An Investigation into Happiness, Dynamics and Adaptation

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ABSTRACT: This investigation discusses and employs dynamic panel analysis to provide new insights into the concept of happiness, and particularly its dynamics. Arguments are advanced for its use both in terms of the advantages such analysis offers, and also because it takes into account dynamics omitted by more standard panel data estimation methods like fixed effects. Using the British Household Panel Survey, it is demonstrated that happiness is largely (but not wholly) contemporaneous. This helps to provide explanations for previous findings, inform the adaptation discussion, and generate new understanding regarding well-being. An event – no matter when entered into - must have a contemporaneous impact on either the life of an individual or an individual's perception of their life (or both) for it to be reflected in self-reported life satisfaction scores. Similarly, this contemporaneous finding also explains other results in the literature about the well-being legacy of events.

Keywords: Life Satisfaction, Dynamic Panel Analysis, GMM, Adaptation, Happiness

JEL codes: I31, J12, J64

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** This paper is prepared for the EALE 2014 conference, and is a substantial evolution from an earlier paper with a similar title (publicly available since late 2013). The (slight) name change here reflects a hope that this newer version will be read rather than the older one, of which this version is an improvement in a couple of significant ways. For useful comments I am grateful to Nick Adnett and Geoff Pugh as well as two anonymous reviewers. I have also benefited from suggestions from Andrew Clark, Yannis Georgellis, Gerd Grözinger, and Mehtap Hisarciklilar. The data used here were made available by the UK data archive. Neither the original collectors of the data nor the Archive bears any responsibility for the analyses or interpretations presented here.

An Investigation into Happiness, Dynamics and Adaptation

1. Introduction

The economic analysis of well-being has, over the past decade, largely settled on using fixed effects analysis with panel data.[1] This enables researchers to take advantage of the rich nature of nationally representative samples, like the British Household Panel Survey (BHPS) and the German Socio-Economic Panel (SOEP). With fixed effects analysis, researchers can control (to some extent) for individuals' dispositions and personalities in the sample, which is useful on the grounds that they may have different tendencies for feeling satisfied with their life. Clark and Oswald (2002) discuss some of the benefits and issues regarding examining well-being within panel surveys. Furthermore, panel data can track individuals before, during and after events which has proved helpful for insights into adaptation, which, broadly, asks if individuals get used to things, as well as anticipation. Use of fixed effects estimations was strongly supported by Ferrer-i-Carbonell and Frijters (2004), with an influential and highly cited analysis, who demonstrated the importance of taking into account fixed effects.[2] Assuming that well-being is ordinal or cardinal is much less important, they show, than utilising information from fixed effects, giving scholars 'permission' to make confident use of fixed effects analysis. Such an analysis has provided many insights for the scientific understanding of well-being. Useful reviews of studies (not restricted to results from fixed effects analysis) include Dolan et al. (2008), Clark et al. (2008a), and Becchetti and Pelloni (2013). In section 2 below, this investigation uses fixed effects, the 'workhorse' model before discussing and employing dynamic panel methods.

[1] Like much of this literature I use happiness, life satisfaction, and well-being interchangeably.

[2] In the ten years since its publication Ferrer-i-Carbonell and Frijters (2004), has been cited nearly 1,300 times (at the time of writing): an indication of just how important fixed effects has become in the analysis of well-being. Incidentally, this is over six times less than some of the key dynamic panel model papers referenced in this investigtion: an indication of the overall popularity of such models.

In other areas, for example corporate finance (Flannery and Hankins 2013), economic growth (Lee et al. 2012) foreign aid (Dutta et al. 2013) and school expenditure and school performance (Pugh et al. 2014) dynamic panel analysis has been shown to be worthwhile and useful, providing insights not available to static fixed effects analysis. This is what this paper does for the well-being area, discussing and utilising dynamic panel analysis for the assessment and investigation of life satisfaction. This provides new information regarding well-being (that could not be obtained via static fixed effects analyses), provides an additional viewpoint regarding current work in the area of adaptation, and provides an explanation for some existing results regarding the well-being legacy of events. In short, dynamic panel analyses of life satisfaction are useful, though not without challenges.

This paper joins, and comments on, the handful of papers that employ dynamic panel analysis utilising General Method of Moments (GMM) estimation. As Roodman, the architect of the software often used to run such estimations, states, reflecting recent advances permitting their use for applied research, these "difference and system GMM estimators can be seen as part of a broader historical trend in econometric practice toward estimators that make fewer assumptions about the underlying data-generating process and use more complex techniques to isolate useful information. The plummeting costs of computation and software distribution no doubt have abetted the trend" (2009, p.99). Other well-being studies that use this model include: Powdthavee (2009); Della Giusta et al. (2010); Bottan and Perez-Truglia (2011); Piper (2012); Wunder (2012). As well as the advantages over fixed effects listed above, this study explains (and remedies) the problem that fixed effects analyses neglect to consider the possibility of omitted dynamics in such estimations. The presence or otherwise of serial correlation is rarely tested for in the literature, and the analysis here, using a well-known and well-utilised data set, demonstrates that this is a substantial issue: the presence of serial correlation in the idiosyncratic error term means that there are omitted dynamics in the FE estimates (and in panel estimates generally). As King and Roberts (2012) forcefully argue, this should not be treated as a problem to be fixed by adjusting the standard error but instead as an opportunity to take advantage of this information and respecify the model.

