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Abstract

This study examines the role of people's subjective well-being in relation to one of the most important economic shocks – unemployment. It empirically investigates the impact of well-being on (i) unemployment propensity, (ii) maintaining employment and (iii) exiting from unemployment. We find that being more satisfied with life and having better mental health in the previous wave predict a lower probability of being currently unemployed. We further show that life satisfaction and mental health may matter significantly for maintaining employment. These effects are qualitatively similar across genders and ethnic groups of the respondents. The current paper thus provides new empirical evidence on the link between well-being and job loss by highlighting the importance of having high levels of well-being.

Keywords: life satisfaction, mental distress, well-being, unemployment

JEL codes: D03, I31

1. Introduction

Economists and other social scientists are becoming increasingly interested in the study of people's subjective well-being. Within this rapidly-expanding literature, recent research has examined the causal effect of well-being on life events and labor market outcomes, including childbearing behavior (Le Moglie et al., 2015) and earnings (Mishra and Smyth, 2013). Common to these studies is an emerging new approach for studying causal effects; an approach based on a novel identification method proposed by Lewbel (2012). The current study contributes to the literature on subjective well-being, but on a different theme. It focuses on the relatively unexplored role of well-being for one of the most important economic shocks – unemployment.

It is reasonable wonder why well-being may affect people's chances of becoming unemployed. Currently there is a large body of empirical evidence on the relationship between well-being and labor market outcomes. Studies in this area come primarily from psychology and organizational behavior, showing that people high in well-being are more likely to secure a call-back second job interview (Burger and Caldwell, 2000). They may also be more likely to receive higher ratings from supervisors (Wright and Staw, 1999), because they generally tend to show lower job burnout (Wright and Cropanzano, 1998), higher levels of organizational citizenship (Donovan, 2000) and reduced absenteeism (Pelled and Xin, 1999). In addition to this, people who have high levels of well-being tend to show superior job performance (Wright and Cropanzano, 2000) and tend to handle managerial jobs better (Staw and Barsade, 1993). Another interesting finding among happy people is that they are able to secure generally "better" jobs along three key dimensions – autonomy, meaning and variety (Staw et al., 1994) – and tend to get paid relatively more for their efforts (Mishra and Smyth, 2013).

Despite a large body of empirical work linking well-being with desirable work outcomes, there is little theoretical work on this topic. One of the most notable studies is Lyubomirsky, King and Diener (2005). They offer an extensive review of the literature on subjective well-being and favorable outcomes – not only work-related outcomes – in people's lives. According to Lyubomirsky et al.

(2005), the key idea supporting why having high levels of well-being can lead to successful outcomes is that

> "Positive emotions produce the tendency to approach rather than to avoid and to prepare the individual to seek out and undertake new goals (p. 804)."

This seems to suggest that individuals who enjoy higher levels of well-being tend to actively engage in the achievement of certain goals. They may also be more likely to have built human capital and psychological capital during past periods of high well-being, both of which may be of value to current or future employers (Lyubomirsky et al., 2005). This latter idea of a greater stock of human capital is also implicitly embedded in the concept of hedonic capital; that is, the accumulation of certain key resources over time, including, but not limited to, social relationships, self-esteem, health, status, and even religious faith, for some people (Graham and Oswald, 2010).[1]

Previous studies thus imply that happy people may possess certain key skills and resources and therefore may be in better position overall to maintain employment than their less happy peers. Consistent with this view is also another theory – the 'abundancy' theory of motivation (e.g. Verkley and Stolk, 1989). It suggests that people with high levels of well-being tend to perceive work as an opportunity for using their skills and resources. As a result, they may be more likely to show greater work involvement than people with lower levels of well-being. These theories thus lead us to hypothesize that being generally more satisfied with life or having better mental health may play an important and

[1] The concept of hedonic capital has also been linked with psychological resilience to unemployment and other economic shocks. In two exceptional studies, it has been shown that certain childhood characteristics can predict the extent of psychological resilience to job loss in adulthood (Powdthavee, 2014); and that locus of controls can buffer the negative effects arising from adverse events in people's lives (Buddelmeyer and Powdthavee, 2016).

positive role regarding people's ability to maintain employment or exit from unemployment.

