A Note on Modelling Dynamics in Happiness Estimations

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Abstract: This short note discusses two alternative ways to model dynamics in happiness regressions. A explained, this may be important when standard fixed effects estimates have serial correlation in the residuals, but is also potentially useful when serial correlation is not a problem for providing new insights in the happiness of economics area. The note discusses modelling dynamics two ways the note discusses are via a lagged dependent variable, and via an AR(1) process. The usefulness and statistical appropriateness of each is discussed with reference to happiness. Finally, a flow chart is provided summarising key decisions regarding the choice regarding, and potential necessity of, modelling dynamics.

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[1] Address for correspondence: alan.piper@uni-flensburg.de. I am very grateful to Geoff Pugh, who has been instrumental in my understanding of dynamic analysis generally. The usual caveat applies. Additionally, I am also grateful to Nick Adnett, Andrew Clark, and Sandra Hlivnjak for useful comments and suggestions.

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1 Introduction

"We strongly echo what the best data analysts have been saying for decades: use all the standard diagnostic tests; be sure that your model actually fits the data; seek out as many observable implications as you can observe from your model. And use all these diagnostic evaluation procedures to respecify your model" King and Roberts (2012, p.8).

This note discusses the incorporation of dynamics into economic estimates of happiness. The standard 'workhorse' model in this area is, for panel data, static fixed effects estimation. Diagnostic testing demonstrates that this is preferred to other static possibilities such as random effects estimation and to pooled OLS estimation. This makes sense conceptually too: happiness, very likely, has a genetic and personality component that is perhaps unique to each individual. Thus researchers are concerned with changes 'within' an individual, and hence use 'within' analysis (i.e. fixed effects). However, there is evidence to suggest that this static model is misspecified because it omits dynamics. Estimates with two of the more widely used panel data sets, the British Household Panel Survey (BHPS) and the German Socio-Economic Panel (GSOEP) exhibit serial correlation in the idiosyncratic error term.[2] The p-value of 0.0000 for the null hypothesis of no autocorrelation emphasises that static estimates are omitting dynamics, potentially important information. This short paper discusses the two main options available to the empirical 'happiness' researcher who wants to consider these normally omitted dynamics, providing advice (including diagnostic information) regarding this choice.

As the opening paragraph asserts, a central reason to investigate happiness dynamics is because static panel regressions exhibit serial correlation. The presence of serial correlation in the idiosyncratic error term means that there are omitted dynamics in the FE estimates. As

[2] These are perhaps the two main panel data sets that happiness researchers use, and the two that I am somewhat familiar with. Given the strength of the rejection of the null of no autocorrelation, the bigger surprise would be if other panel data sets did not exhibit serial correlation than if they did.

King and Roberts (2012) forcefully argue, this should not be treated as a problem to be fixed by adjusting the standard error but instead as an opportunity to take advantage of this information and respecify the model:

> Robust standard errors now seem to be viewed as a way to inoculate oneself from criticism. We show, to the contrary, that their presence is a bright red flag, meaning "my model is misspecified"… it appears to be the case that a very large fraction of the articles published across fields is based on misspecified models. For every one of these articles, at least some quantity that could be estimated is biased (p. 2).

So how should happiness models be respecified? There are two main options: dynamics can either be modelled in the explanatory part of the equation via the inclusion of a lagged dependent variable, or incorporated into the residual part of the equation. This is a choice that needs to be made based on both statistical appropriateness and a judgement regarding whether it is likely to lead to informative results or not. This note provides suggestions based on both of these considerations. Empirical work, which this note is partly based on, demonstrates that happiness has a low level of persistence with a coefficceint on the lagged dependent variable of approximately 0.1 (see Piper 2012a), and in such situations Beck and Katz (2011) argue that "for fast dynamics (where the coefficient on the lagged dependent variable is close to zero) it will be hard to distinguish between the lagged dependent variable and the AR1 specifications, or, alternatively, it does not make much difference which specification we use" (p.13). This is an argument that the models are statistically equivalent, which is not necessarily the same as not making much difference which specification is used' (given successful diagnostic testing). Below I discuss both options, the lagged dependent variable and the AR1 specification, the key necessary diagnostic tests for each, and explain why for happiness estimations (and potentially other fast moving diagnostics) the choice between them does matter.

