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The relationship between well-being and commuting revisited: Does the choice of methodology matter? ☆

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ABSTRACT

This paper provides an assessment of a range of alternative estimators for fixed-effects ordered models in the context of estimating the relationship between subjective well-being and commuting behaviour. In contrast to previous papers in the literature we find no evidence that longer commutes are associated with lower levels of subjective well-being, in general. From a methodological point of view our results support earlier findings that linear and ordered fixed-effects models of life satisfaction give similar results. However, we argue that ordered models are more appropriate as they are theoretically preferable, straightforward to implement and lead to easily interpretable results.

1. Introduction

Measures of subjective well-being are increasingly used as a proxy for individual welfare in applied economics. Summaries and overviews of this rapidly expanding literature include: Frey and Stutzer (2002a,b), Layard (2005), Kahneman and Krueger (2006), Di Tella and MacCulloch (2006), Clark et al. (2008), Dolan et al. (2008), Stutzer and Frey (2010) and MacKerron (2012). Survey respondents are typically asked a question like 'How satisfied are you with your life overall?' and asked to give a response on a Likert scale with the lowest and highest values corresponding to 'Not satisfied' and 'Completely satisfied', respectively. Econometrically this raises the question of how to model this type of data. Since well-being as a proxy for individual welfare or utility is strictly speaking an ordinal rather than a cardinal measure – a 1-point increase from 2 to 3 on the well-being scale may not imply the same increase in well-being as an increase from 6 to 7, for example – the standard econometric approach would be to use an ordered logit or probit model. However, in an influential paper, Ferrer-i-Carbonell and Frijters (2004) compare the results from a linear fixed-effects (FE) model, and thus implicitly treating well-being as a cardinal measure, with those from their FE ordered logit specification, and find that they obtain similar results. An equivalent finding has been documented by Frey and Stutzer (2000). This has led authors in several subsequent studies to analyse their data using linear models (e.g. Stutzer and Frey (2008)), presumably because linear FE models are considered to be more straightforward to implement in practice and lead to more easily interpretable results than ordered FE models. More recently, however, Baetschmann et al. (2011) have shown that the FE ordered logit estimator used in the Ferrer-i-Carbonell and Frijters (2004) comparison is, in fact, inconsistent. Hence, the similarity between the linear FE and the ordered FE results is not particularly informative.

In this paper we revisit the debate surrounding the appropriate methodology for modelling subjective well-being data in the context of the relationship between commuting and well-being. According to microeconomic theory, individuals would not choose to have a longer commute unless they were compensated for it in some way, either in the form of improved job characteristics (including pay) or better housing prospects (Stutzer and Frey, 2008). Even if commuting in itself is detrimental to well-being we would therefore not expect individuals with longer commutes to report lower levels of life satisfaction. As far as we are aware, Stutzer and Frey (2008) and Roberts et al. (2011) are the only previous papers that attempt to test this hypothesis by modelling the relationship between commuting and subjective well-being.

☆ We are grateful to the Data Archive at the University of Essex for supplying the data from the British Household Panel Survey. We thank Stephen Hall, Anita Ratcliffe, Jenny Roberts, Sandy Tubeuf, Aki Tsuchiya, participants at the 2012 Health Econometrics workshop in Siena and the 2nd Applied Health Econometrics Symposium in Leeds and seminar participants at Loughborough, Toulouse and Sheffield for valuable comments and advice. Luke Munford is grateful to the UKTRC for a Studentship.

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Using data from the German Socio-Economic Panel (GSOEP), Stutzer and Frey (2008) estimate linear FE models in which satisfaction with life overall (measured on a scale from 1 to 10) is specified as a function of commuting time and a set of control variables. The authors find that a one standard deviation (18 min) increase in commuting time lowers reported satisfaction with life overall by 0.086. To put this estimate into context Stutzer and Frey (2008) report that it is equivalent to about 1/8 of the effect on well-being of becoming unemployed. The authors conclude that commuting is a stressful activity which does not pay off, a result which they refer to as the 'commuting paradox' as it does not correspond to the predictions from microeconomic theory.

Using data from the British Household Panel Survey (BHPS), Roberts et al. (2011) model the relationship between well-being, commuting times and other personal and household characteristics. Well-being is measured by the GHQ (General Health Questionnaire) score, which is derived as the sum of the responses to 12 questions related to mental health. Using linear FE models, the authors find that longer commutes are associated with lower levels of subjective well-being among women but not among men. They suggest that this is likely to be a result of women having greater responsibilities for day-to-day household tasks, such as childcare and housework, and that this makes them more sensitive to longer commuting times. The authors of both papers acknowledge that the dependent variable in their models is categorical, but justify the use of a linear model based on the findings in the study by Ferrer-i-Carbonell and Frijters (2004).

While there is limited empirical evidence on the relationship between commuting and well-being, there is a substantial body of work on commuting in the urban economics literature with recent contributions including van Ommeren and Gutiérrez-i-Puigarnau (2011), Ross and Zenou (2008) and Pierrard (2008). For example, van Ommeren and Gutiérrez-i-Puigarnau (2011) examine the impact of commuting on workers' productivity as manifested through higher levels of absenteeism for those with longer commutes. They find evidence consistent with this hypothesis for Germany using the German Socio-Economic Panel. Their work builds on earlier research by Ross and Zenou (2008) who find a positive relationship between commuting and both unemployment and wages using the US Public Use Microdata Sample from the 2000 Decennial Census, at least for more highly supervised occupations. These findings are consistent with their urban efficiency wage model. Of direct relevance to our study is the large literature devoted to estimating the value of travel time; Abrantes and Wardman (2011) present a recent meta-analysis of UK estimates. As we will demonstrate, models of well-being can provide an alternative to more traditional travel demand models for estimating the value of time spent commuting.

Using data from the British Household Panel Survey, we compare the results from linear FE models and ordered logit models with and without fixed-effects. We find that while the results from the pooled ordered logit models suggest that there is a negative relationship between longer commutes and reported satisfaction with life overall, no such relationship is found in the (linear and ordered) FE models. This confirms Ferrer-i-Carbonell and Frijters' finding that the results from linear and ordered models of subjective well-being are qualitatively similar once unobservable individual fixed-effects are controlled for. We also find that the choice of estimator for the fixed-effects ordered logit model has little qualitative impact on the results. However, unlike Stutzer and Frey (2008) and Roberts et al. (2011) we do not find evidence that commuting is related to lower levels of subjective well-being, in general. This suggests that the relationship between well-being and commuting times may depend on differences in culture (the UK vs. Germany) and the choice of well-being measure (overall life satisfaction vs. the GHQ score).

