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The Dynamics of Individual Happiness

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Abstract

This paper unveils the role played by state dependence in self-assessed happiness. It estimates a dynamic nonlinear model of subjective well-being on longitudinal data, primarily from France, as well as from Australia, Germany, and the UK. Life satisfaction is found to be highly persistent over time, which static models ignore. The impact of state dependence is large in comparison with usual determinants of happiness in static models. Moreover, this persistence is heterogeneous across individuals and concerns those already happy with their lives.

Keywords: Happiness; subjective well-being; life satisfaction; dynamic model; state dependence; correlated random effects; initial condition.

JEL Classification: I31.

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1 Introduction

"[Among] unalienable Rights [...] are Life, Liberty and the pursuit of Happiness."
United States Declaration of Independence, July 4, 1776.

Longitudinal surveys on subjective well-being have enabled researchers to isolate the role played by different time-varying factors (e.g., income, unemployment, marriage, widowhood) on self-assessed happiness. On top of observed characteristics, unobserved heterogeneity accounts for a large part of the dispersion in individual subjective well-being: omitted variables, optimism or pessimism bias, scale effects or pure heterogeneity in preferences can nevertheless be controlled for thanks to panel data combined with appropriate econometrics, including fixed effects for instance. Surprisingly, the dynamics of happiness at the individual level has been largely unexplored: though subjective well-being is likely to exhibit much inertia, the quantification of this autocorrelation is still absent from the literature. However, in the pursuit of happiness invoked by the US Declaration of Independence, governments do not ignore that it takes time to modify subjective well-being. Missing the dynamic part of the picture sounds also impossible from an academic perspective.

In this paper, I propose to document the persistence of subjective well-being and to provide with a measure of that state dependence. Subjective well-being is often proxied by life satisfaction, self-assessed by individuals on a Cantril scale, i.e., on a discrete scale that ranges from 0 to 10. I estimate a dynamic, ordered Logit model with correlated random effects; this nonlinear model allows to disentangle state dependence from unobserved heterogeneity, and hence to emphasize the role played by persistence in reported life satisfaction. It also enables me to deal with self-assessed life satisfaction as a polytomous variable, to model the initial condition, and to approximate unobserved heterogeneity as parsimoniously as possible. The current analysis is primarily based on a French panel dataset, SRCV, from 2013 to 2017, but I show that these results hold in Australia, Germany and the UK, these countries disposing of longitudinal surveys that include a measure of subjective well-being, and whose access is easily provided to researchers. The main findings are: (i) state dependence is significant at usual levels; (ii) its magnitude is strong when compared to usual determinants of happiness considered so far; (iii) it is asymmetric: happier people tend to remain happy more than less happy people; (iv) happiness is rather persistent while unhappiness is rather transitory.

Usual determinants of subjective well-being remain significant once state dependence has been controlled for: having a partner improves life satisfaction while unemployment has a depressing effect -and so do deprivation indicators measuring quality of life, or negative capabilities (Sen, 1979). Current or transitory income tends to matter less than average or permanent income. Education, gender and occupation turn out to be mostly non-significant at usual levels. Overall, most usual, individual determinants of subjective well-being are still correlated with the latter even after correcting for the omitted variable bias. However, the current empirical evidence suggests that misspecification of static models is substantial, given the magnitude of the autocorrelation at stake: top past happiness would cushion the impact of unemployment, poor health and weak social ties altogether. Hence controlling for persistence achieves both a better fit and a more accurate description of the whole story of individual happiness.

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), and which has 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 the estimations from the same econometric model as the one estimated on French data concur to close findings: happiness is significantly persistent, especially at the top of the distribution. Having therefore neutralized the role played by the institutional setting, these results strengthen the previous ones, and give some credit to the idea of having unveiled an empirical regularity of individual behavior.

Where does this state dependence come from? The intuition suggests that people don't change their mind every year about their subjective well-being, which generates mechanically autocorrelation. 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 happiness persistence, namely the asymmetry between upward and downward mobility in reported subjective well-being, suggests either that unhappiness is more transitory, or that it is more costly to revise downwards one's self-evaluation of life satisfaction.

The rest of the paper is organized as follows. The next section is devoted to a literature review. Section 3 describes the French SRCV data and 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 (objective indicators of the quality of life, income, age, labor force status, 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); (iii) spatial determinants (rural *versus* urban areas, regional effects, the price of gasoline, among others). However, the dynamics of subjective well-being, often proxied by life satisfaction, has been completely ignored by most studies.

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. To deal with ordinality, researchers have estimated ordered polytomous models that rely on a latent, unobserved but cardinal propensity to happiness. In practice though, estimating linear models does not affect the sign of the covariates,[1] and yields qualitatively similar results.

Moreover, many studies on subjective well-being relied first on cross-sectional

[1] That sign is identified non-parametrically.

data, which limited 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. 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. Panel data enables either to look at differences of subjective well-being over time, or to control for individual effects, but in any case to deal with that issue.

To address previous concerns, the 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 more demanding exclusion restrictions. Moreover, in the econometric dilemma between state dependence and unobserved heterogeneity that dates back to Heckman (1981), much emphasis has been put on unobserved heterogeneity. In contrast, very few dynamic models have been considered so far in happiness economics: the role of state dependence has not been explored, while praised by Clark (2018). To the best of my knowledge, Kešeljević et al. (2016) is the only paper that includes lagged subjective well-being in a linear model which is estimated thanks to Arellano and Bond (1991)'s method. This paper proposes to fill in this gap.

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. SRCV is a rotating panel. 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 offers 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.[2]

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 19,253 individuals followed from 2013 to 2017 with at least two consecutive observations, which will matter for a proper identification of the role played by state dependence (see *infra*) and whose annual income exceeds €1. Subjective well-being is measured on a Cantril scale ranging from 0 to 10. It has an average score of 7.17, 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 (62% of the sample aged 55 on average), which is usual in French household surveys. Average income amounts to nearly €26,000 per year. Income exhibits sizeable dispersion: its coefficient of variation is roughly 1.41, and the richest household surveyed earns about €4,500,000 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, which is not surprising since the sample is mostly comprised of old individuals. One half of the sample is made up of current or former clerks (28%) or individuals with an intermediate occupation (22%); the others are (or were) mainly blue collars (17%)

[2] 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.

or white collars (13%). 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%), three children at least (5%) and single parents (4%). Finally, indicators measuring the objective quality of life are available in the survey: the exposition to psycho-social hazard, health problems, environment troubles, poor living conditions, (economic or general) insecurity as well as the weakness of social ties. Between 2% and 14% of individuals are exposed to at least one of such problems.

