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WHAT DOES DYNAMIC PANEL ANALYSIS TELL US ABOUT LIFE SATISFACTION?

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Static fixed effects estimation of life satisfaction often gives rise to serial correlation in the residuals, indicating omitted dynamics. Rather than correcting the standard errors, "to make them robust," this study explores dynamic panel analysis to incorporate the otherwise omitted dynamics into the estimation of life satisfaction models. The analysis utilizes the System General Method of Moments approach to dynamic analysis. The results indicate that overall life satisfaction is largely (though not wholly) contemporaneous; correspondingly, the persistence of satisfaction from previous periods is limited. This finding is robust to a variety of different specification choices. Accordingly, the issue of omitted dynamics in a life satisfaction context is a minor one. This use of dynamic panel analysis, therefore, offers support for the ongoing use of static models (like fixed effects), even though they omit dynamics. Given the highlighted challenges of dynamic panel analysis, static fixed effects analyses will often be preferred.

JEL Codes: C23, I31

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1. INTRODUCTION

Dynamic panel analysis contributes to our collective understanding of life satisfaction in ways not possible with the more common static analyses. This is, in part, because dynamic panel analysis enables researchers to do useful things that static models do not. In particular, dynamic models account for the past—i.e. they can discover and take into account what is traditionally called state dependence—and, thereby, enable the measurement of the current impact of independent variables on the dependent variable conditional on the history of those variables. Static estimates cannot do this, and are, in this respect, unconditional. Static models, by definition, omit dynamics whereas dynamic models acknowledge that history can matter for life satisfaction (or anything else under investigation). Tests for serial correlation in typical fixed effects (FE) life satisfaction models typically provide evidence that history matters; i.e. there are omitted dynamics in such models. The use of dynamic panel analysis below illustrates how much the past matters, and

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thus how much of a problem omitted dynamics are for typical FE specifications. In short, the more the past matters, or put another way, the more evidence there is of persistence (or state dependence), the greater the problem posed by omitted dynamics for static FE models. Conversely, the less the past matters, the less of a problem the more traditional models have with respect to omitted dynamics.

Accordingly, a dynamic panel analysis of life satisfaction can inform about issues that conventional static analysis cannot. How important is our current situation or status for our current life satisfaction? What is the influence of the past on our subjective well-being? And, correspondingly, what is the ratio between the influence of the past and the present for our subjective well-being? All of these questions can be answered with dynamic panel analysis. Further gains to knowledge from dynamic panel analysis of life satisfaction are uncovered and discussed below.

Despite this usefulness, dynamic panel analysis has rarely been used for investigations into life satisfaction, although this approach has been successfully employed in other areas of enquiry. For example, its use has enabled new insights to be found regarding corporate finance (Flannery and Hankins, 2013), the effect of foreign aid on political institutions (Dutta *et al.*, 2013) as well as the relationship between school expenditure and school performance (Pugh *et al.*, 2015) and the influence a partner has on one's health behavior (Downward and Rasciute, 2016). Furthermore, as an indication of the popularity in general of dynamic panel models, the key papers introducing and developing this method of analysis each have several thousand citations (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Despite this popularity in economics generally, the use of such models to understand life satisfaction is sparse. Remedying this, this article uses dynamic panel analysis with a popular dataset to highlight some of the benefits and challenges of such an analysis, as well as to address the issues outlined above. In essence, the major contributions of the article are to explain what dynamic panel analysis tells us about the persistence of life satisfaction (i.e. the influence of the measured past) as well as how such an analysis compares to the more standard static fixed effects estimation, and as a guide to system GMM dynamic panel analysis in the context of the economics of life satisfaction.

The defining feature of dynamic panel modelling is the inclusion of one or (sometimes) more lags of the dependent variable on the right-hand side of the regression equation.[1] This means that the entire history of the model is itself contained within the lagged dependent variable(s) (Greene, 2008, p. 469; and see Appendix 3 below for the algebra). This inclusion changes the interpretation of the right-hand side variables, which now indicate contemporaneous effects conditional on the history of the independent variables, while the estimated effect of the lagged dependent variable also gives the possibility to determine the cumulative influence of the measured past. Furthermore, estimating with a lagged dependent variable provides a measure of persistence in the dependent variable. This, in turn, enables

[1]The earlier "distributed lag" approach to dynamics in time-series econometrics models lags of the *independent* variable(s). However, in recent decades, dynamic modelling has come to be more or less defined by specification of regression models with one or more values of the lagged dependent variable.

comparison of the short-run (or contemporaneous) coefficients on the independent variables with their corresponding long-run effects, which can be derived post estimation. All of this is illustrated with life satisfaction data from the British Household Panel Survey. To anticipate, the results reported below indicate a low level of persistence and, as a consequence, the short-run (contemporaneous) coefficients are, in general, not so far away from those obtained via the much more typical fixed effects estimation. Essentially, this means that the results of this article are supportive of previous work undertaken with fixed effects.

In employing dynamic panel analysis, this investigation makes use of the System General Method of Moments (GMM) approach, which offers advantages of its own. Two of which are mentioned here. First, GMM estimation allows not only the lagged dependent variables but also any potentially endogenous explanatory variables to be instrumented by "internal" instruments (i.e. lagged levels and lagged differences), which is an issue of perhaps especial importance for life satisfaction studies as well as for studies using survey data (which often lacks valid "external" instruments). Second, System GMM estimation proceeds by estimating models in both levels and differences and thus enables the effects of time-invariant variables to be identified.