To our knowledge, there is but one prior study on how well-being affects people's employment chances (Verkley and Stolk, 1989). Using the Affect Balance Scale as a measure of individual happiness, they found that happy people are less likely to lose their job, as well as more likely to be reemployed once entering unemployment than their less happy peers. Although this finding contributes meaningfully to our understanding of the link between well-being and unemployment, it utilized data from a specific region of the Netherlands – the western urbanized part – in 1983 and 1984, and was based on simple correlations only. The available empirical evidence is thus relatively small, and the nature of the relationship between well-being and unemployment continues to be imperfectly understood in the economics literature.

Drawing data from a nationally representative dataset, and using a novel identification approach proposed by Lewbel (2012), the current paper attempts to estimate one of the first micro-econometric equations in order to examine the importance of well-being with respect to three key dimensions: (i) unemployment propensity; (ii) maintaining employment; and (iii) exiting from unemployment. The analysis reveals that being more satisfied with life and having better mental health in the previous wave predict a lower probability of being currently unemployed. We also show that life satisfaction and mental health may matter significantly for maintaining employment. These effects continue to hold even after controlling for people's Big Five personality traits. The current paper thus provides new empirical evidence on the link between well-being and one of the most important economic shocks – job loss – by highlighting the importance of having high levels of well-being.

The paper is organized as follows. Section 2 describes the data. Section 3 discusses our empirical model and strategy. Section 4 presents the results, and Section 5 extends our analysis in various ways. Section 6 concludes the paper.

2. Data

Our data comes from Waves 1-5 (2009-2014) of Understanding Society, the UK Household Longitudinal Study (UKHLS), which is a nationally representative longitudinal survey of the members of approximately 40,000 households in the United Kingdom. Our main independent variable of interest is surveyed every year via two separate measures, both of which have been used extensively in different disciplines, including within economics: (i) a single question about overall life satisfaction; and (ii) multiple questions about mental distress (GHQ-12).

The life satisfaction question asks individuals to evaluate how satisfied they are with their overall life, with possible responses reported on a scale of 1 (not satisfied at all) to 7 (completely satisfied). Consistent with earlier studies, the life satisfaction distribution is skewed to the right, with a mean of about 5 and a standard deviation of 1.5.

Our second well-being variable is a multi-item measure on mental distress derived from responses to 12 questions of the General Health Questionnaire (GHQ-12). Individuals were asked to what extent over the past few weeks they had been able to concentrate on whatever they were doing, with answers ranging from 1 (better than usual) to 4 (much less than usual). They were also asked on a scale from 1 (not at all) to 4 (much more than usual) how often over the past few weeks they had lost sleep over worry, felt constantly under strain, felt they could not overcome difficulties, had been feeling unhappy or depressed, had been losing confidence, and had been thinking of themselves as a worthless person. Finally, on a scale from 1 (more so than usual) to 4 (much less than usual), individuals were asked how often over the past few weeks they felt they were playing a useful part in things, felt capable of making decisions, had been able to enjoy normal day-to-day activities, had been able to face up to problems, and had been feeling reasonably happy. Across all questions, responses were recoded on a 0-3 scale so that 0 indicates, for instance, “Not at all” and 3 indicates “Much less than usual”.

This paper uses the Likert version of the GHQ-12 score, which is obtained by adding the responses to questions 1 through 12. The resulting score ranges from 0 to 36, with higher numbers indicating greater mental stress. The GHQ-12 measure has often been used by economists and other social scientists, and has been shown to be a good proxy for an individual's mental well-being. Unlike life satisfaction, which has been shown in the literature to represent a measure of cognitive well-being, the GHQ-12 is a measure of affective well-being (Diener et al., 1985; Powdthavee, 2015). For ease of interpretation, we standardized both our well-being measures so that the mean is 0 and standard deviation is 1.

