Adult life satisfaction: largely (though not wholly) contemporaneous?
A System General Method of Moments dynamic panel analysis

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Abstract: This study discusses and employs System Generalised Methods of Moments (GMM) dynamic panel analysis to investigate adult life satisfaction. This method enables an investigation of the dynamics of life satisfaction, and is undertaken with and without lags of the independent variables. The results indicate that, for this particular dynamic panel model, life satisfaction is largely (though not wholly) contemporaneous. Some caveats are offered with this general result, and nuance provided with the inclusion of lagged independent variables. A key exception is with regard to health, with past and current health contributing significantly to current life satisfaction. Given the complexity of the econometric method and its limited previous use in the well-being area, advice is given and potential pitfalls highlighted. Furthermore, while static models (like fixed effects) omit dynamics and are often misspecified, the results from the dynamic panel analysis are supportive of the more common fixed effects analysis.

Keywords: Life Satisfaction, Dynamic Panel Analysis, GMM, Happiness, Subjective Well-Being

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"After receiving a particularly grand prize, he was asked by his wife 'are you happy?' He replied sombrely: if not now, when?" From *The Economist's* obituary of historian Fritz Stern, May 2016.

## 1. Introduction

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? What factors have a particularly long-running influence and are thus quite important? A dynamic panel assessment of life satisfaction can offer evidence addressing these (and other) questions. Dynamic panel models have become increasingly popular in many areas of economic enquiry, and their use has provided new insights. Some examples include investigations into corporate finance (Flannery and Hankins 2013), economic growth (Lee et al. 2012), and foreign aid (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 behaviour (Downward and Rasciute 2016). This increase in use is due, in part, to increasingly sophisticated software which has followed a greater theoretical understanding of dynamic panel analysis. As an indication of their popularity, key papers for the development of these models have (at the time of writing) several thousand citations. Despite this popularity in economics generally, the use of such models in well-being research is sparse.

The defining feature of dynamic modelling is the inclusion of one or (sometimes) more lags of the dependent variable on the right-hand side of the regression equation.[1] The entire history of the

[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.

model is itself contained within the lagged dependent variable(s) (Greene 2008, p.469). This changes the interpretation of the right-hand side variables, which now indicate contemporaneous effects conditional on the history of the model, while the estimated effect of the lagged dependent variable also gives the possibility to determine the influence of the measured past. There are substantial benefits available for researchers who undertake a dynamic panel analysis of well-being, rather than the currently more standard, static fixed effects analysis. Static estimation relegates dynamics in the data to the regression error terms, which is likely to impair point estimates and statistical inference alike.[2] In contrast, dynamic estimation by its nature includes dynamics in the relationship under consideration in the estimated part of the model, thereby providing both (i) greater assurance that the statistical assumptions of the model are reflected in the data and (ii) more informative estimates. For example, estimating with a lagged dependent variable provides a measure of persistence in the dependent variable which, in turn, enables comparison of the short-run (or contemporaneous) coefficients on the independent variables with their corresponding long-run effects, which can be derived post estimation. In addition, the General Method of Moments (GMM) approach to dynamic estimation offers advantages of its own. 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, GMM estimation allows time-invariant group effects to be modelled within a composed error term rather than by group fixed effects, which enables more legitimate – compared to fixed effects estimation – out of the sample generalisation. Thirdly, System GMM estimation, which we use in this investigation, proceeds by estimating models in both levels and differences and thus enables the effects of time-invariant variables to be

[2] Tests of life satisfaction panel data frequently indicate serial correlation in the residuals, which is indicative of omitted dynamics. In the opinion of the author, evidence of within-group serial correction in static fixed effects estimation is an invitation to model the dynamics of the relationship under investigation rather than a problem that can be assumed to be "fixed" by reporting appropriately robust standard errors.

identified. This investigation displays all these benefits employing a sample from the British Household Panel Survey (BHPS).

This is not the first well-being investigation to use a dynamic model, though the existing literature has some problems in its use of dynamic models (Piper and Pugh, 2016). This literature, which uses dynamic analysis as a main focus of their investigation (Powdthavee 2009; Della Guista et al. 2010; Bottan and Perez-Truglia; 2011; Piper 2012; Wunder 2012), or as a small part (for example Frijters et al. 2014), contains some omissions and misunderstandings. For example, none of these studies address the important 'initial conditions' issue (Blundell and Bond 1998); some of the studies misunderstand the necessary diagnostic tests, or do not report all (or any) of the important diagnostic test results. Furthermore, some of the studies listed above do not appropriately interpret of the model, which is different from the more standard fixed effects analysis. In general, future well-being work which wants to take advantage of the benefits that a dynamic panel assessment offers, needs to be more appreciative of the assumptions of dynamic modelling and its corresponding diagnostic tests. A contribution of this investigation is to aid this collective understanding, hopefully eliciting more successful dynamic panel work within the life satisfaction area in the future.[3]

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[4]; 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 4.1 discusses the results for the same samples when lags of the independent variables are also modelled; Section 4.2 asks what this dynamic result may mean for the research investigating the association of childhood with adult life satisfaction; Section 5 offers concluding remarks. After the

[3] Indeed, Crivelli et al. (2016) cite several times an earlier working paper version of this article, and avoid many of the issues mentioned just above.

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

appendices there is some supplementary material, which continues the discussion of system GMM and particularly its diagnostic testing.

## 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 where the interviewee is asked '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. Appendix 2 contains a table which shows the distribution of responses to this question for males and females, a pattern typical for life satisfaction data generally. As an aim of this investigation is to demonstrate the benefits of dynamic panel analysis, the right-hand side variables employed are common to many other investigations from this area, and thus an explicit strategy: a continuous variable for real income; and dummy variables accounting for labour force status, marital status, education, health, age range, wave, and region. Appendix 2 provides a table giving brief 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 15 and 60. This represents over 100,000 person-year observations.

This investigation is explicitly focused on dynamics. However, as Bond states, 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" (2002, p.1, see also p.20). Furthermore, this argument of considering dynamics is 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* command (Drukker 2003), rejects the null hypothesis of no first order autocorrelation with a p-value of 0.0000. (i.e., in practical terms, the null can be rejected with certainty).

