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Issues in the Estimation of Dynamic Happiness Models: A Comment on "Does Childhood Predict Adult Life Satisfaction?"

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Abstract
This paper offers methodological comments on a recent (November 2014) Economic Journal article. The comments consider its use of a dynamic model – the inclusion of a lagged dependent variable – and its approach to estimation. By way of critique, the authors highlight general issues regarding dynamic panel analysis that are still less fully appreciated in the economics of happiness literature than elsewhere in economics and other quantitative social sciences. This discussion of methodological issues arising from dynamic estimation may be of practical assistance to researchers new to the field and/or to dynamic modelling.

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Two papers published in the *Economic Journal* in 2014 have attempted to investigate the influence of the past on adult well-being (Frijters et al. 2014; Layard et al. 2014). To do so they have used two sets of British Cohort data: the National Child Development Survey (NCDS), which tracks individuals born in a particular week in 1958; and the British Cohort Survey (BCS), which follows individuals born in a particular week in 1970. Every few years, individuals (or, for the early years, parents and teachers of the individuals) are asked many questions about their development, behaviour and contextual influences; in turn, these two studies link the answers of, and for, the child with later survey responses of the individual as an adult. This comment will focus on two problems of the empirical analysis of Frijters et al. (2014).[1] The putative problems will be illustrated with analysis of panel data sets commonly used for the investigation of well-being, the British Household Panel Survey (BHPS) and the German Socio-economic Panel (SOEP). Although we use different datasets for convenience – neither author has access to either the NCDS or to the BCS – the force of the critique is not thereby reduced.[2] It is sufficient to our purpose to present evidence that the authors' approach to estimation is unlikely to yield results that are generally valid. Our purpose is not to replicate Frijters et al. (2014) but rather, by way of critique, to highlight issues regarding dynamic panel analysis that are still less fully appreciated in the economics of happiness literature than elsewhere in economics and other quantitative social sciences.

The problems arise when the studies address dynamics in their analysis. In Section 3.4 of Frijters et al. (2014) lagged life satisfaction is introduced as an explanatory variable, and the estimation undertaken with OLS. This is problematic because the OLS point estimates for the lags of the life satisfaction variables are biased upwards (Bond, 2002), substantially overestimating the impact of past life satisfaction on current life satisfaction. Indeed, due to this upward bias, OLS can be usefully used as the upper limit for a plausible estimate of the lagged dependent variable. The lower limit comes from fixed effects estimation of the same equation, in which the coefficient on the lagged dependent variable is biased downwards (Nickell 1981). In Table 1, we demonstrate these biases with the

[1] Though the first problem discussed below is also shared by Appendix B of Layard et al. (2014).

[2] This was the main source of critique when this article was a discussion paper. However the two substantive points made in this note are valid generally, regardless of what datasets are used.

BHPS and SOEP, by estimating a standard life satisfaction model using OLS (following Frijters et al. 2014), fixed effects (FE) (for comparison) and system GMM (widely regarded as appropriate for "wide-N, shallow-T" panels).[3]

We cannot know to what extent the Frijters et al. (2014) estimation by OLS of a model with a lagged dependent variable gives rise to biased estimates. However, the results reported in Table 1 suggest that other researchers would do best to avoid this approach. If OLS estimation is to be used, then it should be combined with FE to provide upper and lower bounds, respectively, to check the validity of the estimates of candidate consistent estimators like difference and system GMM (Bond, 2002).

Frijters et al. (2014) do employ GMM to investigate what they call shocks to well-being. This is a simple autoregressive model regressing current life satisfaction on lagged life satisfaction with no other explanatory variables. However, the number of instruments is not reported and no diagnostic test outcomes are reported. Yet the number and type of instruments together with diagnostic outcomes affect greatly the size and validity of the reported estimates. Simple experiments with the SOEP and BHPS (see below) replicating equation 8 in Frijters et al. (2014) suggest that there may be no acceptable diagnostic outcomes. Our inability to estimate their Equation 8 with acceptable model

Table 1: Illustration of biases from estimating dynamic models with OLS and FE

	Lagged dependent variable (OLS)	Lagged dependent variable (FE)	Lagged dependent variable (GMM)
SOEP	0.409	0.033	0.093
BHPS	0.487	–0.177	0.115

The standard GMM diagnostic tests are satisfactory as is the standard check that the GMM estimate lies in between the OLS and FE estimates. The full results, including details regarding the instrumentation choices made, are available on request.