This is not the first life satisfaction investigation to use a dynamic model, and some early attempts are as follows: Powdthavee, 2009; Della Giusta *et al.*, 2010; Bottan and Perez-Truglia, 2011; Piper, 2012; Wunder, 2012. However, most of this limited literature has technical problems in its use of dynamic models, particularly related to diagnostic testing: indeed, this is the central reason for the detailed explanation of the diagnostic testing below (and particularly in the Appendix). For example, only one of the twelve System GMM models presented in Bottan and Perez-Truglia (2011) seems to have statistical validity. Moreover, none of these studies address the important "initial conditions" issue (Blundell and Bond, 1998); some of the studies misunderstand the necessary diagnostic tests (e.g. Bottan and Perez-Truglia, 2011), and all of those listed do not report all of the important diagnostic test results. Furthermore, some prior studies do not appropriately interpret the coefficients obtained by the model (e.g. Della Giusta *et al.*, 2010). There is a need, in general, for future life satisfaction work which employs dynamics in its analysis to be more appreciative of the assumptions of dynamic modelling and its corresponding diagnostic tests. An aim of this investigation is to aid collective understanding of such models, and what can be learned from them. This aim also comes with a strong note of caution: sometimes analysis of life satisfaction via System GMM analysis is not statistically supported (in other words the statistical tests sometimes do not find the "internal" instruments to be exogenous). Despite this, however, there is a very consistent finding from dynamic analyses of life satisfaction—that of low persistence—and this finding can be used in support of the more conventional static fixed effects estimation approach which does omit dynamics.

At the outset, it should be noted that the dynamics considered here are different from those studies that consider, via lags and leads, specific events like entering unemployment or becoming married (e.g. Lucas *et al.*, 2004; Clark *et al.*, 2008; Qari, 2014). Instead, this investigation is a general one about overall life satisfaction and not about a specific event. The use of system GMM also ensures that this study investigates dynamics in a different way than the, typically, fixed effects estimated lags and leads investigations, which relate to moving from, for example, the second year of unemployment to the third.

The remainder of the article is organised as follows: Section 2 introduces the data set used and continues the discussion of the system GMM estimator; Section 3 presents and discusses the first set of results;[2] Section 4 contains a discussion of the dynamics of life satisfaction reflecting the robust coefficient obtained for the lagged dependent variable (i.e. lagged life satisfaction); Section 4 also discusses the results for the same samples when lags of the independent variables are also modeled; and briefly asks what these dynamic results may mean for the research investigating the association of childhood with adult life satisfaction; Section 5 offers concluding remarks. After the appendices there is some Supporting Information, which continues the discussion of system GMM and particularly its diagnostic procedures.

2. Data and Methodology

The data come from the British Household Panel Survey, a nationally representative longitudinal survey, which was established in 1991 and is a major source of micro-level panel data in the UK. From 1996, the BHPS contains a direct satisfaction question asking the interviewee "how dissatisfied or satisfied are you with your life overall" with possible responses running from 1 to 7, representing not satisfied at all to completely satisfied. Figure A1 in Appendix 2 shows the distribution of responses to this question for males and females separately, which are left skewed indicating that people are, in general, satisfied with life. As an aim of this investigation is to demonstrate what is learned from dynamic panel analysis, the right-hand side variables employed are common to many other investigations from this area: a continuous variable for real income; and dummy variables accounting for labour force status, marital status, education, health, age range, wave, and region. Table A2 found in Appendix 2 provides basic descriptive statistics for many of these controls (the exceptions are the wave and region dummy variables). The sample used in this investigation uses everyone in the dataset from the years 1996 to 2007, aged between 16 and 60 thus covering typical working life. This represents over 100,000 person-year observations.

This investigation is explicitly focused on dynamics. However even when the dynamics themselves are not of direct interest "allowing for dynamics in the underlying process may be crucial for recovering consistent estimates of other parameters" (Bond, 2002, p. 1, see also p. 20). This relates to the notion introduced in the introduction that fixed effects, and other static models, ignore dynamic processes. The argument for considering dynamics, i.e. allowing for them in the estimated part of the model, is firmly supported by a test for omitted dynamics. Wooldridge's (2002) test for serial correlation in the idiosyncratic error term in panel data, implemented in Stata by the user-written *xtserial*

[2]For comparison purposes, Appendix 1 contains the results from a fixed effects analysis of the same dataset.

command (Drukker, 2003), rejects the null hypothesis of no first order autocorrelation with a p-value of 0.0000. We interpret evidence of serial correlation as an invitation to specify a dynamic model. This discussion now turns to the dynamic panel model itself.

I estimate the following standard equation (see, e.g. Roodman, 2009a):

$$y_{it} = \beta y_{i,t-1} + \delta X_{i,t} + \left(v_i + \varepsilon_{it}\right) \tag{1}$$

As this is a panel model each observation is indexed over i (= 1 … N) cross-section groups (here, individuals) and t (= 1 … T) time periods (here, 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 ($y_{i,\ t-1}$). $X_1, X_2, \ldots X_k$ are k other explanatory variables, which are (in this equation and the first set of results below) contemporaneous with current life satisfaction. The composed error term in parentheses combines an individual-specific effect to control for all unobservable influences on the dependent variable that are unique to the individual and do not vary over time (v_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 determinants of y_{it}.

An OLS estimator of β in equation (1) is inconsistent, because the explanatory variable $y_{i,t-1}$ is positively correlated with the error term due to the presence of the individual effects. Estimation by first differencing does not have this inconsistency because the equation is transformed to remove the individual effect, as in equation (2) (shown without the independent variables for clarity).

$$y_{it} - y_{i,t-1} = \beta\left(y_{i,t-1} - y_{i,t-2}\right) + \left(\varepsilon_{it} - \varepsilon_{i,t-1}\right) \tag{2}$$

However, equation (2) exhibits the different problem of correlation between the transformed lagged dependent variable and the transformed error term. Due to this problem, the standard approach to estimating model (2) is to find a suitable instrument that is correlated with the endogenous differenced lagged dependent variable (the more strongly correlated the better), but uncorrelated with the differenced error term. In the GMM approach to estimation, the possibility exists of defining more than one moment condition per parameter to be estimated, hence instrumentation is not confined to one instrument per endogenous parameter. It is this possibility that is exploited in the GMM estimation of dynamic panel models, as first proposed by Holtz-Eakin *et al*. (1988).[3] 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 come from within the dataset: the lagged

