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ABSTRACT: This investigation employs dynamic panel analysis to provide new insights into the phenomenon of adaptation. Using the British Household Panel Survey, it is demonstrated that happiness is largely (but not wholly) contemporaneous. This can help provide explanations for previous findings, where many events entered into in the past are often adapted to (like marriage and divorce), and others are not adapted to (like unemployment and poverty). 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. This contemporaneous finding also explains other results in the literature about the well-being legacy of events.

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Happiness, Dynamics and Adaptation

> When we have an experience . . . on successive occasions, we quickly begin to adapt to it, and the experience yields less pleasure each time... Psychologists calls this habituation, economists call it declining marginal utility, and the rest of us call it marriage (Gilbert 2006, p.144).

1. Introduction

The economic analysis of well-being has provided evidence that, in terms of happiness, individuals get used to, or adapt to, some events and not to others, but has not yet offered an explanation why some events are adapted to and others are not. Previous research (references at the end of this paragraph) suggests that events that are adapted to include marriage, divorce, widowhood, having a child, and exogenous income boosts like winning a lottery, whereas the events that are not adapted to (or not fully adapted to) include unemployment, disability and poverty. This has been demonstrated largely with panel data from Britain and Germany, and to a lesser extent Australian and Korean data, often with static fixed effects estimation methods utilising dummy variables to represent years after the event (as well as, in some cases, dummy variables for lead or anticipation effects). Some prominent examples are as follows: Lucas et al. 2004; Lucas 2005; Gardener and Oswald 2006; Stutzer and Frey 2006; Clark et al. 2008a; Oswald and Powdthavee 2008; Frijters et al. 2011; Rudolph and Kang 2011; Clark et al. 2013; Clark and Georgellis 2013.

The contribution of this investigation is to provide a general explanation of why individuals adapt to some things and not others. To do so, this study employs a relatively new method for the economic analysis of the concept of happiness: dynamic panel analysis utilising General Method of Moments (GMM) estimation. 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. Because dynamics are explicitly modelled, insights are provided for the analysis of adaptation. The 'workhorse' model for the investigation of adaptation, like the economic analysis of well-being generally, is commonly fixed effects analysis taking advantage of the rich nature of nationally representative samples, like the British Household Panel Survey (BHPS) and the German Socio-Economic Panel (SOEP). Such an analysis has provided many insights for a scientific understanding of well-being. Useful reviews of these studies include Dolan et al. (2008), Clark et al. (2008b) and MacKerron (2012). This study demonstrates that fixed effects analyses neglect to consider the possibility of omitted dynamics in such estimations. The presence or otherwise of serial correlation is rarely (if ever) 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. 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 the 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 endogenous and exogenous. Such a choice can substantially change the significance of any association between well-being and some important independent variables. A further advantage of dynamic panel methods over standard fixed effects analysis is the ability to distinguish between long-run effects and 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 do not discuss the key diagnostics. By discussing these and highlighting these diagnostic related concerns regarding other studies, this investigation also aims to help future well-being research.

This paper is organised as follows. Section 2 discusses the data used, presents results from fixed effects analysis, and demonstrates that the fixed effects analysis contains serial correlation, an indicator of omitted dynamics. Section 3 discusses a solution to the problem of omitted dynamics: dynamic panel analysis. 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 the implications of using dynamic panel analysis, and these particular results, for the on-going adaptation discussion. Section 6 concludes.

2. The Economics of Happiness: static panel analysis

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, before explaining why dynamic panel analysis is often necessary. The data come from the British Household Panel Survey (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'.[1] The chosen independent variables, common to most previous studies, are income, job status, marital status, education, and

[1]As is typical in the literature this is treated as cardinal data. See Ferreri-i-Carbonell and Frijters (2004) for an explanation of the reasons why this is the current practice.

health. Wave and regional dummies are also included in the estimates.[2] The other variables in the regression account for age bands.

Initial diagnostic tests (not reported here) establish that the workhorse model, FE, is the preferred static model, being more appropriate than RE and 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. Arguably, the most important benefit is that individual heterogeneity can be controlled for, and this helps us overcome 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. Results for these regressions are presented in table 1.

[TABLE ONE ABOUT HERE]

[2]Chapter 3 of the World Happiness Report provides a summary of the current state of knowledge, regarding happiness and subjective well-being that is obtained via economic analysis (Layard et al. 2012).