The respecification presented here, which results from this strongly significant finding of serial correlation in the idiosyncratic error term, is to employ dynamic panel methods. In practice, this introduces a lagged dependent variable on the right-hand-side of the equation, which substantially changes the interpretation of the coefficients for the independent variables. Such an analysis also introduces more methodological considerations, including the ability to choose whether the independent variables are potentially endogenous or exogenous. A further advantage of dynamic panel methods over standard fixed effects analysis is the ability to distinguish between long-run effects and the contemporaneous effect of various variables on happiness. The results directly obtained from such an analysis are the new information or contemporaneous effects, and a quick post-estimation calculation can provide the long-run coefficients. Such models are more complex than the more standard fixed effects models and require careful consideration of the necessary diagnostic tests. A weakness of the majority of the existing studies that make use of dynamic panel models in a well-being context is that they either appear to misunderstand or neglect to discuss the key diagnostics.[3] By discussing these and highlighting diagnostic related concerns regarding other studies, this investigation also aims to help future well-being research. Investigating the dynamics of happiness is useful and interesting, but not without challenges too.

This paper is organised as follows. Section 2 discusses the data used, presents results from fixed effects analysis, and demonstrates that fixed effects analysis contains serial correlation in the idiosyncratic residual, an indicator of omitted dynamics. Section 3 discusses a solution

[3] Also, the substantial change necessary for the interpretation of the coefficients is not discussed in some of these papers too. A situation remedied in sections 4 and 5 below.

to the problem of omitted dynamics: dynamic panel analysis and the general method of moments. As mentioned above, such a method adds complexity to the standard fixed effects analysis and its key advantages and issues are more fully explained in Section 3. Using the same data employed in Section 2, Section 4 presents and discusses the results from the dynamic panel analysis. Section 5 discusses implications of using dynamic panel analysis, and these particular results, for the on-going adaptation discussion. Section 6 concludes.

2. A typical static panel analysis of well-being

This section briefly discusses the data, and the choice of a particular static panel model. Subsequently, the results are presented from the preferred static panel model, and following this is an explanation of why dynamic panel analysis can often be seen as necessary. The data come from the BHPS, a widely used data set within the economics of happiness literature, with the dependent variable being life satisfaction, measured on an ordinal scale from 1 to 7, 'not at all satisfied' to 'completely satisfied'.[4] The chosen independent variables, common to most previous studies, are income (deflated by the CPI and measured in thousands), job status, marital status, education, and health. Age range, wave and regional dummies are also included in the estimations.

Initial diagnostic tests (not reported here) establish that the workhorse model, FE, is the preferred static model, being more appropriate than random effects (RE) and ordinary least squares (OLS). This finding is typical in the literature and somewhat expected: the benefits of panel analysis as compared to pooled cross section analysis are numerous. An important benefit is that individual heterogeneity can be controlled for, and this helps us overcome

[4]As is typical in the literature this is treated as cardinal data. As mentioned in the introductory paragraph Ferrer-i-Carbonell and Frijters (2004) is an analysis that explains, as well as a chief reason why, this has become current practice.

Bentham's well-known apples and oranges concern. Fixed effects estimations investigate variation within an individual, which removes the need to compare between individuals. This estimation method effectively 'controls' for the time invariant characteristics of each individual, meaning that FE regressions allow (or control) for differences in personality and disposition that may be important determinants of life satisfaction.

The specification adopted here is typical of the estimations in the empirical economic literature, and is as follows:

$$LS_{it} = \alpha_0 + X_i'\beta + v_i + \epsilon_{it} \qquad (1)$$

Where LS_{it} is the response of individual i at time t to the life satisfaction question. χ_i is a 1 x k vector of covariates and β is a k x 1 conformable vector of parameters. v_i is the individual specific residual (the individual fixed effect) and ϵ_{it} is the 'usual' residual. The estimations also include time and regional dummies, and results for these regressions are presented in table 1.

[TABLE ONE ABOUT HERE]

The results in table 1 are similar to results of previous studies in this area, and qualitatively the same as those obtained when using robust standard errors. For both genders together, the following are positive and statistically significant for life satisfaction: real annual income (though with a p-value of 0.091); having a labour force status as other[5];being married; being divorced[6] and categorising health as good or excellent. The education variables, like real income, are also positive for life satisfaction at a confidence level above 90%. Being

[5] This might be caring for someone 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.

