j^0 \mathbb{1}[y_{i0} = j] + x'_{i0} \gamma^0 + \bar{x}'_i, \sigma_u^2 \right). \quad (2)$$

This parametric restriction enables me (i) to get rid of the incidental parameter problem, (ii) to model the initial condition, and (iii) to avoid programming the maximization of the conditional likelihood. Lastly, I follow Rabe-Hesketh and Skrondal (2013) who propose a more parsimonious specification of the individual effect. They show that including initial  $(x_{i0})$  and mean values  $(\bar{x}_i)$  of covariates is sufficient,<sup>8</sup> as opposed to including the whole set of covariates at all dates  $x_i = (x_{i0}, \dots, x_{i,T_i-1})$  when disposing of  $T_i$  observations for individual  $i$  as in Wooldridge (2005). This approximation of unobserved heterogeneity is reminiscent of Mundlak (1978).

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<sup>7</sup>Ordinality is important in this setting: one wants in particular partial effects to vary across the distribution of life satisfaction.

<sup>8</sup>Time-constant variables, including education covariates, and time dummies are dropped from the list of initial and mean covariates.

In the end, the estimating equation is:

$$y_{it}^* = \sum_{j=0}^J (\rho_j \mathbb{1}[y_{i,t-1} = j] + \rho_j^0 \mathbb{1}[y_{i0} = j]) + x'_{it}\beta + x'_{i0}\gamma^0 + \bar{x}'_i\gamma + u_i + \epsilon_{it} \quad (3)$$

with  $u_i \sim \mathcal{N}(0, \sigma_u^2)$ .<sup>9</sup>

As usual in dynamic models, strict exogeneity can't be assumed because of the presence of lagged variables in (3), which is a source of endogeneity, i.e., of correlation between current shocks and past outcomes. The identification of the model requires predetermination, but also strict exogeneity of the covariates conditional on the individual effects  $\alpha_i$ .

Two normalizations are required for the joint identification of agents preferences and of unknown thresholds viewed as parameters to be estimated: (i) location:  $\beta_0 = 0$ , for shifting the constant and the thresholds simultaneously by some constant yields an observationally equivalent model; (ii) scale  $\sigma_\epsilon^2 = \pi^2/3$  (Logit) or  $\sigma_\epsilon^2 = 1$  (Probit), for multiplying the latent and all its parameters yields the same likelihood. Under these normalizations, the vector of parameters  $\theta = (\beta, \gamma, \gamma^0, \rho, \rho^0, s, \sigma_u)$  is identified.

As regards estimation, Wooldridge (2005) shows that the MLE is CAN as  $N$  grows large even for small, fixed  $T$ . This holds as soon as  $T \geq 3$ , which is required in order to disentangle the role of initial from that of past subjective well-being.

Two ways may still be ahead as far as the idiosyncratic shocks  $\epsilon$  are concerned, a standard normal distribution (Probit) or a logistic distribution (Logit). Empirically, the latter produces a better fit, i.e., yields a higher likelihood.<sup>10</sup> Robustness checks are nevertheless provided with respect to that choice in section 6.1. Besides, average partial effects are close in both specifications. Moreover, the Logit permits an interpretation in terms of odds ratios, which the Probit does not allow.

A last concern is the selection of covariates, i.e., of explanatory variables  $x_{it}$  in the estimating equation. First, the literature devoted to the individual determinants of subjective well-being provides with some guidance. Second, statistical methods based either on the BIC, on the (rigorous) Lasso, or on a stepwise algorithm provide with useful tools to select the most relevant variables. In practice, I

<sup>9</sup>Lee (2016) considered an equation of this form when focusing on health status in Korea.

<sup>10</sup>Due to the fatter tails of the logistic distribution, the Logit model puts more weight on extreme events.

find that both the literature and statistical criteria (estimated on the static model) are globally consistent: the list of relevant covariates include labor force status, family status, income and age. To be exhaustive though, education, occupation, gender and year dummies are also included.

## 5 Results

Tables 4 to 6 display the results from the main specification, namely equation (3), estimated on the unbalanced panel.<sup>11</sup> Carefully comparing columns allows me to disentangle the role played by unobserved heterogeneity from that played by state dependence. While column (1) omits individual effects in a pooled, cross-sectional regression fashion, column (2) includes a pure, random effect that is uncorrelated with covariates. Column (3) consists of the same correlated random effect approach as in column (4) but does not include the lagged dependent variable as an explanatory covariate, which column (4) does. Put differently, column (3) imposes the constraint  $\rho = 0$  with respect to the dynamic model of column (4), the preferred specification; column (2) assumes further that  $\gamma = \gamma^0 = \rho^0 = 0$  and column (1) adds up  $u_i = u, \forall i$ . On the one hand, state dependence is encompassed by  $\rho$ : hence its role can be isolated by a direct comparison between columns (3) and (4), given that the sample is voluntarily identical (hence the need of restricting my attention to individuals with at least two consecutive observations), so that observations contributing to the identification of the parameters of the model are the same in all columns. On the other hand,  $\gamma, \gamma^0, \rho^0$  as well as the residual variance account for unobserved heterogeneity, the role of initial conditions being encompassed by  $\rho^0$ . As a *caveat*, an eyeball, quantitative comparison across columns would be misleading since the coefficients do not have a common scale (see, e.g., [Contoyannis et al., 2004](#)); however, this warning concerns neither relative, nor qualitative comparisons (namely, significance). Average partial effects permit nevertheless a quantitative comparison across columns.

I find empirical evidence of state dependence, which confirms the eyeball impression given by Table 3. The estimated autocorrelation vector  $\rho$  is statistically significant at usual levels:  $H_0 : \rho_1 = \dots = \rho_{10} = 0 (= \rho_0)$  is rejected at 5%, the

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<sup>11</sup>For the sake of readability, the same Table of results has been cut into three parts. Though available upon request,  $\gamma$  and  $\gamma_0$  coefficients are not reported, at the exception of the estimate corresponding to mean income.

$\chi^2(10)$  statistic being 193.7. Moreover, state dependence turns to have a nonlinear impact on the latent propensity to happiness:  $H_0 : \rho_j - \rho_{j+1} = \rho_{j+1} - \rho_{j+2}, \forall j = 0, \dots, J-2$ , is also rejected at 5% with a  $\chi^2(9)$  statistic of 35.4, which justifies the specification of state dependence adopted here with respect to a (more parsimonious) linear one. Such a nonlinearity can be observed by plotting the estimated  $\rho_j$  against the lagged level of life satisfaction  $j$ , as Figure 3 does. Only the highest levels of life satisfaction do exhibit state dependence: the lowest levels comprised between 0 and 4 do not. This empirical evidence confirms thus the asymmetry documented above by the descriptive analysis. Formally,  $H_0 : \rho_1 = \dots = \rho_5 = 0 (= \rho_0)$  is rejected at 5%, the  $\chi^2(5)$  statistics being 22.5, while  $H_0 : \rho_1 = \dots = \rho_4 = 0 (= \rho_0)$  cannot be rejected at 5%, the  $\chi^2(4)$  statistics being 5 with a  $p$ -value of .31. In that sense, these estimates enable me to conclude that 'happiness', defined as a self-reported level of life satisfaction higher than 7, is persistent, while 'unhappiness', defined as a self-reported level of life satisfaction lower than 4, is not, which does not support the hypothesis of unhappiness traps.