A further argument for modelling dynamics with a lagged dependent variable, not necessarily predicated on finding serial correlation in the static models, is given by Bond (2002) who asserts that "even when coefficients on lagged dependent variables are not of direct interest, allowing for dynamics in the underlying process may be crucial for recovering consistent estimates of other parameters" (p.1; see also p.20). This is good general advice, but as I discuss below, not always appropriate for happiness estimations (and perhaps from other areas with fast moving dynamics). The remainder of the note discusses the main options available to the happiness researcher: Section 2 discusses the lagged dependent variable option, Section 3 discusses the AR1 alternative and Section 4 concludes

2 **Modelling dynamics via a lagged dependent variable**

Adding dynamics to the model is usually undertaken by including a lag of the dependent variable as a right hand side variable. Hence what is estimated is the following standard equation (with the independent variables excluded for clarity):

$$y_{it} = \beta y_{i,t-1} + (\alpha_i + \varepsilon_{it}) \qquad (1).$$

As this is a panel model each observation is indexed over i (= 1…N) cross-section groups (for happiness, this is almost always individuals so the discussion below will refer to individuals) and t (= 1…T) time periods (often for happiness estimations, annual observations). Equation 1 is a first-order dynamic panel model, because the explanatory variables on the right-hand side include the first lag of the dependent variable ($y_{i,\,t-1}$). The composed error term in parentheses combines a group-specific random effect to control for all unobservable effects on the dependent variable that are unique to the individual and do not vary over time (α_i), which captures specific ignorance about individual i, and an error that varies over both individuals and time (ε_{it}), which captures our general ignorance of the determinates of y_{it}. However, this cannot be estimated accurately by OLS or by fixed effects estimation. An OLS estimator of β in equation 1 is inconsistent, because the explanatory variable $\beta y_{i,t-1}$ is positively correlated with the error term due to the presence of individual effects. A fixed effects estimation does not have this inconsistency because the equation is transformed to remove the individual effect, as in equation 2.

$$y_{it} - y_{i,t-1} = \beta(y_{i,t-1} - y_{i,t-2}) + (\varepsilon_{it} - \varepsilon_{i,t-1}) \qquad (2).$$

However, equation (2) exhibits the different problem of correlation between the transformed lagged dependent variable and transformed error term. The overall impact of the correlations is negative, and is the well-known Nickell (1981) bias. Bond (2002) states that these biases provide an informal test for an estimator of the lagged dependent variable. He suggests that the estimated coefficient should be bounded below by the outcome from OLS (which gives the maximum upwards bias) but above by the fixed effects estimate (which gives the maximum downwards bias).[3]

Due to these problems, the standard approach is to find a suitable instrument that is correlated with the potentially endogenous variable (the more highly correlated the better), but uncorrelated with ε_{it}. Because instrumentation is not confined to one instrument per parameter to be estimated, the possibility exists of defining more than one moment condition per parameter to be estimated. It is this possibility that is exploited in the General Method of Moments (GMM) estimation of dynamic panel models, first proposed by Holtz-Eakin et al. (1988). The two models popularly implemented are the "difference" GMM estimator (Arellano and Bond, 1991) and the "system" GMM estimator (Arellano and Bover 1995). Greene (2002, p.308) explains that suitable instruments fulfilling the criteria mentioned

[3] Work utilising a lagged dependent variable should undertake this test for verification purposes.

above come from within the dataset: the lagged difference ($y_{it-2} - y_{it-3}$) ;and the lagged level y_{it-2}. Both of these should satisfy the two conditions for valid instruments, since they are likely to be highly correlated with ($y_{i,t-1} - y_{i,t-2}$) but not with $(\varepsilon_{it} - \varepsilon_{i,t-1})$. It is this easy availability of such "internal" instruments (i.e., from within the dataset) that the GMM estimators exploit. The "difference" GMM estimator follows the Arellano and Bond (1991) data transformation, where *differences are instrumented by levels*. The "system" GMM estimator adds to this one extra layer of instrumentation where the original *levels are instrumented with differences*.