Our dependent variable is a binary indicator that equals 1 if an individual is currently unemployed. To test whether an individual's well-being matters for (i) maintaining employment and (ii) exiting from unemployment, we follow Heineck (2010) and focus our attention on those individuals who – at the beginning of the panel – were employed and those who were unemployed, respectively.[2]

Our analytical sample consists of individuals of working age between 20 and 59 years old.[3] After excluding individuals with missing responses to the questions required for our analysis, the final sample corresponded to an unbalanced panel of 17,571 individuals and 56,693 observations. The corresponding subsamples conditional on those who were employed (unemployed) in Wave 1 are 13,188 (1,212) individuals and 43,189 (3,723) observations. Table 1 provides descriptive statistics.

3. Model and Empirical Strategy

Studies in psychology and organizational behavior show that current levels of well-being influence future work outcomes (see e.g., Verkley and Stolk, 1989; Staw et al., 1994; Wright and Staw, 1999; Pelled and Xin, 1999). Consistent with earlier studies, the current paper also assumes that reported well-being has a

[2] Heineck (2010) shows that people's cognitive skills are negatively related to unemployment propensity. There is little evidence, however, that cognitive abilities may help to exit unemployment.

[3] According to the Pensions Act, the lower bound of females' eligible age for retirement is 60. For the sake of consistency this paper applies the same age range, 20-59, for both genders.

lagged rather than a contemporaneous impact on unemployment. We thus estimate an unemployment regression equation that takes the form

$$UE_{it} = \alpha + W_{i(t-1)}\beta + X'_{i(t-1)}\gamma + Z'_i\delta + u_i + \varepsilon_{it} \qquad (1)$$

where UE_{it} is a dummy variable representing whether or not individual i is unemployed at time t; $W_{i(t-1)}$ is either life satisfaction or mental distress of individual i at time $t-1$; $X_{i(t-1)}$ is a vector of time-varying predictor variables lagged to time $t-1$; Z_i is a vector of predictor variables that do not vary over time; u_i is a person-specific error (i.e. the individuals' fixed effects), and ε_{it} is the idiosyncratic error. [4]

One issue with equation (1) is that $W_{i(t-1)}$ is likely endogenous. As the well-being variables are taken at time $t-1$, reverse causality does not seem to be a source of potential bias here. However, there may still be omitted variables affecting both well-being and employment status, or measurement error in well-being itself.

One possible way of overcoming these issues is to use past values of an individual's well-being as instruments for his/her well-being at time $t-1$. Doing so, however, seems to raise a natural concern: past values of well-being are unlikely to be fully exogenous in an unemployment regression equation; there may have substantial correlations with variables included in the error term such as an individual's genetic make-up. This implies is that, although past values of well-being are available in most datasets and could thus be readily used for identification, they are unlikely to be reliable instruments for $W_{i(t-1)}$. Another approach might be to use the "weekly time that individuals spend for hobbies" as an instrument for well-being. However, in addition to this variable being weak as

[4] In Section 5 we extend our analysis to allow for a two-year lagged effect of well-being on unemployment.

an instrument (see Le Moglie et al., 2015, for a thorough empirical testing), it is also not currently available in the UKHLS dataset used in our study. [5]

Researchers are thus faced here with the practical difficulty of finding appropriate instruments for reported well-being. It is reasonable wonder whether such instruments – sufficiently correlated with individuals' well-being and orthogonal to the error term – exist in the first place. And, if they do, are such variables available in most datasets used by economists and other social scientists?

When ordinary instruments are lacking, Arthur Lewbel has proposed a novel identification approach (Lewbel, 2012). Lewbel's method has been successfully implemented by other scholars in a variety of settings ranging from health economics and labor economics to agricultural economics, economic growth and even finance.[6] The general consensus from these studies is clear: the empirical results obtained from Lewbel's method are more plausible than those obtained using conventional IVs of questionable validity.

Following Lewbel (2012), equation (1) can be identified in the presence of heteroskedasticity associated with at least some elements of the vector of model regressors X. This requirement can be stated as $Cov(X, \varepsilon_2^2) \neq 0$, where ε_2 is the error term from linearly regressing W at time $t-1$ on X.[7] A second requirement for identification concerns the existence of a vector of variables Z (which can be a subset of X or equal to X) that are uncorrelated with the product of the errors; namely, $Cov\,(Z, \varepsilon_1\varepsilon_2) = 0$, where ε_1 is the error term of the second-stage

[5] When such variables are available in the dataset, even though they might be weak, they can be used alongside internal instruments generated by Lewbel's (2012) method to help identify the equation of interest.