Average partial effects (APEs)<sup>12</sup> enable me to quantify previous statements, to compare the relative effects of state dependence and of other explanatory variables, and to answer the question: by how much is the impact of the main determinants of subjective well-being attenuated when taking initial conditions and state dependence into account? Though APEs are computed for all covariates and for each of the eleven levels of self-assessed life satisfaction, Table 7 summarizes the APEs of selected variables only (current and mean income, unemployed, some family statuses, and lagged life satisfaction) on the probability to report the highest level, i.e., level 10, of life satisfaction – for the sake of readability.<sup>13</sup> It is for instance confirmed that becoming parent of 2 children or more does not increase significantly their propensity to report more frequently level 10 than other parents or childless couples, contrary to what a naive analysis would suggest. Finding a partner raises by 2-3pp the propensity of being most satisfied with one's life. A 1% increase in permanent income raises that probability by 3pp. Interestingly, the effect of pure state dependence, i.e., of reporting level 10 the year before, increases the probability of reporting that very level by 11.2 points. This is a very large

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<sup>12</sup>For continuous regressors such as income, these APEs are obtained by taking the derivative of the ordered Logit probabilities with respect to the variable in question. For discrete regressors, such as lagged life satisfaction, they are obtained by taking differences.

<sup>13</sup>All other APEs are available upon request.

impact compared for instance with unemployment: losing one's job makes this probability decrease by nearly 1/4 of this amount.

The current analysis encompasses main well-known facts in happiness economics. It must yet be acknowledged that the identifying source of variation for the effects of covariates differs substantially when moving from a RE specification (column (2)) to a CRE specification (column (3)). The former relies on inter-individual differences while the latter stems mostly from intra-individual, or temporal, differences. On top of that, the CRE specification considered here allows to disentangle the role played by average covariates (say, the level) from the one played by initial covariates (say, the growth). The  $\gamma^0$  coefficients are not reported in the Tables for the sake of readability, but they are available upon request. First, unemployment is a major cause of misery, and stems mostly from the fact of losing one's job. Second, the role of family status can be precised: partners and parents do not differ much from singles in the sense that their  $\gamma$  coefficients are not significantly different from each other at usual levels. However, finding a partner and having children both increase self-assessed well-being: their  $\beta$  coefficients are positive and significant. In other words, these people are not happier *per se* but unions and children make them temporarily happier. However, this interpretation is complicated by composition effects, the reference category here being the 'always singles', and not the 'once singles' as in the RE specification. Third, the CRE approach makes it possible to identify the channel through which income affects life satisfaction, i.e., average income. In other words, transitory income, i.e., current shocks of income viewed as deviations from average or permanent income, matters less than the latter in this regard, which is reminiscent of the result obtained by [Frijters et al. \(2004\)](#), among many others. Fourth, the U-shape with age is retrieved, though not significant in the CRE specifications. Fifth, gender is not significant at usual levels. Sixth, neither is education, and seventh, neither is occupation – farmers aside, who are significantly far less satisfied with their lives.

Finally, from a purely statistical perspective, the most parsimonious model is the dynamic ordered Logit with correlated random effects, i.e., the model estimated in column (4). According to the Bayesian information criterion, it is worth improving the fit despite the subsequent increase in the number of parameters with respect to the other specifications. The residual variance in subjective well-being, i.e., the dispersion of subjective well-being that remains unexplained after con-

trolling for covariates, initial condition and state dependence in the corresponding specifications, shrinks mechanically when moving from column (2) to column (4): it is divided by a factor 2 in the CRE specification (resp. 3 in the dynamic CRE specification) comparison with a pure RE specification.

## 6 Robustness checks

I perform several robustness checks to assess the sensitivity of previous results with respect to (i) functional form, (ii) attrition, and (iii) data. The last point deserves particular attention since it guarantees that the point made in this paper unveils some empirical regularity that is not specific to the French database; on the contrary, I find that it is common to several countries.

### 6.1 Parametric assumptions

First, I estimate an alternative parametric specification, namely a Probit model. I replicate the entire analysis by assuming that the idiosyncratic error terms  $\varepsilon_{it}$  follow a normal distribution instead of a logistic distribution, although both the fit, as measured by the log-likelihood, and the parsimony, proxied by the BIC, would be worsened. From a qualitative point of view, they turn out to be very close to the previous ones. From a quantitative point of view, the same holds as regards average partial effects.<sup>14</sup>

### 6.2 Attrition

Second, I address statistical concerns related to endogenous attrition. Appendix Tables A.1 to A.3 display the estimates obtained on the balanced panel. From a qualitative point of view, they yield similar results as those obtained on the unbalanced panel. Even though there might be some issues regarding the consistency of the estimation of dynamic ordered models with correlated random effects on unbalanced panels (Albarran et al., 2019),<sup>15</sup> these empirical findings suggest that this concern would not affect the main qualitative conclusions at stake here. Moreover, to the best of my knowledge, there is no satisfying treatment of the incomplete

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<sup>14</sup>All these estimates are available upon request.

<sup>15</sup>Their recommended procedure consists basically in estimating the model on an average of minimum distance estimators corresponding to balanced subsets.



case analysis, i.e., of the (current) case where observations are not necessarily consecutive.

I explore next the role played by sample attrition. I resort to a statistical test for possible attrition bias as recommended by [Verbeek and Nijman \(1992\)](#). Their test consists in introducing a dummy for being part of the balanced panel and the number of times an individual is present in the unbalanced sample as further explanatory variables in the previous model. In practice, both covariates turn out to be non-significant, which indicates that endogenous attrition is not too much of a problem here.<sup>16</sup>

### 6.3 Replication: Australia, Germany and the UK

Third, I replicate the current analysis on other databases issued from three other countries (Australia, Germany and the UK), finding more or less similar effects in these different institutional settings (including survey design). In all these countries, the correlations of subjective well-being with observed characteristics are retrieved.<sup>17</sup>

First, I use the Household, Income and Labour Dynamics in Australia (HILDA) Survey for which I resort to 17 waves from 2001 to 2017.<sup>18</sup> More than 20,000 individuals report their self-assessed overall satisfaction with life on a similar Cantril scale. [Table 8](#) depicts annual transitions of individual answers to that question; it suggests once again that state dependence cannot be ignored. The asymmetry between happy states and unhappy states in this regard is confirmed by [Figure 4](#), and is even more striking in this country: happy states look even more persistent while unhappy states look even more transitory. More than 90% of the time, trajectories of subjective well-being which include at least one occurrence of happiness (resp. unhappiness) contain in fact more than 50% of happy (resp. happy) occurrences. This impression is confirmed by an econometric analysis that controls for age, age squared, gender, income (measured at the household level), education,

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<sup>16</sup>In case it were, a method to deal with it could have been to use the inverse probability weighting solution proposed by [Wooldridge \(2002\)](#).