Turning now to the persistence of subjective well-being, the main insight from Figure 1 that 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, though the concentration around levels 7 and 8 tends to increase over time.

Focusing at the *individual* level, about 1/5 of surveyed individuals systematically report the same level of life satisfaction over the 5 waves (Table 2). For slightly more than 1/3 of them, the difference between their highest and lowest level of life satisfaction is equal to 1 while for about 1/4 of them, this difference is equal to 2. That difference exceeds 3 for a last 1/4 of individuals, which suggests that subjective well-being is persistent over time at the individual level. This would confirm the intuition 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. Interestingly, the most plausible past level of life satisfaction, given any current, self-assessed level of life satisfaction, is that very same level, few exceptions aside (namely, levels 2 and 4). Yet most models of subjective well-being are static and ignore state dependence, i.e., they do not include any lagged variable as an explanatory variable. Hence they 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 can almost be qualified of an absorbing state.

Moreover, 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 35.4% (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 31% with a probability of having a higher subjective well-being higher than 1/2. To sum up, from levels 0 to 6, upward mobility is more likely while inertia is more plausible from level 7 onwards.[3] To confirms this eyeball impression and to check that is 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 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 $k = 0$ to $k = K \equiv 10$. 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, latent variable y^*_{it} such that $\forall k \in [\![0, K]\!]$,

$$y_{it} = k \Longleftrightarrow y^*_{it} \in [s_k, s_{k+1}[$$

or equivalently,

$$y_{it} = \sum_{k=0}^{K} k \ \mathbb{1}\{s_k \leq y^*_{it} < s_{k+1}\}. \tag{1}$$

The main advantage of this approach consists in retrieving both linearity and cardinality for the latent variable y^*_{it}. $\{s_k\}_{k=1}^{K}$ are the unknown thresholds with $s_0 = -\infty$

[3] Put differently, defining happiness as reporting a level 8 or more, the transition matrix of the latter would be symmetric with 3/4 on its diagonal and equally distributed states among the population; doing the same with unhappiness defined as reporting a level 5 or less would yield a 40% chance of departing from unhappiness for the 6% concerned individuals.

and $s_{K+1} = +\infty$.

The departure from most empirical specifications consists in introducing explicitly state dependence, i.e., the persistence of subjective well-being over time, through the lagged dependent variable as a covariate. I consider a dynamic model on the latent variable of the form:

$$y_{it}^* = \sum_j \rho_j \mathbb{1}[y_{i,t-1} = j] + x_{it}\beta + \alpha_i + \varepsilon_{it},$$

where idiosyncratic shocks ε_{it} follow the logistic distribution with mean 0 and variance $\frac{\pi^2}{3}$. As praised by Wooldridge (2005), state dependence is allowed to be nonlinear, too – namely specific to every value of past subjective well-being: the ρ_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 α_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 $(y_{i1}, \ldots, y_{iT})$ 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. 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.

Another option consists in assuming some parametric form for the individual effects α_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. 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. First, Heckman (1981) proposed to specify the law of the initial condition y_{i0} conditional on the individual effect; this solution requires to write down explicitly the likelihood of the model. Second, Chamberlain (1980) and Wooldridge (2005) praised to do the reverse, namely to specify the law of the individual effect given the initial condition y_{i0}. I follow the latter approach and assume that

$$\alpha_i | y_{i0}, \boldsymbol{x_i} \sim \mathcal{N}\left(\sum_{j=0}^{K} \rho_j^0 \mathbb{1}[y_{i0} = j] + \boldsymbol{x'_{i0}} \boldsymbol{\gamma^0} + \overline{\boldsymbol{x'_i}} \gamma, \sigma_u^2\right), \tag{2}$$

where $\boldsymbol{x_i} = (x_{i0}, \ldots, x_{i,T_i-1})$ if the researcher disposes of T_i observations for individual i. This parametric restriction enables me (i) to get rid of the incidental parameter problem; (ii) to model the initial condition; (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 $\boldsymbol{x_{i0}}$ and mean values of covariates $\overline{\boldsymbol{x_i}}$ is sufficient,[4] as opposed to including the whole set of covariates at all dates (Wooldridge, 2005). This approximation of unobserved heterogeneity is reminiscent of Mundlak (1978).

In the end, the estimating equation is:

$$y_{it}^* = \sum_{j=0}^{K} \left(\rho_j \mathbb{1}[y_{i,t-1} = j] + \rho_j^0 \mathbb{1}[y_{i0} = j]\right) + \boldsymbol{x'_{it}\beta} + \boldsymbol{x'_{i0}} \boldsymbol{\gamma^0} + \overline{\boldsymbol{x'_i}} \gamma + u_i + \epsilon_{it} \tag{3}$$

with $u_i \sim \mathcal{N}(0, \sigma_u^2)$.[5]

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

[4]Time-constant variables and time dummies are dropped from the list of initial and mean covariates.

[5]Lee (2016) considered an equation of this form when focusing on health status in Korea.

correlation between current shocks and past outcomes.[6] The identification of the model requires predetermination, but also strict exogeneity of the covariates $\boldsymbol{x_i}$ conditional on the individual effects α_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 $\sigma_\varepsilon^2 = \pi^2/3$ (Logit) or $\sigma_\varepsilon^2 = 1$ (Probit), for multiplying the latent and all its parameters yields the same likelihood. Under these normalizations, the vector of parameters $\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\gamma^0}, \boldsymbol{\rho}, \boldsymbol{\rho^0}, \boldsymbol{s}, \sigma_u)$ 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 ε 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.[7] 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 $\boldsymbol{x_{it}}$ in the estimating equation. First, the literature devoted to the individual determinants of subjective well-being provides with some guidance (see *supra*). 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 find that both the literature and statistical criteria are globally consistent: the list of relevant covariates include objective quality of life, labor force status, family status, income and age. To be exhaustive, education, occupation, gender and year dummies are also included.

[6] Even in linear models, OLS do not converge, neither in levels nor in differences; the solution proposed by Anderson and Hsiao (1981, 1982) and its GMM-optimal version by Arellano and Bond (1991) consist in differencing and in instrumenting $\Delta y_{i,t-1}$ with past outcomes $y_{i,t-2}$.