[6] A simple Google Scholar search revealed 234 citations of Lewbel's method. For example, Le Moglie et al. (2015) uses the method to estimate the causal effect of subjective well-being on childbearing behavior, while Mishra and Smyth (2013) applies it to a model relating subjective well-being to male and female earnings. Other applications of Lewbel's method include estimating the causal effect of body weight on academic performance (Sabia, 2007), access to domestic and international markets on household consumption (Emran and Hou, 2013), market size on the pattern of agricultural specialization in a village economy (Emran and Shilpi, 2012), inequality on growth (Lin and Yeh, 2009), and class size on educational attainment (Denny and Oppedisano, 2013).

[7] The use of heteroscedasticity to facilitate estimation is not new in the econometrics literature, and dates back to seminal study of Wright (1928).

regression in two-stage least squares.[8] Importantly, as Lewbel shows, the existence of such a Z is feature of many models – including measurement error and omitted factor models – where error correlations are due to an unobserved common factor. In our model, it is likely that unemployment propensity and well-being share a common unobserved factor over time (for instance, an individual's genetic make-up that is largely unobserved to researchers), thus suggesting that the identification assumption that Z is uncorrelated with the product of the heteroskedastic errors holds. As Lewbel (2012) notes

> "These are all standard assumptions except that one usually either imposes homoskedasticity or allows for heteroskedasticity, rather than <u>requiring</u> heteroskedasticity (p. 69)."[9]

Instruments can then be generated as $(Z - \overline{Z})\widehat{\varepsilon_2}$, where $\widehat{\varepsilon_2}$ is the vector of residuals from the linear regression of Wat time $t - 1$ on X. The strength of the instruments will depend on the degree of heteroskedasticity of $\varepsilon_2$with respect to Z. This is relatively straightforward to test by using a Breusch-Pagan/Cook-Weisberg test and/or a White test (the latter relaxing the assumption that ε_2 is normally distributed). Both tests strongly reject the null hypothesis of homoskedasticity,[10] suggesting that the identification assumption of Lewbel's method about heteroskedasticity holds.

Once instruments have been generated and the heteroscedasticity requirement has been verified, equation (1) can be estimated as a pooled IV regression using two-stage least squares. We implement this in STATA using the *ivreg2h* command of Baum and Schaffer (2014). For comparative purposes, we also report estimates based on linear fixed effects and random effects models with

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[8] Although the requirement $Cov(Z, \varepsilon_1\varepsilon_2) = 0$ cannot be empirically tested, Lewbel shows that, if it fails to hold, bounds on the estimated parameters can be obtained as long as this covariance is not too large. Such bounds are shown to be quire narrow (Lewbel, 2012).

[9] It is also assumed that X is uncorrelated with the errors ε_1 and ε_2, which is a standard (minimal) regression assumption of exogeneity of the model regressors.

[10] Across all our models, the chi-square statistic is highly significant (the p-value is zero to four decimal places).

standard errors clustered at the individual level (Cameron and Miller, 2013), although similar conclusions can also be reached using a conditional/fixed effects logit model.

4. Results

4.1 Main sample

To shed some light on the relationship between unemployment and well-being, Figures 1 and 2 provide simple plots of the unemployment rate, which is defined as the number of unemployed observations divided by the total number of observations at each point of each well-being scale (life satisfaction and GHQ-12). As might be expected, the figures indicate an overall decreasing pattern for life satisfaction, and an increasing pattern for GHQ-12. It is important, nonetheless, to control for a variety of economic, social and personal factors that may confound any associations observed in the raw data.