<sup>17</sup>The estimates of state dependence do not vary by much when the list of covariates is reduced to the smallest common set of covariates that are available in all countries; the corresponding estimates are available upon request. In all these countries, the most parsimonious model, i.e., the one that minimizes the BIC, turns out to be the dynamic ordered Logit with correlated random effects.

<sup>18</sup>My code is adapted from the one provided by PanelWhiz on <http://www.panelwhiz.eu>.

labor force status and family status, on top of state dependence and initial conditions. Appendix Tables A.4 to A.6 suggest that the very same results as those found in France hold in Australia. To be precise, state dependence is all the more pronounced that one gets higher in the distribution of subjective well-being, and the respective effects of initial conditions and of state dependence look pretty similar. The inertia parameters have a slightly convex profile, different than the one obtained in France though (see Figure 5). The average partial effects for reporting a level 1 are for instance not significantly different from those related to reporting a level of 0, contrary to what prevails at the top of the distribution. To sum up, dissatisfaction with life looks also like a rare event that everyone may face once, but which does not persist over time.

Second, I resort to the GSOEP in Germany. This exceptional longitudinal survey has been available from 1984 to 2017<sup>19</sup> and has no less than 34 waves, which permits to follow accurately the evolution of life satisfaction for more than 50,000 individuals. As in Australia and in France, the latter is self-reported on a Cantril scale. Table 9, Appendix Tables A.7 to A.9 and Figure 6 display very similar results as Australia, from a qualitative point of view. State dependence is increasing all over the distribution of subjective well-being, as Figure 7 shows. No evidence of unhappiness trap can be found. The GSOEP is the sole case where initial conditions provided by the vector of coefficients  $\rho^0$  have a smaller impact on current life satisfaction than state dependence (encompassed by  $\rho$ ), which is conform to the rationale since initial conditions in the GSOEP may date back up to 33 years ago.

Third, I use the UK Understanding Society (UKUS) panel. This survey takes over the British Household Panel Survey (BHPS), starting from 2009. Eight waves are available for about 50,000 individuals. These people are asked about their overall satisfaction with life and their answer is available on a discrete, ordered scale ranging from 1 to 7. Table 10 suggests as previously that state dependence cannot be ignored, in particular for individuals who are already satisfied with their life, which will be confirmed by a *ceteris paribus* analysis. The same holds for Figure 8, defining here 'unhappiness' as the fact of reporting levels 1 or 2 of life satisfaction, and 'happiness', level 5 or more. Following the recommendations of Clark and Georgellis (2013) on how to estimate subjective well-being equations

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<sup>19</sup>In West Germany only; East Germany has been surveyed from the reunification onwards.

on the BHPS, I control for age, age squared, gender, income (measured at the household level), the number of children, dummies for married, unemployed and self-employed individuals, as well as dummies for having a high or a medium degree, on top of year dummies. Appendix Tables A.10 to A.12 exhibit very similar results to those that prevail in the other countries. Yet state dependence exhibits some non-monotonicity, namely a U-shape here (Figure 9). It is more pronounced for level 2 than it is for level 3 since the null hypothesis of the unilateral test  $H_0 : \rho_2 < \rho_3$  is strongly rejected at 5% (the  $p$ -value being  $1.8 \cdot 10^{-13}$ ), which suggests that bad states of life satisfaction are somehow more persistent in the UK. Hence, and interestingly, the asymmetry observed in Australia, in France and in Germany as regards persistence at the top and at the bottom of the distribution of happiness was thus neither a mechanical effect, nor a statistical artifact. Finally, initial conditions have a greater impact on current life satisfaction than past life satisfaction, as was the case in Australia and in France.

## 7 Conclusion

This paper has investigated the existence of unhappiness traps based on longitudinal data of subjective well-being in different OECD countries. After disentangling carefully state dependence from unobserved heterogeneity in self-assessed life satisfaction, the empirical evidence at stake does not make it possible to assess the existence of such traps. An exception concerns nevertheless the UK where some levels of dissatisfaction are found slightly persistent. On the whole, every individual is more or less exposed to some idiosyncratic risk of turning once unsatisfied with her life.

From an econometric perspective, there are at least three limits of the current approach. First, the dynamic, nonlinear model estimated here does not include fixed effects. A natural extension would thus consist in considering a dynamic, ordered model with fixed effects in the vein of [Frijters et al. \(2004\)](#), [Bartolucci and Nigro \(2010\)](#) or [Carro and Traferri \(2014\)](#). Second, state dependence could be modelled by higher-order Markov processes than the first-order process used here: more lags could be included in the estimating equation. Third, serial correlation in the error term could be taken into account, which requires to estimate dynamic models with some AR(1) error term component.

From a social science perspective, further research should try to understand which mechanisms explain why unhappiness looks transitory, and in particular whether the level of social protection plays a role in this domain (see, e.g., a survey of such studies by [Odermatt and Stutzer, 2018](#)), remembering that the US are not part of the current analysis. The reverse viewpoint could be adopted: one could rather wonder why happiness is persistent? Are cognitive biases at stake? Do anchoring effects matter? Is it more costly for individuals to revise downwards their self-assessed evaluation of life satisfaction?

## Supplementary material

Supplementary material is available online at the OUP website. This comprises the online appendix and the replication files. The online appendix provides additional results tables. The replication files include SAS and Stata programs. The data used in this article are available from the French research data center <http://quetelet.progedo.fr/> (last accessed 25 July 2021), the Australian data archive <https://ada.edu.au/> (last accessed 25 July 2021), the German research data center for SOEP [https://www.diw.de/en/diw\\_01.c.678568.en/research\\_data\\_center\\_soep.html](https://www.diw.de/en/diw_01.c.678568.en/research_data_center_soep.html) (last accessed 25 July 2021), and the UK data archive <https://www.data-archive.ac.uk/> (last accessed 25 July 2021).