[3]GMM was developed by Lars Peter Hansen; work that led, in part, to him being selected as one of the three Nobel Prize winners for Economics in 2013. See Hansen (1982) for more information on the initial development of General Method of Moments and Hall (2004) for a detailed textbook treatment.

difference (y_{it-2}–y_{it-3}) (and deeper lagged differences) and the lagged level y_{it-2} (and deeper lagged levels). Both of these should satisfy the two conditions for valid instruments, particularly the more recent lags since they are more likely to be highly correlated with ($y_{i,t-1} - y_{i,t-2}$) but not with ($\epsilon_{it} - \epsilon_{i,t-1}$). It is this easy availability of such "internal" instruments (i.e. from within the dataset) that GMM estimators exploit. The "difference" GMM estimator follows the Arellano and Bond (1991) first difference transformation, in which *differences are instrumented by levels*. The "system" GMM estimator adds to this one extra layer of instrumentation whereby the original *levels are instrumented by differences* (Arellano and Bover, 1995).

For three main reasons we use system GMM estimation rather than difference GMM. Firstly, system GMM allows for more instruments and can dramatically improve efficiency (compared to difference GMM) (Roodman, 2009a, p. 86), especially when estimating with large datasets. Secondly, any gaps in a panel—and this BHPS dataset is unbalanced—are magnified by difference GMM (when compared to system GMM, a motivating factor for the creation and development of system GMM) (Roodman, 2009a, p. 104).[4] And thirdly, unlike difference GMM, system GMM does not expunge the fixed effects (which are important in a life satisfaction context) (Roodman, 2009a, p. 114). For these reasons, future life satisfaction work which employs GMM estimations should employ system GMM rather than difference GMM when the diagnostic tests support such an analysis (discussed in the Supporting Information). These estimators 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 investigation, but the references provided above and papers by Roodman (e.g. 2009a, 2009b) are very informative.[5]

The use of GMM necessitates the consideration of two important (and linked) questions. Firstly, which of the regressors are to be treated as potentially endogenous and which as strictly exogenous? Secondly, how many instruments to use? With life satisfaction equations some of the typical regressors are potentially endogenous: does marriage, for example, make someone happy or are happy people more likely to get married (or are both determined by underlying but omitted variables)? There is (as yet) little theoretical guidance to help with this decision, though some evidence suggests that marriage is potentially endogenous (Stutzer and Frey, 2006). Arguments could also be advanced for income and health being variables endogenous with respect to life satisfaction. The actual choice made below is based on theoretical considerations of the likely relationships between life satisfaction and the right-hand side variables, and subsequent diagnostic testing. Diagnostic tests are available in *xtabond2*, the Stata command employed for the empirical analysis, to check the validity of the models that result from this choice. The diagnostic test outcomes resulted in, initially, the treatment of marital status

[4]A further possibility in a panel with gaps is to use orthogonal differencing to generate the instruments. However, in this investigation the relevant diagnostics were not fully supportive of this choice.

[5]Both Roodman (2009a, 2009b) are particularly useful for applied researchers, because they explain how to use the Stata software program, xtabond2, which he created to implement the GMM dynamic panel estimators.

only as potentially endogenous, and everything else treated as exogenous. For females, in an additional estimate, health and income are also treated as endogenous. Importantly for the main message of this study, the results from these choices are consistent despite differing diagnostic test outcomes.[6]

Roodman (2009b, section 4) also discusses diagnostic testing, and in the conclusion of the same article offers advice regarding what diagnostic tests should be reported along with the results:

> … several practices ought to become standard in using difference and system GMM. Researchers should report the number of instruments generated for their regressions. In system GMM, difference-in-Hansen tests [i.e. the C tests] for the full set of instruments for the levels equation, as well as the subset based on the dependent variable, should be reported. (Roodman, 2009b, p. 156)[7]

As recommended, these are presented in the results tables, Tables 1 and 2, of the next section.

The next section commences with a discussion regarding how the coefficients need to be interpreted. An understanding of the interpretation of the coefficients (which is different than that for the more standard static panel models like fixed effects), and particularly the coefficient on the lagged dependent variable, is important for the subsequent discussion in Section 4.

3. Results

This section presents and discusses the results from dynamic panel estimation. To aid this discussion an explanation of how the coefficients need to be interpreted is offered, followed by a discussion of the diagnostic test results. Regarding interpretation, the coefficients obtained via OLS or FE are substantially different from those obtained by dynamic panel methods and thus cannot directly be compared. As Greene 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) x_{it} represents the effect of *new* information. (2008, p. 468, emphasis added)

[6]A discussion of the necessary diagnostic tests for System GMM dynamic panel analysis is presented in the Supporting Information.

[7]Almost none of the studies mentioned previously report the number of instruments the estimation generates, nor test the robustness of results to alternative instrument counts. Furthermore, as so few of the previous dynamic panel life satisfaction studies discuss these *C* tests, or report test results, it is not evident that their estimations successfully address the initial conditions concern.