[7] Due to the fatter tails of the logistic distribution, the Logit model puts more weight on extreme events.

5 Results

Tables 4 to 6 display the results from the main specification, namely equation (3), estimated on the unbalanced panel.[8] Carefully comparing columns allows 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 $\boldsymbol{\rho} = 0$ with respect to the dynamic model of column (4), i.e., the preferred specification; column (2) assumes further that $\boldsymbol{\gamma} = \boldsymbol{\gamma^0} = \boldsymbol{\rho^0} = 0$ and column (1) adds up $u_i = u, \forall i$. On the one hand, state dependence is encompassed by $\boldsymbol{\rho}$: 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 our 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, $\boldsymbol{\gamma}, \boldsymbol{\gamma^0}, \boldsymbol{\rho^0}$ as well as the residual variance account for unobserved heterogeneity. 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). Moreover, average partial effects (see *infra*) will permit a quantitative comparison across columns.

I find empirical evidence of persistence, which confirms the eyeball impression given by Table 3. The estimated autocorrelation vector $\boldsymbol{\rho}$ is statistically significant at usual levels: $H_0 : \rho_1 = \ldots = \rho_{10} = 0$ is rejected at 5%, the $\chi^2(10)$ statistic being 196.22. Moreover, state dependence turns to have a nonlinear impact on the latent propensity to happiness: $H_0 : \rho_j - \rho_{j+1} = \rho_{j+1} - \rho_{j+2}, \forall j = 0, \ldots, K-2$, is also rejected at 5% with a $\chi^2(9)$ statistic of 57.71, which justifies the specification of state dependence adopted here with respect to a more parsimonious, linear one. Finally, it is striking to remark that the highest levels of life satisfaction only exhibit state dependence, while lower levels of subjective well-being are more transitory, which confirms the asymmetry observed in the descriptive analysis.

[8] For the sake of readability, the same Table of results has been cut into three parts.

Formally, one cannot reject $H_0 : \rho_1 = \ldots = \rho_5 = 0$ at 5%, the $\chi^2(6)$ statistics being 10.27; but $H_0 : \rho_1 = \ldots = \rho_6 = 0$ is rejected at 5%, the $\chi^2(7)$ statistics being 22.02. In that sense, happiness – defined as a reported level of life satisfaction higher than 6 – is persistent, while unhappiness – defined as a reported level of life satisfaction lower than 5 – is not.

Average partial effects (APEs)[9] enable me to quantify by how much the impact of the main determinants of subjective well-being is attenuated when taking state dependence into account; they also allow to compare the relative effects of state dependence and of other explanatory variables. 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 kinds of marital status, poor health, weak social ties and lagged life satisfaction) on the probability to report the highest level, i.e., level 10, of life satisfaction – for the sake of readability.[10] We already knew that unemployment diminished that probability, now we learn that controlling neither for unobserved heterogeneity, nor for state dependence leads to overestimate its impact by 1/3. The same holds as regards weak social ties and poor health, for which the overestimation bias is even more pronounced, the attenuation factor being strictly higher than 2. It is also confirmed that parents of more than 2 children do not report more frequently level 10 than other couples, contrary to what a naive analysis would conclude. Having a partner raises by 2pp the propensity of being most satisfied with one's life. A 1% increase in permanent income raises that probability by 1.6pp. Finally, the effect of state dependence itself, i.e., of reporting level 10 the year before, increases the probability of reporting that very level by 7.1 points: state dependence has thus a quite large impact since it would compensate elements like unemployment, poor health and weak social ties altogether.

Moreover, it is also useful to check that the main stylized facts of happiness economics remain, even after controlling for persistence of life satisfaction. First, objective deprivation indicators measuring the quality of life are the strongest predictors of a lower life satisfaction, especially the weakness of social ties, poor living conditions, and poor health, which is consistent with the previous evidence

[9]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.

[10]All other APEs are available upon request.

found by Godefroy and Lollivier (2014). Taking persistence of life satisfaction into account has little impact on the strength of the link between these objective indicators and subjective well-being. Second, unemployment is still a major cause of misery. Third, the same holds, more or less, as regards family status; interestingly, the only significant dimension in that respect relates to having a partner: singles and single parents report equally lower levels of life satisfaction than individuals living with a partner. Children do not matter, contrary to what the evidence from column (1) based on observed heterogeneity only would suggest. Parents of three children or more look apparently happier than parents of one or two children, and than couples without a child, yet this difference vanishes after controlling for unobserved heterogeneity. Fourth, the effect of current income disappears after controlling for past life satisfaction; the CRE approach makes it possible to identify the channel through which income matters, i.e., average income. In other words, *transitory income*, i.e., current shocks of income viewed as deviations from average or *permanent income*, matter less than the latter, which is reminiscent of Frijters et al. (2004). Fifth, the U-shape with age remains after controlling for unobserved heterogeneity and state dependence. Sixth, gender does not matter. Seventh, neither does education. Eighth, neither does occupation – farmers aside, who are significantly far less satisfied with their lives.

Finally, from a purely statistical perspective, the fit of the model, as measured by the average individual log-likelihood, reaches -1.51 in the restricted model. Put differently, the average likelihood of an observation is .22, which is quite satisfying. By construction, the fit improves as one moves from most constrained specification (column 1) to least constrained specification (column 4). Moreover, the residual variance in subjective well-being, i.e., the dispersion of subjective well-being that remains unexplained by the full model including covariates, correlated random effects and state dependence, shrinks also mechanically as one moves from column (2) to column (4): it has been divided by a factor 2 (resp. 3 in the dynamic CRE specification) in comparison with a pure RE specification. Finally, the correlation between the initial condition and unobserved heterogeneity, measured by $\boldsymbol{\rho}^0$, is strong. The magnitude of the impact of that initial condition $\boldsymbol{\rho}^0$ is even higher than the one related to the lagged dependent variable $\boldsymbol{\rho}$, which was already the case in Wooldridge (2005).

6 Robustness checks

I perform several robustness checks to assess the sensitivity of previous results with respect to (i) functional form; (ii) attrition; (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 ε_{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.[11]

6.2 Attrition

Second, I address statistical concerns related to endogenous attrition. Tables 8 to 10 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. The only qualitative difference is related to the age effect, which disappears after controlling for state dependence on top of unobserved heterogeneity. However, this loss of significance stems from a lack of statistical power that is due to low sample size, which is less worrying.