The results in table 1 are similar to results of previous studies. The following are positive and statistically significant for life satisfaction: log real wage; being married; being divorced[3] and categorising health as good or excellent. Being unemployed, having a labour force status classed as other[4], being separated or widowed, are all statistically significant and negative for life satisfaction. Not shown, but by gender separately the results are similar with two exceptions: for males education is positive and statistically significant with life satisfaction, while for females unemployment is only significant at a 90% confidence level (with a p-value of around 0.06). Furthermore, for both genders separately and together, the coefficients on the age range dummy variables are in line with the familiar U-shape relationship of age with life satisfaction found in the wider literature. However, analysis does not (and should not) end here with static analysis.

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 0.000. (i.e., in practical terms, the null can be rejected with certainty).[5]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

[3]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.

[4]This might be caring for someone, on maternity leave, a student, on a government training scheme, a family carer, long-term sick, disabled or one of a handful of people in the dataset who fit none of the possible categories.

[5] 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 at routinely check for omitted dynamics, and proceed based on the outcome of such an inspection.

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).[6]

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

3. The Economics of Happiness: dynamic panel analysis discussion

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. 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):

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

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

[6] "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.8).

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 a 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).[7]

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 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.

[7]This bias has been misunderstood in some of the well-being work which estimates similar equations. Della Giusta et al (2010) states 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. This is an important point for GMM analysis, and is discussed later to aid results interpretation and informs the subsequent adaptation discussion.

(1988).[8] 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 $(\varepsilon_{it} - \varepsilon_{i,t-1})$. 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 the original *levels are instrumented with differences* (Arellano and Bover 1995).

These estimators, unlike OLS and conventional 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.[9] Powdathee (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. A key choice with GMM panel analysis, and the discussion

[8]GMM was developed by Lars Peter Hansen, work that led, in part, to him being selected as one of the 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.

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

below will show how important this decision is. Similarly, the discussion below will focus on the diagnostic tests and the interpretation of the results in some detail because other studies that use this method (in the context of a dynamic panel analysis of happiness) 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 the methods more commonly used therein.

Thus, before estimating any dynamic panel model there are two important (and linked) considerations. Firstly, are the regressors potentially endogenous or strictly exogenous? Secondly, how many instruments to use? With happiness equations many 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) – and the choice of endogeneity or exogeneity can influence the coefficients subsequently estimated. Diagnostics are available and built in with *xtabond2*, the Stata command employed for empirical analysis, to help with this choice.

The choice of which regressors are to be treated as endogenous and exogenous is also bound up with the consideration of how many instruments should be used, because that choice generates the instruments. More regressors treated as endogenous means more 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). Diagnostic tests are available for the appropriateness of the instrumentation collectively, and 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 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.[10] For this investigation, the "system" GMM estimation was undertaken twice, with the difference being gender. The reason is largely pragmatic: such estimations are computationally intensive and it was not possible to perform the estimate for the whole sample.[11] In both cases, the diagnostics of the chosen models indicate that first order autocorrelation is present, but second order is not (as shown in table 2). This is expected (and necessary): the difference of lags and the difference of levels are correlated (first order), However, the second differences are not and thus are valid for instrumentation.[12]

The serial correlation diagnostics in the above paragraph reflect the outcome of the chosen model for each gender, a decision that was made after testing many variants regarding lag lengths, instrumentation, and the choice regarding the endogeneity or exogeneity of regressors. These choices matter. They matter for the coefficients of the independent variables (but not really for the lagged dependent variable for which the coefficient which was fairly stable in all of the estimates), and the necessary exogneiety of the instruments. Unsurprisingly, with the models ultimately chosen, the various tests of the instruments indicate that they are suitable in each case – the null hypothesis of exogenous instruments

[10] Recall the explanation presented above utilising Greene (2002).

[11] 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).

[12] Initial work with the SOEP suggests this is not the case with similar equations, and using one lag of the dependent variable is not supported diagnostically. For BHPS estimations, these and others I have undertaken, there is no such problem.

(what we want) cannot be rejected. The Hansen (1982) test *J* statistic[13] of all overidentifying restrictions, with a p-value of approximately 0.76 (for males) and 0.60 for females, does not reject the null of instrument validity indicating at least a sixty percent chance of a type one error if the null is rejected. This is higher than Roodman's recommended threshold of a p-value of 0.25 where 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.