TABLE 1
LIFE SATISFACTION OF BRITISH PEOPLE, ASSESSED VIA GMM DYNAMIC PANEL ANALYSIS

Variables	Males	Females	Females	Females‡
	All	All	Age 16–35	Age 16–50
Lagged life satisfaction	0.09***	0.09***	0.10***	0.09***
	(0.014)	(0.012)	(0.019)	(0.013)
Real annual income (‘000s)	0.001***	−0.00007	−0.00008	−0.005*
	(0.000)	(0.000)	(0.001)	(0.003)
Self-employed	0.04*	0.04	0.02	0.05
	(0.023)	(0.031)	(0.058)	(0.036)
Unemployed	−0.43***	−0.30***	−0.33***	−0.34***
	(0.039)	(0.043)	(0.061)	(0.050)
Retired	0.01	0.12**		−0.31
	(0.058)	(0.047)		(0.204)
LT sick or disabled	−0.75***	−0.57***	−0.56***	−0.55***
	(0.063)	(0.052)	(0.108)	(0.087)
FT student	0.01	0.06*	0.06*	0.02
	(0.036)	(0.033)	(0.034)	(0.035)
Family carer	−0.38***	−0.15***	−0.20***	−0.19***
	(0.097)	(0.025)	(0.036)	(0.032)
Other labor force status	−0.31***	0.11***	0.14***	0.12***
	(0.091)	(0.039)	(0.045)	(0.039)
Married	0.45***	0.47***	0.43***	0.47***
	(0.096)	(0.100)	(0.081)	(0.095)
Separated	−0.10	−0.17	−0.27	−0.08
	(0.200)	(0.176)	(0.283)	(0.175)
Divorced	0.19	−0.06	−0.08	−0.04
	(0.161)	(0.145)	(0.157)	(0.138)
Widowed	0.17	−0.24	−0.13	0.19
	(0.328)	(0.252)	(0.573)	(0.237)
Education: High	−0.12***	0.01	0.11**	0.06*
	(0.028)	(0.028)	(0.045)	(0.035)
Education: Medium	−0.10***	−0.02	0.08*	0.03
	(0.029)	(0.028)	(0.045)	(0.033)
Health: Excellent	0.62***	0.71***	0.70***	0.90***
	(0.022)	(0.020)	(0.030)	(0.141)
Health: Good	0.41***	0.45***	0.43***	0.58***
	(0.019)	(0.017)	(0.026)	(0.131)
Age: 21–30 years old	−0.29***	−0.12***	−0.09**	−0.09**
	(0.037)	(0.041)	(0.037)	(0.041)
Age: 31–40 years old	−0.53***	−0.29***	−0.20***	−0.26***
	(0.071)	(0.078)	(0.059)	(0.076)
Age: 41–50 years old	−0.61***	−0.39***		−0.36***
	(0.085)	(0.092)		(0.089)
Age: 51–60 years old	−0.44***	−0.23**		
	(0.090)	(0.096)		
Wave dummies	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Constant	4.53***	4.30***	4.22***	4.17***
	(0.086)	(0.077)	(0.112)	(0.115)
Number of observations	34801	41644	17064	32858
Number of instruments	274	278	255	418
Number of individuals	7820	8963	4765	7547
AR (2)	0.147	0.016	0.842	0.365
Hansen’s *J* test	0.935	0.053	0.551	0.448
Diff-in-Hansen for levels	0.552	0.456	0.917	0.770

(Continues)

TABLE 1 (CONTINUED)

Variables	Males	Females	Females	Females‡
	All	All	Age 16–35	Age 16–50
Diff-in-Hansen (lag depvar)	0.382	0.005	0.288	0.134

Notes: Data from individuals in the BHPS, 1996–2007, aged 15 to 60. Standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1. Missing categories: employed, single, low education, fair to very poor health, 16–20 years old. In the first three columns marital status is treated as endogenous. Key, ‡: here, health and real income are treated as endogenous as well as marital status.

Thus, in a dynamic panel model, the "independent variables" only reflect new or contemporaneous information conditional both on the other controls and the lagged dependent variable, which itself represents the history of the model (i.e. the measured past).[8]

Table 1 displays the results for four estimations, one of which is for males and three are for females (for reasons explained below).[9] For males, the estimation uses default instrumentation, i.e. it uses all available lags as instruments, utilising the full time-series depth of the sample, for both the lagged dependent variable (endogenous by construction) and for marital status (as noted in the previous section, treated as endogenous on theoretical grounds). The coefficients obtained are robust to other choices of lag length for instrument selection, which start at the first available lag and do not employ every additional available lag (unlike the default instrumentation employed here).

The most important results in this table are those obtained for the lagged dependent variable. Here we note that the estimated coefficient is approximately 0.1, and discuss the implications of this in the next section. For males, positive and statistically significant for life satisfaction are: real annual income, though the size is negligible with an income increase of £1000 increasing life satisfaction by less than 0.002 (on the BHPS 1 to 7 life satisfaction scale); marriage; and health (both self-reported as good or excellent relative to a dummy variable capturing fair health and worse responses). Conversely, negative and statistically significant for male life satisfaction are: unemployment; being long-term sick or disabled; being a family carer; and medium and high levels of education, as assessed by qualifications obtained. The coefficients on the age-range dummy variables are in line with the well-known and oft-found U-shape. Thus this longitudinal evidence directly supports the arguments of Blanchflower and Graham (2021) and not those of Galambos *et al*. (2020) in the current debate about the relationship between age and well-being.

Most importantly, these results are robust to the number of instruments used which, for most variables, give qualitatively the same outcome (not shown). In the male case, the diagnostic tests are all supportive of the estimation choices made. Second order autocorrelation in the errors is ruled out, and the p-values for

[8]In Appendix 3, the lagged dependent variable is shown algebraically to capture the entire history of the independent variables.

[9]Employed in every GMM estimation is the twostep robust procedure that utilizes the Windmeijer (2005) finite sample correction for the two-step covariance matrix; without which, standard errors have been demonstrated to be biased downwards (Windmeijer, 2005).

TABLE 2
Life Satisfaction of British People, Including Independent Variable Lags, Assessed via GMM Dynamic Panel Analysis