I explore next the role played by sample attrition. I resort to a statistical test for possible attrition bias as praised 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.[12]

[11] All these estimates are available upon request.

[12] In case it were, a method to deal with it could have been to use the inverse probability weighting solution proposed by Wooldridge (2002).

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), which permits to neutralize the role played by the institutional setting. In all these countries, stylized facts of subjective well-being are retrieved.

First, I use the Household, Income and Labour Dynamics in Australia (HILDA) Survey for which I dispose of 17 waves from 2001 to 2017.[13] More than 20,000 individuals report their self-assessed overall satisfaction with life on a similar Cantril scale. Table 11 depicts annual transitions of individual answers to that question; it suggests once again that state dependence can't be ignored, in particular for individuals who are already satisfied with their life. An econometric analysis confirms this impression. The same model as previously is estimated, except that quality of life indicators are missing in the survey. Controls include age, age squared, gender, income (measured at the household level), education, labor force status and family status. Table 12 suggests that the very same results as those found in France hold in Australia.

Second, I resort to the GSOEP in Germany. This exceptional longitudinal survey has been available from 1984 to 2017[14] 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. Tables 13 and 14 display very similar results as before, from a qualitative point of view. The GSOEP is the unique case where the initial condition (namely, the vector of coefficients $\boldsymbol{\rho^0}$) matters less than state dependence encompassed by $\boldsymbol{\rho}$, which is quite reasonable and conform to the rationale since the initial condition in the GSOEP may date back up to 34 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 15 suggests as previously that state dependence can't be ignored, in particular for individuals who are already satisfied with their life, which is confirmed by a *ceteris paribus* analysis. Following the recommendations praised

[13] My code is adapted from the one provided by PanelWhiz on http://www.panelwhiz.eu.

[14] In West Germany only; East Germany has been surveyed from the reunification onwards.

by Clark and Georgellis (2013) on how to estimate subjective well-being equations 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. Table 16 exhibits very similar results to those that prevail in the other countries. Yet state dependence exhibits some non-monotonicity here: for instance, it is more pronounced for level 2 than it is for level 3, which suggests that bad states of life satisfaction are somehow more persistent in the UK. 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 therefore neither a mechanical effect, nor a statistical artefact.

7 Conclusion

This paper has stressed the role played by state dependence in self-assessed life satisfaction, a much ignored issue in happiness economics. Not only is subjective well-being found to be persistent over time at both aggregate and individual levels, but this persistence turns out to be more pronounced at the top of the distribution of self-reported happiness. Thanks to the estimation of a dynamic, ordered Logit model with correlated random effects which permits to take unobserved heterogeneity into account, I have shown that this empirical evidence held in at least three other countries: Australia, Germany and the UK, hence neutralizing the role played by the institutional setting. In the UK, the asymmetry is slightly less pronounced: bad states are somehow persistent, too. I have also quantified the impact of state dependence, which is rather large compared with the roles played by other usual determinants of happiness.

From an econometric perspective, there are at least two 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. 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.

From a social science perspective, further research should try to understand which mechanisms explain such an inertia. Are cognitive biases at stake? Do anchoring effects matter? Why is it revealed as more costly for individuals to revise downwards their self-assessed evaluation of life satisfaction? Why does unhappiness look more transitory? Determining the profound causes that lie behind persistence of happiness sounds like a challenging and exciting task.

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A Figures

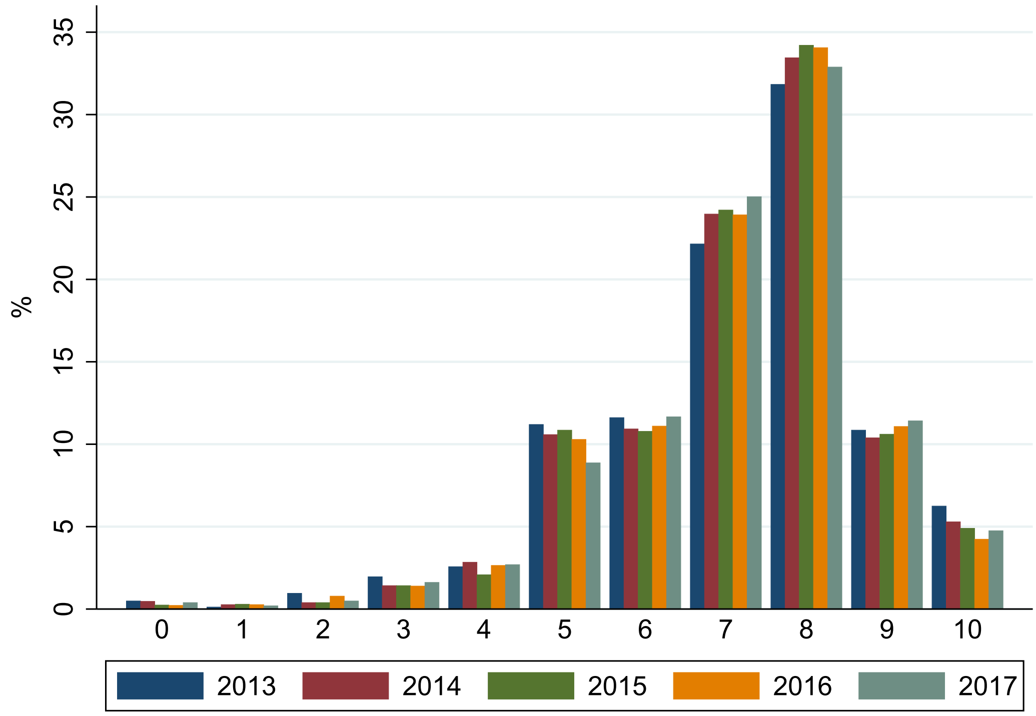

Figure 1: Evolution of life satisfaction in France

B Tables

Table 1: Summary statistics

	mean	sd	min	max
Life satisfaction	7.17	1.67	0	10
Female	0.62	0.49	0	1
Age	55.0	16.8	17	100
Income	25,799	36,408	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	0.02	0.12	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	0.13	0.34	0	1
Self-employed	0.06	0.23	0	1
Intermediate	0.22	0.42	0	1
Blue collar	0.17	0.38	0	1
Other	0.10	0.30	0	1
Family status				
Single	0.24	0.42	0	1
Two adults, w/o child	0.39	0.49	0	1
Two adults, 1 child	0.09	0.29	0	1
Two adults, 2 children	0.11	0.32	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	0.22	0	1
Others with children	0.03	0.16	0	1
Undetermined	0.01	0.08	0	1
Quality of life				
Poor living conditions	0.10	0.30	0	1
Environmental troubles	0.03	0.18	0	1
Psycho-social hazard	0.12	0.33	0	1
Economic insecurity	0.02	0.16	0	1
Poor health	0.09	0.29	0	1
Insecurity	0.14	0.35	0	1
Weak social ties	0.14	0.34	0	1
Observations		44,085		

Source. French SRCV survey, 2013-2017.
Sample. Unbalanced panel of 19,253 individuals with at least two consecutive observations.