The J tests, Hansen and Sargan, inspect all of the generated instruments together, with a null 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.[14]

Valuable, but perhaps even more neglected, are the difference-in-Hansen (or C) tests. These are diagnostic tests that inspect the exogeneity of a particular subset of instruments, and are reported by *xtabond2*.[15] This means that researchers can test their choice (and alternative

[13]This has the advantage over the Sargan*J* test 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.

[14]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). In this study, only once is the p-value of the Sargan test above 0.25. However, this may not necessarily invalidate all of its results because, for the reason put forward in footnote 11, the Hansen test (unreported) is the 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 an incorrect claim.

[15]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.

choices) of which regressors should be treated as exogenous and which endogenous. This is crucial since it can affect the overall *J* test result, and the choice considerably alters the coefficients obtained for the independent variables (although not the lagged dependent variable). This is discussed more in the results section with reference to other studies and is well explained in Baum et al. (2003, sections 4.2 and 4.4) as well as the Roodman papers referred to elsewhere. Here, such testing led to the treatment of marital status and health as potentially endogenous for males, marital status, health, labour force status, and education for females.[16]

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 given 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).

As recommended these are presented in the results table of the next section, where there is also a discussion regarding how the coefficients should be interpreted. The introduction of the lagged dependent variable means that the interpretation of the coefficients is somewhat

[16]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, this is potentially invalid.

different from more conventional static fixed effects analysis. 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. The Economics of Happiness: 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. A footnote above states that coefficients obtained via OLS or FE were different from those obtained by dynamic panel methods and could not 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. This means that contemporaneous associations of variables with life satisfaction can be usefully assessed via dynamic panel methods, whereas anything historic (e.g. typically education) is captured in the 'black box' of the lagged dependent variable itself.[17]

As a consequence of the lagged dependent variable being estimated (and the internal instruments used), the number of observations will shrink somewhat because two consecutive years are needed. In 2001, i.e. wave 11 of the BHPS, the life satisfaction question was not

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

asked which will mean two years of no data due to the missing lags. Given the necessity of (a minimum of) two consecutive years, the number of observations from dynamic estimates will be smaller than the observations used in the static analysis of section 2.

Table 2 displays the results for four estimations, two of which are for males and two for females. The difference in the two columns for each gender is in the number of instruments generated to obtain the coefficients. The estimation with the higher number of instruments (for each gender) makes use of default instrumentation, which utilises the full length of the sample to create instruments. In the other estimations for each gender, the lag length used is restricted to the first available. The robustness (or otherwise) of the results to different instrumentation will be discussed just after the discussion about the independent variable coefficients.

[TABLE TWO ABOUT HERE]

For males, positive and statistically significant for life satisfaction are log wage, 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 life satisfaction are unemployment and medium and high levels of education, assessed by qualifications obtained. The coefficients on the age dummy variables are in line with the well-known U shape. These results are robust to the number of instruments used being, for most variables, qualitatively the same. In both male cases, the diagnostic tests are all supportive of the estimation choices made. For females, the results are similar. The major exception is unemployment: the new information coefficient (controlling for the history of the model) is insignificant. Recall that the coefficient obtained by static fixed effects estimation was significant only at the 10% level. The labour force status variables (treated as endogenous, as mentioned above) exhibit some change based on the choice regarding the length of lags for instrumentation. The diagnostic tests indicate which results we should lean towards being more accepting of.

Based on the AR(2) in first differences test and the Hansen *J* test the diagnostics, which are now turned to, are acceptable and supportive of the estimation choices. However, this hides the problem found by the difference-in-Hansen test for the instruments created by the lagged dependent variable. The diagnostic problems for GMM estimation regarding females in the BHPS are also found by Della Giusta et al (2010), where the null of having exogenous instruments overall (i.e. Hansen *J* test) is comfortably rejected. This was often the case in many of the estimations undertaken for this investigation, and this work here suggests that a change in their choice of which regressors to treat as exogenous and endogenous would lead to a more favourable Hansen *J* test result, leading to the non-rejection of the null of exogenous instruments overall.[18] The results presented are the best diagnostic outcomes for the various possible choices regarding the endogeneity and exogeneity of the regressors and yet there are still diagnostic problems. Based on the diagnostics, the preferred female model is the one with lower instrumentation, be we must still be cautious about the results obtained for females.