Variables	Males	Females	Females	Females‡
	All	All	Age 16–35	Age 16–50
Lagged life satisfaction	0.09***	0.10***	0.11***	0.12***
	(0.015)	(0.014)	(0.023)	(0.015)
Real annual income (‘000s)	0.00004	−0.0008**	−0.0007	−0.006***
	(0.001)	(0.000)	(0.001)	(0.001)
First lag	0.001	−0.00008	0.0002	−0.0003
	(0.001)	(0.001)	(0.001)	(0.001)
Second lag	−0.0002	−0.0001	0.0001	0.00008
	(0.001)	(0.000)	(0.000)	(0.000)
Third lag	0.0007	−0.0004	−0.0003	0.0002
	(0.001)	(0.000)	(0.000)	(0.001)
Self-employed	0.01	0.08*	0.15**	0.12**
	(0.033)	(0.042)	(0.075)	(0.048)
First lag	0.04	−0.03	−0.09	−0.05
	(0.035)	(0.045)	(0.074)	(0.052)
Second lag	0.04	0.04	0.05	0.07
	(0.035)	(0.046)	(0.089)	(0.055)
Third lag	0.02	−0.01	0.01	−0.03
	(0.033)	(0.044)	(0.080)	(0.052)
Unemployed	−0.44***	−0.30***	−0.35***	−0.37***
	(0.053)	(0.052)	(0.084)	(0.063)
First lag	0.04	−0.09*	−0.16*	−0.13**
	(0.046)	(0.052)	(0.083)	(0.061)
Second lag	−0.01	−0.07	−0.10	−0.08
	(0.043)	(0.048)	(0.070)	(0.057)
Third lag	0.01	0.04	0.04	0.04
	(0.041)	(0.044)	(0.068)	(0.052)
Retired	0.06	0.10*		−0.28
	(0.070)	(0.057)		(0.224)
First lag	0.05	0.11		−0.07
	(0.070)	(0.071)		(0.245)
Second lag	0.04	0.02		0.00
	(0.077)	(0.070)		(0.196)
Third lag	0.04	0.04		−0.09
	(0.072)	(0.070)		(0.228)
LT sick or disabled	−0.59***	−0.36***	−0.32**	−0.37***
	(0.088)	(0.062)	(0.133)	(0.081)
First lag	−0.11	0.03	−0.13	0.02
	(0.078)	(0.062)	(0.122)	(0.080)
Second lag	0.02	−0.09	0.10	−0.15*
	(0.078)	(0.064)	(0.130)	(0.084)
Third lag	0.05	0.01	−0.13	0.00
	(0.076)	(0.063)	(0.159)	(0.086)
FT student	0.03	0.09	0.09	0.02
	(0.063)	(0.055)	(0.061)	(0.055)
First lag	0.00	−0.09	−0.10	−0.05
	(0.063)	(0.057)	(0.064)	(0.059)
Second lag	0.01	0.01	0.03	0.00
	(0.062)	(0.048)	(0.052)	(0.050)
Third lag	−0.01	−0.01	−0.02	0.00
	(0.052)	(0.043)	(0.048)	(0.045)
Family carer	−0.30**	−0.10***	−0.09*	−0.11***
	(0.141)	(0.034)	(0.051)	(0.038)

(Continues)

TABLE 2 (CONTINUED)

Variables	Males	Females	Females	Females‡
	All	All	Age 16–35	Age 16–50
First lag	0.00	0.01	−0.03	−0.00
	(0.155)	(0.033)	(0.058)	(0.038)
Second lag	−0.07	−0.04	−0.05	−0.04
	(0.116)	(0.032)	(0.054)	(0.037)
Third lag	−0.17	0.02	−0.04	0.02
	(0.150)	(0.030)	(0.051)	(0.033)
Other labour force status	−0.39***	0.19***	0.17***	0.20***
	(0.117)	(0.045)	(0.053)	(0.046)
First lag	0.17*	0.06	0.02	0.03
	(0.093)	(0.045)	(0.056)	(0.048)
Second lag	−0.19**	0.02	−0.05	0.02
	(0.092)	(0.047)	(0.063)	(0.050)
Third lag	−0.01	0.05	0.05	0.06
	(0.094)	(0.047)	(0.065)	(0.051)
Married	0.39***	0.37***	0.38***	0.33***
	(0.062)	(0.058)	(0.070)	(0.058)
First lag	−0.13**	−0.05	−0.02	−0.01
	(0.063)	(0.058)	(0.074)	(0.061)
Second lag	0.05	0.01	0.01	−0.00
	(0.058)	(0.055)	(0.067)	(0.058)
Third lag	−0.19***	−0.10**	−0.14**	−0.11**
	(0.044)	(0.047)	(0.057)	(0.048)
Separated	−0.24**	−0.15	−0.14	−0.16
	(0.103)	(0.094)	(0.205)	(0.101)
First lag	0.05	−0.02	0.13	0.02
	(0.087)	(0.083)	(0.150)	(0.089)
Second lag	0.16*	0.07	−0.05	0.07
	(0.085)	(0.077)	(0.135)	(0.085)
Third lag	−0.15**	−0.14*	−0.16	−0.11
	(0.074)	(0.075)	(0.136)	(0.078)
Divorced	0.00	−0.05	0.09	−0.02
	(0.106)	(0.086)	(0.143)	(0.093)
First lag	−0.01	−0.06	0.03	−0.09
	(0.088)	(0.076)	(0.133)	(0.085)
Second lag	0.15*	0.06	0.04	0.05
	(0.089)	(0.077)	(0.148)	(0.087)
Third lag	−0.14**	−0.10	−0.08	−0.03
	(0.070)	(0.068)	(0.120)	(0.073)
Widowed	−0.20	−0.45***		−0.44*
	(0.172)	(0.156)		(0.230)
First lag	0.16	0.24		0.33
	(0.205)	(0.181)		(0.210)
Second lag	0.32	0.19		0.15
	(0.241)	(0.140)		(0.230)
Third lag	−0.40	−0.05		−0.12
	(0.271)	(0.122)		(0.183)
Education: High	0.08	0.01	0.15	0.06*
	(0.083)	(0.028)	(0.129)	(0.035)
First lag	−0.10	0.11	0.07	−0.07
	(0.103)	(0.071)	(0.135)	(0.245)
Second lag	−0.05	0.02	−0.11	0.00
	(0.087)	(0.070)	(0.137)	(0.196)
Third lag	−0.11	0.04	−0.05	−0.09
	(0.071)	(0.070)	(0.112)	(0.228)
Education: Medium	0.08	−0.02	0.11	0.03
	(0.087)	(0.028)	(0.131)	(0.033)

(Continues)

TABLE 2 (CONTINUED)