The paper is structured as follows: section **2** describes the econometric methodology, section **3** presents the data used in the analysis and section **4** presents the modelling results. Section **5** concludes.

2. Methodology

In this section we briefly review various estimators for the FE ordered logit model that have been suggested in the literature.[1] Our starting point is a latent variable model:

$$y_{it}^* = x_{it}'\beta + \alpha_i + \varepsilon_{it}, \quad i = 1, \ldots, N \quad t = 1, \ldots, T \tag{1}$$

where y_{it}^* is a latent measure of the well-being of individual i in period t, x_{it} is a $(L \times 1)$ vector of observable characteristics related to well-being and β is a $(L \times 1)$ vector of coefficients to be estimated. α_i is a time-invariant unobserved component which may be correlated with x_{it}, and ε_{it} is a white noise error term. We observe y_{it} which is related to y_{it}^* as follows

$$y_{it} = k \quad if \quad \mu_k < y_{it}^* \le \mu_{k+1}, \quad k = 1, \ldots, K \tag{2}$$

The threshold parameters, μ_k, are assumed to be strictly increasing in k ($\mu_k < \mu_{k+1}\ \forall\, k$) with $\mu_1 = -\infty$ and $\mu_{K+1} = \infty$. Assuming that ε_{it} is IID logistic, the probability of observing outcome k for individual i at time t is

$$Pr(y_{it} = k | x_{it}, \alpha_i) = \Lambda(\mu_{k+1} - x_{it}'\beta - \alpha_i) - \Lambda(\mu_k - x_{it}'\beta - \alpha_i) \tag{3}$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function. As explained by Baetschmann et al. (2011), there are two problems with direct maximum likelihood estimation of this expression. The first is that only the difference between the thresholds and the fixed-effect $\alpha_{ik} = \mu_k - \alpha_i$ can be identified. The second is that under fixed-T asymptotics α_{ik} cannot be estimated consistently due to the incidental parameter problem (Neyman and Scott, 1948). This unfortunately also affects the estimates of β, and it has been found that the bias can be substantial in short panels (Greene, 2004).

Winkelmann and Winkelmann (1998) suggest that a way of getting around this problem is to collapse y_{it} to a binary variable and use Chamberlain's estimator for fixed effects binary logit models.[2] Following Baetschmann et al. (2011) we define a variable $d_{it}^k = I(y_{it} \ge k)$ where $I(\cdot)$ is the indicator function and k is a cutoff value. In other words, d_{it}^k is equal to one if y_{it} is greater than or equal to the chosen cutoff value and zero otherwise. The probability of observing a particular sequence of outcomes $d_i^k = (d_{i1}^k, \ldots, d_{iT}^k)$ conditional on the number of ones in the sequence (a_i) is given by

$$Pr\left(d_i^k \middle| \sum_{t=1}^{T} d_{it}^k = a_i\right) = \frac{exp\left(\sum_{t=1}^{T} d_{it}^k x_{it}'\beta\right)}{\sum_{l_i \in B_i} exp\left(\sum_{t=1}^{T} l_{it} x_{it}'\beta\right)} \tag{4}$$

where l_{it} is either zero or one, $l_i = (l_{i1}, \ldots, l_{iT})$ and B_i is the set of all possible l_i vectors with the same number of ones as d_i^k. Chamberlain (1980) shows that maximising the conditional log-likelihood $LL^k = \sum_{i=1}^{N} ln[Pr(d_i^k | \sum_{t=1}^{T} d_{it}^k = a_i)]$ gives a consistent estimate of β.

While in principle any cutoff $2 \le k \le K$ can be used in the estimation it is important to note that individuals with constant d_{it}^k do not contribute to the likelihood.[3] This implies that any particular choice of cutoff is likely to lead to some observations being discarded and the question is then whether we can do better than choosing a single cutoff. We will

[1] For simplicity we omit some technical details and focus on what we believe are the most important practical issues. We refer interested readers to the comprehensive review by Baetschmann et al. (2011).

[2] Another possible solution is to make the assumption that $\alpha_i = \overline{x}'_i\delta + v_i$ where v_i is IID normal with mean zero. Under this assumption the parameters in the model can be consistently estimated by including x_{it} and $\overline{x}_i$ as regressors in a random effect ordered logit model. This approach, which was originally proposed by Mundlak (1978) in the context of linear models, is not pursued in this paper as we prefer not to have to make this additional strong assumption.

[3] This is because $Pr(d_i^k = 1 | \sum_{t=1}^{T} d_{it}^k = T) = Pr(d_i^k = 0 | \sum_{t=1}^{T} d_{it}^k = 0) = 1$.

review three alternative estimators that have been proposed in the literature: the Das and Van Soest (1999) estimator, the 'Blow-up and Cluster' estimator (Baetschmann et al., 2011) and the Ferrer-i-Carbonell and Frijters (2004) estimator.

2.1. The Das and Van Soest (DvS) estimator

Since the estimator of β at any cutoff $\left(\hat{\beta}^{k}\right)$ is consistent, Das and Van Soest (1999) proposed estimating the model using all K-1 cutoffs and combine the estimates in a second step. The efficient combination weights the estimates by their variance so that

$$\hat{\beta}^{DvS} = arg\min_{b}\left(\hat{\beta}^{2'}-b',\ldots,\hat{\beta}^{K\prime}-b'\right)\hat{\Omega}^{-1}\left(\hat{\beta}^{2\prime}-b',\ldots,\hat{\beta}^{K\prime}-b'\right)' \quad (5)$$

where $\hat{\Omega}^{-1}$ is an estimate of the variance–covariance matrix of the coefficients. The solution to this problem is

$$\hat{\beta}^{DvS} = \left(H'\hat{\Omega}^{-1}H\right)^{-1}H'\hat{\Omega}^{-1}\left(\hat{\beta}^{2\prime},\ldots,\hat{\beta}^{K\prime}\right)' \quad (6)$$

where H is a matrix of K-1 stacked identity matrices of dimension L. The variance–covariance matrix of $\hat{\beta}^{DvS}$ is given by

$$Var\left(\hat{\beta}^{DvS}\right) = \left(H'\hat{\Omega}^{-1}H\right)^{-1} \quad (7)$$

Appendix B.1 presents code for implementing the DvS estimator in Stata.