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 indeed the estimations that formed part of the testing for the results ultimately presented). 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

[18]Recall that here, for females, marital status, labour force status, health and education have been treated as endogenous. This is fewer independent variables than chosen by Della Giusta et al (2010), and it is likely that their estimation generated too many instruments leading to the rejection of their collective exogeneity This illustrates the importance of diagnostically testing the choices made regarding the endogeneity and exogeneity of the independent variables.

for a good estimator (mentioned above): the coefficient 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).

5. Adaptation implications and discussion

The coefficient on lagged happiness 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 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

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

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).

Thus, the lagged dependent variable tells us the influence of the past. In section 4 (and elsewhere, as discussed below) this coefficient is positive, suggesting a persistence or inertia effect from previous happiness: lagged happiness being positively associated with current happiness. That the coefficient is small (around 0.1) means 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; Bottan and Perez-Truglia 2010; Della Giusta et al 2010; Wunder 2012).[19],[20] 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: in the equation estimated; the datasets employed; alternate choices of exogneneity and endogeneity; and the use of lags for other independent variables.

[19]Although, as mentioned earlier, many of these studies either don't fully consider diagnostic tests or have results with inappropriate diagnostic test results my analysis suggests that altering the instrumentation choices has a substantial impact on the coefficients for the independent variables but only a small impact on the lagged dependent variable. In my regressions, testing the differing choices of endogeneity and exogeneity, the coefficient was almost always between 0.09 and 0.12. This means that studies where the independent variable coefficents are crucial (like Powdthavee 2009 and Della Giusta et al 2010) should be extra diligent with respect to the modelling choices discussed earlier.

[20]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. Wunder obtains almost exactly the same coefficient as those obtained in section 4 in regressions that do not employ the additional lags of the dependent variable. This is not reported in Wunder (2011) 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 for this to be anything more than a footnote.

Below, it is argued that this result is entirely consistent with current work on adaptation, however in the literature another possible hypothesis and expectation has been put forward for the coefficient on lagged happiness. Bottan and Perez-Truglia (2011) assert that past happiness should be negatively correlated with current happiness (i.e. they expect negative coefficient on lagged life satisfaction) supporting their notion of what they call general habituation (in contrast to specific habituation which is getting used to a single event like, for example, marriage or a pay rise). Because specific habituation occurs, they argue that general habituation should occur: we adapt to marriage and divorce so perhaps we adapt to happiness overall (an argument that ignores events like unemployment, to which people do not appear to adapt (as in, for example, Clark et al. 2008a)). Bottan and Perez-Truglia (2011, p.224) argue for general adaptation in their opening paragraph with this rationale (the oft-found adaptation in the literature to specific incidents means that there is a general adaptation effect too). In a later version of this paper, in support of general adaptation they refer to "what we might recognise as the evolutionary origins of hedonic adaptation. The basic intuition is that positive and negative hedonic states are costly from a fitness perspective: e.g. generating feelings is a waste of energy for the brain. In order to minimise those fitness costs, humans have adapted with hedonic states that quickly return to 'normal levels'" (Bottan and Perez-Truglia 2011, p.225). A little later on the same page they expand on this idea and suggest that "the reward centers in the brain may work as a spring: i.e. as soon as an individual excites some area in the brain, the corresponding reward system will automatically start pushing in the opposite direction". Their empirical results for the (Arellano-Bond) autoregressive happiness estimates (Tables 1A-1D), based on panel data from four countries overwhelmingly find a small positive and statistically significant coefficient like the results in section 4 and the other studies mentioned. That the sign on the coefficient for lagged happiness is positive and significant and not negative (as they expect), they suggest presents a 'puzzle'. Rather than being a puzzle, instead the results suggest that their conjectures regarding the lagged dependent variable and general adaptation are likely to be incorrect.