Variables	Males	Females	Females	Females‡
	All	All	Age 16–35	Age 16–50
First lag	−0.09	0.11	0.02	−0.07
	(0.107)	(0.071)	(0.138)	(0.245)
Second lag	0.01	0.02	−0.05	0.00
	(0.095)	(0.070)	(0.135)	(0.196)
Third lag	−0.13*	0.04	−0.03	−0.09
	(0.074)	(0.070)	(0.109)	(0.228)
Health: Excellent	0.49***	0.71***	0.59***	0.90***
	(0.026)	(0.020)	(0.041)	(0.141)
First lag	0.22***	0.11	0.17***	−0.07
	(0.026)	(0.071)	(0.040)	(0.245)
Second lag	0.17***	0.02	0.17***	0.00
	(0.025)	(0.070)	(0.037)	(0.196)
Third lag	0.16***	0.04	0.15***	−0.09
	(0.024)	(0.070)	(0.035)	(0.228)
Health: Good	0.33***	0.45***	0.39***	0.58***
	(0.021)	(0.017)	(0.036)	(0.131)
First lag	0.14***	0.11	0.12***	−0.07
	(0.021)	(0.071)	(0.033)	(0.245)
Second lag	0.11***	0.02	0.13***	0.00
	(0.020)	(0.070)	(0.033)	(0.196)
Third lag	0.11***	0.04	0.11***	−0.09
	(0.020)	(0.070)	(0.030)	(0.228)
Age: 21–30 years old	−0.14***	−0.07	−0.06	−0.05
	(0.049)	(0.052)	(0.053)	(0.053)
Age: 31–40 years old	−0.21***	−0.14**	−0.10	−0.13**
	(0.056)	(0.057)	(0.060)	(0.058)
Age: 41–50 years old	−0.26***	−0.24***		−0.21***
	(0.059)	(0.060)		(0.062)
Age: 51–60 years old	−0.08	−0.07		
	(0.060)	(0.062)		
Wave dummies	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Constant	4.19***	4.02***	3.97***	3.84***
	(0.103)	(0.095)	(0.144)	(0.107)
Number of observations	22500	27639	9692	21092
Number of instruments	274	304	275	432
Number of individuals	5712	6930	3087	5558
AR (2)	0.745	0.204	0.342	0.302
Hansen's *J* test	0.649	0.227	0.351	0.061
Diff-in-Hansen for levels	0.441	0.298	0.611	0.559
Diff-in-Hansen (lag depvar)	0.248	0.019	0.267	0.040

Notes: data from individuals in the BHPS, 1996–2007, aged 15 to 60. Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Missing categories: employed, single, low education, fair to very poor health, 16–20 years old. In the first three columns marital status is treated as endogenous. Key, ‡: no retired or widowed individuals Ψ: here, health and real income are treated as endogenous as well as marital status.

the Hansen *J* and *C* tests ("Diff-in-Hansen" in Table 1) are all above Roodman's "common sense" minimum threshold of 0.25 but less than 1.0 (as discussed in the Supporting Information).

For females, there are three columns of results (reflecting differences in the diagnostic test outcomes, discussed just below). The first of these three female columns reports estimates for every female in the sample with only marital status treated as potentially endogenous. However, the diagnostics for this model indicate that the instrument sets are invalid. Second order autocorrelation cannot be ruled out, and the null of instrument validity for the overidentifying instruments (the *J* test) can be rejected; although the *p*-value of 0.053 indicates non-rejection at conventional levels of significance, it is substantially lower than the 0.25 threshold recommended by Roodman (2009a). The *C* test for the validity of the instruments created for the lagged dependent variable can likewise be rejected ($p = 0.005$). Thus, for the first female sample estimation, the instruments are highly likely to be invalid. The problem regarding the presence of second order autocorrelation can be solved by using longer lag lengths (i.e. starting further back in the dataset). Unfortunately, this solution to the problem of instrument validity may be acquired at the cost of estimating with weaker instruments. There is a debate in the wider literature about weak and strong instrumentation, and not just valid and invalid instrumentation (Clemens *et al*., 2004; Bazzi and Clemens, 2009). However, this concern over weak—as opposed to valid—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.

Different samples result in different diagnostic test outcomes. Unlike the column just discussed, the third column (in Table 1) focuses on females aged between 16 and 35 and has valid instrumentation. When restricting the sample to those females aged 35 and under, the four diagnostic tests support the instruments used for estimation: the null hypothesis of exogenous instruments is supported (i.e. not rejected) in each case. Here, again, only marital status was treated as potentially endogenous.

The final column treats health and income as potentially endogenous as well as marital status, and increases the sample's upper age limit to 50. Here, three of the four diagnostic tests indicate valid (i.e. exogenous) instruments, and one test—the *C* test for the lagged dependent variable—indicates that some caution is necessary. This last column is a good example of the need to not stop diagnostic testing with AR(2) and the *J* test (which is, in the main, as far as much of the most conscientious dynamic panel GMM work currently goes in the life satisfaction area). Subsets of instruments should also be investigated. Despite the differences in the diagnostic test results in the three female columns, the age ranges examined, and the differing choice of what is potentially endogenous, the coefficients obtained are very similar and, while not directly comparable, similar to those obtained by fixed effects (shown in Table A1 of Appendix 1). This consistency of results is an important finding and suggests that the coefficients obtained by dynamic panel analysis can be valuable even if the diagnostics do not uniformly indicate statistical support.[10]

For females (based on the consistency of results from all three estimates), positive and statistically significant for life satisfaction are the following: being married; reporting health as good or excellent; and having a labour force status as "other" (this may reflect maternity leave, which is included in "other").[11] Negative

[10]In such cases, given the advantages of dynamic panel analysis, I would suggest only using dynamic panel analysis as an additional method to a more conventional static estimation technique like fixed effects. For example, when using the German Socio-Economic Panel (SOEP) I have never been able to specify a dynamic panel estimation of life satisfaction with fully acceptable diagnostics. See Piper (2019) for an example of this supportive though cautious use of GMM analysis.