Table 2 provides our first econometric evidence, starting with a simple random effects model. The estimates in Column 1 of Table 2 suggest that having more mental distress in the previous wave is positively related to the probability of being currently unemployed (at p-values < 0.01). In Column 2 of Table 2, we use the fixed effects estimator to correct potential bias emanating from unobserved heterogeneity at the individual level. The estimates show that scoring higher on the mental distress scale continues to be associated with a higher probability of being unemployed.[11] In Columns 3 and 4, we re-estimated our model with life satisfaction as the key independent variable. While the random effects estimates suggest a negative association between life satisfaction and unemployment propensity (at p-values < 0.01), the fixed effects coefficient is not statistically well-determined at conventional levels.[12]

[11] Our set of independent variables includes the 'Big Five' personality traits (agreeableness, conscientiousness, extraversion, neuroticism and openness). Because data on personality traits are collected only in Wave 3 of the UKHLS, the corresponding variables naturally drop out from the fixed effects estimation.

[12] We also estimated equation (1) using a conditional/fixed effects logit model to take into account the binary nature of the dependent variables, and found our results to be unchanged. These estimates are available from the authors on request.

Although the fixed effects estimator can overcome bias emanating from the presence of time-invariant omitted variables, it cannot address the other sources of potential endogeneity in people's well-being – omitted variables that may be specific to particular time points and measurement error in well-being itself. Hence, we next attempt to address the potential endogeneity of the mental distress and life satisfaction measures by using Lewbel's (2012) method. The IV estimates reported in Column 5 of Table 2 show that GHQ-12 enters positively the unemployment regression equation, while life satisfaction has a negative coefficient. This implies that a standard deviation increase in the GHQ-12 score (relative to the sample mean of all our respondents) raises unemployment propensity by about 2 percentage points (at p-values < 0.01). Similarly, a standard deviation increase in life satisfaction lowers unemployment propensity by 2.87 percentage points (again at p-values < 0.01). Importantly, the first-stage F statistics for the joint significance of the excluded instruments are above the rule-of-thumb value of 10 suggested by Staiger and Stock (1997), which leads us to reject the null hypothesis of weak IVs.

In Tables 3 and 4 we test whether an individual's well-being matters for (i) maintaining employment and (ii) exiting from unemployment. We do this by following Heineck (2010), and focusing our attention on those individuals who – at the beginning of the panel – were employed and those who were unemployed, respectively. It should be noted, however, that the study of unemployment exit comes at the cost of losing a significant number of observations, given that it requires focusing only on people who were unemployed at the beginning of the panel (see Table 1). As the resulting loss of power in the analysis is a likely cause of concern for the validity of the estimates, we pursue such analysis only as far as the data allows, i.e. instruments are not weak.

Our IV estimates in Columns 5 and 6 of Table 3 provide some evidence that mental health and life satisfaction may matter significantly for maintaining employment (or may help individuals avoid entering unemployment). The same cannot be said, however, about exit from unemployment, as the estimated effects in Columns 5 and 6 of Table 4 appear to be statistically insignificant at conventional levels.

More specifically, we find that a standard deviation increase in the GHQ-12 score (relative to the sample mean of all employed respondents in Wave 1) increases the probability of entering unemployment by about 1.54 percentage points (at p-values < 0.01). There is also a negative coefficient on life satisfaction, suggesting that a standard deviation increase in this well-being measure decreases the probability of entering unemployment by 1.01 percentage points (at p-values < 0.05). Again, the first-stage F statistics are sufficiently large and therefore indicate rejection of the null hypothesis of weak IVs.

However, the estimates in Columns 5 and 6 of Table 4 suggest that neither mental health nor life satisfaction have a significant effect on an individual's probability of exiting unemployment. This most certainly reflects the small sample sizes in the exit from unemployment equation, a likely cause of weak instruments problems that are evident in the form of imprecise estimates with large standard errors.

Overall, our findings indicate that people who are generally more satisfied with life and have better mental health in the previous wave are less likely to be currently unemployed. Conditioning on people who were employed at the beginning of the panel, we also find that life satisfaction and mental health may raise the likelihood of maintaining employment. These effects continue to hold after controlling for the Big Five personality traits, which have been shown in the literature to predict people's well-being (e.g. Myers and Diener, 1995; Steel et al., 2008; Boyce et al., 2013).

4.2 Sub-sample analyses

We now look for evidence of heterogeneity across individuals in how well-being impacts unemployment. A question of interest is whether the estimated effects of life satisfaction and mental distress on unemployment are quantitatively and qualitatively similar across genders. To address this question, we focus our attention on unemployment propensity and unemployment entry, as splitting the sample further to examine unemployment exit would result in a significant loss of power in the analysis and weak instruments problems.