The small positive coefficient on lagged life satisfaction is consistent with our current understanding of adaptation, which does not indicate that general adaptation should necessarily occur.[21] This small happiness 'carry-over' (i.e. impact from the past) means that happiness is largely contemporaneous: to a large extent the happiness scores of individuals reflect current concerns and situations. Knowing this, we can speculate about reasons for reasonably complete adaptation for some events (like marriage and divorce) and limited adaptation for others (like unemployment and disability), previously found in the literature. The literature provides evidence that we get used to some events, and others we do not. The results above indicate that an explanation may lie in the contemporaneous impact of being married or divorced for a few years, compared with a contemporaneous impact of being unemployed for a few years. A major reason for this differing degree of adaptation could well be due to the event's 'day-to-day' impact on the lives of individuals. Marriage may have, for most people, a large impact around the time it occurs (and for an initial 'honeymoon' period immediately afterwards), reflecting changes in lifestyle, responsibilities, and personal and social relations, but perhaps has, a few years later, little impact on how the individual thinks about her current day-to-day life (which is largely responsible for self-ratings of life satisfaction). Conversely, it is quite conceivable that unemployment affects the day-to-day life of individuals, even if the initial entry into unemployment was some time ago.[22] This has been understood for some time. For example, Sinfield (1981), in a book length investigation of unemployment, argues that prolonged unemployment is a highly corrosive experience,

[21]If individuals adapt to some events but not others (for example unemployment and poverty), then, logically, general adaptation cannot necessarily be expected to take place.
[22] It is not difficult to imagine that a lengthy unemployment spell goes hand in hand with repeated rejection and frustration in a job search.

which undermines personality and weakens future work possibilities. Other possibilities for such a dichotomy which refer to contemporaneous experience include social status or reflect cultural norms (perhaps British individuals are happier to see themselves as divorced than as unemployed as they think it is more accepted by society). Similarly an individual may feel (rightly or wrongly) individually responsible for prolonged unemployment, or prolonged poverty (see below), but recognise that marriage, divorce, having a child, all depend on another person too.[23]

Thus to explain the differing results regarding adaptation of individuals to different live events, perhaps the initial question should be whether this event is likely to affect individuals in their daily lives some years after entering in to the event (marriage, divorce, unemployment). If yes, the event is likely to be reflected in the contemporaneous happiness scores and thus not adapted to. If no, the event will have been adapted to and not associated with the contemporaneous happiness score. Viewed in this way, the finding of a low influence of the past (i.e. that happiness is largely contemporary) complements well the findings on adaptation in the literature. Recent research supports this. Clark et al. (2013) investigate the well-being impact of poverty and find that individuals do not adapt to it. Poverty, the argument above suggests, affects the day-to-day lives of individuals, and hence shows up in the happiness estimates, years after individuals enter poverty. Anything that has a substantial influence on an individual's day-to-day life (sometime after the event is entered into) is not going to be something that they can fully adapt to.

[23] Alternatively, rather than feeling individually responsible, prolonged unemployment or poverty could lead an individual to adopt a defeatist attitude and blame the government (or other relevant institutions) for their situation and see no hope or possibility to leave their situation (here unemployment or poverty). Such individuals may perceive themselves as 'second class' citizens which would be reflected in well-being scores.

As well as providing a general explanation for specific adaptation, this analysis can also explain other results in the 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.[24] Our results regarding the dynamics of happiness suggest that it 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. Again, our general explanation provides a reason for this finding. In summary, the small, positive and significant coefficient on lagged life satisfaction is consistent with what is known about adaptation and provides a general reason for the adaptation or non-adaptation to specific events. For an event to have a legacy or long term impact on an individual's life satisfaction it must have a profound effect on the individual's day to day life sometime after the event happens or is entered into.

6. Concluding remarks

This investigation has taken advantage of theoretical advances, and 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. However, as Roodman (2009) warns, such apparent simplicity, *xtabond2* can easily seem like a black box, can mean that such models are estimated without full diagnostic testing. As this paper has shown, studies in the well-being area sometimes misunderstand the diagnostics or fail to

[24] The authors suggest that this negative effect may reflect dissatisfaction with the high levels of public expenditure, transport disruptions, general overcrowding or an increase in housing prices.

report them (or even 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 large impact on the subsequent results, as well as on the subsequent diagnostics, and these need to be explained. Particularly important is the choice of which regressors are to be considered exogenous and which endogenous.

The analysis and results of this study both support and extend recent research. The 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. This is consistent with much work on adaptation, which finds that, for most things (for example marriage and divorce), humans get used to them. However, prolonged poverty and unemployment are, the literature finds, not adapted to, and the experience of them are one of few things that have an impact on an individual's life satisfaction long after being entered into. Policy focused on the happiness of a nation's citizens should aim to alleviate poverty and create jobs, if it is to have a long-term impact. 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 poverty (for example) could.