[11]See D'Addio *et al*. (2013) for more information regarding the well-being effect of maternity leave and other birth-related policies.

and statistically significant for female life satisfaction (again in all three estimates) are the following: unemployment; being long-term sick or disabled; and being a family carer. Once again, the age coefficients are in line with the U-shape finding. For females in the younger age range only, education has a positive effect on life satisfaction, perhaps reflecting the possibility that, on average, any contemporaneous life satisfaction effects of education fade. Overall, none of these results—for females or males—are surprising, and the results from dynamic panel analysis support, reasonably well, results from most fixed effects analyses in the life satisfaction area (and those presented in Table A1 of Appendix 1 using the same dataset).[12]

The next section considers these results further with an especial focus on the consistent 0.1 coefficient size obtained in every case for the lagged dependent variable. This is followed by consideration of a dynamic panel model which introduces lags of the independent variables, and a paragraph linking the findings from these dynamic panel models to literature which uses cohort data to investigate the relationship between childhood and adult life satisfaction.

4. Discussion: the lagged dependent variable coefficient

A key finding from the results of Table 1 is the coefficient obtained for the lagged dependent variable. In all four columns it is small (around 0.1), positive and significant. This, as the quote from William Greene (in Section 3) asserts, and as the algebra (in Appendix 3) shows, captures the entire history of the model. Thus, the entire history of the model has only a small influence (0.1) on current life satisfaction, an outcome indicative of life satisfaction being largely contemporaneous. Thus most of what contributes to life satisfaction are current circumstances and events, with this small influence from the measured past. History matters, but not that much. The result that determines this, the 0.1 value, is robust, being found in other studies too. To a greater or lesser degree, every study mentioned previously that uses GMM for dynamic estimation finds a small, positive coefficient for the lagged dependent variable (Powdthavee, 2009; Bottan and Perez-Truglia, 2011; Piper, 2012; Wunder, 2012; Piper, 2015a; Piper and Pugh, 2016; Piper, 2019). These similar results for the lagged dependent variable are obtained despite many differences in the various studies including the following: the equation estimated; the datasets employed; alternate choices regarding the exogeneity/endogeneity of variables; diagnostic test results (and their differing appropriateness); and the use of lags for other right hand side variables. This seems to be an exceptionally robust finding. Despite this consistency, the import of the approximate 0.1 value has, previously, either not been discussed or, when discussed, not really understood.[13]

[12]One interesting exception is education for males. GMM finds medium and high levels of education to have a negative association with life satisfaction compared to having a low level of education, whereas FE finds no significant difference between these three education groups (low, medium and high). As most people do not change their level of education generally (and in this representative sample too) there is likely to be insufficient within-individual variation for fixed effects estimation to provide estimates of the coefficients on education with precision. This illustrates one of the advantages of GMM analysis, which takes into account both within and between variation.

[13]Note well that this 0.1 figure does not change its meaning or importance when the scales are different in these different studies. The scales of life satisfaction in the current year and previous years are the same and it is this that is important.

The size of the coefficient for the lagged dependent variable influences the ratio between the contemporaneous influence and the measured "historical influence." A coefficient size of 0.1 indicates only a tiny difference between the contemporaneous effect and the cumulative long-run effect. In general, the long-run effect of a time-varying independent variable is obtained by dividing the estimated (impact or short-run) coefficient by 1 minus the estimated coefficient on the lagged dependent variable.[14] For example, a coefficient of 0.1 implies a multiplier of 1.1 recurring, while a coefficient on the lagged dependent variable of 0.8 implies that the short-run coefficient has to be multiplied by 5 to obtain the long-run effect. As it is, at 0.1, most of any life satisfaction effect is contemporaneous.[15] This low level of persistence means that the difference between short- and long-run effects is minimal. Furthermore, that the short-term and long-term coefficient estimates being very close to each other explains why the coefficients obtained via dynamic panel analysis are, in most cases, not too dissimilar to those obtained by fixed effects analysis. Thus, despite the discussed inadequacies of static FE modelling and the corresponding advantages of dynamic modelling, if these results are at all representative, then—in spite of its methodological flaws—the results from this (static FE) literature are likely to be reliable for practical purposes (i.e. subject to only minimal levels of bias).

In addition to the lagged dependent variable, lags of the independent variables can also be included on the right hand side of the equation to be estimated by dynamic panel analysis. This gives us specific information about the association between a situation or status in the previous year(s) and current life satisfaction. Table 2 provides results for the same samples as Table 1, but with the addition of lags for income, the labor force and marital status dummies, education and health.

The first thing of note is that two of the female samples (the second and fourth results columns) fail the diagnostic testing, thus our discussion will only refer to the male sample (Column one), and the young females (i.e. no older than 35) sample (Column three), while noting that the coefficient on the lagged dependent variable remains consistently around 0.1, despite the different diagnostic statistics. For males, there is no direct influence of current real income or real income in the past, on current life satisfaction. Also, almost all of the different labour force statuses in the past have no direct impact on current life satisfaction.[16] In contrast, previous years of very good (or good or satisfactory) health contribute directly to current life satisfaction, with the size of the coefficients for the health statuses indicating that more recent years have more of an influence than more distant years. Some of the marital status variables also indicate an influence of the past on current life

[14]Of course, this procedure should not be applied to time-invariant dummy variables, which measure between group effects, tending to reflect long-run equilibrium effects (Baltagi, 2005, pp. 157–158 and 200–201). Application of this procedure to other dummy variables may make sense if they exhibit considerable time variation and there is an economic case for distinguishing short-run effects from long-run effects. (A potentially cumulative scarring effect of many separate unemployment spells might be a case in point; this remains to be investigated.)

[15]As correctly pointed out by a reviewer, the bounded scales for life satisfaction may mean that the low level of persistence found could even be biased upwards.