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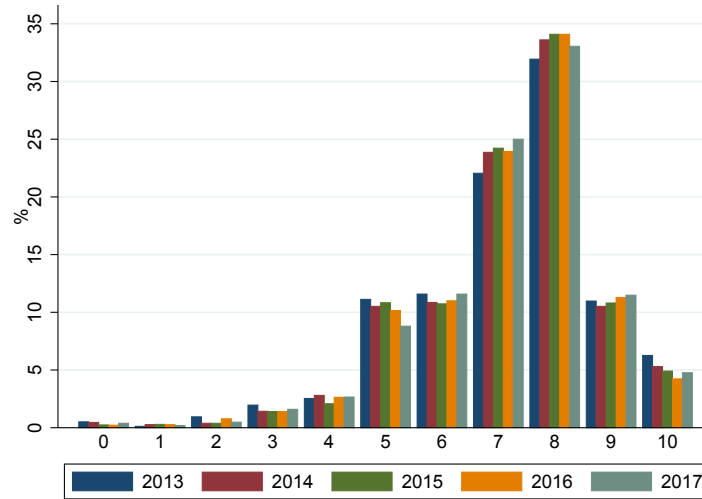
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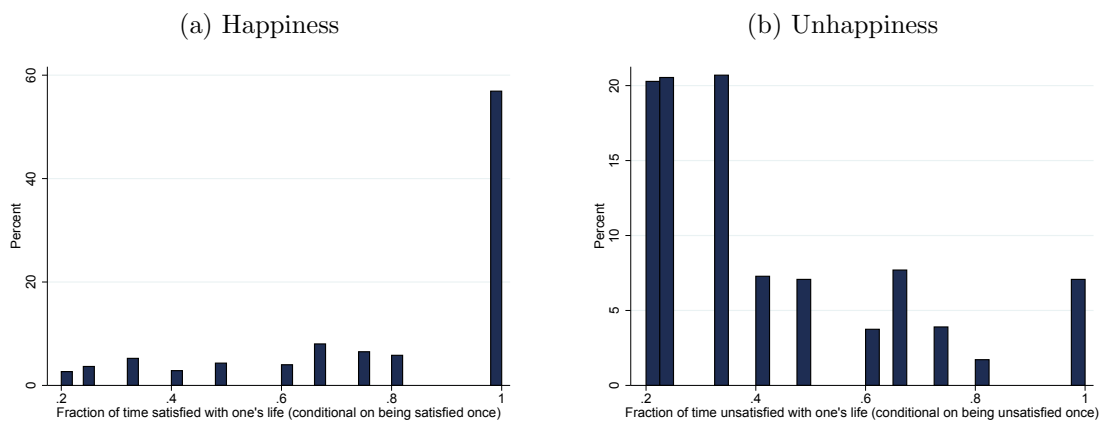
# A Figures

Figure 1: Evolution of life satisfaction in France



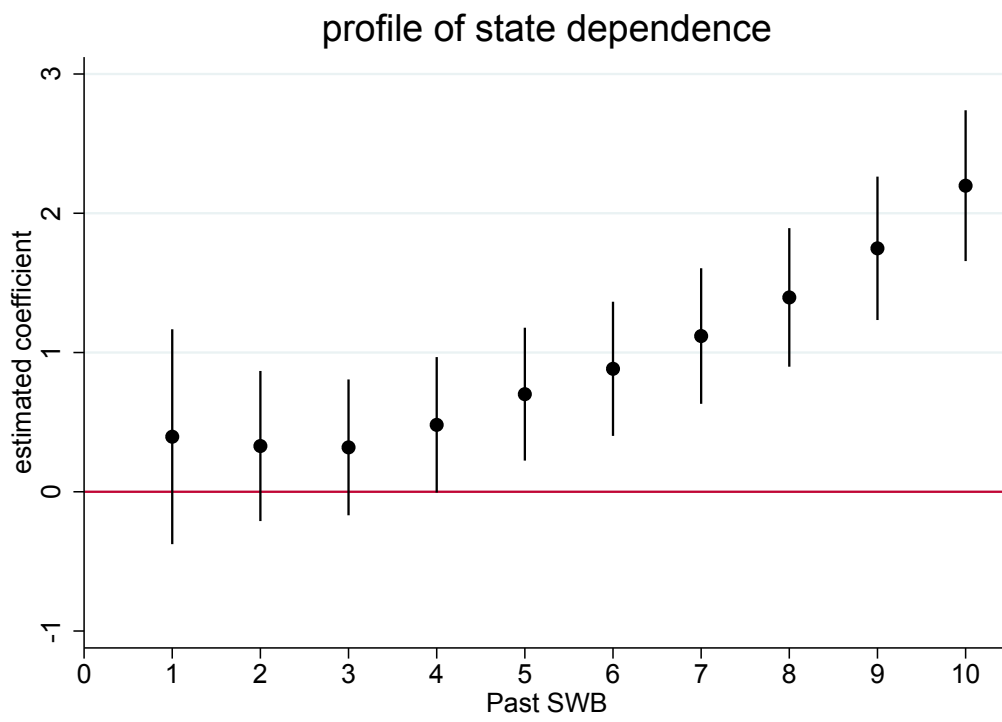
*Note.* French SRCV survey, 2013-2017. Life satisfaction measured on a Cantril scale.

Figure 2: Persistence of satisfaction with life



*Note.* Happiness: answer of 7 or more on the Cantril scale. Unhappiness: answer of 4 or less on the Cantril scale.

Figure 3: Estimated profile of state dependence



*Note.*  $x$ -axis: level  $j$  on the Cantril scale;  $y$ -axis: estimated coefficient  $\hat{\rho}_j$ .

## B Tables

Table 1: Summary statistics

	mean	sd	min	max
Life satisfaction	7.18	1.65	0	10
Female	0.60	0.49	0	1
Age	55.4	16.6	17	100
Income	25,877	38,444	20	4,468,733
Education				
No degree	0.23	0.42	0	1
High-school	0.29	0.45	0	1
Vocational	0.32	0.47	0	1
College	0.16	0.37	0	1
Other degree	0.00	0.06	0	1
Labor force status				
Employed	0.47	0.50	0	1
Unemployed	0.06	0.23	0	1
Student	0.01	0.11	0	1
Inactive	0.05	0.23	0	1
Retired	0.39	0.49	0	1
Undetermined	0.02	0.13	0	1
Occupation				
Clerk	0.28	0.45	0	1
Farmer	0.03	0.17	0	1
White collar	0.14	0.34	0	1
Self-employed	0.05	0.23	0	1
Intermediate	0.23	0.42	0	1
Blue collar	0.17	0.38	0	1
Other	0.10	0.30	0	1
Family status				
Single	0.24	0.43	0	1
Two adults, w/o child	0.39	0.49	0	1
Two adults, 1 child	0.09	0.28	0	1
Two adults, 2 children	0.11	0.31	0	1
Two adults, 3+ children	0.05	0.22	0	1
Single parent	0.04	0.20	0	1
Others w/o child	0.05	0.21	0	1
Others with children	0.03	0.16	0	1
Undetermined	0.01	0.08	0	1
Observations			38,483	

*Source.* French SRCV survey, 2013-2017.

*Sample.* Unbalanced panel of 13,574 individuals.

Table 2: Within-individual heterogeneity in reported life satisfaction

Absolute maximal difference in reported life satisfaction	Frequency (%)
0	12.3
1	35.2
2	27.0
3	14.5
4	5.6
5	3.5
6-10	2.1

*Source.* French SRCV survey, 2013-2017.

*Sample.* Unbalanced panel of 13,574 individuals.

*Lecture.* Highest minus lowest level of life satisfaction over the period.