The drawback of the DvS estimator is that in many real settings some cutoff values are going to lead to very small estimation samples. This may lead to convergence problems and/or imprecise estimates of the variance–covariance matrix $\hat{\Omega}^{-1}$, and it may therefore be necessary to use only some of the possible cutoffs when implementing the DvS estimator in practice.

2.2. The 'Blow-up and Cluster' (BUC estimator)

Baetschmann et al. (2011) have recently suggested an alternative to the DvS estimator which avoids the problem of small sample sizes associated with some cutoff values. Essentially the BUC estimator involves estimating the model using all K-1 cutoffs simultaneously, imposing the restriction that $\beta^2 = \beta^3 = \cdots = \beta^K$. In practice this can be done by creating a dataset where each individual is repeated K-1 times, each time using a different cutoff to collapse the dependent variable. The model is then estimated on the expanded sample using the standard Chamberlain approach. Since some individuals contribute to several terms in the log-likelihood function it is necessary to adjust the standard errors for clustering at the level of the respondent, hence the name 'Blow-up and Cluster' (Baetschmann et al., 2011). Appendix B.2 presents code for implementing the BUC estimator in Stata with an example using simulated data.[4]

2.3. The Ferrer-i-Carbonell and Frijters (FF) estimator

An alternative estimator to the ones described above was proposed by Ferrer-i-Carbonell and Frijters (2004). As opposed to the DvS and BUC estimators, which make use of every possible cutoff, the Ferrer-i-Carbonell and Frijters (FF) estimator involves identifying an optimal cutoff for each individual. The optimal cutoff is defined as the value which minimises the (individual) Hessian matrix at a preliminary estimate of β. Many applied papers have instead used a computationally simpler rule for choosing the cutoff, such as the individual-level mean or median of y_{it} (e.g. Booth and Van Ours, 2008, 2009; Kassenboehmer and Haisken-DeNew, 2009; Jones and Schurer, 2011). Baetschmann et al. (2011) show that FF-type estimators are in general inconsistent since the choice of cutoff is endogenous. In a simulation experiment they find that the bias in the FF estimates can in some cases be substantial, while the DvS and BUC estimators generally perform well.[5] Code for implementing the Ferrer-i-Carbonell and Frijters (2004) estimator in Stata is available from the authors on request.

3. Data

This paper uses data from waves 6 to 18 (1996–2008) of the British Household Panel Survey (BHPS), a nationally representative panel survey conducted by the Institute for Economic and Social Research, based at the University of Essex, UK. The households in the sample are re-interviewed on an annual basis and by wave 18 (2008), about 16,000 individuals participated in the survey. Waves 6 to 18 were chosen as they represent the only waves for which data on overall life satisfaction are available (although no data are available for wave 11 (2001) when the life satisfaction question was omitted from the survey questionnaire).

We restrict the sample to include only respondents of working age, defined to be individuals between the ages of 17 and 65 inclusive. Similarly only people who respond that they are employed are retained in the sample. Self-employed respondents are not included, since they are more likely to work from home and generally have different commuting patterns to employees (Roberts et al., 2011).

As our dependent variables we use data from the following two questions: 'How dissatisfied or satisfied are you with your life overall' and 'How dissatisfied or satisfied are you with the amount of leisure time you have'. The respondents are asked to give a response on a 7-point scale, where the lowest value (1) is labelled 'Not Satisfied at all' and the highest value (7) is labelled 'Completely Satisfied'.[6] Figs. 1 and 2 present the distribution of the satisfaction with life overall and satisfaction with leisure time variables using data from all 12 waves available. It can be seen from the figure that the distribution of the overall life satisfaction data is highly skewed, with the majority of the responses at the top end of the distribution. This is a common finding in the literature on subjective well-being (Dolan et al., 2008). The distribution of the satisfaction with leisure time data is less skewed, but again the majority of the respondents report relatively high values.

As a robustness check, and to be consistent with Roberts et al. (2011), we also use the GHQ score as an alternative dependent variable in our analysis. The GHQ score is derived as the sum of the responses to 12 questions related to mental health each scored on a 4-point scale (from 0 to 3), where a high value represents a low level of mental health. In our analysis the score has been reversed so that a higher score represents better well-being. The distribution of the GHQ score using data from all 12 waves is shown in Fig. 3.

The BHPS includes information on both commuting time and the mode of transport used for commuting trips.[7] The respondents are

[4] Baetschmann et al. (2011) also present Stata code for estimating the BUC model, but we have found that their code can inadvertently drop observations from the estimation sample in some circumstances. The root of the problem is that a new individual ID variable is generated by multiplying the original ID by 100 and adding a small number. Since the new ID variable is stored as a 'long' and the maximum value for longs is 2,147,483,620 in Stata, any individual with an original ID greater than 21,474,836 will drop out of the sample as their new ID will be set to 'missing'. This is an issue of practical importance using the original ID variable in the BHPS data – in our estimation sample a substantial proportion of respondents are incorrectly dropped when using the code by Baetschmann et al.

[5] As expected the DvS estimator performs less well in situations where some cutoffs are associated with very small sample sizes.

[6] From wave 12 (2002) onwards the number 4 on the satisfaction scale was labelled 'Not satisfied/dissatisfied', while it was unlabelled in earlier waves. Conti and Pudney (2011) find evidence that whether or not textual labels are assigned to values can have an impact on the results. As a robustness check we have therefore run the analysis in the paper on both the full (1996–2008) sample and the 2002–2008 sub-sample. As the results are very similar we only report the full-sample analysis.

[7] The BHPS does not have data on commuting distance, but commuting time may in any case be argued to be more closely related to the opportunity cost of commuting than the distance travelled (Stutzer and Frey, 2008) and is therefore a more relevant variable in this context.