We estimate the following standard equation (with the other explanatory variables excluded for clarity):

$$y_{it} = \beta y_{i,t-1} + (v_i + \epsilon_{it}) \tag{1}$$

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 ($y_{i,\ t-1}$). The composed error term in parentheses combines an individual-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 ($v_i$), which captures specific ignorance about individual $i$, and an error that varies over both individuals and time ($\epsilon_{it}$), which captures our general ignorance of the determinates of $y_{it}$.

An OLS estimator of $\beta$ 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. Fixed effects estimation does not have this inconsistency because the equation is transformed to remove the individual effect, as in equation 2.

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

However, equation (2) exhibits the different problem of correlation between the transformed lagged dependent variable and transformed error term. Here the overall impact of the correlation is negative, and is the well-known Nickell (1981) bias. Bond (2002) states that these biases can be used to provide an informal test for an estimator of the lagged dependent variable: 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).[5]

Due to these problems, the standard approach is to find a suitable instrument that is correlated with the potentially endogenous variable (the more strongly correlated the better), but uncorrelated with $\varepsilon_{it}$. With GMM, instrumentation is not confined to one instrument per parameter to be estimated, thus the possibility exists of defining more than one moment condition per parameter to be estimated. It is this possibility that is exploited in the GMM estimation of dynamic panel models, as first proposed by Holtz-Eakin et al. (1988).[6] 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 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 $\left(\varepsilon_{it} - \varepsilon_{i,t-1}\right)$. 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 whereby, additionally, the original *levels are instrumented with differences* (Arellano and Bover 1995). Here, for three main reasons, system GMM is used rather than difference GMM. Firstly, system GMM allows for more instruments and can dramatically improve efficiency (compared to difference GMM) (Roodman 2009a, p.86). 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

5 For an illustration of these biases see Piper and Pugh (2016), a brief comment paper which complements this investigation into the dynamics of life satisfaction.

6 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 (2005) for a detailed textbook treatment.

system GMM) (Roodman 2009a, p. 104).[7] And thirdly, unlike difference GMM, system GMM does not expunge the fixed effects (which are important in a well-being context) (Roodman 2009a, p.114). For these reasons future well-being work which employs GMM estimations should employ system GMM rather than difference GMM when the diagnostic tests support such an analysis (discussed in the supplementary material). These estimators, unlike OLS, 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 investigation, but the references provided above and papers by Roodman (e.g. 2009a; 2009b) are very informative.[8]

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 strictly exogenous? Secondly, how many instruments to use? With happiness 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 be advanced for income and health being variables endogenous with respect to life satisfaction too. The actual choice made 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. This resulted in, initially, the treatment of marital status only as potentially endogenous, and everything else treated as exogenous. For females, in additional estimates, health and income are also treated as endogenous. As explained below, the results from

[7] 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.

[8] The Roodman papers are particularly useful for applied researchers because they explain how to use the Stata software programme, xtabond2, which he created to implement the GMM dynamic panel estimators.

these choices are consistent despite differing diagnostic test outcomes. A discussion of the necessary diagnostic tests for such a model is presented in the supplementary material.

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 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).[9]

As recommended these are presented in the results table 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 results, and 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*

[9] 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.

*influence is conditional on this history*; in this case, any impact of (the independent variables) $\boldsymbol{x}_{it}$ represents the effect of *new* information. (2008, p.468, emphasis added).

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).[10]

Table 1 displays the results for four estimations, one of which is for males and three are for females (for reasons explained below).[11] 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.[12] Furthermore, as discussed in the previous section, only marital status is treated as potentially endogenous. 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).

[TABLE ONE ABOUT HERE]

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; having a labour force status as other;[13] 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. Furthermore, these results are

[10] In Appendix 3, the lagged dependent variable is shown algebraically to be the entire history of the model and not just a fixed effect (as sometimes assumed).

[11] Employed in every GMM estimation is the twostep robust procedure that utilises 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).

[12] As mentioned in section 2.1, the instruments come from within the model, i.e. previous values. Refer to the discussion there for more specific information regarding System (and difference) GMM.

[13] This represents those who are on maternity leave, on a government training scheme or one of a handful of people in the dataset who fit none of the possible labour force categories.

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 the *J* and *C* tests ('Diff-in-Hansen' in the table) are above Roodman's 'common sense' minimum of 0.25 but less than 1.0 (as discussed in the supplementary material).[14]

For females, there are three columns of results (reflecting differences in the diagnostic test outcomes, discussed just below). The first of the three female columns is every female in the sample with only marital status treated as potentially endogenous, and the diagnostics of this estimation highlight that the created instruments are invalid.[15] Second order autocorrelation cannot be ruled out, and the null of instrument validity for the whole set of instruments (the *J* test) can be rejected with only a 0.053 chance of Type I error. The *C* test for the validity of the instruments created for the lagged dependent variable can be rejected with a chance of error less than 0.01. Thus, for the first female sample estimation, the instruments are highly likely to be endogenous and therefore invalid. Any discussion of the results from the second column needs a large caveat. 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) but this is only a technical solution. The AR (2) test would then result in a preferred outcome, but the appropriateness of instrumenting for life satisfaction levels (and other explanatory variables) and differences, the differences and levels of at least two years previous is questionable. 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

[14] Important for an analysis of dynamics, the coefficient obtained for the lagged dependent variable is discussed below (in Section 4).

[15] These diagnostic problems for GMM estimation regarding females in the BHPS are also found by Della Giusta et al (2010). In that paper, the null hypothesis of having exogenous instruments overall (i.e. Hansen *J* test) is comfortably rejected; on page 9 there is a comment that 'only the male model passes the Hansen test of over identification' but the consequences of this are not highlighted.

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 15 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. For the final column of results, three of the four diagnostic tests indicate 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 well-being 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 appendix 1).

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 latter effect appears to reflect maternity leave, which (investigation not shown) is a reason for the different sign when compared to males.[16] Negative and statistically significant for female well-being (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,

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

any contemporaneous well-being 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 well-being area (and those presented in Appendix 1 using the same dataset).[17] This latter point, the support for fixed effects analysis, is important and returned to below in the next section.