Table 3: Life satisfaction in France: annual transitions

Destination → Initial ↓	0	1	2	3	4	5	6	7	8	9	10
0	24.5	5.1	10.2	9.2	9.2	22.5	6.1	7.1	4.1	0.0	2.0
1	3.5	15.5	13.8	10.3	3.5	22.4	5.2	5.2	17.2	0.0	3.5
2	4.4	7.0	11.4	10.8	13.3	23.4	12.7	12.0	2.5	2.5	0.0
3	2.7	2.2	6.2	15.3	19.1	26.6	12.4	9.4	4.8	1.1	0.3
4	1.7	0.3	4.3	9.8	15.1	32.2	16.2	11.6	6.3	1.9	0.6
5	0.6	0.3	1.8	4.2	7.5	32.3	20.2	18.4	11.3	1.9	1.4
6	0.2	0.3	0.5	2.0	4.0	16.6	25.7	31.6	15.7	2.4	1.1
7	0.1	0.1	0.2	0.7	1.4	7.7	13.8	40.0	30.3	4.5	1.3
8	0.0	0.1	0.1	0.3	0.6	4.0	5.5	20.8	52.2	12.9	3.4
9	0.1	0.0	0.1	0.2	0.5	1.1	2.3	10.1	38.9	35.3	11.3
10	0.1	0.0	0.1	0.4	0.2	2.2	2.2	6.5	24.2	24.9	39.2
Total	0.4	0.3	0.7	1.6	2.6	10.1	11.1	23.8	33.2	11.1	5.2

*Source.* French SRCV survey, 2013-2017.

*Sample.* Unbalanced panel of 13,574 individuals.

Table 4: Ordered Logit model - unbalanced panel (1)

Dependent	Life satisfaction (LS <sub>t</sub> )			
	(1)	(2)	(3)	(4)
Current log income ( $\beta$ )	0.608*** (0.032)	0.615*** (0.044)	0.083 (0.056)	0.050 (0.054)
Mean log income ( $\gamma$ )			0.661*** (0.121)	0.587*** (0.110)
Initial log income ( $\gamma^0$ )			-0.182** (0.083)	-0.157** (0.072)
Age	-0.029*** (0.005)	-0.047*** (0.009)	-0.009 (0.008)	-0.007 (0.007)
Age <sup>2</sup> /100	0.015*** (0.005)	0.026*** (0.008)	-0.006 (0.007)	-0.006 (0.006)
Female	-0.005 (0.029)	-0.008 (0.048)	-0.031 (0.038)	-0.029 (0.033)
Education (ref=no degree)				
High-school	0.008 (0.221)	-0.184 (0.325)	0.015 (0.284)	0.040 (0.252)
Vocational	-0.070 (0.221)	-0.350 (0.328)	-0.010 (0.285)	0.018 (0.253)
College	0.042 (0.222)	-0.072 (0.328)	0.014 (0.286)	0.036 (0.253)
Other	-0.131 (0.223)	-0.476 (0.331)	0.011 (0.288)	0.033 (0.255)
Labor force status (ref=unemployed)				
Employed	0.944*** (0.060)	1.160*** (0.083)	0.671*** (0.106)	0.618*** (0.104)
Student	1.141*** (0.133)	1.318*** (0.194)	0.392 (0.276)	0.252 (0.268)
Inactive	0.646*** (0.090)	0.571*** (0.125)	0.334* (0.185)	0.300* (0.179)
Retired	0.963*** (0.073)	1.172*** (0.100)	0.544*** (0.139)	0.481*** (0.134)
Undetermined	-0.066 (0.123)	0.189 (0.155)	0.359* (0.198)	0.304 (0.190)
Occupation (ref=farmer)				
Clerk	0.285*** (0.087)	0.526*** (0.137)	1.521** (0.670)	1.481** (0.641)
Blue collar	0.243*** (0.089)	0.417*** (0.140)	1.268* (0.660)	1.259** (0.629)
Intermediate	0.357*** (0.088)	0.684*** (0.139)	1.348** (0.671)	1.302** (0.642)
White collar	0.477*** (0.093)	0.960*** (0.147)	1.695** (0.680)	1.606** (0.651)
Self-employed	0.287*** (0.102)	0.561*** (0.160)	1.460** (0.700)	1.366** (0.670)
Other	0.280*** (0.098)	0.463*** (0.152)	1.223* (0.666)	1.215* (0.637)
Undetermined	0.359 (0.219)	0.304 (0.280)	0.647 (0.719)	0.631 (0.693)
Family status (ref=single)				
Two adults (no child)	0.642*** (0.035)	1.060*** (0.054)	0.760*** (0.118)	0.649*** (0.114)
Other (no child)	0.484*** (0.066)	0.743*** (0.091)	0.462*** (0.158)	0.343** (0.152)
Single parent	-0.145** (0.070)	0.006 (0.103)	0.242 (0.173)	0.173 (0.165)
Two adults (1 child)	0.550*** (0.050)	0.939*** (0.076)	0.688*** (0.147)	0.551*** (0.140)
Two adults (2 children)	0.737*** (0.050)	1.106*** (0.077)	0.582*** (0.168)	0.441*** (0.161)
Two adults (3+ children)	0.766*** (0.068)	1.166*** (0.103)	0.688*** (0.210)	0.530*** (0.201)
Other (children)	0.705*** (0.081)	1.068*** (0.106)	0.638*** (0.179)	0.523*** (0.171)
Undetermined	0.529*** (0.138)	1.100*** (0.174)	0.864*** (0.224)	0.728*** (0.219)

Table 5: Ordered Logit model - unbalanced panel (2)

	(1)	(2)	(3)	(4)
Initial life satisfaction ( $\rho^0$ ) - (ref=0)				
LS <sub>2013</sub> = 1			-0.221 (0.522)	-0.293 (0.474)
LS <sub>2013</sub> = 2			0.393 (0.394)	0.220 (0.368)
LS <sub>2013</sub> = 3			1.268*** (0.353)	1.000*** (0.326)
LS <sub>2013</sub> = 4			1.363*** (0.332)	1.047*** (0.313)
LS <sub>2013</sub> = 5			2.420*** (0.322)	1.871*** (0.306)
LS <sub>2013</sub> = 6			2.985*** (0.322)	2.303*** (0.308)
LS <sub>2013</sub> = 7			3.780*** (0.321)	2.909*** (0.309)
LS <sub>2013</sub> = 8			5.061*** (0.323)	3.921*** (0.315)
LS <sub>2013</sub> = 9			6.303*** (0.328)	4.868*** (0.325)
LS <sub>2013</sub> = 10			7.383*** (0.336)	5.634*** (0.338)
Past life satisfaction ( $\rho$ ) - (ref=0)				
LS <sub>t-1</sub> = 1				0.395 (0.394)
LS <sub>t-1</sub> = 2				0.329 (0.275)
LS <sub>t-1</sub> = 3				0.319 (0.249)
LS <sub>t-1</sub> = 4				0.481* (0.248)
LS <sub>t-1</sub> = 5				0.701*** (0.243)
LS <sub>t-1</sub> = 6				0.883*** (0.246)
LS <sub>t-1</sub> = 7				1.118*** (0.248)
LS <sub>t-1</sub> = 8				1.396*** (0.254)
LS <sub>t-1</sub> = 9				1.748*** (0.263)
LS <sub>t-1</sub> = 10				2.198*** (0.276)

Table 6: Ordered Logit model - unbalanced panel (3)