Table 2: Within-individual heterogeneity in reported life satisfaction

Absolute maximal difference in reported life satisfaction	Frequency (%)
0	19.4
1	36.0
2	23.7
3	12.0
4	4.6
5	2.8
6-10	1.6

Source. French SRCV survey, 2013-2017.
Sample. Unbalanced panel of 19,253 individuals with at least two consecutive observations.
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	15.4	19.2	26.8	12.2	9.2	4.9	1.1	0.3
4	1.7	0.3	4.3	9.8	15.1	32.3	16.1	11.7	6.3	1.9	0.6
5	0.6	0.3	1.8	4.2	7.5	32.4	20.3	18.4	11.3	1.9	1.4
6	0.2	0.3	0.5	2.0	4.0	16.6	25.8	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	20.9	52.2	12.9	3.5
9	0.1	0.0	0.1	0.2	0.5	1.1	2.3	10.1	38.9	35.4	11.3
10	0.1	0.0	0.1	0.4	0.2	2.2	2.2	6.5	24.0	24.9	39.3
Total	0.4	0.3	0.7	1.6	2.6	10.2	11.1	23.8	33.1	11.1	5.2

Source. French SRCV survey, 2013-2017.
Sample. Unbalanced panel of 19,253 individuals with at least two consecutive observations.

Table 4: Dynamic ordered Logit model - unbalanced panel (1)

Dependent	Life satisfaction (LS_t)			
	(1)	(2)	(3)	(4)
Current log income (β)	0.408***	0.510***	0.073	0.046
	(0.028)	(0.038)	(0.055)	(0.053)
Mean log income (γ)			0.430***	0.400***
			(0.114)	(0.105)
Age	-0.039***	-0.060***	-0.025***	-0.022***
	(0.005)	(0.007)	(0.006)	(0.006)
$Age^2/100$	0.026***	0.039***	0.013**	0.011**
	(0.004)	(0.007)	(0.006)	(0.005)
Female	-0.005	-0.003	-0.023	-0.021
	(0.026)	(0.039)	(0.033)	(0.029)
Education (ref=no degree)				
High-school	-0.051	-0.028	-0.124	-0.114
	(0.041)	(0.060)	(0.258)	(0.246)
Vocational	-0.092**	-0.096*	0.071	0.065
	(0.036)	(0.053)	(0.229)	(0.219)
College	0.018	0.104	0.038	0.046
	(0.050)	(0.074)	(0.304)	(0.289)
Other	-0.051	0.206	0.411	0.434
	(0.199)	(0.300)	(0.345)	(0.313)
Labor force status (ref=employed)				
Unemployed	-0.817***	-1.164***	-0.771***	-0.716***
	(0.054)	(0.073)	(0.108)	(0.105)
Student	-0.012	-0.006	-0.338	-0.381
	(0.101)	(0.144)	(0.270)	(0.262)
Inactive	-0.168***	-0.374***	-0.439**	-0.426**
	(0.064)	(0.091)	(0.174)	(0.167)
Retired	-0.150***	-0.194***	-0.256**	-0.258**
	(0.043)	(0.060)	(0.113)	(0.108)
Undetermined	-0.508***	-0.690***	-0.392**	-0.394**
	(0.098)	(0.126)	(0.189)	(0.181)
Occupation (ref=clerk)				
Farmer	-0.503***	-0.715***	-1.761**	-1.715**
	(0.077)	(0.113)	(0.696)	(0.671)
Blue collar	0.006	-0.011	-0.227	-0.204
	(0.039)	(0.056)	(0.152)	(0.145)
Intermediate	0.033	0.125**	-0.146	-0.160
	(0.034)	(0.050)	(0.133)	(0.128)
White collar	0.154***	0.329***	0.142	0.089
	(0.045)	(0.065)	(0.169)	(0.162)
Self-employed	-0.126**	-0.142*	-0.114	-0.175
	(0.058)	(0.084)	(0.235)	(0.226)
Other	0.034	0.017	-0.311**	-0.287*
	(0.052)	(0.076)	(0.154)	(0.147)
Undetermined	0.010	-0.183	-0.760**	-0.739**
	(0.183)	(0.232)	(0.320)	(0.312)
Family status (ref=single)				
Two adults (no child)	0.554***	0.881***	0.732***	0.637***
	(0.031)	(0.046)	(0.117)	(0.112)
Other (no child)	0.495***	0.741***	0.479***	0.380**
	(0.058)	(0.078)	(0.155)	(0.148)
Single parent	-0.049	-0.026	0.246	0.184
	(0.060)	(0.086)	(0.169)	(0.161)
Two adults (1 child)	0.557***	0.862***	0.692***	0.575***
	(0.044)	(0.064)	(0.144)	(0.137)
Two adults (2 children)	0.672***	0.978***	0.592***	0.481***
	(0.043)	(0.064)	(0.165)	(0.157)
Two adults (3+ children)	0.763***	1.112***	0.695***	0.568***
	(0.058)	(0.085)	(0.205)	(0.196)
Other (children)	0.690***	0.938***	0.653***	0.563***
	(0.071)	(0.093)	(0.176)	(0.168)
Undetermined	0.657***	1.088***	0.910***	0.811***
	(0.126)	(0.163)	(0.221)	(0.215)