[6]Using the same dataset as the analysis here, the BHPS, Clark and Georgellis (2013), via a static panel analysis using lead and lag dummy variables, demonstrate that, on average, the newly divorced receive a boost to their happiness that they eventually adapt to. A result supported by the dynamic panel analysis of section 4.

unemployed, having a labour force status as long term sick or full-time carer, a marital status as being separated or widowed, are all statistically significant and negative for life satisfaction. The results for age are in line with the well-known U-shape pattern.

The genders individually, and particularly females, exhibit some differences from the whole sample. For males, widowed is statistically insignificant in its association with life satisfaction, and 'other' labour force status (see footnote 5 for details) is now negatively associated with life satisfaction. The statistical significance of the other right-hand side variables for males follows that of both genders together for the other variables however the size of many of the coefficients is higher than those obtained for the other two groups (both genders together and females). For females, real income is insignificantly related to well-being, being a full-time student is positive for life satisfaction, as is having an 'other' labour force status. For females, age is now (largely) statistically insignificant though the age range typically associated with minimum happiness over the lifecycle (41-50) is negative and statistically significant for life satisfaction. In summary these results, from fixed effects static panel analysis, are not unusual and reflect a substantial majority of previous findings in the 'economics of happiness' literature. The discussion and analysis, however, does not (and should not) end here with static analysis.

A further step is to 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).[7] This is potentially useful information, and it is clear that such a firm rejection of the assumption of no autocorrelation needs, somehow, to be modelled. One possibility is to recognise the clusters involved in the panel regression and to correct the standard errors accordingly. However this treats the omitted dynamics detected by the diagnostic test as a problem, rather than an invitation to respecify the model to include the omitted dynamics in the estimated part of the model, thus exploiting this additional information in estimation. This argument has recently been strongly supported by King and Roberts (2012) in a study of robust standard errors:

> Robust standard errors now seem to be viewed as a way to inoculate oneself from criticism. We show, to the contrary, that their presence is a bright red flag, meaning "my model is misspecified"… it appears to be the case that a very large fraction of the articles published across fields is based on misspecified models. For every one of these articles, at least some quantity that could be estimated is biased (p. 2).[8]

Accordingly, a potentially more interesting solution is to estimate a dynamic panel model.

3. Dynamic panel analysis discussion[9]

This section is informed by finding the presence of first order serial correlation in the idiosyncratic error term in the static estimation of section 2. Such a result can mean that the estimates generated by static panel analysis are inefficient and potentially misspecified. As Bond states, even when the dynamics themselves are not of direct interest "allowing for

[7] 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 SOEP (and perhaps other panels) should routinely check for omitted dynamics, and proceed based on the outcome of such an inspection.

[8] "We strongly echo what the best data analysts have been saying for decades: use all the standard diagnostic tests; be sure that your model actually fits the data; seek out as many observable implications as you can observe from your model. And use all these diagnostic evaluation procedures to respecify your model" (King and Roberts 2012, p.18).

[9] Two anonymous reviewer comments varied substantially regarding the amount of information provided in this section: one reviewer thought that parts, particularly the discussion of the diagnostics, could be considerably cut, and another reviewer was very appreciative and wanted more explanation. Because of the novelty of the method and the limited appreciation of the diagnostics in the well-being area, the discussion aims to introduce and explain important elements of the model. Incidentally, the results indicate that, perhaps, some of the diagnostics tests may not be so important in a well-being context. This possibility is discussed in the results section.

dynamics in the underlying process may be crucial for recovering consistent estimates of other parameters" (2002, p.1. see also p.20), a statement returned to in the discussion of the results. Adding dynamics to the model is usually undertaken by including a lag of the dependent variable as a right hand side variable. Hence, what is estimated is the following standard equation (with the independent variables excluded for clarity):

$$y_{it} = \beta y_{i,t-1} + (\alpha_i + \epsilon_{it}) \quad (2)$$

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 2 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 (α_i), which captures specific ignorance about individual i, and an error that varies over both individuals and time (ε_{it}), which captures our general ignorance of the determinates of y_{it}. However, this cannot be estimated accurately by OLS or by fixed effects estimation. An OLS estimator of β in equation 2 is inconsistent, because the explanatory variable $\beta y_{i,t-1}$ is positively correlated with the error term due to the presence of individual effects. A fixed effects estimation does not have this inconsistency because the equation is transformed to remove the individual effect, as in equation 3.

$$y_{it} - y_{i,t-1} = \beta(y_{i,t-1} - y_{i,t-2}) + (\epsilon_{it} - \epsilon_{i,t-1}) \quad (3)$$

However, equation (3) 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).[10]