Also important but not yet discussed is the lagged dependent variable, including its obtained coefficient. This provides a central insight of this investigation, providing information about the dynamics of life satisfaction, and enabling the determination of the influence of the past history of the model which, in turn, is necessary for the calculation of the long-run effects on life satisfaction for the explanatory variables. This is discussed in detail in the next section, along with greater consideration of the contemporaneous coefficients. A subsection introduces lags of the independent variables for more nuance (4.1), and a further subsection links these results to recent literature which uses cohort data to investigate the relationship between childhood and adult life satisfaction (4.2).

## 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, represents 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 much of what contributes to life satisfaction are current circumstances and events, with this small influence from the measured past. The result that determines this, the 0.1 value, is robust, being

[17] One interesting exception is with 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 groups. 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.

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; Della Giusta et al 2010; Bottan and Perez-Truglia 2011; Piper 2012; Wunder 2012; Piper 2015a). 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. Despite this consistency, the import of the approximate 0.1 value has, previously, either not been discussed or, when discussed, not really understood.

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 0.05 would further decrease the influence of the past, increasing the contemporaneous effect of, for example, marriage; a coefficient of 0.4 would have the opposite effect: the past would matter considerably, nearly as much as the contemporaneous effect. As it is, at 0.1, much of any well-being effect (unemployed, enjoying very good health, or any other statistically significant variable) is contemporaneous.

While dynamics are present in the relationships under investigation, they are minor, which is reflected in the uniformly small size of the coefficient on the lagged dependent variable. 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 are very close to each other explains why the coefficients 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).

The introduction mentioned the ability of dynamic panel analysis in splitting up contemporaneous (or short-run) effects and overall (or long-run effects). Overall effects can be found via a quick post-estimation calculation: the contemporaneous coefficient divided by 1 minus the coefficient of the lagged dependent variable. Taking unemployment as an example, its contemporaneous effect for males (column 1 of table 1), compared to being employed, is approximately -0.43, indicating that unemployed people are, on average, nearly half a point less satisfied with life (ceteris paribus) on the BHPS 1-7 scale. The overall value (or long-run value) is -0.48 (= 0.43/ (1-0.1)), approximately 90% of which reflects the contemporaneous effect of being unemployed. Thus being unemployed in the past, in this general model, contributes only a small amount to the loss of life satisfaction.[18]

Thus, in this general model, much of the negative impact of being unemployed is contemporaneous and the impact is cumulative over time. As an individual remains unemployed, his life satisfaction decreases a little more (until a new equilibrium is reached) though most of the effect is contemporaneous. Thus, for the long-term unemployed, most of the overall life satisfaction penalty is due to being currently unemployed, with prior years of unemployment adding a little to this penalty. The contemporaneous experience is what is important, whether for unemployment or other statistically significant variable (but see section 4.2).

That most of the impact of well-being is contemporaneous may explain some previously found results in the well-being literature. Steiner et al. (2013) investigate the individual life satisfaction or well-being impact of a city being the European Capital of Culture. They find, on average, a significant negative impact in the year a city is the European Capital Culture, but no impact in the years before or after.[19] The results here regarding the dynamics of happiness suggest that an event like this is unlikely to have a substantial effect (if any) on the day-to-day lives of individuals in any other year than the year of the associated celebrations, life satisfaction being a largely contemporaneous

[18] A more nuanced understanding follows in section 4.1 when lags of the independent variables are included.
[19] The authors suggest that this negative effect may reflect dissatisfaction with associated high levels of public expenditure, transport disruptions, general overcrowding or an increase in housing prices.

phenomenon. Similarly explained, potentially, is the result of Kavetsos and Szymanski (2010) who find that hosting the FIFA World Cup or the Olympics increases life satisfaction only in the year of the event and has no long term effect on life satisfaction.

To these overall results, the next section offers some nuance by including lags of the major right hand side variables.

4.1 Discussion: Independent variable lags.

The previous results and discussion come from estimations that contained no lags of the right hand side variables, providing an overall idea of what system GMM estimation indicates for the general relationship between the present and the measured past. As was seen, this estimation technique suggests that life satisfaction is largely contemporaneous but not wholly so.[20] However, we can be more nuanced in our understanding with the inclusion of lags of the independent variables on the right hand side. This gives us specific information about the association between a situation or status in the previous year(s) and current life satisfaction. For example, we can find out whether previous unemployment has (or has not) any direct influence on current life satisfaction. Table 2 provides results for the same samples as table 1, but with the addition of lags for income, the labour force and marital status dummies, education and health.

[TABLE TWO ABOUT HERE]

The four columns represent the same samples as the four in table 1. 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, and the young females (i.e. no older than 35) sample. 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 (for

[20] There are other dynamic panel models are available, and while this investigation might represent substantial evidence and information about what system GMM says about life satisfaction, it cannot claim to be exhaustive for dynamic models in general.

example unemployment) have no direct impact on current life satisfaction.[21] The big story is with respect to health. 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 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 happiness 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.[22]

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 2008; Hetschko et al. 2014). For these young females, there is (perhaps unsurprisingly) 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)

[21] The exception is the ‘other’ labour 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.

[22] 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.

of education for current life satisfaction. Again, health is the big story: 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.

### 4.2 Discussion: What about childhood?

This result of adult life satisfaction appearing largely (but not wholly) contemporaneous – with the important exception of health - 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 behaviour 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).[23] 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.

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 twelve years previous. Additionally, the BHPS sample only included people who were at least 16 years old. Thus the BHPS, along with other annual nationally representative

[23] Also see Clark et al. (2018) for a book length discussion of these issues.

panel surveys, ignores the role of childhood when investigating life satisfaction.[24] Thus a possibility 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 'socialisation' which took place pre-adulthood (and thus, importantly, before entering annual large scale panel data surveys).