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

Quality of life				
Poor living conditions	-1.258***	-1.494***	-0.718***	-0.693***
	(0.041)	(0.055)	(0.070)	(0.068)
Environmental troubles	-0.367***	-0.391***	-0.076	-0.071
	(0.055)	(0.069)	(0.083)	(0.082)
Insecurity	-0.233***	-0.229***	-0.053	-0.056
	(0.029)	(0.037)	(0.043)	(0.043)
Weak social ties	-1.157***	-1.269***	-0.687***	-0.670***
	(0.032)	(0.041)	(0.049)	(0.048)
Psycho-social hazard	-0.614***	-0.703***	-0.393***	-0.384***
	(0.031)	(0.041)	(0.050)	(0.049)
Economic insecurity	-0.344***	-0.358***	-0.049	-0.023
	(0.063)	(0.087)	(0.108)	(0.104)
Poor health	-1.087***	-1.252***	-0.713***	-0.675***
	(0.042)	(0.053)	(0.065)	(0.063)
Initial life satisfaction (ρ^0) - (ref=0)				
$\text{LS}_{2013} = 1$			-0.127	-0.385
			(0.441)	(0.440)
$\text{LS}_{2013} = 2$			0.388	0.168
			(0.327)	(0.333)
$\text{LS}_{2013} = 3$			1.154***	0.878***
			(0.296)	(0.297)
$\text{LS}_{2013} = 4$			1.240***	0.922***
			(0.281)	(0.290)
$\text{LS}_{2013} = 5$			1.963***	1.504***
			(0.273)	(0.283)
$\text{LS}_{2013} = 6$			2.399***	1.839***
			(0.274)	(0.284)
$\text{LS}_{2013} = 7$			3.103***	2.363***
			(0.274)	(0.286)
$\text{LS}_{2013} = 8$			4.228***	3.234***
			(0.275)	(0.291)
$\text{LS}_{2013} = 9$			5.469***	4.157***
			(0.280)	(0.300)
$\text{LS}_{2013} = 10$			6.479***	4.817***
			(0.286)	(0.312)
Past LS (ρ) - (ref=0)				
$\text{LS}_{t-1} = 1$				0.558
				(0.383)
$\text{LS}_{t-1} = 2$				0.367
				(0.274)
$\text{LS}_{t-1} = 3$				0.348
				(0.246)
$\text{LS}_{t-1} = 4$				0.465*
				(0.247)
$\text{LS}_{t-1} = 5$				0.580**
				(0.242)
$\text{LS}_{t-1} = 6$				0.712***
				(0.244)
$\text{LS}_{t-1} = 7$				0.936***
				(0.246)
$\text{LS}_{t-1} = 8$				1.200***
				(0.251)
$\text{LS}_{t-1} = 9$				1.555***
				(0.258)
$\text{LS}_{t-1} = 10$				2.023***
				(0.270)

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

Cut-offs				
s_1	-3.551***	-5.406***	-2.610***	-2.324***
	(0.301)	(0.415)	(0.721)	(0.665)
s_2	-3.082***	-4.846***	-2.046***	-1.781***
	(0.297)	(0.411)	(0.719)	(0.663)
s_3	-2.305***	-3.894***	-1.087	-0.861
	(0.293)	(0.408)	(0.717)	(0.661)
s_4	-1.462***	-2.819***	-0.011	0.171
	(0.291)	(0.406)	(0.717)	(0.661)
s_5	-0.709**	-1.824***	0.984	1.121*
	(0.291)	(0.405)	(0.717)	(0.661)
s_6	0.680**	0.110	2.924***	2.967***
	(0.291)	(0.404)	(0.718)	(0.662)
s_7	1.504***	1.329***	4.153***	4.134***
	(0.291)	(0.404)	(0.719)	(0.663)
s_8	2.723***	3.217***	6.067***	5.948***
	(0.292)	(0.404)	(0.719)	(0.664)
s_9	4.491***	5.978***	8.873***	8.610***
	(0.293)	(0.406)	(0.722)	(0.667)
s_{10}	5.724***	7.763***	10.682***	10.332***
	(0.294)	(0.408)	(0.724)	(0.670)
σ_u^2		3.952***	2.196***	1.379***
		(0.105)	(0.069)	(0.083)
Year dummies	Yes	Yes	Yes	Yes
Individual effects	No	RE	CRE	CRE
# of individuals	19,253	19,253	19,253	19,253
# of observations	44,085	44,085	44,085	44,085
$\log(L)/N$	-1.699	-1.604	-1.517	-1.514

Source. French SRCV survey, 2013-2017.

Sample. Unbalanced panel of 19,253 individuals with at least two consecutive observations.

Robust standard errors clustered at the individual level.

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 - (β)	0.022***	0.019***	0.003	0.002
	(0.002)	(0.001)	(0.002)	(0.002)
Mean log income - (γ)			0.017***	0.016***
			(0.004)	(0.004)
Unemployed	-0.034***	-0.034***	-0.027***	-0.025***
	(0.002)	(0.002)	(0.003)	(0.003)
Two adults (no child)	0.025***	0.028***	0.026***	0.023***
	(0.001)	(0.002)	(0.004)	(0.004)
Two adults (1 child)	0.025***	0.028***	0.024***	0.021***
	(0.002)	(0.002)	(0.005)	(0.005)
Two adults (2 children)	0.032***	0.033***	0.020***	0.017***
	(0.002)	(0.002)	(0.006)	(0.006)
Two adults (3+ children)	0.038***	0.039***	0.025***	0.020***
	(0.004)	(0.004)	(0.008)	(0.008)
Weak social ties	-0.061***	-0.048***	-0.027***	-0.027***
	(0.002)	(0.002)	(0.003)	(0.002)
Poor health	-0.057***	-0.047***	-0.028***	-0.027***
	(0.003)	(0.002)	(0.003)	(0.003)
Past life satisfaction (ρ) - (ref=0)				
$LS_{t-1} = 1$				0.011
				(0.008)
$LS_{t-1} = 2$				0.006
				(0.005)
$LS_{t-1} = 3$				0.006
				(0.004)
$LS_{t-1} = 4$				0.009**
				(0.004)
$LS_{t-1} = 5$				0.011***
				(0.004)
$LS_{t-1} = 6$				0.015***
				(0.004)
$LS_{t-1} = 7$				0.021***
				(0.004)
$LS_{t-1} = 8$				0.030***
				(0.004)
$LS_{t-1} = 9$				0.045***
				(0.005)
$LS_{t-1} = 10$				0.071***
				(0.006)
Individual effects	No	RE	CRE	CRE
# of individuals	19,253	19,253	19,253	19,253
# of observations	44,085	44,085	44,085	44,085

Source. French SRCV survey, 2013-2017.
Sample. Unbalanced panel of 19,253 individuals with at least two consecutive observations.
Robust standard errors clustered at the individual level.