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 General Method of Moments (GMM) estimation of dynamic panel models, first proposed by Holtz-Eakin et al. (1988).[11] The two models popularly implemented are the "difference" GMM estimator (Arellano and Bond, 1991) and the "system" GMM estimator (Arellano and Bover 1995). Greene (2002, p.308) explains that suitable instruments fulfilling the criteria mentioned above come from within the dataset: the lagged difference ($y_{it-2} - y_{it-3}$) ;and the lagged level y_{it-2}. Both of these should satisfy the two conditions for valid instruments, since they are likely to be highly correlated with ($y_{i,t-1} - y_{i,t-2}$) but not with $\left(\varepsilon_{it} - \varepsilon_{i,t-1}\right)$. 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 where the original *levels are*

[10]This bias has been misunderstood in some of the well-being work which estimates similar equations. Della Giusta et al. (2010) 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 lagged dependent variable)" (p.10). This is also wrong because the coefficients for the independent variables of dynamic GMM analysis and those of 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 (as well as informing the subsequent adaptation discussion).

[11]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 General Method of Moments,or Hall (2005) for a detailed textbook treatment.

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 2009, p.86). Secondly, any gaps in a panel – and this BHPS sample is unbalanced - are magnified by difference GMM (when compared to system GMM. Indeed this was a motivating factor for the creation and development of system GMM) (Roodman 2009, p. 104). And thirdly, unlike difference GMM, system GMM does not expunge the fixed effects (which are important in a well-being context) (Roodman 2009, p.114). 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. 2006, 2007, and 2009) are very informative.[12]

Such general advantages are useful in a specific well-being context. Powdthavee (2009), in a study that is wonderfully titled and quotes the singer Barry Manilow, investigates marriage and well-being using GMM estimation, arguing that this can also solve the problem of measurement error bias with self-reported life satisfaction. A further advantage of GMM estimation and the use of "internal" instruments is that applied researchers can select which regressors are potentially endogenous and which exogenous with respect to life satisfaction. This is a key choice with GMM panel analysis, and one that can often substantially change the coefficients for the right-hand side variables. Piper (2014) demonstrates this with a health variable: for young males, treating health as endogenous or exogenous changes the statistical significance of health being self-reported as good. The discussion below focuses on the

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

diagnostic tests and the interpretation of the results in some detail because (as mentioned in a footnote above) other well-being studies that use this method do not discuss them, partially discuss them, or appear to misunderstand them. Furthermore, this is also discussed in some detail because the method employed is relatively new in the well-being literature, and somewhat more complex than more standard methods like fixed effects.

Thus, 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). 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 help with this choice.

The choice of which regressors are to be treated as endogenous and exogenous is coupled with the consideration of how many instruments should be used, because that choice, in part, generates the instruments. A high number of regressors treated as endogenous means that a higher number of instruments are employed, ceteris paribus. Researchers can also affect the instrument count by changing the lag length to be used for instrumentation, and good practice is to test results for their robustness to different lag length choices (and hence different instrument counts).[13] Diagnostic tests are available for the appropriateness of the instrumentation collectively, and also for the subsets of instruments created by the regressors that are treated as exogenous or endogenous, as well as those generated by the lagged dependent variable. (Indeed, with *xtabond2* any subset of instruments can be tested, should the researcher want or need to.) These tests are asking whether the instruments are exogenous to the error term, and are returned to below.

Additionally, *xtabond2* contains a built in check on first and second order autocorrelation in first differences, which is an additional check on the appropriateness of the instrumentation.[14] For this investigation, the "system" GMM estimation was undertaken with the sample separated by gender. The reason is wholly pragmatic: such estimations are computationally intensive and it was not possible to perform the estimate for the whole sample.[15] The diagnostics of the chosen models should indicate that first order autocorrelation is present, but second order is not. This is discussed with specific reference to the models estimated in the next section, along with other diagnostic tests including the Hansen *J* and *C* test.

The Hansen (1982) test *J* statistic[16] has a null hypothesis of exogenous and refers to all of the instruments collectively. 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.

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[13]Iin a life satisfaction context, this choice appears to makes little difference to the subsequently obtained coefficients, but can matter for the autocorrelation diagnostic tests (discussed below). The association of well-being with the various right-hand side variables of the next section are robust to different lag length choices.

[14] Recall the explanation presented above utilising Greene (2002), regarding suitable instruments.

[15]Every dynamic regression both shown here, and undertaken as part of the diagnostic testing, employed the twostep robust procedure that utilises the Windmeijer (2005) finite sample correction for the two-step covariance matrix. Without this, standard errors have been demonstrated to be biased downwards (Windmeijer 2005).

[16]This 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 believed to be homoscedastic then the Hansen test is the same as the Sargan test.