These estimators, unlike OLS and conventional FE and RE estimation, do not require distributional assumptions, like normality, and can allow for heteroscedasticity of unknown form (Verbeek, 2000, pp. 143 and 331; Greene, 2002, pp.201, 525 and 523). A more extensive discussion of these methods is beyond the scope of this paper, but the references provided above and papers by Roodman (e.g. 2006, 2007, and 2009) are very informative.[4] A further advantage of GMM estimation and the use of 'internal' instruments is that applied researchers can select which variables are endogenous and which exogenous, potentially very useful for happiness research.[5]

There are important diagnostic tests to consider when introducing a lagged dependent variable via GMM estimation, and more detailed information is provided in Roodman's papers referenced above. Roodman's user written program for Stata *xtabond2* provides diagnostic tests for the statistical appropriateness, or otherwise, regarding dynamic panel analysis, and these focus on testing for instrument validity. Two tests relate to

[4] The Roodman papers are particularly useful for applied researchers because they explains how to use the Stata software programme, xtabond2, that he created to implement the GMM dynamic estimators.
[5] Another advantage is the ability to separately quantify the short-run impact and the long-run effect of various independent variables, discussed in more detail towards the end of this section.

autocorrelation, and an appropriate model will have first order autocorrelation in the differenced error term but not second order. This is expected (and necessary) for good internal instruments: the difference of lags and the difference of levels should be correlated (first order), but the second differences are not (second order). A further test regarding instrument validity tests a null hypothesis of exogenous (i.e. valid) instruments. The Hansen (1982) test *J* statistic[6], automatically calculated with *xtabond2*, tests for correlation between the error term and the instruments. Roodman (2007) cautions here that when ruling out correlation (and thus supporting the choice of instrumentation) a "*p* value as high as, say, 0.25 should be viewed with concern. Taken at face value, it means that if the specification is valid, the odds are less than 1 in 4 that one would observe a *J* statistic so large" (p.10).[7] Roodman (2007) and Roodman (2009) are particularly useful for diagnostic testing, and these papers should be consulted when undertaking GMM dynamics panel analysis.

It is important to note that the interpretation of coefficients from estimates that include a lagged dependent variable is not the same as interpretation from more conventional static models. This is often not clearly understood or explained in literature that uses lagged dependent variables (for example, Fayissa et al. 2001). As Greene (2008) explains

> Adding dynamics to a model … creates a major change in the interpretation of the equation. Without the lagged variable, the "independent variables" represent the full set of information that produce observed outcome y_{it}. With the lagged variable, we now have in the equation the entire history of the right-hand-side variables, *so that any measured influence is conditional on this history*; in this case, any impact of (the independent variables) $\boldsymbol{x}_{it}$ represents the effect of *new* information. (Greene, 2008, p.468, emphasis added)

[6]This has the advantage over the Sargan *J* test because it works in the presence of heteroscedasticity. Indeed, if the errors are believed to be homoscedastic then the Hansen test is the same as the Sargan test.

[7] Roodman (2007) contrasts this with the conventional levels of 0.05 and 0.1 for deciding on the significance of a coefficient estimate, which he describes as quite conservative.

This understanding is instructive for the choice regarding whether to model the dynamics in the observed part of the model or in the residual, as well as providing the ability to separately quantify the short-run impact and the long-run effect of various independent variables. The short-run impacts are given by the coefficient estimations themselves, and the long-run effects are calculated by dividing these short-run coefficients by 1 minus the coefficient on lagged happiness.[8] With happiness regressions the long-run values are not far from the short-run values because the lagged dependent variable is often a low figure. Piper 2012a shows that it is about 0.1 for different subsamples from the BHPS, a figure robust to measuring happiness via an overall life satisfaction survey answer or via both of the two main ways (Likert and Caseness) of making a composite from the General Health Questionnaire. Thus the long-run coefficients are the short-run coefficients divided by approximately 0.9 (reflecting 1 minus 0.1). This 0.1 finding informs us that happiness is largely contemporary: the influence of the past on contemporaneous well-being is low, being approximately ten percent. This finding can also inform ongoing work within the 'economics of happiness' on adaptation.

