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Danish-German Research Paper No. 4:

The Benefits, Challenges and Insights of a Dynamic Panel Assessment of Life Satisfaction

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Abstract:

This study discusses and employs System Generalised Methods of Moments (GMM) dynamic panel analysis to investigate life satisfaction. There are many benefits that such an investigation provides, though commensurate challenges too. Previous attempts to employ dynamic models within life satisfaction research have, in the main and for different reasons, not been wholly successful. This article explains why, how such research can be improved and undertaken in the future, as well as offering insights into life satisfaction and its dynamics. A key insight is that much of the impact of any commonly measured variable on well-being is contemporaneous.

Abstrakt:

Diese Studie diskutiert eine dynamische Panelanalyse in Form einer System Generalised Methods of Moments (GMM) und untersucht auf deren Basis Lebenszufriedenheit. Solch ein Ansatz bietet viele Vorteile, ist jedoch mit einigen methodischen Herausforderungen verbunden. Früherer Versuche, dynamische Panelanalysen auf Lebenszufriedenheit anzuwenden, haben aus verschiedenen Gründen eher gemischte Ergebnisse erbracht. Dieser Beitrag zeigt auf, wie dieser Forschungsansatz zukünftig verbessert werden kann und liefert Einsichten in die Dynamik von Lebenszufriedenheit. Ein wichtiges Ergebnis ist, dass ein Großteil des Einflusses der üblichen Einflussvariablen auf die Lebenszufriedenheit zeitgleich erfolgt.

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

The Benefits, Challenges and Insights of a Dynamic Panel Assessment of Life Satisfaction

1. Introduction

Dynamic panel models have become increasingly popular in many areas of economic enquiry, and their use has provided new insights. Some recent 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. 2014). 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. This paper describes the benefits and challenges of dynamic panel analysis in a well-being context, and employs the model to provide new insights for the understanding of well-being. In doing so, this paper is somewhat atypical because it does not have a specific research question to investigate; rather, it provides a general illustration of a popular dynamic panel analysis model can be applied to the investigation of well-being, an area where (at the time of writing) the model is little understood.

There are substantial benefits available for researchers who undertake a dynamic panel analysis of well-being (particularly when compared to the currently more standard static fixed effects analysis). These benefits include the ability to obtain short-run (or contemporaneous) coefficients as well as long-run estimates; the ability to obtain coefficients for time-invariant variables; results obtained, unlike fixed effects results, are generalizable out of the sample; and researchers can account for potentially endogenous explanatory variables (an issue of perhaps especial importance for life satisfaction). Regarding well-being, this model has recently been used to investigate the popular issue regarding the existence or otherwise of a U-shaped relationship between age and life satisfaction, taking advantage of some of these benefits to offer new evidence for this debate (Piper 2015). These models also enable researchers to learn about the dynamics of well-being. Furthermore, tests of life satisfaction panel data frequently indicate that there is serial correlation in the residuals which is indicative of omitted dynamics. The residuals could be 'corrected' but a better solution is to incorporate dynamics explicitly into the estimation. This investigation discusses all these benefits employing a sample from the British Household Survey.

This is not the first investigation to use the model, though the existing literature has some problems in its use of dynamic models. This literature 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) and contains omissions and misunderstandings. For example, none of these studies address the well-known 'initial conditions' issue (Blundell and Bond 1998); many of them misunderstand the necessary diagnostic tests, or do not report all (or any) of the important diagnostic test results; some of the studies listed just above do not understand the interpretation of the model which is different from the more standard fixed effects analysis. Specific instances are detailed in this paper, often in footnotes, but in general future well-being work taking advantage of the benefits that a dynamic panel assessment offers needs to be more appreciative of the complexity of the model and its necessary diagnostic tests (collectively the challenges of this article's title). 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. As mentioned above, such models have proven useful in other areas of economic enquiry, and they should for life satisfaction too.