	(1)	(2)	(3)	(4)
Cut-offs				
$s_1$	0.885** (0.407)	-1.751*** (0.577)	3.540*** (1.033)	3.279*** (0.947)
$s_2$	1.349*** (0.403)	-1.199** (0.573)	4.095*** (1.032)	3.814*** (0.945)
$s_3$	2.076*** (0.399)	-0.305 (0.571)	4.993*** (1.030)	4.681*** (0.944)
$s_4$	2.870*** (0.397)	0.725 (0.570)	6.028*** (1.030)	5.676*** (0.944)
$s_5$	3.559*** (0.397)	1.673*** (0.569)	6.979*** (1.030)	6.586*** (0.944)
$s_6$	4.789*** (0.397)	3.523*** (0.569)	8.833*** (1.031)	8.354*** (0.946)
$s_7$	5.517*** (0.397)	4.708*** (0.569)	10.023*** (1.032)	9.482*** (0.947)
$s_8$	6.634*** (0.398)	6.604*** (0.570)	11.925*** (1.034)	11.285*** (0.949)
$s_9$	8.339*** (0.400)	9.442*** (0.571)	14.768*** (1.036)	13.981*** (0.953)
$s_{10}$	9.581*** (0.401)	11.319*** (0.573)	16.638*** (1.038)	15.762*** (0.956)
$\sigma_u^2$		4.988*** (0.123)	2.574*** (0.076)	1.594*** (0.092)
Year dummies	Yes	Yes	Yes	Yes
Individual effects	No	RE	CRE	CRE
# of individuals	13,574	13,574	13,574	13,574
# of observations	38,483	38,483	38,483	38,483
$\log(L)/N$	-1.761	-1.614	-1.530	-1.526
BIC	135,935	124,705	118,786	118,568

*Source.* French SRCV survey, 2013-2017.

*Sample.* Unbalanced panel of 13,538 individuals.

Robust standard errors clustered at the individual level.

Estimates for initial and average covariates not reported (income aside).



Table 7: Average partial effects on probability of reporting level 10 of life satisfaction (selected variables only)

Dependent	Life satisfaction ( $LS_t$ )			
	(1)	(2)	(3)	(4)
Current log income - ( $\beta$ )	0.031*** (0.002)	0.022*** (0.002)	0.003 (0.002)	0.002 (0.003)
Mean log income - ( $\gamma$ )			0.025*** (0.005)	0.030*** (0.006)
Unemployed	-0.034*** (0.002)	-0.032*** (0.002)	-0.022*** (0.003)	-0.030*** (0.005)
Two adults (no child)	0.028*** (0.002)	0.033*** (0.002)	0.026*** (0.004)	0.032*** (0.005)
Two adults (1 child)	0.023*** (0.002)	0.028*** (0.003)	0.023*** (0.005)	0.027*** (0.007)
Two adults (2 children)	0.034*** (0.003)	0.035*** (0.003)	0.019*** (0.006)	0.021*** (0.008)
Two adults (3+ children)	0.036*** (0.004)	0.038*** (0.004)	0.023*** (0.008)	0.026*** (0.010)
Past life satisfaction ( $\rho$ ) - (ref=0)				
$LS_{t-1} = 1$				0.015 (0.015)
$LS_{t-1} = 2$				0.012 (0.010)
$LS_{t-1} = 3$				0.012 (0.008)
$LS_{t-1} = 4$				0.018** (0.008)
$LS_{t-1} = 5$				0.028*** (0.008)
$LS_{t-1} = 6$				0.036*** (0.008)
$LS_{t-1} = 7$				0.048*** (0.008)
$LS_{t-1} = 8$				0.064*** (0.009)
$LS_{t-1} = 9$				0.084*** (0.010)
$LS_{t-1} = 10$				0.112*** (0.012)
Individual effects	No	RE	CRE	CRE
# of individuals	13,574	13,574	13,574	13,574
# of observations	38,483	38,483	38,483	38,483

*Source.* French SRCV survey, 2013-2017.

*Sample.* Unbalanced panel of 13,538 individuals.

Robust standard errors clustered at the individual level.

## C Australia

Table 8: Life satisfaction in Australia: annual transitions

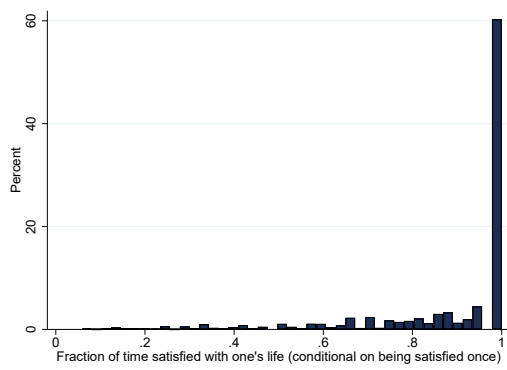
Destination → Initial ↓	0	1	2	3	4	5	6	7	8	9	10
0	14.1	11.1	13.1	9.1	4.0	21.2	7.1	3.5	7.6	2.5	6.6
1	4.3	12.7	12.4	16.2	8.5	17.8	7.3	8.1	7.0	4.6	1.2
2	3.1	6.2	12.2	13.7	8.8	20.7	9.4	11.3	10.8	2.3	1.5
3	1.3	2.9	6.6	13.0	11.5	22.2	14.6	14.0	9.3	2.9	1.7
4	0.6	0.9	3.2	7.5	12.8	23.0	18.2	17.9	10.2	3.7	2.0
5	0.6	0.7	1.7	3.2	6.2	23.9	17.9	23.0	15.7	4.1	3.0
6	0.1	0.1	0.6	1.7	3.9	11.4	21.9	34.2	19.3	4.7	2.0
7	0.1	0.1	0.3	0.5	1.1	4.4	10.4	40.0	34.2	7.2	1.9
8	0.0	0.0	0.1	0.2	0.4	1.9	3.3	19.4	49.7	20.4	4.5
9	0.0	0.1	0.1	0.1	0.2	0.8	1.2	6.5	32.1	46.2	12.8
10	0.1	0.0	0.1	0.1	0.2	1.1	1.1	3.5	14.9	26.2	52.8
Total	0.1	0.2	0.4	0.7	1.1	3.9	5.9	19.6	34.7	22.3	11.2

*Source.* The Household, Income and Labour Dynamics in Australia (HILDA), 2001-2017.

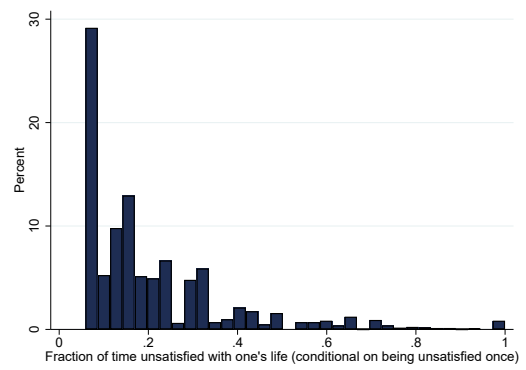
*Sample.* Unbalanced panel of 22,654 individuals.