Modelling dynamics is important, yet involves not only statistical tests but also judgement about the method that will be likely to generate the most informative results. This last finding, happiness being largely (though not wholly) contemporaneous, is at the heart of whether to model the omitted dynamics in the observed part of the model or in the residual part. For examples of each situation consider overeducation and education (explored in Piper 2012b and Piper 2012c respectively). Overeducation is arguably a contemporary variable: an individual is either overeducated or not overeducated *now*. Thus the independent variable

[8] See Piper (2012b) for short and long-run coefficients with respect to an analysis of the effect of being overeducated on life satisfaction.

representing overeducation is informative for its relationship with happiness, which is a largely contemporaneous phenomenon. Whereas for education, which is for most people a historic measure, the variable(s) of interest will be captured in the 'black box' of the lagged dependent variable and thus not be very revealing regarding the issue under investigation. Of course, long-run values can be calculated but, as in this case, with a low weighting of past values the long-run values are not that different from the current 'new information' value. An alternative, in such cases, is to model the dynamics as unobserved by assuming that residuals in a static fixed effects model follow an AR(1) process which is an acceptable modelling strategy if and only if the common factor restrictions cannot be rejected (discussed in the next section).

In summary, happiness investigations that deals with contemporary phenomena (e.g. health, marital status) can be usefully analysed via the system GMM model, because, as the Greene quote above informs us, the independent variables relate to new or contemporaneous information. However where the happiness investigation centres on a more historic measure, the impact of this past variable would be captured, in the dynamic panel model, by the 'black box' lagged dependent variable, which contains the entire history of the model, and is thus not particularly informative.

3 Modelling dynamics via an AR1 process

Section 2 argued that modelling dynamics via a lagged dependent variable is not always informative. Coefficients estimated for the independent variables are based on current or new information, and when a variable of interest is historic there is limited (if any) new or current information to investigate its association with happiness. Any impact or association will be captured in the 'black box' of the lagged dependent variable, along with the history of all of the other independent variables and thus not informative. If we wish to take into account dynamics an alternative is to model them in the residual and estimate according to the Cochrane-Orcutt method, in which the slope coefficients of the static model are estimated conditional on an AR(1) dynamic in the residuals (Cochrane-Orcutt, 1949).

McGuirk and Spanos (2003) note that this method is only valid if and only if the often unrealistic Common Factor (CF) restrictions first proposed by Sargan (1964) hold. They assert that this finding in the econometrics literature is often not heeded by applied researchers: "despite additional warnings concerning the unrealistic nature of the CF restrictions… the practice of autocorrelation correction without testing the CF restrictions is still common. In fact, its use may even be on the rise…" (McGuirk and Spanos, 2003, p.3). Testing these restrictions is akin to asking whether the dynamics can be modelled in the residuals, and if the CF restrictions hold, modelling dynamics in the residual is an alternative approach to dynamic analysis.

Using the analysis of Piper (2012c), a education and happiness investigation which employs an AR1 modelling strategy, I now demonstrate that the unobserved components model estimated by the Cochrane-Orcutt (or similar) estimator is a restricted version of the dynamic linear regression model. A corollary of this is that the unobserved components model and thus the Cochrane-Orcutt (or similar) estimator are legitimate only if the CF restrictions cannot be rejected. Using only the continuous variables an equation estimated in Piper (2012c) the unobserved components model is specified as follows:

$$LS_{it} = \alpha + \alpha_2 educ_{it} + \alpha 3 lnwage_{it} + \alpha_4 jobsat_{it} + \varepsilon_{it} \qquad (3.1)$$

Where $\varepsilon_{it} = \rho\varepsilon_{it-1} + \upsilon_{it}$ (3.2)

- LS_{it} denotes life satisfaction of individual i at time t

- α is the intercept

- $educ_{it}$ represents the education of individual i at time t as measured by years of schooling

- $lnwage_{it}$ is log wage of individual i at time t

- $jobsat_{it}$ is the self-reported job satisfaction of individual i at time t

- ε_{it} is the disturbance term, with v_{it} as the white noise component.