A further possibility is that childhood has an impact on adult life satisfaction, but that this impact is largely indirect, and difficult to measure. The evidence of the previous section demonstrates the importance of contemporaneous states and situations for life satisfaction – being married now mattering more than being married in the past and so on – and such contemporaneous factors may have been influenced by childhood or early life. For example, the child of divorced parents may have decided, because of childhood experiences, not to get married when an adult. In such a case, and in related situations, early life exerts an influence on adulthood (and thus adult life satisfaction) but this is not possible to pick up in common regression equations.

Layard et al. (2014) warn that an excessive focus on childhood and adolescence can potentially leave little room for a policy focus on adult life. The investigations linking childhood and adulthood with their cross-section OLS regressions find that adulthood still has a substantial connection with adult life satisfaction. For example, Frijters et al. (2014) find that "the contemporaneous association between socio-economic variables and life satisfaction remains strong, even when we control for extensive childhood and early family characteristics."[25] These findings support the finding of the previous section that adult life satisfaction is a largely contemporaneous, though this may mask more indirect impacts from the past on adulthood.[26] Layard et al. (2014) estimate that about half of

[24] Indeed, this was one of the key motivations for the studies using cohort data.
[25] Layard et al. (2014) make a similar statement: "adult life still has an important impact on life satisfaction even after we have allowed for the influence of family and childhood."
[26] Future work, more focused on the childhood and adulthood debate, will address this. In the dynamic panel system GMM regressions, childhood effects will be fully absorbed into the individual fixed component of the error term. How large a part of the variability of current well-being is accounted for by this fixed component is of interest here.

the effect of childhood on adult life-satisfaction is mediated by the impact on other adult outcomes (including whether the individual has a partner, is employed, and their income).

Future research could use GMM analysis and its ability to determine contemporaneous effects and long-term associations to address the contemporaneous impact of an aspect (or more) of childhood. With data on, for example, parental income it might be possible to determine the direct association of current life satisfaction with the household income the individual experienced as a child. Here parental household income could be seen as a proxy (however imperfect) for conditions in childhood, and the techniques of GMM dynamic panel analysis could reveal how much of a direct impact that has on current adult life satisfaction. Another proxy could be the socio-economic status of parents. In short, if a large annual panel dataset has (remembered or actual) information about an individual's childhood or early years this can be included on the right-hand side of a dynamic panel equation and, thus, its contemporaneous impact can be assessed. This is akin to answering the question of how much someone's childhood impacts their (adult) life satisfaction now, and represents a likely fruitful avenue for future research.

Layard et al. (2014) state that they want to decide at what point in the life-cycle interventions would be most effective. The largely contemporaneous result does not answer this question, but does suggest that well thought out interventions, and policy, have the potential to be effective whenever they are undertaken. A related question is how long any interventions may last. The dynamic panel investigation suggests that any direct impact will not be long lasting (unless the interventions relate to health), though may exhibit an impact indirectly through other variables. Given the contemporaneous nature of adult life satisfaction, and the likely import of indirect or mediated effects, perhaps other 'outcome' variables should also be investigated along with life satisfaction. As a conclusion Layard et al. (2014) argue that future research should try to investigate the issues of direct and indirect effects of childhood and life satisfaction and, thus, when intervening might be most effective for policymakers. This contemporaneous result, which suggests that childhood has more of an indirect than a direct impact on current adult life satisfaction, supports this argument. Future research, with new models and more data, can usefully attempt to provide evidence for this important policy issue.

## 5. Conclusion

The analysis and results of this study both support and extend recent research. The use of both dynamic panel analysis and General Method of Moments estimation within the well-being research area is unusual, and has provided new insights. In summary, 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 life satisfaction scores reflects contemporaneous concerns and situations. For example, most of the contribution to life satisfaction of being married comes from being currently married (as opposed to previous years of marriage); most of the negative contribution of unemployment to life satisfaction comes from being currently unemployed with a little bit of persistence from the past. One important exception is health: past health directly contributes to current well-being, even when current health is controlled for. This investigation has also demonstrated the need to consider independent variable lags too, to offer a more nuanced insight into the dynamic behaviour of life satisfaction.

An initial reason for the dynamic panel analysis was the likelihood that many static well-being 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 well-being. Given that life satisfaction appears to be a largely contemporaneous phenomenon, models (like system GMM) which can estimate contemporaneous coefficients are very useful. A further advantage of such models is the ability to straightforwardly instrument potentially endogenous variables, perhaps better accounting for the relationship between well-being and some commonly used explanatory variables, and thus enabling the estimation of coefficients for variables previously thought impossible to satisfactorily investigate. 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 fixed effects analysis and support.

As well as offering insights into the dynamics of well-being, a further aim of this investigation was to help foster an increased understanding of such models, particularly in the well-being area. 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 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 well-being area have started to employ dynamic panel methods, but often have not adequately considered the necessary diagnostics nor appreciate how such models need to be interpreted. Such methods are considerably more complex than the standard fixed effects method and this additional complexity needs to be better understood. At present, dynamic analyses of well-being are at a nascent stage but have many benefits (and challenges) and offer an interesting path for future well-being research.

References


Arellano, M. and Bond. S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *The Review of Economic Studies* 58, pp. 277 – 297.

Arellano, M, and Bover, O. (1995) Another look at the instrumental variable estimation of error -components models, *Journal of Econometrics* 68, pp. 29–51.

Baum, C. F., Schaffer, M. E. and Stillman, S. (2003) Instrumental variables and GMM: Estimation and testing. *Stata Journal* 3, pp. 1–31.

Bazzi, S. and Clemens, M. (2009) Blunt Instruments: On Establishing the Causes of Economic Growth, *Working Papers* 171 *Center for Global Development*.

Blundell, R. and Bond, S. (1998) Initial Conditions and Moment Restrictions in Dynamic Panel Data Models, *Journal of Econometrics* 87, 1, pp. 115-143.

Bond, S. R. (2002) Dynamic Panel Models: A Guide to Micro Data Methods and Practice. *Institute for Fiscal Studies / Department of Economics, UCL, CEMMAP (Centre for Microdata Methods and Practice) Working Paper* No.CWPO9/02.