[16]The exception is the "other" labor force category. As a previous footnote stated, individuals here undertaking maternity leave, or a government training scheme, or are one of the few individuals classed as 'other' in the BHPS. Given the other lagged controls, and the lagged dependent variable itself, these results should not be compared to the fixed effects lags and leads results of, for example, Lucas *et al*. (2004), Clark *et al*. (2008) and Frijters *et al*. (2011).

satisfaction. While being married currently contributes positively to current life satisfaction, there is evidence that (controlling for this positive association) being married in the past is negatively associated with current life satisfaction. One reading of this is that being in the first year of marriage is unequivocally positive for marriage, but it being your second or third (and, perhaps, above) year of marriage then current life satisfaction is mitigated somewhat. Past divorce and separation is, at different moments, both negative and positive for life satisfaction in a way that likely cancels out for individuals who have been divorced or separated for some time. Being newly divorced (i.e. within the last year) has no bearing on current life satisfaction whereas being newly separated does and is negative for current life satisfaction. Interestingly, including lags of being separated on the right-hand side substantially changes the coefficient on current separation.[17]

For young females (column 3), the results are broadly as those for males but with some important exceptions. As well as current unemployment being negatively associated with current life satisfaction, being unemployed in the previous year is also negative for current life satisfaction: a result perhaps supportive of the notion that unemployment can scar (Knabe and Rätzel, 2011; Hetschko *et al.*, 2019). For these young females, there is no significant average effect of being divorced or separated now or in the recent past on current life satisfaction. Including lags of education in the estimation removes the significant positive effect (found in Table 1) of education for current life satisfaction. Again, health is important: being healthy in the past contributes directly to current life satisfaction even when current health status is controlled for, and more recent years matter more than more distant years. In general, including lags of the independent variables offers additional nuance to the dynamic findings that rely on just a lagged dependent variable. This is presented here as an initial step, though clearly more investigation is required.

Our finding that the determinants of overall life satisfaction are largely (but not wholly) contemporaneous is one piece of the puzzle in our attempts to better understand life satisfaction. Other recent research demonstrates an association between adult life satisfaction with factors from childhood, including behavior and emotional health. See particularly the evidence provided by Frijters *et al.* (2014) and Layard *et al.* (2014), which comes from cohort data (specifically the British Cohort Survey and the National Child Development Survey).[18] This evidence for an association with the past, and the finding presented earlier that life satisfaction is a largely contemporaneous variable are not necessarily contradictions. Recall that the finding of a limited influence of the past for current life satisfaction refers to the measured past which, in the BHPS, is never more than 12 years previous. Additionally, the BHPS sample only included people who were at least 16 years old. Thus analyses of the BHPS, along with many other annual nationally

[17]This is not discussed further, apart from the following note of caution: any interpretation might simply be interpreting the effects of multicollinearity. In the current study, the sample size mitigates against this possibility.

[18]This evidence, which comes from cross-section regressions, demonstrates a link between childhood and adulthood with, for example, teacher assessments of the child being significantly associated with that child's life satisfaction as an adult. Despite the chronological nature of the data, the authors are cautious about invoking causality because of the numerous possible causes of these associations. See also Clark *et al.* (2018) for a book length discussion of these issues.

representative panel surveys, ignore the role of childhood when investigating life satisfaction.[19] In the present study, the limitations of the data preclude separate estimation of childhood effects. However unobserved individual specific influences—including childhood experiences—are controlled for by the time-invariant individual component of the error term. Thus a possibility for overall life satisfaction, suggested by these two results, is that the past does matter, but only the distant past: the formative years of childhood being more important than the past several years of an adult's life. Adult life satisfaction may perhaps be bounded by "socialization," which took place pre-adulthood (and thus, importantly, before entering annual large scale panel data surveys).

5. Conclusion

The use of both dynamic panel analysis and General Method of Moments estimation within the life satisfaction research area is unusual, and has provided new insights. A central finding is the small, positive coefficient on the lag of life satisfaction (which represents the history of the model) means that most of what makes up current overall life satisfaction scores reflects contemporaneous concerns and situations.

An initial reason for the dynamic panel analysis was the likelihood that many static life satisfaction models are misspecified. Such models often exhibit serial correlation in the residuals, indicating missing dynamics. One way of taking advantage of this finding is to employ a dynamic panel model. Indeed such a model may be important to obtain more accurate associations between the right-hand side variables and life satisfaction. This key result of life satisfaction being largely (though not wholly) contemporaneous could not be found via standard fixed effects (or other non-dynamic) methods; at the same time, this result also lends support to the much more common static fixed effects analysis: even though dynamics are present in the life satisfaction relationships investigated they are minor, indicating that static fixed effects models are subject to only minimal levels of bias. Thus dynamic panel analysis offers both a critique of, and support for, fixed effects analysis, at least in a life satisfaction context. This support is also pragmatic: given the frequent lack of model specifications that result in the statistical validity of dynamic panel models, as evidenced by the results presented above and those cited above by other scholars, fixed effects analysis might actually be preferred in some cases. This support for existing practice is one of the key findings of this investigation: System GMM estimation of life satisfaction finds that the dynamics that are omitted by static fixed effects analysis are minor.

As well as offering insights into the dynamics of life satisfaction, a further aim of this investigation was to help foster an increased understanding of such models, particularly in the context of life satisfaction. An example of this is with respect to instrumentation. The choices that a researcher makes regarding instrumentation can have a substantial impact on the subsequent results, as well as on the diagnostic test outcomes, and these need to be explained. Here the diagnostics did not always fully support the estimations, though the coefficients obtained were qualitatively very robust, offering some confidence regarding the estimations. Future work may well encounter similar concerns regarding the diagnostic test results, and these results should be

[19]Indeed, this was one of the key motivations for the studies using cohort data.

shown and a note of caution attached to them. Testing the robustness of the obtained coefficients is important and, as explained, there are many ways to do this.

Studies in the life satisfaction area have started to employ dynamic panel methods, but often have not adequately considered the necessary diagnostics nor appreciated how such models need to be interpreted. Such methods are more complex than the standard fixed effects method and this additional complexity needs to be better understood. In summary, dynamic analyses of life satisfaction are currently at a nascent stage but have many benefits (and challenges) and offer a potentially interesting path for future life satisfaction research.

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Diagnostic testing of GMM dynamic panel models