Roodman's 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* 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 well-being studies report a very low p-value and incorrectly assume that this indicates that the instruments are appropriate for estimation.[17] As is discussed in the next section, for 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 perhaps even more neglected in the well-being GMM literature, are the difference-in-Hansen (or C) tests. These are diagnostic tests that inspect the exogeneity of a particular subset of instruments, and are, by default, reported by *xtabond2*.[18] Thus, this means that researchers can test their choice (and alternative choices) of which regressors should be treated as exogenous and which endogenous. This is crucial since it can affect the overall *J*

[17]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 this 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 footnote 11, 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.
[18]It does this by re-estimating the Hansen test without the subset of interest, and comparing the result with that for the overall (full instrumentation) Hansen test.

test result and, as mentioned above, the choice can considerably alter the coefficients obtained for the independent variables (although not qualitatively the lagged dependent variable). This test is well explained in Baum et al. (2003, sections 4.2 and 4.4) as well as the Roodman papers referred to above. Here, such testing (along with a consideration of the likely relationships between life satisfaction and the right-hand side variables) led, for males, to the treatment of marital status only as potentially endogenous, and everything else treated as endogenous.[19] For females, there are no suitable outcomes (in terms of the diagnostic testing) regarding which variables should be treated as endogenous and which exogenous. Consistent with the male estimation, initially marital status only is treated as endogenous for females and this lack of good diagnostic tests is returned to when the results are presented.

The 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*. Roodman (2009, section 4) discusses this, and in the conclusion to 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 2009, p.156).

[19]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 reported *J* test result suggests that, for females, like the outcome here, this is likely to be invalid. It seems that there is potentially no diagnostically valid outcome for British females, and my early work suggests this is possibly the case with both genders for the SOEP too.

As recommended these are presented in the results table of the next section, and potential consequences, for well-being, of not being able to reject the null of no exogeneity (for females) are discussed. Importantly, the next section commences with a discussion regarding how the coefficients need to be interpreted. An understanding of the interpretation of the coefficients, and particularly the coefficient on the lagged dependent variable, is important generally, and for the discussion of adaptation in Section 5.

4. Dynamic panel analysis 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, a footnote above states that coefficients obtained via OLS or FE are substantially different from those obtained by dynamic panel methods and cannot directly be compared. As Greene asserts

> *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 past). This means that contemporaneous associations of variables with life satisfaction can be usefully assessed via dynamic panel methods, whereas anything historic (perhaps, for example, education) is captured in the 'black box' of the lagged dependent variable itself.[20]In section 5, 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 2 displays the results for four estimations, one of which is for males and three are for females. The 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. 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 start at the first available lag and do not employ every additional available lag (unlike default instrumentation).

[TABLE TWO 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 (see footnote 5) 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 U shape. The coefficient obtained for the lagged dependent variable is discussed below. These results are robust to the number of instruments used which, for most variables, give qualitatively the same outcome. In the male case, the

[20]Piper (2013) discusses this in more detail along with the implications for modelling.

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* 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. The first column is every female in the sample, only marital status is treated as potentially endogenous, and the diagnostics of this estimation highlight that the instruments created are invalid.[21] 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 a 0.053 chance of error. The *C* test for valid instruments created for the lagged dependent variable can be rejected with a chance of error less than 0.01. Thus for the second column (the first female column) the instruments are endogenous with the error term and therefore invalid. Thus 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 how appropriate is it to instrument for life satisfaction levels and differences, the differences and levels of at least two years previously? 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. Piper (2014), for example, uses system GMM to investigate the well-being of young people and has marginal

[21] The 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.

concern with the diagnostics. The third column here (in table 2) focuses on females aged between 15 and 35 and has similarly valid instrumentation.

When restricting the sample to those females aged 35 and under, the diagnostic tests support the instruments used for estimation. The various null hypotheses tests 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 extends the sample's age range upwards 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 checking with AR(2) and the *J* test (which is, in the main, as far as the most conscientious dynamic panel work goes (in terms of diagnostic testing) in the well-being area). Subsets of instruments should also be investigated. Remarkably, despite the differences in the diagnostic test results, 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 (discussed below).[22]

In table 2, for females, 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 may be the reason for the different sign when compared to males.[23] Negative and statistically significant for

[22] This similarity perhaps indicates that researchers should report the results and add a caveat regarding the diagnostic results rather than just dismissing the obtained results. 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 valuable panel data surveys.

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

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 well-being effects of education, on average, fade as individuals age. None of these results – for females and males – are surprising, and the results from dynamic panel analysis support, reasonably well, results from most fixed effects analyses in the well-being area.

For both genders, there is one large difference between the results of table 2 and the results of table 1. With fixed effects analysis (table 1), having a marital status of separated is negative for well-being whereas with dynamic panel analysis it has an effect that is insignificantly different from zero. The reason for this may well lie in the differences with what the coefficients refer to. Table 1 results reflect full information, whereas table 2 results are based on contemporaneous (or new) information while controlling for the past. This helps with the insights about adaptation, discussed in more detail in the next section. As there is no contemporaneous effect of being separated, an argument can be made that being separated is adapted to whereas unemployment, marriage, health, being long-term sick or disabled, or a full-time carer, which all have a contemporaneous effect, are not. Additionally, for males only, analogous arguments indicate that being separated, divorced or widowed is adapted to; each of these, when reflecting 'full information', has an impact on well-being, but no contemporaneous effect. The well-being impact of each of these marital statuses is likely to be in the past.