The model is transformed, as follows:

First step: lag (3.1) once:

$$LS_{it-1} = \alpha + \alpha_2 educ_{it-1} + \alpha 3lnwage_{it-1} + \alpha_4 jobsat_{it-1} + \varepsilon_{it-1} \qquad (3.3)$$

Second step: solve for ε_{it-1}

$$\varepsilon_{it-1} = LS_{it-1} - \alpha - \alpha_2 educ_{it-1} - \alpha 3lnwage_{it-1} - \alpha_4 jobsat_{it-1} \qquad (3.4)$$

Third step: substitute (3.4) into (3.2)

$$\varepsilon_{it} = \rho(LS_{it-1} - \alpha - \alpha_2 educ_{it-1} - \alpha 3lnwage_{it-1} - \alpha_4 jobsat_{it-1}) + \upsilon_{it} \qquad (3.5)$$

$$\varepsilon_{it} = \rho LS_{it-1} - \rho\alpha - \rho\alpha_2 educ_{it-1} -\rho\, \alpha 3lnwage_{it-1} -\rho\, \alpha_4 jobsat_{it-1} + \upsilon_{it} \qquad (3.6)$$

Fourth step: substitute (3.6) into (3.1)

$$LS_{it} = \alpha + \alpha_2 educ_{it} + \alpha 3lnwage_{it} + \alpha_4 jobsat_{it} + \rho LS_{it-1} - \rho\alpha - \rho\alpha_2 educ_{it-1} -\rho\, \alpha 3lnwage_{it-1} -\rho\, \alpha_4 jobsat_{it-1} + \upsilon_{it} \qquad (3.7)$$

Fifth step: collect terms, hence

$$LS_{it} = (1-\rho)\alpha + \alpha_2 educ_{it} + \alpha_3 lnwage_{it} + \alpha_4 jobsat_{it} + \rho LS_{it-1} - \rho\alpha_2 educ_{it-1} -\rho\, \alpha 3lnwage_{it-1} -\rho\, \alpha_4 jobsat_{it-1} + \upsilon_{it} \qquad (3.8)$$

Ignoring the constant term (α) equation (3.8) has four independently estimated coefficients: ρ, $\alpha_{2,}$ and $\alpha 3$and α_4

It is now shown that this is a restricted version of the dynamic linear model of order one (i.e. specified with the first lag of both the dependent variable with each independent variable) (equation 3.9), which has seven independently estimated coefficients: $\alpha_{1,}$ $\alpha_{2,}$ $\alpha_{3,}$ α_4 , $\alpha_{5,}$ α_6 and α_7 (ignoring the constant term):

$$LS_{it} = \alpha + \alpha_1 LS_{it-1} + \alpha_2 educ_{it} + \alpha_3 lnwage_{it} + \alpha_4 jobsat_{it} + \alpha_5 educ_{it-1} + \alpha_6 lnwage_{it-1} + \alpha_7 jobsat_{it-1} + \varepsilon_{it} \quad (3.9)$$

On comparing the dynamic linear regression model (equation 3.9), i.e. the unrestricted model, the following can be noticed:

- in both (3.8) and (3.9), there is one coefficient on LS_{it-1} , which is, respectively, ρ and α_1

- in (3.8) the coefficient on $educ_{it-1}$ is - $\rho\alpha_2$, the coefficient on - $lnwage_{it-1}$ is -$\rho\alpha_3$, and the coefficient on $jobsat_{it-1}$ is -$\rho\alpha_4$

- in (3.9) the coefficient on $educ_{it-1}$ is α_5 , the coefficient on - $lnwage_{it-}1$ is α_6, and the coefficient on $jobsat_{it-1}$ is α_7

Hence,- $\rho\alpha_2$ is the negative of the product of the coefficients on LS_{it-1} and $educ_{it-1}$

- $\rho\alpha_3$ is the negative of the product of the coefficients on LS_{it-1} and $lnwage_{it-1}$

- $\rho\alpha_4$ is the negative of the product of the coefficients on LS_{it-1} *and* $jobsat_{it-1}$

Now the dynamic linear regression model (9) can be transformed into (8) if and only if the following restrictions hold: $-\alpha_5 = \alpha_1 * \alpha_2$; $-\alpha_6 = \alpha_1 * \alpha_3$; and $-\alpha_7 = \alpha_1 * \alpha_4$.