Bottan, N. L. and Perez-Truglia, R.N. (2011) Deconstructing the Hedonic Treadmill: Is Happiness Autoregressive? *Journal of Socio-Economics* 40, 3, pp. 224-236.

Clark, A. E., Flèche, S., Layard, R., Powdthavee, N., & Ward, G. (2018) *The Origins of Happiness: The Science of Well-Being over the Life Course.* Princeton University Press.

Clemens, M., Radelet, S., and Bhavnani, R. (2004) Counting Chickens When They Hatch: The Short-term Effect of Aid on Growth, *Working Papers* 44*, Center for Global Development.*

Crivelli, L., Della Bella, S. and Lucchini, M. (2016) Happiness and Health. Chapter 17 In Handbook of Research Methods and Applications in Happiness and the Quality of Life (Edited by Bruni, L. and Porta, P. L.) Edward Elgar: Cheltenham, pp. 372-399.

D'Addio, A. C., Chapple, S., Hoherz, A., & Van Landeghem, B. (2013) Using a quasi-natural experiment to identify the effects of birth-related leave policies on subjective well-being in Europe. *OECD Journal: Economic Studies* 1, pp.1-34.

Della Giusta, M.,Jewell, S., and Kambhampati, U. (2010) Anything to Keep You Happy?, *Economics & Management Discussion Papers* 01, Henley Business School, Reading University.

Downward, P. and Rasciute, S. (2016) 'No man is an island entire of itself.' The hidden effect of peers on physical activity, *Social Science and Medicine* 169, C, pp.149-156.

Drukker, D. M. (2003) Testing for serial correlation in linear panel-data models. *Stata Journal* 3, pp. 168-177.

Dutta, N., Leeson, P. T. and Williamson, C. R. (2013) The Amplification Effect: Foreign Aid's Impact on Political Institutions, *Kyklos* 66, 2, pp. 208-228.

Flannery, M. J., & Hankins, K. W. (2013) Estimating dynamic panel models in corporate finance *Journal of Corporate Finance* 19, pp.1-19.

Frijters, P., Johnston, D. W. and Shields, M. A. (2014) Does Childhood Predict Adult Life Satisfaction? Evidence from British Cohort Surveys. *The Economic Journal* 124: 580, pp. F688-F719

Godfrey, L. G. (1991) *Misspecification Tests in Econometrics*. Cambridge Books, Cambridge University Press.

Greene, W. (2002) *Econometric Analysis,* Fifth Edition. Upper Saddle River, New Jersey: Prentice Hall.

Greene, W. (2008) *Econometric Analysis,* Sixth Edition. Upper Saddle River, New Jersey: Prentice Hall.

Hall, A. R. (2004) *Generalized Method of Moments*. Oxford: Oxford University Press.

Hansen, L. P. (1982) Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society* 50, 4, pp.1029-1054.

Hetschko, C., Knabe, A., & Schöb, R. (2014) Looking Back in Anger?: Retirement and Unemployment Scarring, *SOEP Papers* 652, DIW Berlin, Germany.

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988) Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society* 56, 6, pp. 1371-1395.

Kavetsos, G. and Szymanski, S. (2010) National well-being and international sports events. *Journal of Economic Psychology* 31, 2, pp. 158-171.

Knabe, A. and Rätzel, S. (2008) Scarring or Scaring? The Psychological Impact of Past Unemployment and Future Unemployment Risk, *Economica* 78, 310, pp. 283-293.

Layard, R. Clark, A.E., Cornaglia, F., Powdthavee, N., and Vernoit, J. (2014) What Predicts a Successful Life? A Life-Course Model of Well-Being, *Economic Journal* 124, 580, pp. F720–F738.

Lee, S. H., Levendis, J., & Gutierrez, L. (2012) Telecommunications and economic growth: an empirical analysis of sub-Saharan Africa. *Applied Economics* 44, 4, pp.461-469.

Nickel, S. J. (1981) Biases in Dynamic Models with Fixed Effects, *Econometrica* 49, 6, pp. 1417-1426.

Piper, A. T. (2012) Dynamic Analysis and the Economics of Happiness: Rationale, Results and Rules, *MPRA Paper* 43248, University Library of Munich, Germany.

Piper, A. T. (2015a) Heaven knows I'm miserable now: Overeducation and reduced life satisfaction, *Education Economics* 23, 6, pp. 677-692.

Piper, A. T. (2015b) Sliding down the U-shape? A dynamic panel investigation of the age-well-being relationship, focusing on young adults, *Social Science & Medicine* 154, C, pp. 54-61.

Piper, A. T. and Pugh, G. T. (2016) Issues in the estimation of dynamic "happiness" models: A Comment on 'Does Childhood Predict Adult Life Satisfaction? ' *Economics: The Open-Access, Open-Assessment E-Journal* 10, pp. 1-6.

Powdthavee, N. (2009) I can't smile without you: Spousal correlation in life satisfaction, *Journal of Economic Psychology*, vol. 30: 4, pp. 675-689.

Pugh, G., Mangan, J., Blackburn, V., & Radicic, D. (2015) School expenditure and school performance: evidence from New South Wales schools using a dynamic panel analysis. *British Educational Research Journal* 41, 2, pp. 244-264.

Roodman, D. (2007) A Note on the Theme of Too Many Instruments, *Center for Global Development, Working Paper* No.125.

Roodman, D. (2009a) How to do xtabond2: An Introduction to Difference and System GMM in Stata, *The Stata Journal* 9, 1, pp. 86-136.

Roodman, D. (2009b) A Note on the Theme of Too Many Instruments, *Oxford Bulletin of Economics and Statistics* 71, 1, pp. 135-158.

Steiner, L., Frey, B.S. and Hotz, S. (2013) European capitals of culture and life satisfaction, *ECON - Working Papers* 117, Department of Economics - University of Zurich.

Stutzer, A. and Frey, B.S. (2006). Does Marriage Make People Happy, Or Do Happy People Get Married? *Journal of Socio-Economics* 35, 2, pp. 326-347.

Verbeek, M. (2000) *A Guide to Modern Econometrics.* Chichester: Wiley.

Windmeijer, F. (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics* 126, pp. 25-51.