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. Studies in the well-being area have started to do this, but often do not adequately consider the diagnostics. As such methods are more complex than the standard fixed effects models this should be taken more seriously. This investigation has discussed this nascent literature and offered comments for future research. With more consideration regarding what such a model means and appropriate diagnostic test results, dynamic panel analysis has many advantages (and challenges) and offers 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	Life Satisfaction
Log Wage	0.014***
	(0.009)
Self-employed	-0.01
	(0.063)
Unemployed	-0.20***
	(0.063)
Retired	0.05
	(0.162)
Other Labour Force Status	-0.06***
	(0.021)
Married	0.08***
	(0.021)
Separated	-0.12***
	(0.036)
Divorced	0.10***
	(0.032)
Widowed	-0.13*
	(0.073)
Education: High	0.04
	(0.030)
Education: Medium	0.03
	(0.033)
Health: Excellent	0.40***
	(0.013)
Health: Good	0.27***
	(0.010)
Age: 21-30	-0.09***
	(0.023)
Age: 31-40	-0.011***
	(0.031)
Age: 41-50	-0.13***
	(0.039)
Age: 51-60	-0.13***
	(0.47)
Wave Dummies	Yes
Region Dummies	Yes
Constant	4.73***
	(0.062)
Observations	72,973
Number of individuals	15,836
R-squared	0.023

Note: data from individuals in the BHPS, 1996-2007; robust 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.

	Males	Males	Females	Females
Number of observations	24777	24777	28070	28070
Number of instruments	147	564	237	1058
Lagged Life Satisfaction	0.10***	0.10***	0.11***	0.10***
	(0.015)	(0.015)	(0.014)	(0.014)
Log wage	0.07***	0.08***	0.01	0.02
	(0.022)	(0.020)	(0.026)	(0.023)
Self-employed	0.12	0.13	2.10**	0.57
	(0.077)	(0.83)	(0.938)	(0.451)
Unemployed	-0.22*	-0.29***	0.46	0.86
	(0.118)	(0.110)	(1.195)	(0.670)
Retired	0.000	-0.02	-0.54	0.13
	(0.204)	(0.250)	(1.041)	(0.186)
Other Labour Force Status	0.05	0.064	0.253	0.30**
	(0.053)	(0.055)	(0.206)	(0.131)
Married	0.32***	0.33***	0.51***	0.40***
	(0.089)	(0.081)	(0.109)	(0.088)
Separated	-0.31	-0.13	0.21	0.12
	(0.250)	(0.204)	(0.226)	(0.190)
Divorced	0.13	0.14	0.166	0.072
	(0.181)	(0.161)	(0.165)	(0.128)
Widowed	0.085	0.15	0.27	0.17
	(0.191)	(0.162)	(0.232)	(0.210)
Education: High	-0.12***	-0.11***	0.15	0.02
	(0.032)	(0.033)	(0.193)	(0.173)
Education: Medium	-0.10***	-0.09***	0.40	-0.12
	(0.033)	(0.034)	(0.232)	(0.210)
Health: Excellent	0.63***	0.45***	0.80***	0.66***
	(0.194)	(0.112)	(0.160)	(0.100)
Health: Good	0.45**	0.26***	0.570***	0.40***
	(0.210)	(0.099)	(0.156)	(0.078)
Age: 21 – 30 years old	-0.30***	-0.31***	-0.16**	-0.09
	(0.041)	(0.040)	(0.080)	(0.061)
Age: 31 – 40 years old	-0.50***	-0.052	-0.37***	-0.27***
	(0.070)	(0.064)	(0.123)	(0.092)
Age: 41 – 50 years old	-0.54***	-0.56***	-0.50***	-0.40***
	(0.082)	(0.076)	(0.143)	(0.109)
Age: 51 – 60 years old	-0.37***	-0.40***	-0.37**	-0.28**
	(0.087)	(0.079)	(0.152)	(0.119)
Wave Dummies	Yes	Yes	Yes	Yes
Region Dummies	Yes	Yes	Yes	Yes
Constant	4.30***	4.15***	3.95***	4.18***
	(0.181)	(0.165)	(0.247)	(0.201)
AR (2)	0.161	0.196	0.123	0.221
Hansen's *J* test	0.521	0.759	0.381	0.602
Diff-in-Hansen for Levels	0.421	0.896	0.535	0.346
Diff-in-Hansen (lag depvar)	0.327	0.332	0.144	0.041

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.