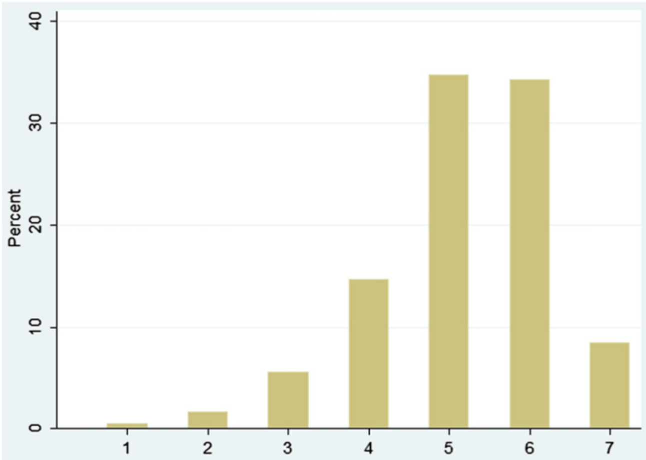

Fig. 1. Distribution of satisfaction with life overall.

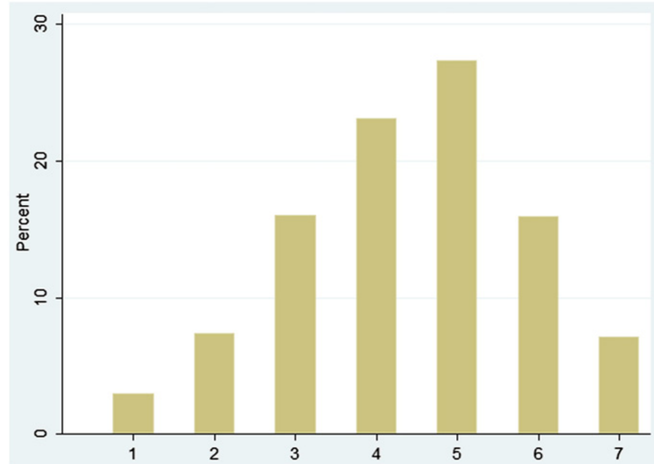

Fig. 2. Distribution of satisfaction with leisure time.

asked 'How long does it usually take you to get to work each day, door to door?'. The answer is recorded in minutes and corresponds to a one-way commute. The respondents are then asked 'And what usually is your main means of travel to work?'. The response is coded as one of the following alternatives: car driver, car passenger, rail, underground, bus, motor bike, bicycle, walking and other. Fig. 4 presents the distribution of the commuting time variable using data from all 12 waves.

In addition to commuting time, which is the main explanatory variable of interest in our analysis, we control for a range of factors that have been found to be related to subjective well-being in previous work. These include age, hours worked, real household income (at 2008 prices), marital status, number of children in the household, a dummy for saving regularly and a dummy for having a university degree. As a sensitivity test we also interact commuting time with gender and commuting mode to investigate whether the impact of an increase in commuting time on well-being varies by gender and mode of transport.

Table 1 provides summary statistics for the estimation sample of the models with overall life satisfaction as the dependent variable.[8] It can be seen that the average daily commute is about 24 min (one way) and that most people drive a car to work. The average age in the sample is 39, about three quarters are married or cohabiting and the average number of children in the household is 0.7. About half of the sample make regular savings, 18% have a university degree and the average real monthly household income is £3900.

4. Results

4.1. Satisfaction with life overall

Table 2 presents the results from the models of satisfaction with life overall.[9] [10] [11] It can be seen that while the coefficient for commuting time is negative and significant in the pooled ordered logit model (Pooled OL), it is insignificant in all the fixed-effects specifications. In line with Blanchflower and Oswald (2008) among others, we find that satisfaction is U-shaped in age, with a minimum at around 54 years of age in the ordered FE specifications. Other significant variables include: (log) real household income (implying diminishing marginal utility of income), whether the respondent is married or cohabiting and whether he/she makes regular savings. These results are consistent with previous findings in the literature (Dolan et al., 2008; Wong et al., 2006).

The insignificant commuting time coefficient in the FE models contrasts with the findings by Stutzer and Frey (2008) and Roberts et al. (2011) who find that increases in commuting time are associated with lower levels of subjective well-being. Since Roberts et al. also use data from the BHPS but a different measure of subjective well-being (the GHQ score), we can test whether it is the choice of well-being measure that is driving the difference in the results. To do this we re-run our analysis using the GHQ score as the dependent variable instead of overall life satisfaction.

The results are reported in Table 3. We find no evidence of a negative relationship between commuting times and the GHQ measure of well-being in our sample, but when we re-run the analysis using data from waves 1–14 of the BHPS (the sample used by Roberts et. al) we are able to replicate their result that longer commuting times are associated with lower levels of well-being. We also find that when we interact the commuting time variable with a dummy for being female this is found to be negative and significant in both samples, which supports Roberts et al.'s finding that longer commutes are associated with lower levels of subjective well-being among women. We also attempted to include this interaction in the life satisfaction models, but it was found to be insignificant. This illustrates that different measures of subjective well-being may lead to different conclusions regarding policy relevant variables.

Stutzer and Frey (2008) use a very similar measure of well-being to ours, i.e. self-reported satisfaction with life overall. In this case the different findings may be due to cultural differences between the UK and Germany, although we concede that this is a somewhat speculative explanation.[12] What is clear, however, is that the 'commuting paradox' documented by Stutzer and Frey (2008) does not hold in general, as we find no evidence of a negative impact of commuting times on life satisfaction in our application.

[8] For the reasons discussed in Section 2 the estimation sample does not include individuals who report constant life satisfaction scores over time, which leads to a decrease in the number of observations from 72,118 to 62,786. The characteristics of the two samples are very similar, however.

[9] We 'Winsorise' the commuting time, hours worked and monthly household income data at the 99th centiles given the extreme upper values for these variables. Similar results to those presented in the paper are obtained if we simply trim the sample at the 99th centiles for these three variables, or Winsorise or trim at the 95th centile (results available on request).

[10] We used 4, 5, 6 and 7 as the satisfaction cutoff-values in the DvS models as very few respondents report lower levels of life satisfaction than 4. This is the reason why the reported sample size for the DvS model is somewhat smaller than for the other models.

[11] For comparison we ran the pooled ordered logit and linear fixed-effects models on the same sample as the ordered fixed-effects models, i.e. excluding those respondents who reported the same level of satisfaction in all waves. Running the pooled ordered logit and linear fixed-effects models on the full sample gives very similar results.