An additional interesting difference between the results from the fixed effects analysis and the dynamic panel analysis relates to the size of the coefficients obtained for being married. In all cases it is considerably higher in the dynamic estimates. This may well indicate that fixed effects analysis underestimates the association of marriage with well-being. Fixed effects information uses full information in the dataset to obtain coefficients, which will include people who have definitely become separated or divorced within the dataset. Information from people who were married but one year later were not (or were married at *any* time) is used in the calculation of the effect of marriage on well-being, whereas dynamic panel effects reflect people who are currently married. Of course, such people may get divorced or become separated in the future but we know for sure that the marriage coefficient reflects people who are currently married and does not have information for people who, it is already known, got divorced or separated (or, perhaps less importantly for this argument, widowed). As much of life satisfaction is contemporaneous, perhaps life satisfaction is better investigated when only contemporaneous coefficients are calculated. The quote from Bond (2002) near the start of section 3 above, based on the different argument of ignoring omitted dynamics, similarly suggests that allowing for dynamics may be important for obtaining consistent values for other (i.e. non lagged dependent variable) parameters.

This splitting up of the past and the current situation is an advantageous aspect of dynamic panel analysis and is discussed just below. Similarly, the lagged dependent variable is interesting, and informs the discussion regarding adaptation of the next section. Here, we note that it is small, positive, statistically significant, and consistent across the estimations And as the next section explains, this result is consistent with other happiness studies that employ a dynamic panel model. To conclude this section, it is worth noting that in all cases, dynamic GMM estimation for life satisfaction also passes Bond's (2002) informal test for a good estimator (also mentioned above near the start of section 3): the coefficient for the lagged dependent variable of 0.1 is lower than that obtained by OLS (which is biased upwards) and higher than that obtained by fixed effects (which is biased downwards).[24]

5. Adaptation implications and discussion

Dynamic panel analyses can isolate contemporaneous effects, controlling for the past. This is useful for issues regarding adaptation which, broadly, asks whether individuals get used to things or not. Similarly, dynamic panel analyses can inform about the impact of the past on current well-being in comparison with contemporaneous events and situations. This is discussed in more detail below, however the overall conclusion for this comparison is that life satisfaction is largely determined by contemporaneous matters with a small, though significant, positive effect from the past. It is the lagged dependent variable that informs about the influence of the past, and the lagged dependent variable also enables researchers to calculate long-run values. All of these issues are complementary and discussed in this section, which first focuses on what the lagged dependent variable means.

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 (4) LS_{it} is the life satisfaction of individual i in year t, $\hat{\beta}x_{it}$ is

[24] These upwards and downwards biases are substantial. Recently lagged dependent variables have been employed in OLS estimations in well-being work, and it is neither clear whether the biases have been taken care of, nor clear whether sufficient diagnostic testing has taken place, nor if the results have been appropriately understood given the complexities involved with introducing a lagged dependent variable (some of which this paper has tried to explain).

an independent variable and ϵ_{it} is the usual error term. Starting with our simplified specification in equation (4), we repeatedly substitute for the lagged dependent variable.

$$LS_{it} = \hat{\alpha}LS_{it-1} + \hat{\beta}x_{it} + \epsilon_{it} \tag{4}$$

Substitute for LS_{it-1} in (4):

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

Substitute (5) into (4)

$$LS_{it} = \hat{\alpha}(\hat{\alpha}LS_{it-2} + \hat{\beta}x_{it-1} + \epsilon_{it-1}) + \hat{\beta}x_{it} + \epsilon_{it} \tag{6}$$

Substitute for LS_{it-2} in (4):

$$LS_{it-2} = \hat{\alpha}LS_{it-3} + \hat{\beta}x_{it-2} + \epsilon_{it-2} \tag{7}$$

Substitute (7) into (6)

$$LS_{it} = \hat{\alpha}(\hat{\alpha}\left[\hat{\alpha}LS_{it-3} + \hat{\beta}x_{it-2} + \epsilon_{it-2}\right] + \hat{\beta}x_{it-1} + \epsilon_{it-1}) + \hat{\beta}x_{it} + \epsilon_{it} \tag{8}$$

Gather terms

$$\mathrm{LS}_{it} = \hat{\alpha}^3\mathrm{LS}_{it-3} + \hat{\alpha}^2\hat{\beta}x_{it-2} + \hat{\alpha}\hat{\beta}x_{it-1} + \hat{\beta}x_{it} + \hat{\alpha}^2\epsilon_{it-2} + \hat{\alpha}\epsilon_{it-1} + \epsilon_{it} \tag{8'}$$

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).