Figure 4: Persistence of satisfaction with life - Australia

(a) Happiness

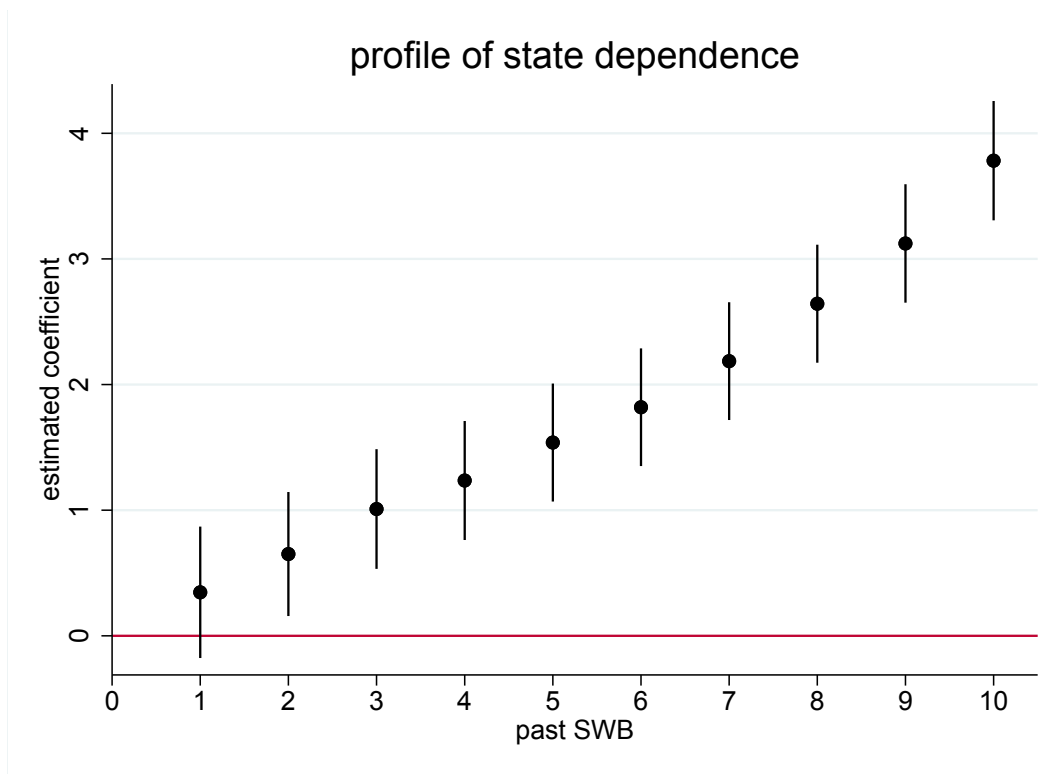


(b) Unhappiness



*Note.* Happiness: answer of 7 or more on the Cantril scale. Unhappiness: answer of 4 or less on the Cantril scale.

Figure 5: Estimated profile of state dependence - Australia



Note.  $x$ -axis: level  $j$  on the Cantril scale;  $y$ -axis: estimated coefficient  $\hat{\rho}_j$ .

## D Germany

Table 9: Life satisfaction in Germany: annual transitions

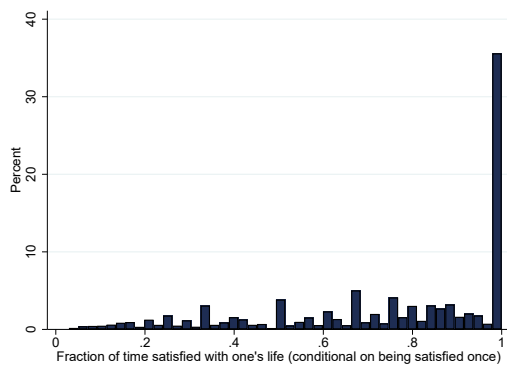
Destination → Initial ↓	0	1	2	3	4	5	6	7	8	9	10
0	21.9	8.7	11.4	11.6	6.7	19.2	5.3	5.5	6.0	1.7	2.1
1	8.7	12.1	15.0	14.9	9.4	17.0	6.2	6.9	5.0	3.3	1.7
2	3.6	5.3	15.2	17.5	11.3	18.9	8.8	8.3	8.0	2.3	1.0
3	1.6	2.4	8.2	16.9	15.0	22.9	11.9	10.9	7.8	1.7	0.8
4	0.8	1.2	4.2	10.8	16.2	26.2	15.8	14.2	8.5	1.7	0.5
5	0.7	0.6	2.0	5.0	7.9	33.3	17.5	17.4	12.2	2.2	1.3
6	0.2	0.3	1.0	2.7	5.0	18.2	23.6	28.2	16.9	2.7	1.2
7	0.1	0.1	0.5	1.5	2.3	9.3	14.4	35.7	29.8	4.9	1.4
8	0.1	0.1	0.3	0.7	1.0	4.8	6.5	22.0	47.5	13.7	3.3
9	0.1	0.1	0.2	0.4	0.6	2.4	3.0	9.8	37.7	36.7	9.1
10	0.2	0.1	0.3	0.5	0.6	3.7	2.6	6.8	22.5	23.9	38.8
Total	0.4	0.4	1.2	2.6	3.5	11.7	11.2	22.1	30.6	11.5	4.7

*Source.* The German Socio-Economic Panel (GSOEP), 1984-2017.

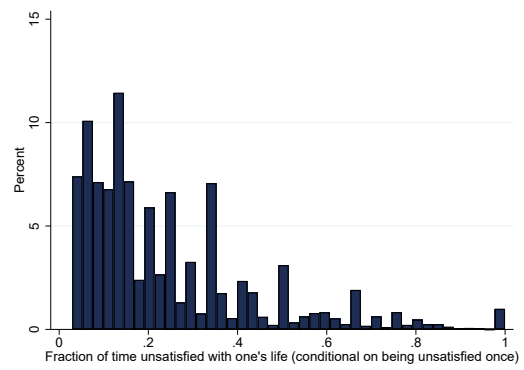
*Sample.* Unbalanced panel of 48,971 individuals.