[12] One hypothesis we considered is that longer average commuting times may impact on social norms which in turn could potentially make the link between commuting times and well-being less strong. However, the average commuting time in our sample is only slightly higher than in the GSOEP sample used by Stutzer and Frey (24 vs 22 min) so this is unlikely to explain the differences in the results.

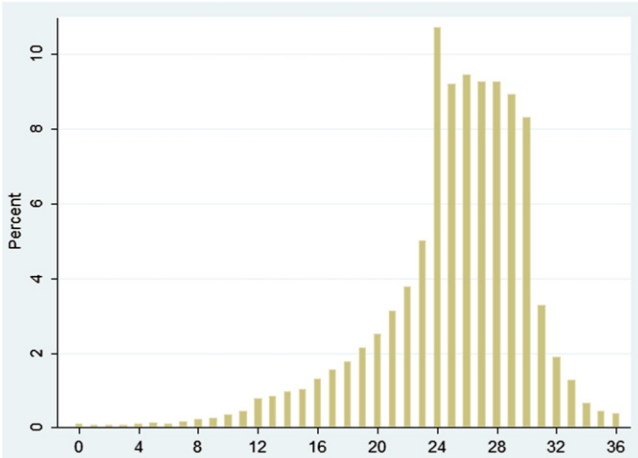

Fig. 3. Distribution of GHQ score.

To test the robustness of the results we ran a further set of models where we interacted the commuting time variable with a set of dummies for commuting mode. None of these interactions were found to be significant. We also re-ran the models including the self-employed, adding a dummy for self-employment status to the models, but this was not found to have a qualitative impact on the results. The latter test was carried out to make our sample as similar as possible to that used by Stutzer and Frey (2008), who included the self-employed in their analysis. Finally we tried controlling for part-time status and occupation in the models, but we do not find evidence of a significant relationship between commuting and well-being for any of the occupational groups. The results from the robustness checks are available from the authors upon request.

In line with Ferrer-i-Carbonell and Frijters (2004) we find that the results from the linear and ordered FE models are quite similar (in that the variables have the same signs and significance, the quadratic in age has a similar minimum point, etc.), considering the different assumptions underlying these models. This finding contributes to the stock of evidence suggesting that a linear FE model is an acceptable substitute for an ordered FE model in the context of modelling life satisfaction. However, this result needs to be tested on a case-by-case basis as there is no guarantee that it holds in general.

One advantage of the linear model over the ordered model is that the coefficients in the linear model can be interpreted as marginal effects, while the coefficients in the ordered model cannot be interpreted

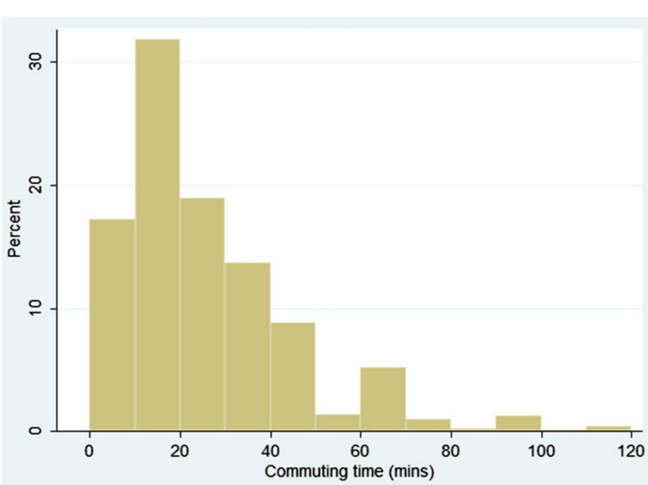

Fig. 4. Distribution of daily commuting time (one way).

Table 1
Summary statistics.

	Mean	SD	Min	Max
Satisfaction with life overall	5.18	1.12	1.00	7.00
Satisfaction with leisure time	4.41	1.45	1.00	7.00
GHQ score	25.07	5.11	0.00	36.00
Commuting time (minutes)	23.50	20.68	0.00	500.00
Age	39.02	11.38	17.00	65.00
Female	0.53		0.00	1.00
Hours worked	34.16	10.12	0.00	99.00
Monthly real household income ('000 s)	3.88	2.29	0.05	96.23
Number of children in household	0.70	0.96	0.00	7.00
Married or cohabiting	0.73		0.00	1.00
Saves regularly	0.51		0.00	1.00
University degree	0.18		0.00	1.00
Car driver	0.66		0.00	1.00
Car passenger	0.07		0.00	1.00
Train	0.03		0.00	1.00
Underground	0.01		0.00	1.00
Bus	0.07		0.00	1.00
Motorbike	0.01		0.00	1.00
Bicycle	0.03		0.00	1.00
Walk	0.11		0.00	1.00
Other mode	0.01		0.00	1.00

quantitatively since they refer to an underlying latent variable. In fact it is not possible to calculate marginal effects based on the FE ordered logit results at all since. However, as shown by Frey et al. (2009), Luechinger (2009), and Luechinger and Raschky (2009) for example, the ratios of the coefficients in the ordered model can be used to evaluate the trade-off between commuting time and income using the so-called 'life satisfaction approach'.

To illustrate, let $U = U(C, Y)$, where C is commuting time and Y is income. Totally differentiating and setting $dU = 0$ yields:

$$\frac{dY}{dC} = -\frac{MU_C}{MU_Y}$$

For our linearised specification with log income, $U = \beta C + \gamma lnY$, this gives $MU_C = \beta$, $MU_Y = \gamma/Y$ and hence

$$\frac{dY}{dC} = -\frac{\beta Y}{\gamma}$$

Evaluating this expression at median household income Y_M gives $dY/dC = £1079$ using the BUC estimates in Column 4 of Table 2. Thus, at the median, commuters require compensation of £1000 of monthly household income per additional hour of (one-way) daily commuting time. This is equivalent to around £25 per hour of commuting time.[13] Since the coefficient for commuting time is imprecisely estimated we cannot reject the null that dY/dC is equal to zero[14] but this example nevertheless shows that the coefficients in the ordered FE models can be given a useful quantitative interpretation.