Table 8: Dynamic ordered Logit model - balanced panel (1)

Dependent	Life satisfaction (LS_t)			
	(1)	(2)	(3)	(4)
Current log income (β)	0.412***	0.438***	0.139*	0.094
	(0.050)	(0.062)	(0.082)	(0.081)
Mean log income (γ)			0.337*	0.322*
			(0.183)	(0.169)
Age	-0.036***	-0.054***	-0.017	-0.015
	(0.009)	(0.014)	(0.013)	(0.011)
$Age^2/100$	0.026***	0.038***	0.008	0.007
	(0.009)	(0.013)	(0.012)	(0.010)
Female	-0.028	-0.067	-0.039	-0.033
	(0.049)	(0.076)	(0.062)	(0.054)
Education (ref=no degree)				
High-school	0.012	0.140	-0.349	-0.329
	(0.077)	(0.116)	(0.467)	(0.443)
Vocational	-0.023	0.045	-0.315	-0.306
	(0.068)	(0.101)	(0.375)	(0.356)
College	0.075	0.220	-0.470	-0.451
	(0.094)	(0.141)	(0.507)	(0.484)
Other	0.092	1.000*	1.355**	1.424***
	(0.446)	(0.519)	(0.572)	(0.519)
Labor force status (ref=employed)				
Unemployed	-0.681***	-0.976***	-0.694***	-0.641***
	(0.108)	(0.133)	(0.165)	(0.163)
Student	-0.138	-0.268	-0.158	-0.243
	(0.289)	(0.311)	(0.387)	(0.390)
Inactive	-0.079	-0.168	0.160	0.131
	(0.110)	(0.148)	(0.242)	(0.234)
Retired	-0.133*	-0.121	-0.070	-0.089
	(0.076)	(0.102)	(0.155)	(0.150)
Undetermined	-0.471***	-0.492**	0.026	-0.018
	(0.181)	(0.212)	(0.280)	(0.271)
Occupation (ref=clerk)				
Farmer	-0.424***	-0.609***	-1.458	-1.322
	(0.142)	(0.221)	(1.034)	(0.989)
Blue collar	0.010	-0.114	-0.547**	-0.505**
	(0.073)	(0.105)	(0.221)	(0.211)
Intermediate	-0.001	0.028	-0.222	-0.223
	(0.063)	(0.092)	(0.199)	(0.196)
White collar	0.142*	0.291**	0.211	0.189
	(0.084)	(0.121)	(0.251)	(0.244)
Self-employed	-0.041	0.020	0.141	0.095
	(0.108)	(0.157)	(0.330)	(0.325)
Other	-0.032	-0.196	-0.669***	-0.616***
	(0.085)	(0.124)	(0.232)	(0.227)
Undetermined	0.048	-0.161	-0.626	-0.599
	(0.441)	(0.425)	(0.489)	(0.483)
Family status (ref=single)				
Two adults (no child)	0.533***	0.840***	0.694***	0.609***
	(0.055)	(0.079)	(0.162)	(0.156)
Other (no child)	0.495***	0.663***	0.334	0.254
	(0.112)	(0.146)	(0.231)	(0.224)
Single parent	0.003	0.140	0.269	0.218
	(0.108)	(0.149)	(0.232)	(0.224)
Two adults (1 child)	0.631***	0.927***	0.617***	0.498**
	(0.081)	(0.117)	(0.210)	(0.203)
Two adults (2 children)	0.713***	1.042***	0.580**	0.463**
	(0.083)	(0.120)	(0.239)	(0.229)
Two adults (3+ children)	0.928***	1.200***	0.405	0.270
	(0.114)	(0.163)	(0.291)	(0.283)
Other (children)	1.039***	1.142***	0.464*	0.366
	(0.139)	(0.156)	(0.253)	(0.245)
Undetermined	0.169	0.727***	0.595**	0.527*
	(0.171)	(0.228)	(0.292)	(0.290)

Table 9: Ordered Logit model - balanced panel (2)

Quality of life				
Poor living conditions	-1.237***	-1.249***	-0.776***	-0.755***
	(0.074)	(0.095)	(0.110)	(0.108)
Environmental troubles	-0.480***	-0.343***	-0.092	-0.098
	(0.099)	(0.113)	(0.118)	(0.116)
Insecurity	-0.236***	-0.128**	0.058	0.050
	(0.050)	(0.057)	(0.062)	(0.061)
Weak social ties	-1.207***	-1.155***	-0.771***	-0.751***
	(0.058)	(0.068)	(0.074)	(0.073)
Psycho-social hazard	-0.564***	-0.624***	-0.475***	-0.473***
	(0.057)	(0.067)	(0.074)	(0.074)
Economic insecurity	-0.237**	-0.206	-0.019	0.022
	(0.120)	(0.147)	(0.157)	(0.154)
Poor health	-1.105***	-1.083***	-0.724***	-0.694***
	(0.073)	(0.085)	(0.093)	(0.092)
Initial LS (ρ^0) - (ref=0)				
$\text{LS}_{2013} = 1$			-1.084	-1.443*
			(0.675)	(0.745)
$\text{LS}_{2013} = 2$			-0.112	-0.248
			(0.673)	(0.672)
$\text{LS}_{2013} = 3$			0.485	0.355
			(0.619)	(0.615)
$\text{LS}_{2013} = 4$			0.335	0.227
			(0.606)	(0.610)
$\text{LS}_{2013} = 5$			1.210**	0.999*
			(0.590)	(0.598)
$\text{LS}_{2013} = 6$			1.454**	1.197**
			(0.590)	(0.598)
$\text{LS}_{2013} = 7$			2.158***	1.758***
			(0.589)	(0.598)
$\text{LS}_{2013} = 8$			3.126***	2.543***
			(0.590)	(0.601)
$\text{LS}_{2013} = 9$			4.348***	3.533***
			(0.596)	(0.611)
$\text{LS}_{2013} = 10$			5.530***	4.432***
			(0.611)	(0.631)
Past LS (ρ) - (ref=0)				
$\text{LS}_{t-1} = 1$				1.049
				(0.750)
$\text{LS}_{t-1} = 2$				0.490
				(0.492)
$\text{LS}_{t-1} = 3$				0.405
				(0.414)
$\text{LS}_{t-1} = 4$				0.380
				(0.414)
$\text{LS}_{t-1} = 5$				0.432
				(0.410)
$\text{LS}_{t-1} = 6$				0.597
				(0.413)
$\text{LS}_{t-1} = 7$				0.821**
				(0.413)
$\text{LS}_{t-1} = 8$				1.095***
				(0.417)
$\text{LS}_{t-1} = 9$				1.418***
				(0.425)
$\text{LS}_{t-1} = 10$				1.889***
				(0.442)