Dynamics are often modelled by including a lag of the dependent variable on the right-hand side of the regression equation. Such an inclusion changes the interpretation of the right-hand side variables, which now indicate contemporaneous correlations conditional on the history of the model. The history of the model is itself contained within the lagged dependent variable (see appendix 1 for the algebra). Discussed in more detail below, the coefficients for right hand side variables and the lagged dependent variable enable researchers to find overall (long-run) coefficients for the explanatory variables as well as contemporaneous (or short-run) ones. Very much connected with this is the possibility to determine the influence of the measured past, which the lagged dependent variable represents.

The dynamic model used here is System Generalised Method of Moments (GMM) (discussed in more detail in section 2) which enables the explanatory variables to be treated as potentially endogenous or exogenous. This is potentially important for well-being, enabling the investigation of variables that may once have been considered *verboten* for analysis (as well as being better suited than standard models for determining coefficients for time invariant variables). An example of this is Piper (2014a) which investigates the relationship between life satisfaction and perceptions of the future, treating the latter as potentially endogenous with respect to life satisfaction. After the choice of endogeneity or exogeneity (informed by theory) there are diagnostic tests available to check the validity of the instruments created as a result of this decision. Furthermore, system GMM does not have to be dynamic so this benefit is available to researchers who are not interested in dynamics, though a central argument of this paper is that dynamics are interesting and should be given consideration even if they are not ultimately included.

The challenges of a dynamic panel analysis provide reasons why researchers may not ultimately undertake such an analysis. This paper provides an illustration of some of the challenges of a dynamic panel analysis for well-being. The complexity of the model and its diagnostic tests are the main sources of these challenges, and a reason why some of the previous well-being studies using this model are not fully successful. A current particular challenge with System GMM dynamic panel models is that its undertaking is computationally intensive and memory hungry and this can mean large samples cannot be investigated. To 'solve' this problem, this investigation has split the sample by gender, estimating the equations separately for males and females. Due to initially poor diagnostic test results in the female case, other female samples were used with differing diagnostic test result outcomes (based as they are on different samples and different choices of endogeneity and exogeneity). The results obtained for the various coefficients, however, are robust to different diagnostic test outcomes. Similarly, the important result regarding the dynamics of life satisfaction is unchanged. A recommendation is made that, due to the seeming difficulty of passing all the diagnostic tests and the novelty of such estimations in the 'life satisfaction' area, researchers should do the following: test different samples; present all of the results from the different samples; present all of the different diagnostic test results; and make sure that the discussion of the results emphasises the necessary caution despite the apparent robustness of the results. The results discussion of section 3 is an example of this.

The remainder of the article is organised as follows: the data and methodology is discussed in Section 2, with separate subsections addressing the choice of the System GMM estimator and its diagnostic tests; Section 3 presents and discusses the results; 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 5 offers concluding remarks. Finally, for comparison purposes, appendix 2 contains the results from a fixed effects analysis of the same dataset.

2. Data and Methodology

This section starts with a brief description of the dataset and sample used, before moving on to discuss, in two subsections, aspects of methodology with respect to dynamic panel modelling. The first subsection explains why system GMM was chosen; the second discusses the diagnostic testing necessary for such a model.

The data come from the British Household Panel Survey (BHPS), a nationally representative longitudinal survey, which was established in 1991. Widely used in the literature within the 'economics of happiness' area, it 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 3 contains a table which shows the distribution of responses to this question for males and females. The pattern shown is typical for life satisfaction data. 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. Thus, included in the investigation is a continuous variable for log wage and dummy variables (thus easily interpreted) accounting for labour force status, marital status, education, health, age range, wave, and region. Appendix 3 also contains 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.