The estimates reported in Table 5 suggest that being more satisfied with life in the previous wave reduces the probability of entering unemployment in the current wave for males (at p-values < 0.05), but not for females. There is also evidence that life satisfaction reduces unemployment propensity for both males and females (at p-values < 0.01); though the corresponding coefficient estimate for males is almost twice the size of that for females. Regarding mental health, we find that scoring higher on the GHQ-12 scale increases unemployment propensity and the probability of entering unemployment for both genders.

Do these effects represent actual differences between genders? To examine this, we use a two sample z-test for which the null hypothesis is that there are no observed differences. The z-test statistic[13] indicates that we cannot reject the null hypothesis, implying that males and females do not differ in terms of how well-being impacts unemployment. Nevertheless, one also needs to acknowledge that extra care must be taken when interpreting statistical differences here. This issue appears to be most relevant regarding the impact of life satisfaction on unemployment entry, the only case in which the first-stage F statistic was below the rule-of-thumb value of 10.

We next ask whether the extent to which reported well-being influences unemployment varies significantly between people who are British (i.e. belong to the British ethnic group) and their non-British peers.[14] To address this question, Table 6 separates the data by ethnic group of the respondent. The estimates show that scoring higher on the GHQ-12 scale in the previous wave increases the

[13] As the samples for male and female groups contain a sufficiently large number of observations, the Central Limit Theorem permits calculation of the z score as opposed to the t score. The corresponding z-test statistic is approximately normally distributed and hence, at the 95% confidence level, the critical values of z are -1.96 and 1.96, with rejection rule $z < -1.96$ or $z > 1.96$. Across all our models, the corresponding z-test statistic was always within the range of the critical values -1.96 and 1.96.

[14] The British ethnic group includes respondents who stated they were British/ English or Scottish. The non-British ethnic group includes Irish, Gypsy or Irish Travelers, any other white background, any mixed, any Asian or Asian/British, any black/ African/ Caribbean/ black British and any other ethnic groups. According to this classification, 21 percent of the observations in our dataset were non-British and 79 percent were British.

likelihood of entering unemployment in the current wave among those who are British (at p-values < 0.01), but not among non-British. Similarly, the negative effect of satisfaction with overall life on the probability of entering unemployment is relevant for those who are British (again at p-values < 0.01), but not for non-British.

Looking at whether the estimated effects represent actual differences between ethnic groups in the United Kingdom, we find little evidence of statistical differences. The only exception appears to be the effect of life satisfaction on unemployment entry: being more satisfied with life reduces the probability of entering unemployment only for those who are British; though this difference seems to have been due to a loss of power in the analysis rather than being statistically significant.[15] Overall, these results thus imply that the regression equations relating unemployment and well-being may have a very similar structure with respect to gender or ethnic group of the respondents.

5. Robustness

We now examine the robustness of our results to issues related to using lagged well-being to time t-2, attrition bias, and implementing an alternative IV estimator.[16]

Previous studies have suggested that individuals who will enter unemployment in the future may experience a drop in their well-being one year prior to becoming unemployed (Powdthavee, 2012; Clark et al., 2008). This implies is that future unemployment is likely to be anticipated and thus may be a source of potential bias in the estimates. To address this issue, we re-conducted our analysis using life satisfaction or GHQ-12 at time $t-2$ (instead of time $t-1$) as the main explanatory variable. As reported in Table A1, our findings are qualitatively similar to those in Tables 2 and 3. Being more satisfied with life and

[15] The corresponding z-test statistic is -2.5426, which is lower than the critical value of -1.96 at the 95% confidence level.

[16] We also attempted to estimate the model separately for each wave with respect to unemployment entry and exit but were faced with a significant reduction in the corresponding sample sizes, and hence we could not pursue this avenue further.

having better mental health continue to be associated negatively and statistically significantly with unemployment propensity or unemployment entry.