Table 10: Ordered Logit model - balanced panel (3)

Cut-offs				
s_1	-3.576***	-5.734***	-2.379*	-2.284*
	(0.545)	(0.714)	(1.413)	(1.284)
s_2	-2.980***	-5.053***	-1.698	-1.616
	(0.534)	(0.705)	(1.406)	(1.277)
s_3	-2.316***	-4.283***	-0.925	-0.858
	(0.526)	(0.697)	(1.401)	(1.272)
s_4	-1.389***	-3.168***	0.197	0.241
	(0.524)	(0.695)	(1.401)	(1.272)
s_5	-0.581	-2.159***	1.208	1.227
	(0.523)	(0.693)	(1.402)	(1.273)
s_6	0.846	-0.248	3.121**	3.084**
	(0.524)	(0.693)	(1.404)	(1.276)
s_7	1.689***	0.971	4.343***	4.269***
	(0.525)	(0.693)	(1.405)	(1.277)
s_8	2.950***	2.890***	6.272***	6.135***
	(0.526)	(0.693)	(1.406)	(1.279)
s_9	4.794***	5.729***	9.138***	8.912***
	(0.528)	(0.696)	(1.409)	(1.283)
s_{10}	6.144***	7.648***	11.082***	10.799***
	(0.530)	(0.701)	(1.414)	(1.288)
σ_u^2		3.729***	2.044***	1.379***
		(0.154)	(0.094)	(0.100)
Year dummies	Yes	Yes	Yes	Yes
Individual effects	No	RE	CRE	CRE
# of individuals	4,081	4,081	4,081	4,081
# of observations	16,324	16,324	16,324	16,324
$\log(L)/N$	-1.667	-1.534	-1.473	-1.468

Source. French SRCV survey, 2013-2017.
Sample. Balanced panel of 4,081 individuals.
Robust standard errors clustered at the individual level.

C Appendix

C.1 Australia

Table 11: 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 24,305 individuals with at least two consecutive observations.

Table 12: Persistence of life satisfaction in Australia (dynamic ordered Logit)

Dependent	Life satisfaction (LS_t)
Past life satisfaction - (ref=0)	
$LS_{t-1} = 1$	0.313
	(0.266)
$LS_{t-1} = 2$	0.644**
	(0.252)
$LS_{t-1} = 3$	1.005***
	(0.243)
$LS_{t-1} = 4$	1.229***
	(0.242)
$LS_{t-1} = 5$	1.534***
	(0.240)
$LS_{t-1} = 6$	1.811***
	(0.239)
$LS_{t-1} = 7$	2.176***
	(0.239)
$LS_{t-1} = 8$	2.631***
	(0.240)
$LS_{t-1} = 9$	3.108***
	(0.241)
$LS_{t-1} = 10$	3.765***
	(0.243)
Controls	Yes
Year dummies	Yes
Individual effects	CRE
# of individuals	24,305
# of observations	208,003
$\log(L)/N$	-1.374

Source. HILDA, 2001-2017.
Sample. Unbalanced panel of 24,305 individuals with at least two consecutive observations.
Model. Dynamic ordered Logit with correlated random effects (CRE): see Tables 4 to 6, column 3.
Controls: age, age squared, gender, income, education, labor force status, family status.
Robust standard errors clustered at the individual level.

C.2 Germany

Table 13: 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 57,637 individuals with at least two consecutive observations.

Table 14: Persistence of life satisfaction in Germany (dynamic ordered Logit)

Dependent	Life satisfaction (LS_t)
Past life satisfaction (ref=0)	
$LS_{t-1} = 1$	0.198**
	(0.096)
$LS_{t-1} = 2$	0.531***
	(0.081)
$LS_{t-1} = 3$	0.798***
	(0.079)
$LS_{t-1} = 4$	1.049***
	(0.078)
$LS_{t-1} = 5$	1.377***
	(0.077)
$LS_{t-1} = 6$	1.664***
	(0.078)
$LS_{t-1} = 7$	2.026***
	(0.078)
$LS_{t-1} = 8$	2.454***
	(0.078)
$LS_{t-1} = 9$	2.944***
	(0.080)
$LS_{t-1} = 10$	3.477***
	(0.082)
Controls	Yes
Year dummies	Yes
Individual effects	CRE
# of individuals	57,637
# of observations	469,408
$\log(L)/N$	-1.615

Source. GSOEP, 1984-2017.
Sample. Unbalanced panel of 57,637 individuals with at least two consecutive observations.
Model. Dynamic ordered Logit with correlated random effects (CRE): see Tables 4 to 6, column 3.
Controls: age, age squared, gender, income, education, labor force status, marital status.
Robust standard errors clustered at the individual level.

C.3 The UK

Table 15: 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 54,593 individuals with at least two consecutive observations.

Table 16: Persistence of life satisfaction in the UK (dynamic ordered Logit)

Dependent	Life satisfaction (LS_t)
Past life satisfaction (ref=1)	
$LS_{t-1} = 2$	0.120**
	(0.054)
$LS_{t-1} = 3$	-0.061
	(0.053)
$LS_{t-1} = 4$	0.098*
	(0.053)
$LS_{t-1} = 5$	0.309***
	(0.053)
$LS_{t-1} = 6$	0.688***
	(0.055)
$LS_{t-1} = 7$	1.297***
	(0.062)
Controls	Yes
Year dummies	Yes
Individual effects	CRE
# of individuals	54,593
# of observations	213,256
$\log(L)/N$	-1.403

Source. UKUS, waves 1 to 8.
Sample. Unbalanced panel of 54,593 individuals with at least two consecutive observations.
Model. Dynamic ordered Logit with correlated random effects (CRE): see Tables 4 to 6, column 3.
Controls: age, age squared, gender, income, # of children, dummies for:
married, self-employment, unemployment, medium degree, higher degree.
Robust standard errors clustered at the individual level.