2.1 Choosing a suitable estimator.

In the second paragraph of the introduction reasons were advanced in the introduction for a consideration of dynamics in an analysis of well-being. And 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 check 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).[1] Adding dynamics to the model is usually undertaken by including a lag of the dependent

[1] This strong rejection of the null of no autocorrelation in panel data was also found after running similar regressions with the German Socio-Economic Panel (GSOEP), another major source of panel data for the economics of happiness literature. On the basis of this evidence, future happiness estimates using the BHPS and the GSOEP (and perhaps other panels) should routinely check for omitted dynamics, and proceed based on the outcome of such an inspection.

variable as a right hand side variable. Hence, what is estimated is 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 (ϵ_{it}), which captures our general ignorance of the determinates of y_{it}. However, this cannot be estimated accurately by OLS or by fixed effects estimation. An OLS estimator of β in equation 1 is inconsistent, because the explanatory variable $y_{i,t-1}$ is positively correlated with the error term due to the presence of 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 correlations 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).[2] These

[2]These biases have been misunderstood in some of the well-being work which estimates similar equations. For example Della Giusta et al. (2010) incorrectly state that the biases are general, and "therefore, we have reported both of the [whole of] OLS and fixed effects results as a comparison (both of which do not include a

biases are illustrated in a brief comment paper (Piper and Pugh, 2015), which complements well this investigation into the dynamics of life satisfaction.

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 ε_{it}. Because, with GMM, instrumentation is not confined to one instrument per parameter to be estimated, the possibility exists of defining more than one moment condition per parameter to be estimated. It is this possibility that is exploited in the GMM estimation of dynamic panel models, 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 difference ($y_{it-2} – y_{it-3}$) and the lagged level y_{it-2}. Both of these should satisfy the two conditions for valid instruments, since they are likely to be highly correlated with ($y_{i,t-1} - y_{i,t-2}$) but not with $(\varepsilon_{it} - \varepsilon_{i,t-1})$. It is this easy availability of such "internal" instruments (i.e., from within the dataset) that the GMM estimators exploit. The "difference" GMM estimator follows the Arellano and Bond (1991) data transformation, where *differences are instrumented by levels*. The "system" GMM estimator adds to this one extra layer of instrumentation where, 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

lagged dependent variable)" (p.10). This is also wrong because the coefficients for the independent variables from dynamic GMM panel analysis and those from OLS and fixed effects are not referring to the same things, and should not be directly compared. This is an important point for dynamic panel analysis, and is discussed later to aid the results interpretation (and subsequent discussion).

[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 (2005) for a detailed textbook treatment.

system GMM) (Roodman 2009a, p. 104). 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 (see section 2.2). 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.[4]

Before estimating any dynamic panel model there are two important (and linked) considerations. 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 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 that marriage is potentially endogenous (Stutzer and Frey 2006). Concerning life satisfaction, arguments could be advanced for income and health being endogenous variables too. Diagnostic tests are available and built in with *xtabond2*, the Stata command employed for the empirical analysis, to check the validity of the models that result from this choice. The actual choice made is based on theoretical considerations of the likely relationships between life satisfaction and the right-hand side variables.[5] This resulted in, initially, the treatment of marital status only as potentially endogenous, and everything else treated as exogenous. For females, in additional

[4] 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.
[5] Future work within the well-being area should focus on the likely endogeneity and exogeneity of typical right hand side variables and life satisfaction. As mentioned above, as yet there is little theoretical guidance.

estimates, health and income are also treated as endogenous. As explained below, the results from these choices are consistent despite differing diagnostic test outcomes.

2.2 Diagnostic tests

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. Some of the following discussion, particularly in the footnotes, illustrates some of the methodological problems of some of this literature. 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 in the remainder of this subsection.

The Hansen (1982) test *J* statistic has a null hypothesis of exogenous instruments and refers to all of the instruments collectively. [6] 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:

[6]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.

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* 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.[7] Discussed below, some of the estimates the p-value for the Hansen *J* test are low and thus caution is 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.[8] These are diagnostic tests that inspect the exogeneity of a particular subset of instruments, and are, by default, reported by *xtabond2*.[9] 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. [10]

[7]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. Powdthavee (2009) reports the Hansen version of the *J* test, but the p-values are often under 0.25. In that article there is a supporting claim that values between 0.1 and 0.25 are within Roodman's (2007) acceptable range: as we can see from the Roodman quote just above this is incorrect.

[8] The exceptions, apart from this article, are a dynamic panel investigation into the well-being of young people (Piper 2015), and an investigation of perceptions of the future on well-being (Piper 2014a).