A typical concern in panel surveys is attrition. It may be a cause of potential bias in the estimates if individuals are leaving the sample in a non-random fashion. In the current setting, individuals who are relatively less satisfied with life or more mentally distressed may be prone to dropping out from the panel survey more frequently. Hence, to check the robustness of our results to the presence of attrition bias, we re-estimated our model using a balanced panel of respondents who participated in all five waves of the UKHLS survey. The estimates reported in Table A2 are qualitatively similar to our previous IV results.

Finally, we checked the robustness of our results by using an alternative IV estimator; the two-step generalized method of moments estimator (GMM) that may be applied (instead of two-stage least squares) in the context of Lewbel's method. The estimates reported in Table A3 are largely consistent with our previous findings. Looking across the columns, we observe that being more satisfied with life and having better mental health continue to predict unemployment propensity or unemployment entry in a negative and statistically significant manner, thus lending further support for our earlier findings.

6. Conclusion

The current paper sets out to test the importance of well-being for unemployment propensity, maintaining employment, and exiting from unemployment. Drawing data from the UKHLS, and using a novel identification approach proposed by Lewbel (2012), we show that people who are generally more satisfied with life and have better mental health in the previous wave are less likely to be currently unemployed. This finding is consistent with what would have been predicted by the 'abundancy' theory of motivation. We further show that life satisfaction and mental health may matter significantly for maintaining employment. These effects are qualitatively similar across genders and ethnic groups of the respondents. There was not enough evidence, however, that would allow us to draw any conclusions on how well-being impacts unemployment exit, and future research will need to return to this issue. Our findings thus provide new empirical evidence on the link between well-being and one of the most important economic shocks – job loss – by highlighting the importance of having high levels of well-being.

The current study, like most that preceded it in social sciences, is not without shortcomings. Although its empirical approach follows some of the most recent studies in the literature in dealing with the potential endogeneity of the well-being variable, the implied estimates rely on the use of higher moments for identification and therefore are likely to be less efficient than estimates based on standard exclusion restrictions. It is difficult to know precisely the extent of potential efficiency loss here, given that we are not able to find an appropriate variable to instrument for well-being. Nevertheless, the latest findings in the literature show that the IV results obtained from Lewbel's method are more plausible than those obtained using conventional IVs of questionable validity. What this implies is that Lewbel's method – being one of the latest tools available in the researcher's toolkit – may be reliably applied in settings where conventional IVs are weak or difficult to obtain. While still extra care needs to be taken when interpreting our results, Lewbel's method could also be seen as a valuable alternative to the use of conventional fixed and random effects models, especially in settings where traditional IVs seem difficult to obtain.

The current paper also offers a new way of thinking about satisfaction with life and mental health. And having identified and better understood their potential role for individuals' employment status, we may then be able to feed this knowledge back into theoretical work in this area by attempting to build more accurate economic models of unemployment duration. More generally, in highlighting the aforementioned findings, we aim to encourage new research that will further our understanding of how having high levels of well-being may have important consequences for the achievement of certain successful outcomes in people's lives, including, but not necessarily limited to, work-related outcomes.