Figure 6: Persistence of satisfaction with life - Germany

(a) Happiness

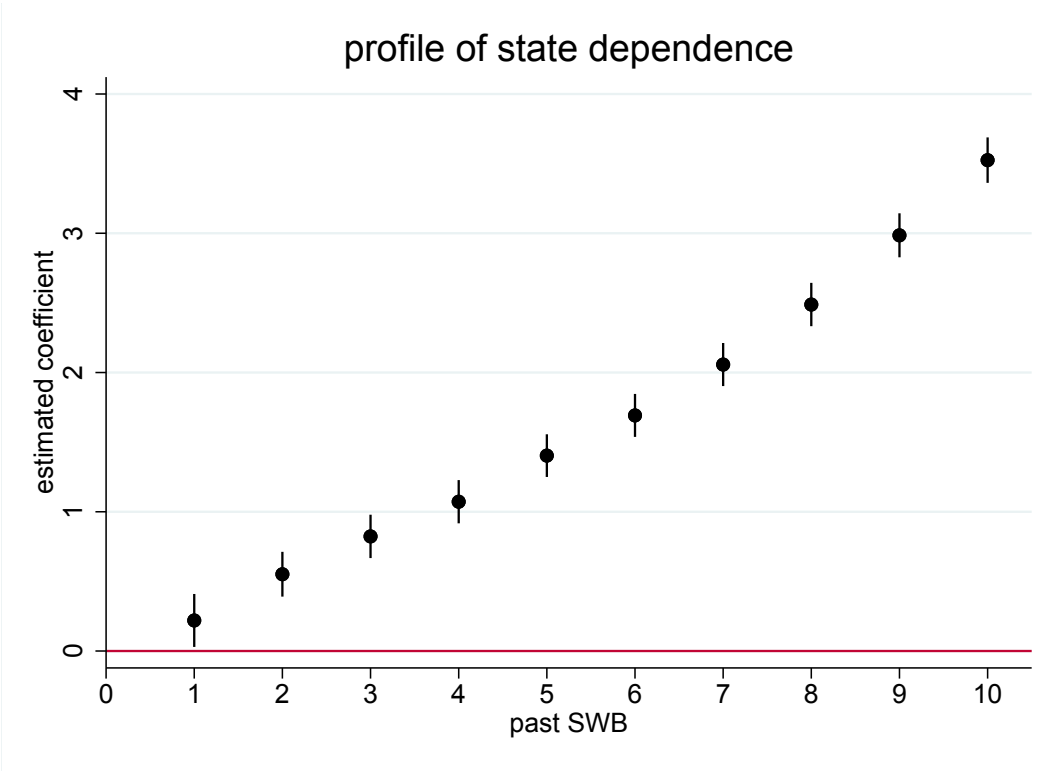


(b) Unhappiness



*Note.* Happiness: answer of 7 or more on the Cantril scale. Unhappiness: answer of 4 or less on the Cantril scale.

Figure 7: Estimated profile of state dependence - Germany



Note.  $x$ -axis: level  $j$  on the Cantril scale;  $y$ -axis: estimated coefficient  $\hat{\rho}_j$ .

# E The UK

Table 10: Life satisfaction in the UK: annual transitions

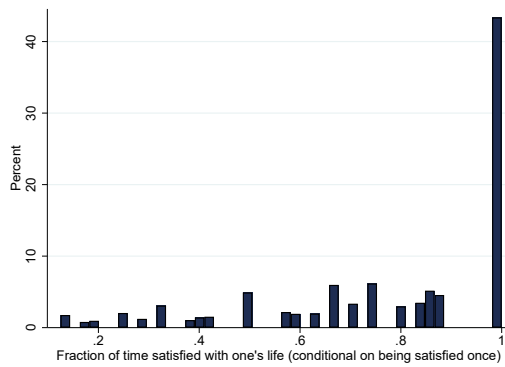
Destination → Initial ↓	1	2	3	4	5	6	7
1	24.1	16.0	8.7	7.6	6.7	19.9	17.0
2	6.5	20.3	14.8	10.0	12.7	31.3	4.3
3	2.6	11.1	28.9	18.2	20.4	17.2	1.7
4	1.7	5.8	15.4	28.2	23.8	22.3	2.7
5	0.8	4.3	9.8	12.8	31.3	37.7	3.4
6	1.0	3.7	3.0	4.5	14.1	63.9	9.8
7	3.4	2.3	1.3	2.5	5.4	40.5	44.7
Total	2.3	5.6	7.9	9.3	17.2	46.5	11.2

*Source.* The United Kingdom Understanding Society (UKUS) survey, waves 1 to 8.

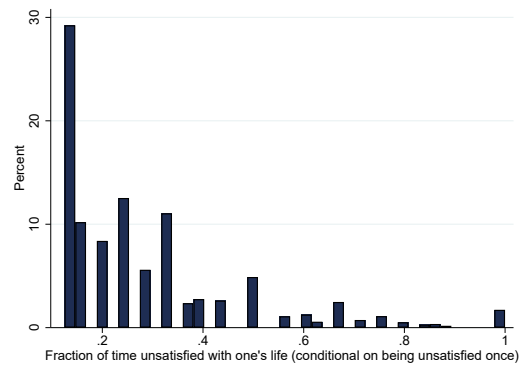
*Sample.* Unbalanced panel of 45,173 individuals.

Figure 8: Persistence of satisfaction with life - UK

(a) Happiness



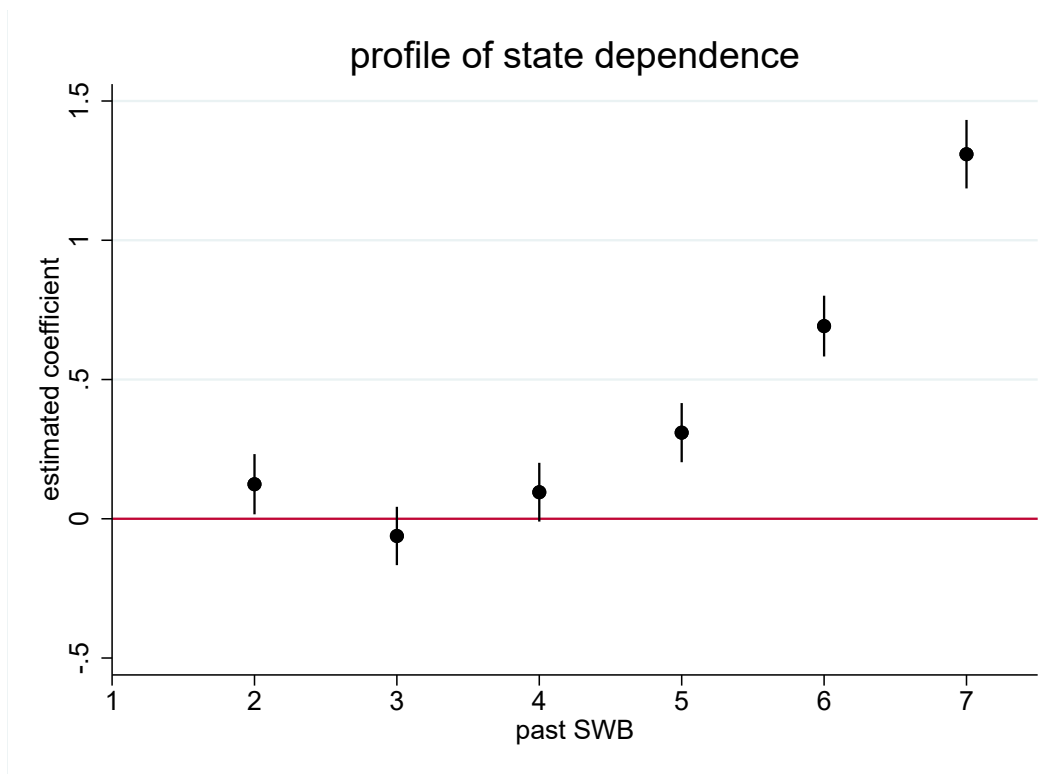
(b) Unhappiness



*Note.* Happiness: answer of 5 or more on the 7 point scale. Unhappiness: answer of 1 or 2 on the 7 point scale.



Figure 9: Estimated profile of state dependence - UK



Note.  $x$ -axis: level  $j$  on the Cantril scale;  $y$ -axis: estimated coefficient  $\hat{\rho}_j$ .