[3] Responses to the life satisfaction question in the BHPS go from 1 (completely unsatisfied) to 7 (completely satisfied) and in the SOEP from 0 (completely unsatisfied) to 10 (completely satisfied). As well as lagged life satisfaction, the right-hand side variables include controls for income, labour force status, marital status, education, health, age, wave and region. Furthermore, whenever GMM is employed – Table 1 and Table 2 – the two step procedure is used and Windmeijer corrected standard errors are reported; the "collapse" command is not used.

diagnostics using the SOEP and the BHPS do not necessarily mean that this model cannot be estimated with validity using the BCS. Yet this comparison does illustrate the need in general to know (much) more about the statistical characteristics of the equation estimated. Table 2 shows that, in our estimates, using various patterns of instrumentation (1 ., all available instruments; 1 1, minimum instrumentation; and 2 3, a representative intermediate level of instrumentation) the size of the coefficient for the lagged dependent variable ranges from about 0.13 to 0.71 for the SOEP and from 0.10 to 0.55 for the BHPS, while the diagnostic tests uniformly reject the null of model validity with complete certainty.

Table 2: Illustration of differing coefficients and diagnostic test results from GMM analysis

SOEP	Coefficient on lagged life satisfaction *	Sargan test of overidentifying restrictions (p-values)	Diagnostic tests: (AR2) (p-values)	Number of instruments
Endogenous lag length (1 .)	0.144 (0.008)	0.000	0.000	36
Endogenous lag length (1 1)	0.136 (0.008)	0.000	0.000	15
Endogenous lag length (2 3)	0.724 (0.044)	0.000	0.000	18
BHPS	Coefficient on lagged life satisfaction *	Sargan test of overidentifying restrictions (p-values)	Diagnostic tests: (AR2) (p-values)	Number of instruments
Endogenous lag length (1 .)	0.115 (0.009)	0.000	0.000	44
Endogenous lag length (1 1)	0.118 (0.009)	0.000	0.000	15
Endogenous lag length (2 3)	0.556 (0.079)	0.000	0.000	15

* Windmeijer corrected SEs in brackets.

Changes in instrumentation have a sizeable impact on the estimates. A different choice in terms of instrumentation by Frijters et al. (2014) is likely to result in a different coefficient for the lagged dependent variable and, therefore, a totally different understanding of, in their terms, happiness shocks, or the influence of the past on current well-being. Overall, the results reported in Table 2 show that with no information about the instrumentation or corresponding diagnostics it is difficult to have much confidence in their results.

Our final point is that the use of GMM raises the question of the acceptability of instruments that come from data that is at least five years previous to the variables being instrumented. There is current debate in the literature about weak and strong instrumentation in the context of GMM estimation, in contrast to the better understood topic of valid and invalid instrumentation (Clemens et al. 2004; Bazzi and Clemens 2009). However, this concern over weak instruments in (difference and) system GMM estimation, and particularly regarding corresponding solutions, still seems to be at a rather tentative stage, with no agreed approaches. However, this should not be an invitation to researchers to ignore the issue. Rather, this concern emphasises the need for explanation and presentation of the chosen instruments together with the available diagnostics.

This short comment has raised two concerns about part of the empirical analysis of Frijters et al. (2014) and one speculative concern about the use of GMM with cohort data. In summary, ordinary least squares should not be used when using a lag (or lags) of the dependent variable as an explanatory variable(s). And when GMM, a more appropriate model for modelling dynamics, is used much more information is necessary to be able to judge, and have confidence in, the obtained results.[4] The speculative point suggests that GMM is unlikely to be appropriate with data where the waves are infrequent.

[4] A recent application of dynamic modelling and GMM in the broad area of "happiness" studies is Piper (2015). See also the associated comments of the discussion paper version of this article for more references regarding GMM and its application; particularly the November 9th response to one of our reviewers: www.economics-ejournal.org/economics/discussionpapers/2015-63

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