It is, of course, also possible to use the results from the linear FE model as a basis for calculating the increase in income necessary to compensate for an increase in commuting time. If we plug the estimated coefficients from the linear FE model into the expression for dY/dC above we get £949, which is similar to the figure derived from the BUC estimates. The question is then whether this is a coincidence or evidence of something more systematic. Based on a Monte Carlo study, Riedl and Geishecker (2012) conclude the latter, and argue that the linear FE model is 'the method of choice' if the goal of the study is to estimate ratios of coefficients. To further examine this conclusion we have carried out a similar simulation study to that by Riedl and

[13] Based on 20 days per month of commuting.
[14] The lower and upper limit of a 95% CI calculated using the delta method are −£2570 and £4727, respectively.

Table 2
Satisfaction with life overall.

	(1)	(2)	(3)	(4)	(5)
	Pooled OL	Linear FE	DvS	BUC	FF
Commuting time/60	-0.237^{***}	-0.0122	-0.0389	-0.0298	-0.0282
	(0.039)	(0.021)	(0.049)	(0.051)	(0.045)
Age	-0.104^{***}	-0.0399^{***}	-0.102^{***}	-0.0958^{***}	-0.108^{***}
	(0.008)	(0.006)	(0.014)	(0.014)	(0.012)
Age squared/100	0.121^{***}	0.0373^{***}	0.0933^{***}	0.0895^{***}	0.104^{***}
	(0.010)	(0.007)	(0.017)	(0.018)	(0.014)
Hours worked	-0.00529^{***}	-0.000744	-0.00267	-0.00162	-0.00140
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Log of real household income	0.197^{***}	0.0448^{***}	0.0995^{***}	0.0962^{***}	0.0852^{***}
	(0.026)	(0.014)	(0.031)	(0.032)	(0.029)
Married or cohabiting	0.589^{***}	0.206^{***}	0.464^{***}	0.466^{***}	0.403^{***}
	(0.032)	(0.021)	(0.047)	(0.049)	(0.040)
Number of children in household	-0.0509^{***}	-0.00936	-0.0348^{*}	-0.0303	-0.0207
	(0.015)	(0.009)	(0.021)	(0.021)	(0.018)
Saves regularly	0.299^{***}	0.0886^{***}	0.212^{***}	0.216^{***}	0.200^{***}
	(0.022)	(0.010)	(0.023)	(0.024)	(0.023)
University degree	-0.0219	0.0530	0.0975	0.126	0.175
	(0.035)	(0.052)	(0.123)	(0.128)	(0.109)
Individuals	9930	9930	9863	9930	9930
Observations	62,786	62,786	62,537	62,786	62,786

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Geishecker (2012), where we find that while the linear FE estimator does indeed do well in some settings, the BUC estimator clearly outperforms it in others. The simulations are described in detail in Appendix A.

We therefore suggest that researchers implement ordered FE models when assessing the determinants of subjective well-being, rather than simply reporting the results from linear FE regressions which has become common in the literature. Treating well-being as an ordinal measure of individual welfare rather than assuming cardinality as is required in the linear model is clearly preferred theoretically. And empirically, given the ease of implementation of the BUC and DvS estimators, plus the ability to interpret the ratio of coefficients in these specifications, means that an ordered approach can also yield interesting and interpretable findings to the researcher.

4.2. Satisfaction with leisure time

Table 4 presents the results from the models of satisfaction with leisure time. In contrast to the life satisfaction results we find that the coefficient for commuting time is negative and significant in all the specifications, suggesting that an increase in commuting time has a negative impact on the satisfaction with leisure time, as expected. Once again, there is evidence of a U-shaped relationship with age (with a minimum at around 40 years of age) and a positive relationship with making regular savings. Satisfaction with leisure time is found to be negatively related to hours worked, household income, the number of children in the household and being married or cohabiting. As in the life satisfaction case, the coefficients in the linear and ordered FE models generally have the same signs and significance.

Table 3
GHQ score.

	(1)	(2)	(3)	(4)	(5)
	Pooled OL	Linear FE	DvS	BUC	FF
Commuting time/60	-0.0760^{**}	-0.168	-0.0650	-0.0793	-0.00470
	(0.036)	(0.106)	(0.045)	(0.049)	(0.041)
Age	-0.0831^{***}	-0.171^{***}	-0.0847^{***}	-0.0804^{***}	-0.0838^{***}
	(0.007)	(0.026)	(0.012)	(0.013)	(0.011)
Age squared/100	0.0918^{***}	0.155^{***}	0.0749^{***}	0.0728^{***}	0.0764^{***}
	(0.009)	(0.031)	(0.015)	(0.016)	(0.013)
Hours worked	0.0113^{***}	-0.00800^{**}	-0.00300^{**}	-0.00385^{**}	-0.00339^{**}
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Log of real household income	0.0892^{***}	0.157^{**}	0.0752^{***}	0.0693^{**}	0.0356
	(0.022)	(0.065)	(0.028)	(0.031)	(0.026)
Married or cohabiting	0.131^{***}	0.384^{***}	0.116^{***}	0.155^{***}	0.146^{***}
	(0.030)	(0.100)	(0.040)	(0.044)	(0.036)
Number of children in household	0.000709	0.0147	0.000870	0.00274	-0.00246
	(0.013)	(0.041)	(0.018)	(0.020)	(0.017)
Saves regularly	0.170^{***}	0.331^{***}	0.145^{***}	0.165^{***}	0.126^{***}
	(0.020)	(0.047)	(0.021)	(0.023)	(0.020)
University degree	-0.00960	0.271	0.132	0.141	0.152
	(0.033)	(0.227)	(0.095)	(0.108)	(0.097)
Individuals	11,410	11,410	11,407	11,410	11,410
Observations	67,871	67,871	67,860	67,871	67,871

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Satisfaction with leisure time.