Wooldridge, J. M. (2002) *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

Wunder, C. (2012) Does subjective well-being dynamically adjust to circumstances?, *Economics Letters* 117, 3, pp. 750-752.

Table 1 life satisfaction of British people, assessed via GMM dynamic panel analysis.

| VARIABLES | Males All | Females All | Females≠ Age 15-35 | FemalesΨ Age 15-50 |
|---|---|---|---|---|
| Lagged Life Satisfaction | 0.09*** | 0.09*** | 0.10*** | 0.09*** |
| | (0.014) | (0.012) | (0.019) | (0.013) |
| Real Annual Income ('000s) | 0.00*** | -0.00 | -0.00 | -0.01* |
| | (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 Labour 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 |
| Diff-in-Hansen (lag depvar) | 0.382 | 0.005 | 0.288 | 0.134 |

Note: 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. Key, Ψ: here, health and real income are treated as endogenous as well as marital status.

Table 2 Life satisfaction of British people, including independent variable lags, assessed via GMM dynamic panel analysis.

| VARIABLES | Males | Females | Females≠ | FemalesΨ |
|---|---|---|---|---|
| | All | All | Age 15-35 | Age 15-50 |
| Lagged Life Satisfaction | 0.09*** | 0.10*** | 0.11*** | 0.12*** |
| | (0.015) | (0.014) | (0.023) | (0.015) |
| Real Annual Income ('000s) | 0.00 | -0.00** | -0.00 | -0.00*** |
| | (0.001) | (0.000) | (0.001) | (0.001) |
| First lag | 0.00 | -0.00 | 0.00 | -0.00 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Second lag | -0.00 | -0.00 | 0.00 | 0.00 |
| | (0.001) | (0.000) | (0.000) | (0.000) |
| Third lag | 0.00 | -0.00 | -0.00 | 0.00 |
| | (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) |
| 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) |
| 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 |

Note: 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. Key, ≠ no retired or widowed individuals Ψ: here, health and real income are treated as endogenous as well as marital status.

APPENDIX 1

**Table** Fixed effects life satisfaction regressions for British individuals aged 15-60

| VARIABLES | Both genders<br>Life Satisfaction | Males<br>Life Satisfaction | Females<br>Life Satisfaction |
|---|---|---|---|
| Real Annual Income ('000s) | 0.00* | 0.00** | -0.00 |
| | (0.000) | (0.000) | (0.000) |
| Self-employed | 0.00 | -0.01 | 0.00 |
| | (0.019) | (0.023) | (0.031) |
| Unemployed | -0.33*** | -0.41*** | -0.26*** |
| | (0.018) | (0.025) | (0.027) |
| Retired | 0.02 | -0.01 | 0.04 |
| | (0.028) | (0.044) | (0.036) |
| LT Sick or Disabled | -0.52*** | -0.70*** | -0.41*** |
| | (0.025) | (0.038) | (0.032) |
| FT Student | 0.03 | -0.01 | 0.05** |
| | (0.019) | (0.029) | (0.026) |
| Family Carer | -0.12*** | -0.20*** | -0.10*** |
| | (0.017) | (0.069) | (0.019) |
| Other Labour Force Status | 0.08*** | -0.12** | 0.14*** |
| | (0.027) | (0.055) | (0.032) |
| Married | 0.08*** | 0.07*** | 0.07*** |
| | (0.019) | (0.027) | (0.027) |
| Separated | -0.10*** | -0.14*** | -0.08** |
| | (0.031) | (0.047) | (0.042) |
| Divorced | 0.06** | 0.06 | 0.06 |
| | (0.028) | (0.041) | (0.038) |
| Widowed | -0.17*** | -0.13 | -0.19*** |
| | (0.060) | (0.114) | (0.073) |
| Education: High | 0.05* | 0.06 | 0.03 |
| | (0.026) | (0.038) | (0.037) |
| Education: Medium | 0.04* | 0.06 | 0.03 |
| | (0.027) | (0.039) | (0.037) |
| Health: Excellent | 0.44*** | 0.43*** | 0.46*** |
| | (0.012) | (0.017) | (0.016) |
| Health: Good | 0.30*** | 0.30*** | 0.30*** |
| | (0.009) | (0.013) | (0.012) |
| Age: 21-30 | -0.10*** | -0.18*** | -0.04 |
| | (0.019) | (0.028) | (0.027) |
| Age: 31-40 | -0.12*** | -0.20*** | -0.05 |
| | (0.027) | (0.039) | (0.038) |
| Age: 41-50 | -0.16*** | -0.23*** | -0.10** |
| | (0.034) | (0.049) | (0.048) |
| Age: 51-60 | -0.11*** | -0.15** | -0.08 |
| | (0.042) | (0.060) | (0.058) |
| Wave Dummies | Yes | Yes | Yes |
| Region Dummies | Yes | Yes | Yes |
| Constant | 4.96*** | 4.94*** | 4.98*** |
| | (0.058) | (0.081) | (0.083) |
| Observations | 107,858 | 49,534 | 58,324 |
| R-squared | 0.033 | 0.040 | 0.030 |
| Number of Individuals | 21,004 | 9,905 | 11,099 |

Note: data from individuals in the BHPS, 1996-2007; standard errors in parentheses; significance levels: *** p<0.01; ** p<0.05; * p<0.1; baseline categories: employed, never married, low education, health self-reported as fair or worse, age range 16-20.