These are the common factor restrictions. The CF restrictions must be tested on each continuous variable in the estimate. Bond (2002) tests them jointly, although they can also be tested individually which presents a more demanding test. Furthermore, the CF restrictions can be tested using OLS, fixed effects, and dynamic panel models.

In the happiness estimates of Piper 2012c, the CF restrictions are not rejected, and it is likely that they would not be rejected for other happiness work too. When the common factor restrictions cannot be rejected, this suggests that the dynamics are in the residuals, i.e. in the unobserved rather than in the observed part of the model. This is perhaps unsurprising when the OLS regressions have an R-squared of about 0.1 and one considers the multitude of unobserved aspects that are potentially important for life satisfaction. Indeed, a recent finding is that the amount of fruit and vegetables eaten enters positively and strongly statistically significantly into happiness equations (Blanchflower and Oswald 2011).[9] This, like many other things, just cannot be captured by most life satisfaction regressions (due simply to lack of data). Such elements that are not explicitly modelled enter in the equations via the residuals and some of these may be autocorrelated. As such it is likely that there are unobserved dynamics, which the non-rejection of the CF restrictions suggests are reflected in the dynamic structure of the residual.

Whether the conjecture about happiness estimates likely to not reject the CF restrictions remains to be seen with future work, but if they are not rejected an acceptable estimation procedure is a fixed effects regression with dynamic residuals. As argued throughout this note, this is preferable to modelling dynamics with a lagged dependent variable when the variable of interest is not contemporaneous.

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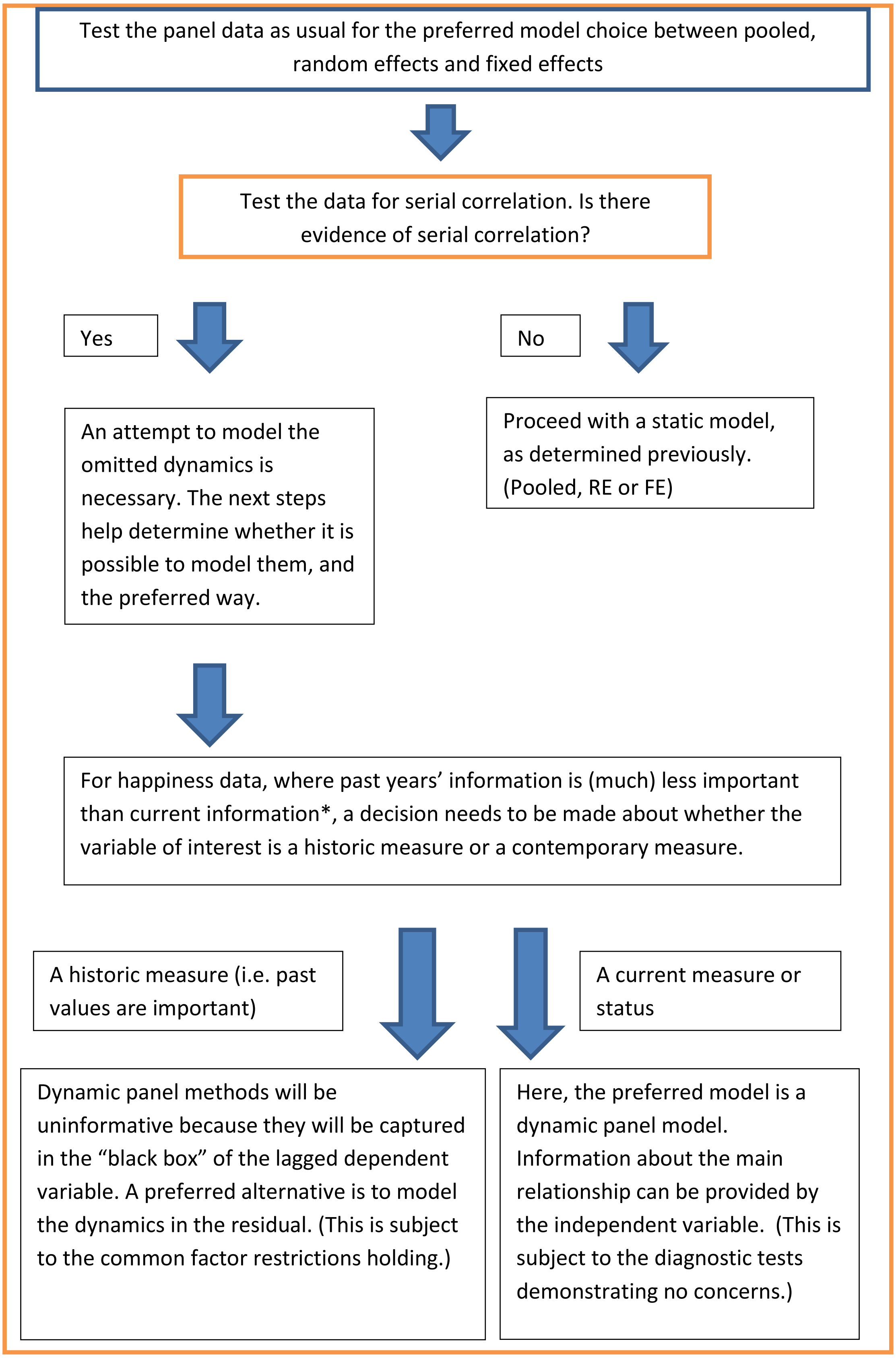
[9] This statement reflected the coefficient estimates in a more general study. Subsequently, the authors have investigated the impact of fruit and vegetables on mental well-being in more detail (Blanchflower et al. 2012).