Thus, the lagged dependent variable informs about us the influence of the past. In section 4 (and in the studies discussed below) this coefficient is positive, suggesting a persistence or inertia effect from previous happiness (which, as shown, is really the past): lagged happiness being positively associated with current happiness. That the coefficient is small (around 0.1) indicates that the influence of the past is minor, demonstrating that what are most important for the determination of current happiness are current circumstances and events. To a greater or lesser degree, every study mentioned previously that uses GMM for dynamic estimation finds a small, positive coefficient (Powdthavee 2009; Della Giusta et al 2010; Bottan and Perez-Truglia 2011; Wunder 2012)[25]. Piper (2012) has also found a very similar coefficient for lagged life satisfaction for the twenties age range, fifties age range, and when using the Caseness and Likert General Health Questionnaire composites as a proxy for life satisfaction. These similar results for the lagged dependent variable are obtained despite many differences including: the equation estimated; the datasets employed; alternate choices of exogneneity and endogeneity; and the use of lags for other independent variables.

That most of the impact of well-being is contemporaneous explains 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 afterwards.[26] 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. Similarly, Kavetsos and Szymanski (2010) 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 effects. In the language of time-series econometrics, such events are crash dummy variables, in comparison with shift dummies which reflect a more permanent change (for example, being

[25]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. With German data Wunder obtains almost exactly the same coefficient as those reported in section 4 in regressions that do not employ the additional lags of the dependent variable. This is not reported in Wunder (2012) because it is not diagnostically appropriate, there is AR(2) serial correlation in the such estimates with the GSOEP (email correspondence). I have also found figures around 0.1 to 0.12 for various estimations using the GSOEP too, but like Wunder's work the diagnostics do not sufficiently support the estimation..

[26] 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.

married). Figure 1 illustrates this, with an assumption that the events (Olympics, marriage) happens in year four.

Figure 1: illustration of crash and shift dummy variables

	Year					
	1	2	3	4	5	6
Crash dummy variable	0	0	0	1	0	0
Shift dummy variable	0	0	0	1	1	1

Given the (largely) contemporaneous nature of life satisfaction, any event or situation that has the property of a crash dummy is highly unlikely to have a well-being effect in the years before or subsequent to the year of the event (i.e. in the years when the dummy variables takes the value 0). For shift dummies, there may well be a contemporaneous effect in the years after event takes place (when the dummy variable takes the value of 1). Marriage, for example, may contribute to well-being in the years after marriage and this is what the adaptation literature tries to determine.

The results from table 2 reflect contemporaneous concerns, indicating somewhat that people do not adapt to labour force statuses such as unemployed, long-term sick or disabled. There is some evidence that marriage is not adapted to, given that the contemporaneous coefficient is positive and statistically significant. However, these contemporaneous information coefficients represent everyone who has that status or situation, i.e. the married coefficient represents everybody who is married from newlyweds up to those individuals who have been married for a long time. One debate in the marriage adaptation literature relates to what the base category should be. If the reference category is the year immediately before marriage, then the results suggest marriage is adapted to (Clark et al 2008b), however when the reference category is some years earlier to compare marriage with being single then marriage is not adapted to (Qari 2014). Because dynamic panel analysis controls for the past, this decision is made for the researcher: everything in the past is controlled for, and being married is thus compared to its missing reference category (which in table 2 is being single). Given the caveat regarding what being married contains, the results here – being married has a contemporaneous positive relationship with well-being – is supportive of Qari (2014).

As mentioned in the introduction to this section, long-run values can be calculated and these, similarly, indicate that life satisfaction is largely (but not) wholly a contemporaneous phenomenon. Long-run values are calculated by dividing the contemporaneous coefficient by 1 – the coefficient for the lagged dependent variable (i.e. is divided by about 0.9). This results in a slightly higher long-run value than the contemporaneous value. The marriage contemporaneous coefficient is 0.45, so the long-run coefficient is (approximately) 0.5. Most of this long-run coefficient compromises the contemporaneous effect, demonstrating (again) that the most of any well-being effect is of marriage contemporaneous.[27] That the long-term values of any right-hand side variable largely reflect their contemporaneous effects is another way of looking at, and asserting, the same thing: the past has only a limited influence on well-being. A helpful way of reframing the adaptation discussion, rather than asking if individuals get used to events like marriage, is to ask does marriage have a contemporaneous effect on well-being. This helps in recognising that the impact of marriage seems to come from being married, and not the act of marriage engaged in (for many people) some years previously.