APPENDIX 2

**Table** The distribution of life satisfaction in the British Household Panel Survey dataset

| | Males | | Females | |
|---|---|---|---|---|
| Life Satisfaction | Count | % | Count | % |
| 1 | 625 | 1.22 | 964 | 1.60 |
| 2 | 1,151 | 2.24 | 1,459 | 2.43 |
| 3 | 3,259 | 6.35 | 3,944 | 6.57 |
| 4 | 7,163 | 13.97 | 9,207 | 15.33 |
| 5 | 1 16,424 | 33.00 | 17,966 | 29.91 |
| 6 | 1 17,418 | 33.96 | 19,570 | 32.58 |
| 7 | 4,744 | 9.25 | 6,959 | 11.59 |
| Total | 51,284 | 100.00 | 60,069 | 100.00 |

**Table** Independent variables and base categories, summary statistics, British Household Panel Survey waves 6-10 and 12-17 (the waves where life satisfaction is included in the survey).

| variable | mean | N | Maximum (minimum is always 0) |
|---|---|---|---|
| Real Annual Income (£'000s) | 12.90 | 127,318 | 1,074.09 |
| Employed | 0.634 | 127,761 | 1 |
| Self-employed | 0.079 | 127,761 | 1 |
| Unemployed | 0.044 | 127,761 | 1 |
| Retired | 0.024 | 127,761 | 1 |
| Long-term sick or disabled | 0.050 | 127,761 | 1 |
| Student | 0.075 | 127,761 | 1 |
| Family carer | 0.081 | 127,761 | 1 |
| Other labour force Status | 0.014 | 127,761 | 1 |
| Married | 0.519 | 127,576 | 1 |
| Separated | 0.025 | 127,576 | 1 |
| Divorced | 0.088 | 127,576 | 1 |
| Widowed | 0.013 | 127,576 | 1 |
| Never Married | 0.354 | 127,576 | 1 |

| | | | |
|---|---|---|---|
| Education: High | 0.409 | 125,709 | 1 |
| Education: Medium | 0.364 | 125,709 | 1 |
| Education: Other | 0.227 | 125,709 | 1 |
| Health: Excellent | 0.253 | 127,749 | 1 |
| Health: Good | 0.486 | 127,749 | 1 |
| Health: Fair/Poor/Very poor | 0.261 | 127,749 | 1 |
| Age: 16-20 | 0.109 | 127,827 | 1 |
| Age: 21-30 | 0.215 | 127,827 | 1 |
| Age: 31-40 | 0.256 | 127,827 | 1 |
| Age: 41-50 | 0.225 | 127,827 | 1 |
| Age: 51-60 | 0.195 | 127,827 | 1 |

Note well that these descriptive statistics represent every person-year that is in the dataset employed for both the dynamic panel investigations of the main part of the paper and the fixed effects estimations of appendix 2. Due to the demands of dynamic panel analysis the actual amount of person-year observations available for use in estimating the coefficients, the number of observations used for dynamic analysis is fewer than those described here and used by the fixed estimates. Descriptive statistics for the four individual samples (from this dataset used for the estimations are available upon request.

APPENDIX 3

The coefficient for lagged life satisfaction in these dynamic estimations is itself interesting and, as Greene informs us (see the quote that introduces the results section), this coefficient represents the 'entire history of the model' i.e. the history of the process that generates current levels of happiness. A little algebra expanding the lagged dependent variable demonstrates this. In equation (1) $LS_{it}$ is the life satisfaction of individual i in year t, $\hat{\beta}x_{it}$ is an independent variable and $\epsilon_{it}$ is the usual error term. Starting with our simplified specification in equation (1), we repeatedly substitute for the lagged dependent variable.

$$LS_{it} = \hat{\alpha}LS_{it-1} + \hat{\beta}x_{it} + \epsilon_{it} \tag{1}$$

Substitute for $LS_{it-1}$ in (1):

$$LS_{it-1} = \hat{\alpha}LS_{it-2} + \hat{\beta}x_{it-1} + \epsilon_{it-1} \tag{2}$$

Substitute (2) into (1)

$$LS_{it} = \hat{\alpha}(\hat{\alpha}LS_{it-2} + \hat{\beta}x_{it-1} + \epsilon_{it-1}) + \hat{\beta}x_{it} + \epsilon_{it} \tag{3}$$

Substitute for $LS_{it-2}$ in (3):

$$LS_{it-2} = \hat{\alpha}LS_{it-3} + \hat{\beta}x_{it-2} + \epsilon_{it-2} \tag{4}$$

Substitute (4) into (3)

$$LS_{it} = \hat{\alpha}(\hat{\alpha}\left[\hat{\alpha}LS_{it-3} + \hat{\beta}x_{it-2} + \epsilon_{it-2}\right] + \hat{\beta}x_{it-1} + \epsilon_{it-1}) + \hat{\beta}x_{it} + \epsilon_{it} \tag{5}$$

Gather terms

$$\mathrm{LS_{it}} = \hat{\alpha}^3\mathrm{LS_{it-3}} + \hat{\alpha}^2\hat{\beta}\mathrm{x_{it-2}} + \hat{\alpha}\hat{\beta}\mathrm{x_{it-1}} + \hat{\beta}\mathrm{x_{it}} + \hat{\alpha}^2\epsilon_{\mathrm{it-2}} + \hat{\alpha}\epsilon_{\mathrm{it-1}} + \epsilon_{\mathrm{it}} \tag{5'}$$

Going back further than four lags introduces more past values and more idiosyncratic error terms too. By repeated substitution, it can be demonstrated that through the lagged dependent variable dynamic specifications contain the entire history of the independent variable(s). Clearly this is not just a fixed effect (as sometimes assumed).

The inclusion of lagged independent variables

In equation (6) $LS_{it}$ is the life satisfaction of individual i in year t, $\hat{\beta}x_{it}$ is an independent variable, $\hat{\beta}_1 x_{it-1}$ is its first lag, and $\epsilon_{\mathrm{it}}$ is the usual error term. Starting with our simplified specification in equation (1), we repeatedly substitute for the lagged dependent variables.

$$LS_{it} = \hat{\alpha}LS_{it-1} + \hat{\beta}_1 x_{it} + \hat{\beta}_2 x_{it-1} + \epsilon_{it} \tag{6}$$

Substitute for $LS_{it-1}$ in (1):

$$LS_{it-1} = \hat{\alpha}LS_{it-2} + \hat{\beta}_1 x_{it-1} + \hat{\beta}_2 x_{it-2} + \epsilon_{it-1} \tag{7}$$

Substitute (2) into (1)

$$LS_{it} = \hat{\alpha}(\hat{\alpha}LS_{it-2} + \hat{\beta}_1 x_{it-1} + \hat{\beta}_2 x_{it-2} + \epsilon_{it-1}) + \hat{\beta}_1 x_{it} + \hat{\beta}_2 x_{it-1} + \epsilon_{it} \tag{8}$$