[9]It does this by re-estimating the Hansen *J* test without the subset of interest, and comparing the result with that for the overall (full instrumentation) Hansen test.

[10]Wunder (2012) does not discuss this decision but treats all the regressors as exogenous. Whether this is appropriate or not, it is impossible to judge from the study. This may be a consequence of the paper's brevity: published in Economic Letters it is just over two pages long. Della Giusta et al. (2010), follows Powdthavee (2009) in treating all of the independent variables as endogenous apart from the age and wave dummies. Their

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 (2015) 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 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 the next section. Roodman (2009b, section 4) discusses this diagnostic test as well as the other tests, 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).[11]

As recommended these are presented in the results table of the next section. Importantly, 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.

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reported *J* test result suggests that, for females, their model is likely to be invalid. Here, as table 1 shows and is discussed further below, the first attempt at estimating female life satisfaction also has this problem.

[11] 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.

3. Results

This section presents and discusses the results from dynamic panel estimation, after an explanation of how the coefficients need to be interpreted, and then proceeds to discuss 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) $\boldsymbol{x}_{it}$ 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). In Appendix 1, the lagged dependent variable is shown algebraically to be the entire history of the model and not just a fixed effect (as sometimes assumed).

Table 1 displays the results for four estimations, one of which is for males and three are for females.[12] This explanation of the table starts with males, as this is easier to explain (and perhaps understand), and then proceeds onto the other three columns. For males, the estimation uses default instrumentation, i.e. it uses all available lags as instruments, utilising the full length of the sample.[13] 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 which

[12] 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).

[13] 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..

start at the first available lag and do not employ every additional available lag (unlike the employed default instrumentation).

[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), marriage, health (both self-reported as good or excellent relative to a dummy variable capturing fair health and worse responses); 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[14] 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. Important for an analysis of dynamics, the coefficient obtained for the lagged dependent variable is discussed below (in Section 4). 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 is ruled out, and the p-values for the *J* and *C* ('Diff-in-Hansen' in the table) tests are above Roodman's 'common sense' minimum of 0.25 (as discussed in the previous section).

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 instruments created 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

[14] This might be 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.
[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, nor is there any attempt at checking the robustness of the obtained coefficients.

with a 0.053 chance of 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 column the instruments are endogenous with the error term 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 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 various null hypotheses of exogenous instruments are supported (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 2).[16]

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 is (investigation not shown) a reason for the different sign when compared to males.[17] 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 any contemporaneous well-being effects of education fade, on average, as individuals age. 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 2 using the same dataset).[18]

Not yet discussed is the lagged dependent variable, including its obtained coefficient. This provides a central insight of this investigation, and enables 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.

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[16] This similarity of coefficients for the different dynamic panel estimates perhaps indicates that researchers should, in future related research, report the results and add a caveat regarding the diagnostic results rather than just dismissing the obtained results (or not reporting all of the diagnostics). A second best solution is to demonstrate robust results to differing diagnostic outcomes, rather than a first best outcome of perfect diagnostic results, which is perhaps not possible with current valuable panel data surveys.

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

[18] 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 not enough variation for fixed effects estimation to provide estimates for the coefficients for education with precision.