	(1) Pooled OL	(2) Linear FE	(3) DvS	(4) BUC	(5) FF
Commuting time/60	−0.350***	−0.167***	−0.298***	−0.284***	−0.309***
	(0.039)	(0.028)	(0.049)	(0.048)	(0.043)
Age	−0.0908***	−0.0270***	−0.0634***	−0.0500***	−0.0441***
	(0.008)	(0.008)	(0.014)	(0.014)	(0.011)
Age squared/100	0.111***	0.0334***	0.0752***	0.0624***	0.0554***
	(0.010)	(0.009)	(0.017)	(0.017)	(0.014)
Hours worked	−0.0209***	−0.0154***	−0.0273***	−0.0262***	−0.0240***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Log of real household income	0.0385	−0.0536***	−0.0885***	−0.0888***	−0.0805***
	(0.025)	(0.018)	(0.032)	(0.031)	(0.028)
Married or cohabiting	−0.0806***	−0.146***	−0.209***	−0.251***	−0.177***
	(0.031)	(0.026)	(0.046)	(0.045)	(0.038)
Number of children in household	−0.233***	−0.146***	−0.251***	−0.258***	−0.224***
	(0.014)	(0.012)	(0.022)	(0.021)	(0.017)
Saves regularly	0.198***	0.0374***	0.0707***	0.0679***	0.0708***
	(0.021)	(0.012)	(0.023)	(0.022)	(0.021)
University degree	−0.218***	0.0633	0.159	0.127	0.135
	(0.035)	(0.068)	(0.116)	(0.118)	(0.103)
Individuals	10,746	10,746	10,239	10,746	10,746
Observations	66,231	66,231	63,895	66,231	66,231

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusion

This paper provides an assessment of alternative estimators for the fixed-effects ordered logit model in the context of estimating the relationship between subjective well-being and commuting behaviour. In contrast to Stutzer and Frey (2008) we find no evidence that longer commutes are associated with lower levels of subjective well-being as measured by self-reported overall life satisfaction. When using the GHQ score as an alternative measure of subjective well-being we find, in line with Roberts et al. (2011), that longer commutes are associated with lower levels of well-being for women but not for men. Taken as a whole these findings suggest that the ‘commuting paradox’ documented by Stutzer and Frey (2008) does not hold in general.

While our empirical results support earlier findings in the literature that linear and ordered fixed-effects models of life satisfaction give similar results, we argue that ordered models are more appropriate since they do not require the researcher to make the questionable assumption that life satisfaction scores are cardinal. We also demonstrate that the ordered models are straightforward to implement in practice and lead to readily interpretable results. We therefore recommend that ordered fixed effects models are used to model life satisfaction instead of linear models, as the latter rely on an empirical regularity that may not always hold. This conclusion is supported by a simulation study which demonstrates that the BUC estimator clearly outperforms the linear FE estimator in some settings.

Finally, we have demonstrated how models of well-being can be used to provide an alternative approach to estimating the marginal willingness to pay for commuting, in contrast to standard hedonic wage regressions and other approaches (see, for example, Van Ommeren et al. (2000)).

Appendix A. Simulations

In this Appendix we investigate using simulated data whether the linear fixed-effects (FE) estimator produces unbiased estimates of coefficient ratios when the true model is an FE ordered logit. As described below we find that the linear FE estimator does well in some settings, while the BUC estimator clearly outperforms it in others.

A.1. Data Generation Process (DGP) 1

The true model is

$$y^*_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + \alpha_i + \varepsilon_{it}, \quad i = 1, \dots, 1000 \quad t = 1, \dots, 10$$

where

$$\begin{aligned}
&\beta_1 = 1, \beta_2 = 0.5, \\
&\alpha_i \sim N(0, 0.5) \\
&x_{it1} = \alpha_i + v_{it}, \quad v_{it} \sim N(0, 0.5) \\
&x_{it2} \sim N(0, 1) \\
&\varepsilon_{it} \sim Logistic(0, 1)
\end{aligned}$$

This implies that the marginal distributions of x_{it1} and x_{it2} are both standard normal, and the correlation between x_{it1} and α_i is about 0.7. The dependent variable y_{it} is generated according to the following rule

$$y_{it} = k \quad if \quad \mu_k < y^*_{it} \le \mu_{k+1}, \quad k = 1, \dots, 7$$

where the values of the threshold parameters, μ_k, are set to mimic the distribution of the life satisfaction variable in the BHPS. We generate 10,000 datasets with 10 observations on 1000 ‘individuals’, and for each of these datasets we estimate the coefficients in the model using three different estimators: pooled ordered logit, linear FE and BUC. The mean of the estimated coefficient ratio and the root-mean-square error (RMSE) of the estimate are reported in the table below:

Table A1
Simulation results — DGP1.

	(1) Pooled OL	(2) Linear FE	(3) BUC
Mean of $\hat{\beta}^1/\hat{\beta}^2$	3.004	2.004	2.004
RMSE	1.012	0.104	0.105

It can be seen from the table that the pooled OL estimator is biased, which is to be expected given the correlation between x_{it1} and the individual effect α_i. The linear FE and BUC estimators are both effectively unbiased, and the RMSE of the linear FE estimator is similar to that of the BUC estimator (in fact it is slightly lower). This confirms the finding in Riedl and Geishecker (2012) that linear FE models can give unbiased results of coefficient ratios when the dependent variable is ordinal. As we will see in the following section, however, this result does not hold in general.

A.2. DGP 2

The true model is

$$y_{it}^{*} = \beta_1 D_{it1} + \beta_2 D_{it2} + \alpha_i + \varepsilon_{it}, \quad i = 1, \ldots, 1000 \quad t = 1, \ldots, 10$$

where

$\beta_1 = 1, \beta_2 = 0.5,$
$D_{it1} = 1$ if $x_{it1} > 1$ and 0 otherwise
$D_{it2} = 1$ if $x_{it2} > 1$ and 0 otherwise

The remaining variables are defined as before and the values of the threshold parameters, μ_k, are set to mimic the distribution of the life satisfaction variable in the BHPS. The key difference between DGP1 and DGP2, therefore, is that the two regressors are now dummy variables, which take the value 1 for about 16% of the observations. The results, based on 10,000 replications, are reported in the table below.

Table A2
Simulation results — DGP2.

	(1) Pooled OL	(2) Linear FE	(3) BUC
Mean of $\hat{\beta}^1/\hat{\beta}^2$	3.884	1.778	2.026
RMSE	1.938	0.325	0.279

In this case it is clear that the BUC estimator outperforms the linear FE estimator: the mean of the BUC coefficient ratio is closer to the true value and its RMSE is lower than that of the linear estimator. These results demonstrate that the linear FE estimator is not an equally good option for estimating coefficient ratios in all cases.