4 Summary

The investigation into the dynamics of happiness investigations was initially inspired by the finding of serial correlation in the residuals of typical happiness regressions. This problem is rarely mentioned in the happiness literature, yet this finding suggests that there may be omitted dynamics in the models estimated in this literature. The argument is made that conventional fixed effect models, which ignore the presence of serial correlation, are correspondingly misspecified. In turn, both theoretical and computational advances now enable empirical researchers to account for the presence of dynamic relationships in the data. One approach, rarely used in 'happiness' research, is to model the otherwise omitted dynamics by specifying a dynamic panel model for estimation by the difference or system GMM model developed by researchers such as Arellano, Bond and Bover, which can be implemented by applied researchers using recently developed software programmes such as Roodman's *xtabond2*.

The use of such a model for happiness estimations has demonstrated that what is (largely) important for the determination of current happiness is current circumstances and events. Past values, whilst highly statistically significant, do not have much impact on current happiness. This finding has methodological implications because the choice of whether to model the dynamics explicitly in the model or in the residual is dependent not only upon statistical diagnostic tests but also upon whether the outcome of the estimation is likely to be informative or not. If the object of enquiry is a current variable or situation (for example overeducation) then the dynamics can, if statistically appropriate, be modelled via dynamic panel methods. This is because the independent variables reflect new or current information only, conditional on past values. This means that where the variable of interest is historic (such as education achieved), then dynamic panel methods are less informative, and an alternative such as an AR(1) process should be considered. When considering dynamics, because of the presence of serial correlation or not, a careful, well-justified decision needs to be made on an individual, study by study basis. A flow chart follows summarising many of the decisions an empirical 'happiness' researcher faces when considering dynamics.



*This is the case with the estimates from happiness estimates, as demonstrated by the low coefficient on the lagged dependent variable. This has wider applicability only if the influence of the lagged dependent variable is very small. For different values of the lagged dependent variable (i.e. a coefficient much higher than the 0.1 found here) a dynamic panel model should (in most cases) be estimated and the long-run values should be reported.

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