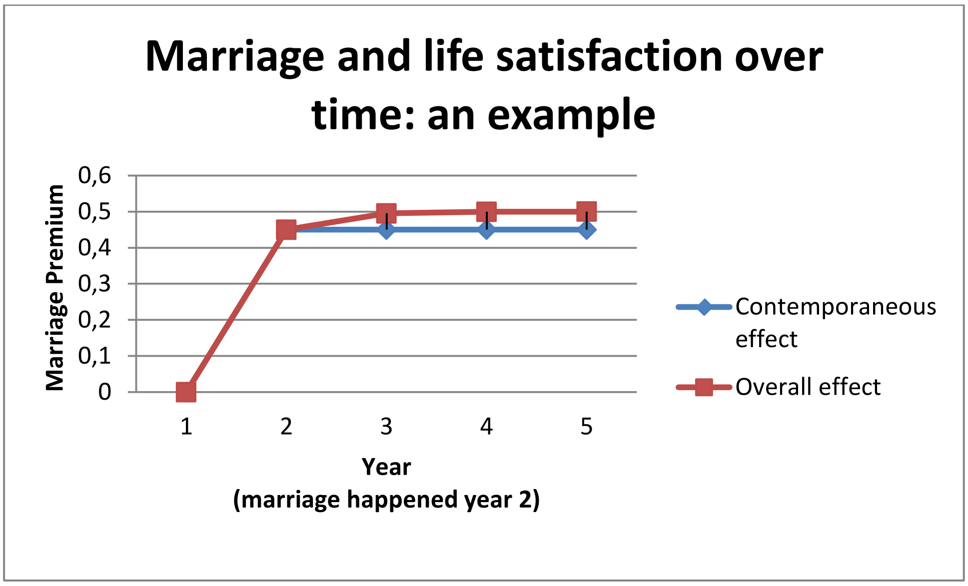
4. Discussion of the lagged dependent variable coefficient

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) and the algebra (in appendix 1) 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 past. 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; Della Giusta et al 2010; Bottan and Perez-Truglia 2011; Piper 2012; Wunder 2012; Piper 2014b).[19] Recently, the GSOEP has been used to investigate the impact of how individuals perceive the future in general, taking advantage of GMM's ability to create exogenous instruments for potentially endogenous explanatory variables, and also finds a small, yet significant positive influence of lagged life satisfaction on current life satisfaction (Piper 2014a). 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 of exogeneity and endogeneity; 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. This is something the next few paragraphs rectify.

[19] Powdthavee (2009) does not consistently find a significant effect of lagged life satisfaction, however as mentioned previously the estimations do not exhibit good diagnostic test results. In the estimations that are closest to those of this investigation, (columns 7 and 8 of Table 2) he finds a small, positive significant effect of past life satisfaction of current life satisfaction. The empirical results of Bottan and Perez-Truglia (2011) for the (Arellano-Bond) autoregressive happiness estimates (Tables 1A-1D), based on panel data from four countries (Britain, Germany, Japan and Switzerland) overwhelmingly find a small positive and statistically significant coefficient. Piper (2012) has also found a very similar coefficient for lagged life satisfaction for the twenties age range, the fifties age range, and when using the Caseness and Likert General Health Questionnaire composites as a proxy for life satisfaction.

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 lagged dependent variable.[20] Taking marriage as an example, the contemporaneous effect of marriage for males (column 1 of table 1) compared to being single is approximately 0.45, indicating that married people are, on average, nearly half a point more satisfied with life (ceteris paribus) on the BHPS's 1-7 scale. The overall value (or long-run value) is of 0.5 (which comes from 0.45/1-0.1), approximately 90% of which reflects the contemporaneous effect of being married. Being married in the past contributes only a small amount to life satisfaction.[21] The following graph illustrates the life satisfaction premium for marriage over time (assuming that the marriage takes place in year 2). On average, being married (compared to being single) contributes to well-being sometime after getting married.

Figure 1: Illustration of life satisfaction effect of marriage



[20] 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.

[21] To help illustrate what this means in practical terms, I paraphrase a colleague: "I think that's right. Most of the well-being effect of marriage for me is being married currently. I feel a residual satisfaction that I have found someone who has put up with me for nearly thirty years – a small sense of satisfaction in that – but most of the happiness effect, for me, is in being married now."

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 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 of being married (unemployed, enjoying very good health, or any other statistically significant variable) is contemporaneous. Unemployment, as another example, is very similar: the contemporaneous coefficient for males is -0.43, so the long run coefficient is approximately -0.48. Much of the negative impact of being unemployed is contemporaneous, and like marriage 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. As a further illustration, consider the long-term unemployed: for them, 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.

Figure 2: Illustration of life satisfaction effect of unemployment

Both of these results help illustrate the highly contemporaneous nature of life satisfaction. 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.[22] 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 phenomenon. Potentially similarly explained 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.