Substitute for $LS_{it-2}$ in (3):

$$LS_{it-2} = \hat{\alpha}LS_{it-3} + \hat{\beta}_1 x_{it-2} + \hat{\beta}_2 x_{it-3} + \epsilon_{it-2} \tag{9}$$

Substitute (4) into (3)

$$\begin{aligned} LS_{it} = {} & \hat{\alpha}(\hat{\alpha}\left[\hat{\alpha}LS_{it-3} + \hat{\beta}_1 x_{it-2} + \hat{\beta}_2 x_{it-3} + \epsilon_{it-2}\right] + \hat{\beta}_1 x_{it-1} + \hat{\beta}_2 x_{it-2} + \epsilon_{it-1}) \\ & + \hat{\beta}_1 x_{it} + \hat{\beta}_2 x_{it-1} + \epsilon_{it} \end{aligned} \tag{10}$$

Gather terms

$$\begin{aligned} \mathrm{LS_{it}} = {} & \hat{\alpha}^3 \mathrm{LS_{it-3}} + \hat{\alpha}^2 \hat{\beta}_1 x_{\mathrm{it-2}} + \hat{\alpha}\hat{\beta}_1 x_{\mathrm{it-1}} + \hat{\beta}_1 x_{it} + \hat{\alpha}^2 \hat{\beta}_2 x_{\mathrm{it-3}} + \hat{\alpha}\hat{\beta}_2 x_{\mathrm{it-2}} + \hat{\beta}_2 x_{it-1} \\ & + \hat{\alpha}^2 \epsilon_{\mathrm{it-2}} + \hat{\alpha}\epsilon_{\mathrm{it-1}} + \epsilon_{\mathrm{it}} \end{aligned} \tag{10'}$$

Supplementary material

Diagnostic testing of GMM dynamic panel models.

David Roodman, the architect of the software popularly used to undertake dynamic panel GMM estimations in Stata, *xtabond2*, warns that the complexity of such estimators, coupled with the simplicity of the software packages employed to undertake such estimations, can cause unwitting misuse (Roodman 2009a). Much of the (currently) small literature that employs such models within the 'economics of life satisfaction' area provides examples demonstrating Roodman's concern is valid. To help somewhat, the following discussion considers diagnostic testing for these models. The important tests are the Hansen *J* test, the various *C* (or 'difference-in-Hansen') tests and the *m2* test for autocorrelation. This latter test, necessary but not sufficient, provides one check on the whether the lags employed as instruments are valid. Typically, and this is the case with the models employed in this investigation, this requires the rejection of the null of no first order autocorrelation and non-rejection of the null of no second order correlation. This is well understood by most of the papers that use this model to investigate life satisfaction. The other tests are more complex and the cause of some misunderstanding (in the well-being literature) and are discussed below.

The Hansen (1982) test *J* statistic has a null hypothesis of exogenous instruments and refers to all of the instruments collectively. [27] Rather than rejecting or (not rejecting) the null hypothesis with the typical value of 0.05, Roodman offers what he calls a 'common sense' value instead. His recommended minimum threshold is a p-value of at least 0.25 and he (2007, p.10) warns that researchers:

> should not view a value above a conventional significance level of 0.05 of 0.10 with complacency. Even leaving aside the potential weakness of the test, those thresholds are conservative when trying to decide on the significance of a coefficient estimate, but they are liberal when trying to rule out correlation between instruments and the error term. A *p*

[27] This test has the advantage over the Sargan *J* test (also reported by default) because it works in the presence of heteroscedasticity. Indeed, if the errors are homoscedastic then the Hansen test is the same as the Sargan test.

> 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.

Thus, the J tests, Hansen and Sargan, inspect all of the generated instruments together, with a null hypothesis of exogenous instruments. Low p-values mean that the instruments are not exogenous and thus do not satisfy the orthogonality conditions for their use. Within the well-being area, some of the GMM studies do not test (or at least report) the Hansen J test result, risking what Sargan calls, more generally, a 'pious fraud' (Godfrey 1991, p.145). Other dynamic well-being studies report a very low p-value and incorrectly assert that this indicates that the instruments are appropriate for estimation.[28] When some of the estimates the p-value for the Hansen *J* test are low much caution must be attached to those results, no matter how plausible they seem.

Valuable, but even more neglected in the well-being GMM literature (almost wholly ignored by the dynamic panel life satisfaction literature so far), are the difference-in-Hansen (or C) tests.[29] These are diagnostic tests that inspect the exogeneity of a particular subset of instruments, and are, by default, reported by *xtabond2*. Thus, this means that researchers can check the model validity that results from their choices of which regressors should be treated as exogenous and which endogenous. This decision is crucial since it can affect the overall *J* test result and can alter somewhat the coefficients obtained for the independent variables (although not qualitatively the lagged dependent variable; see Piper (2015b) for an illustration of this impact). This *C* test is well explained in Baum et al. (2003, sections 4.2 and 4.4) as well as the papers by Roodman referred to above.

These difference-in-Hansen tests also inspect the 'initial conditions' problem, which refers to the relationship between the unobserved fixed effects and the observables at the time of the start of the

[28]Bottan and Perez-Truglia (2011), for example, report p-values of <0.001 (Table 1A) and incorrectly state that they cannot "reject the null of the Sargan test at the 1% level" (p.230). This value, however, is a strong rejection of the null. In their study, only once is the p-value of the Sargan test above 0.25. However, this may not necessarily invalidate all of the results because, for the reason put forward in a footnote just above, the Hansen test (unreported) is the more appropriate *J* test.

[29] An exception is a dynamic panel investigation into the well-being of young people (Piper 2015b).

panel subset employed. For estimation to be valid, it is necessary that changes in the instrumenting variables are uncorrelated with the individual-specific part of the error term. This is tested by the difference-in-Hansen GMM test for levels, reported by *xtabond2.* This diagnostic also gives a test of system GMM or difference GMM, with the former being strongly supported in all of the dynamic panel estimates of section 3.