A.3. DGP 3

From the above it may be tempting to conclude that the linear FE estimator does as well as the BUC estimator as long as the explanatory variables are continuous. However, we will see that that is not the case; it is possible for the linear FE estimator to do less well than the BUC estimator also when the regressors have continuous distributions. To illustrate we will use an example in which the regressors are both discrete mixtures of two log-normally distributed variables. The particular choice of distribution is not important, however; our aim is simply to demonstrate that the BUC estimator can outperform the linear FE estimator when the regressors are continuous.

The true model is

$$y_{it}^{*} = \beta_1 z_{it1} + \beta_2 z_{it2} + \alpha_i + \varepsilon_{it}, \qquad i = 1, \ldots, 1000 \qquad t = 1, \ldots, 10$$

where

$\beta_1 = 1, \beta_2 = 0.5,$
$z_{it1} = D_{it1} u_{it1} + (1 - D_{it1}) u_{it2}$
$z_{it2} = D_{it2} u_{it1} + (1 - D_{it2}) u_{it2}$
$ln(u_{it1}) \sim N(-0.5, 0.5)$
$ln(u_{it2}) \sim N(0.5, 0.5)$

The remaining variables are defined as before and the values of the threshold parameters, μ_k, are set to mimic the distribution of the life satisfaction variable in the BHPS. The results, based on 10,000 replications, are reported in the table below.

Table A3
Simulation results — DGP3.

	(1) Pooled OL	(2) Linear FE	(3) BUC
Mean of $\hat{\beta}^1/\hat{\beta}^2$	1.705	1.907	2.008
RMSE	0.316	0.154	0.139

Again we can see that the BUC estimator does better than the linear FE estimator. While it could be argued that the performance of the linear FE estimator is not *much* worse than BUC, we cannot know whether that will always be the case; other data generation processes may lead to larger differences in performance. The fact that we have evidence that the linear FE estimator can in some cases perform less well suggests that it is prudent to err on the side of caution and use the BUC estimator instead. The argument for this strategy is made more compelling by the fact that the BUC estimator is straightforward to implement and leads to easily interpretable results, as we demonstrate in this paper.

Appendix B. Stata code

B.1. DvS code

```
local y y        // Specify name of dependent variable after the first "y"
local x x1 x2    // Specify names of independent variables after the first "x"
local id id      // Specify name of id variable after the first "id"

* Mark estimation sample
marksample touse
markout ‘touse’ ‘y’ ‘x’ ‘id’

* Run clogit for each cutoff and combine using suest
* Note that with many (most?) datasets this part of the
* code will have to be edited since not all cutoffs can
* be used to estimate the model
qui sum ‘y’ if ‘touse’
local ymax = r(max)
tempvar esample
gen ‘esample’ = 0
tempname BMAT
forvalues i = 2(1)‘ymax’ {
        tempvar y‘i’
        qui gen ‘y‘i’’ = ‘y’ >= ‘i’ if ‘touse’
        qui clogit ‘y‘i’’ ‘x’ if ‘touse’, group(‘id’)
        qui replace ‘esample’ = 1 if e(sample)
        estimates store ‘y‘i’’
        local suest ‘suest’ ‘y‘i’’
        capture matrix ‘BMAT’ = ‘BMAT’, e(b)
        if (_rc != 0) matrix ‘BMAT’ = e(b)
}
qui suest ‘suest’

* Calculate Das and Van Soest estimates
tempname VMAT A B COV
local k : word count ‘x’
matrix ‘VMAT’ = e(V)
matrix ‘A’ = J((‘ymax’-1),1,1)#I(‘k’)
matrix ‘B’ = (invsym(‘A’’*invsym(‘VMAT’)*‘A’)*‘A’’*invsym(‘VMAT’)*‘BMAT’’)’
matrix ‘COV’ = invsym(‘A’’*invsym(‘VMAT’)*‘A’)

* Tidy up matrix names and present results
matrix colnames ‘B’ = ‘x’
matrix coleq ‘B’ = :
matrix colnames ‘COV’ = ‘x’
matrix coleq ‘COV’ = :
matrix rownames ‘COV’ = ‘x’
matrix roweq ‘COV’ = :

qui cou if ‘esample’
local obs = r(N)
ereturn post ‘B’ ‘COV’, depname(‘y’) obs(‘obs’) esample(‘esample’)
ereturn display

* Calculate the number of individuals
tempvar last
bysort ‘id’: gen ‘last’ = _n==_N if e(sample)
cou if ‘last’==1
```

B.2. BUC code

```
capture program drop bucologit
program bucologit
        version 11.2
        syntax varlist [if] [in], Id(varname)

        preserve

        marksample touse
        markout `touse' `id'

        gettoken yraw x : varlist
        tempvar y
        qui egen int `y' = group(`yraw')

        qui keep `y' `x' `id' `touse'
        qui keep if `touse'

        qui sum `y'
        local ymax = r(max)
        forvalues i = 2(1)`ymax' {
                qui gen byte `yraw'`i' = `y' >= `i'
        }
        drop `y'

        tempvar n cut newid
        qui gen long `n' = _n
        qui reshape long `yraw', i(`n') j(`cut')
        qui egen long `newid' = group(`id' `cut')
        sort `newid'
        clogit `yraw' `x', group(`newid') cluster(`id')

        restore
end

/* Example using simulated data */

set more off
set seed 12345

* Generate simulated data
drop _all
set obs 1000
gen id = _n
gen u = sqrt(0.5)*rnormal()
expand 10
sort id
gen x1 = sqrt(0.5)*rnormal() + u
gen x2 = rnormal()
gen e = logit(runiform())
gen y_star = x1 + 0.5*x2 + u + e
gen y = 1 if y_star < -6
replace y = 2 if y_star >= -6 & y_star < -4.5
replace y = 3 if y_star >= -4.5 & y_star < -3.25
replace y = 4 if y_star >= -3.25 & y_star < -1.75
replace y = 5 if y_star >= -1.75 & y_star < 0.5
replace y = 6 if y_star >= 0.5 & y_star < 3.5
replace y = 7 if y_star >= 3.5

*Run BUC model using the -bucologit- command
bucologit y x1 x2, i(id)
*Note: the i() option is equivalent to group() in the -clogit- syntax
```

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