Slightly beyond the scope of this paper is a more detailed investigation of how long any contemporaneous benefits of being married last (if they do not last for ever). Do individuals who have been married for some time still have this well-being boost from being married? A

[27] Paraphrasing a colleague (who will remain anonymous, and is not necessarily listed in the acknowledgements,): "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."

similar question asks whether any well-being effect restricted to the early years of marriage, the so called 'honeymoon period'? There is clearly an overall contemporaneous effect, controlling for the past, but this will include everyone in the sample who is married. A more detailed investigation would need to create dummy variables for the years of marriage (and unemployment, and anything else that is interesting to the researcher) and test them. This is not done here; the aim here was to establish the dynamic analysis of well-being as a valid enquiry, and discuss the initial outcomes. Such research, however, has not insignificant data issues to overcome and may have to resort to using a much smaller sample (than in this analysis) where full information is available for each individual in every year and individuals are seen to get married within the dataset. Additionally unbalanced panels are more problematic for dynamic analysis than static analysis because previous years are used in instrument generation and subsequent coefficient estimation. Regarding the BHPS, the wedding day of individuals within the sample who have been married for a long-time would have predated the dataset.[28]

In summary, the move from static analysis to dynamic analysis and the associated change in what the coefficients for the right-hand side variables represent changes the significance of the impact of being separated (as a marital status). The static finding indicates that separation is negative for well-being; however, the dynamic panel finding is that being separated has no contemporaneous effect on well-being when the past is controlled for. This indicates that being separated is, on average, adapted to. Not adapted to, in summary, and for males and females (despite the differences in the sample, and with the diagnostic test results) is marriage and unemployment. Widowhood is sometimes investigated too in the adaptation literature and the analysis here finds no contemporaneous effect (again controlling for the

[28] Also, that the life satisfaction question was not asked in wave 11 of the BHPS is 'doubly' unfortunate for dynamic panel analysis.

past). This result supports the previous understanding of adaptation and widowhood (Clark et al. 2008b).

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 seems to (largely) reflect what is going on now rather than what happened in the past: being married mattering more than the act of marriage; being unemployed mattering more than entering unemployment. The question researchers should perhaps ask instead is: does this event have a contemporaneous effect on life satisfaction? In other words, is an individual's happiness affected by this situation or status *now*? Such questions call for a dynamic panel assessment of well-being, rather than a fixed effects assessment. Things that impact an individual's life *now* are unlikely to be adapted to. A recent example comes from Clark et al. (2013) who investigate the well-being impact of poverty and finds that individuals do not adapt to it. Poverty, the argument made here thus suggests, affects the day-to-day lives of individuals, and hence shows up in the happiness estimates, years after individuals enter poverty. 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 can discover this.

6. Concluding remarks

The abstract for a recent paper and book chapter opens with this question: "are people condemned to an inherent level of experienced happiness?" (Powdthavee and Stutzer, 2014). Based on a dynamic panel analysis of well-being the answer is an emphatic no. Happiness, as assessed by life satisfaction scores, is heavily influenced by contemporaneous events and circumstances. Any direct influence of the past is somewhat minimal.[29] This is not the same as saying there is no influence however. Serial correlation tests of panel data demonstrate clearly that there are omitted dynamics in many (if not all) static analyses of well-being. Here, a null of no serial correlation in the panel data was rejected with almost no chance of error. This lead to this investigation into the concept of happiness and its dynamics, which has taken advantage of theoretical advances coupled with the increase 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 (2009) warns that such apparent simplicity can mean that such models are estimated without full diagnostic testing. Indeed, as this paper has shown, studies in the well-being area sometimes misunderstand the diagnostics or fail to report them (or discuss them) sufficiently. Future research using these models needs to remedy this, especially because the choices that a researcher makes regarding instrumentation can have a substantial impact on the subsequent results, as well as on the subsequent diagnostic test outcomes, and these need to be explained. Here the diagnostics did not always fully support the estimations, though the coefficients obtained appear 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, rather than ignoring them. Tests of the robustness of the obtained coefficients is important.

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

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

history of the model) means that most of what makes up current life satisfaction scores reflects contemporaneous concerns and situations. This is consistent with some work on adaptation, which finds that, for many things (for example separation, widowhood and divorce), humans get used to them, and this supports prior work in this area (for example, Clark et al. 2008b). The analysis here supports Qari (2014) and indicates that marriage is not adapted to, or to discuss in a different (preferred way) being married seems to contribute to well-being sometime after getting married. This is likely to be in contrast to events that are one-offs. The analysis here suggests that any feel good factor from events like the Olympics are unlikely to have a legacy in terms of individual well-being, but the alleviation of unemployment (for example) might.

Finally, the consistent, positive yet small influence of the past on current life satisfaction could not have been found using the 'workhorse' static model. An initial reason for a dynamic panel analysis was the possibility that many static models are misspecified. They may well suffer from serial correlation, 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. Studies in the well-being area have started to employ dynamic panel methods, but often do not adequately consider the diagnostics nor appear to fully understand how such models need to be interpreted. Such methods are more complex 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. Dynamic analyses of well-being are at a nascent stage but have many advantages (and challenges) and offer an interesting path for future well-being research.

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Table 1 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.

Table 2 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)
Log wage	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	0.364
Hansen's *J* test	0.935	0.053	0.551	0.447
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 20. 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.