Such a result – life satisfaction scores largely reflecting contemporaneous events with a minor influence from the past – offers a reframing of the adaptation question.[23] Thinking about adaptation as getting used to an event from the past (e.g. marriage) can obscure what seems to be occurring with well-being. Well-being appears to (largely) reflect what is going on now rather than what happened in the past: being married now matters more than the historic act of marriage; being unemployed mattering more than entering unemployment in the past. The question researchers should perhaps ask instead is: does this event, or situation, have a contemporaneous effect on life satisfaction? In other words, is an individual's happiness affected by this situation or status *now*? For an event to have a legacy or long term impact on an individual's life satisfaction it seems likely that it must have a profound effect on the individual's day to day life sometime after the event is entered into. Dynamic panel analyses, with their estimates of contemporaneous coefficients for the explanatory variables, can discover this.

[22] 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.
[23] See Luhmann et al (2012) for a meta-analysis regarding subjective well-being and adaptation.

5. Conclusion

Subjective well-being, as assessed by life satisfaction data, is strongly influenced by contemporaneous circumstances and events. Any direct influence of the measured past is somewhat minimal.[24] This key result could not be found via standard fixed effects (or other non-dynamic) methods. This investigation into the concept of life satisfaction and its dynamics has taken advantage of theoretical advances, coupled with increases in our collective understanding of using General Method of Moments procedures, to estimate dynamic panel models. This, along with the subsequent technical and computational advances, makes running such models possible and somewhat straightforward.

Roodman (2009b) warns that such apparent simplicity can mean such models are estimated incorrectly and without full diagnostic testing. Indeed, as this article has shown, studies in the well-being area often misunderstand the diagnostic test outcomes, or fail to report them or discuss them sufficiently. Helping to foster an increased understanding of such models, particularly in the well-being area, is a central aim of this article. Future research using these models needs to remedy current misunderstandings and omissions. 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 appear qualitatively very robust which offers 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.

[24] This does not, however, rule out indirect influences where individuals make contemporaneous decisions which may partly reflect their past.

The analysis and results of this study both support and extend recent research. The central finding of a 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, being married contributes, on average, to well-being years after getting married; most of the contribution for life satisfaction of being married comes from being currently married (as opposed to previous years of marriage). This outcome is likely to be in contrast to events that are one-offs: the analysis here suggests reasons for previous findings that any feel good factor from events like the Olympics do not have a legacy in terms of individual well-being.

The consistent, positive, yet small influence of the measured past on current life satisfaction could not have been found using the current 'workhorse' static models (like fixed effects). An initial reason for a dynamic panel analysis was the likelihood that many static 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) that 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 enabling the estimation of coefficients for variables previously deemed impossible to investigate.

Studies in the well-being area have started to employ dynamic panel methods, but often do not adequately consider the necessary diagnostics nor appear to fully understand how such models need to be interpreted. Such methods are more complex – a substantial part of the challenge of this article's title – than the standard fixed effects and this additional complexity needs to be better understood. It is not enough just to include a lagged dependent variable in standard well-being estimations without considering the additional complexity involved. 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.

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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 ≠: the 10 females aged 35 or lower in the data set are included in the other labour force status category; Ψ here, health and real income are treated as endogenous as well as marital status.

APPENDIX 1

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 ϵ_{it} is the usual error term. Starting with our simplified specification in equation (1), we repeatedly substitute for the lagged dependent variable.

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

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

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

Substitute (2) into (1)

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

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

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

Substitute (4) into (3)

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

Gather terms

$$\mathrm{LS}_{it} = \hat{\alpha}^3\mathrm{LS}_{it-3} + \hat{\alpha}^2\hat{\beta}x_{it-2} + \hat{\alpha}\hat{\beta}x_{it-1} + \hat{\beta}x_{it} + \hat{\alpha}^2\epsilon_{it-2} + \hat{\alpha}\epsilon_{it-1} + \epsilon_{it} \quad (5')$$

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).

APPENDIX 2

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

VARIABLES	Both genders Life Satisfaction	Males Life Satisfaction	Females 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 3

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.

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