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Figures and Tables

Figure 1: Unemployment rate at each level of lagged GHQ 12 score

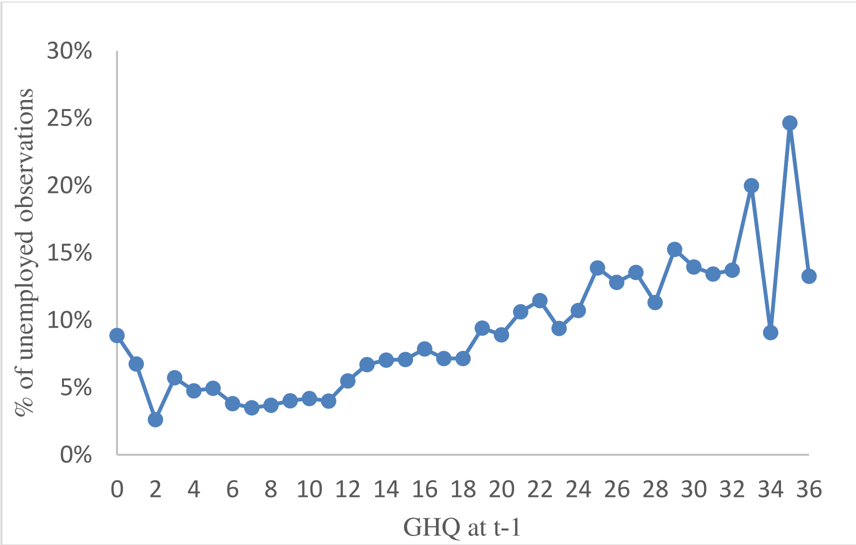

Figure 2: Unemployment rate at each level of lagged life satisfaction score

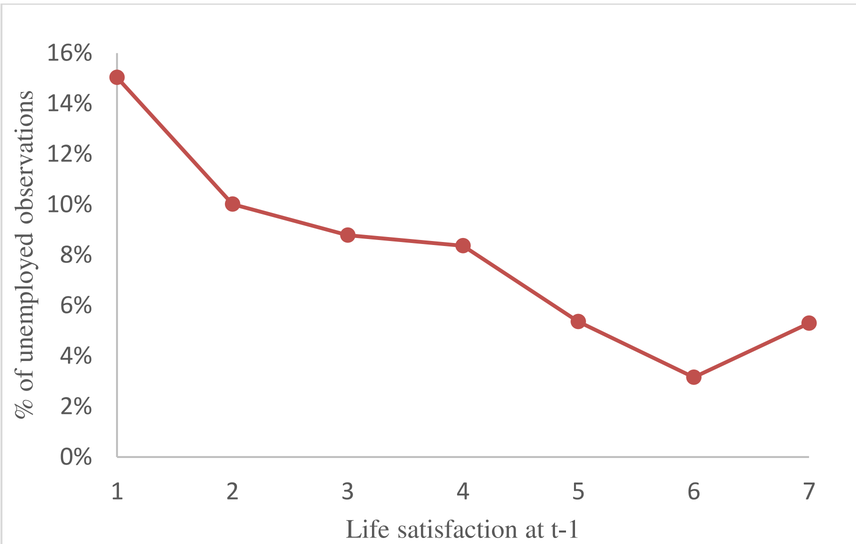

Table 1: Summary statistics (non-standardized)

	Pooled Sample			Working or self-employed in Wave 1			Unemployed in Wave 1		
Variables	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Unemployed	56,693	0.055	0.228	43,189	0.024	0.153	3,723	0.347	0.476
GHQ12-Likert	56,693	11.418	5.583	43,189	10.880	5.031	3,723	13.220	6.834
Life satisfaction	56,693	5.049	1.477	43,189	5.173	1.380	3,723	4.454	1.712
Male	56,693	0.409	0.492	43,189	0.450	0.497	3,723	0.508	0.500
Age	56,693	41.422	9.756	43,189	41.892	9.438	3,723	39.676	10.595
Household income (1,000 pounds)	56,693	4.039	2.766	43,189	4.385	2.785	3,723	2.406	1.937
Having diploma or higher	56,693	0.425	0.494	43,189	0.463	0.499	3,723	0.247	0.432
Non-British	56,693	0.204	0.403	43,189	0.181	0.385	3,723	0.287	0.452
Married/ Civil partner	56,693	0.571	0.495	43,189	0.602	0.490	3,723	0.316	0.465
Separated	56,693	0.028	0.165	43,189	0.027	0.162	3,723	0.037	0.190
Number of children in the household	56,693	0.861	1.075	43,189	0.780	1.004	3,723	0.794	1.113
Having children aged 0-5 in household	56,693	0.070	0.327	43,189	0.064	0.312	3,723	0.061	0.312
Having children aged 6-15 in household	56,693	0.117	0.453	43,189	0.107	0.425	3,723	0.106	0.441
Not having long-standing illness or disability	56,693	0.708	0.455	43,189	0.745	0.436	3,723	0.624	0.485
Agreeableness	56,693	16.921	2.968	43,189	16.892	2.912	3,723	16.649	3.285
Conscientiousness	56,693	16.642	3.064	43,189	16.844	2.904	3,723	15.771	3.496
Extraversion	56,693	13.759	3.797	43,189	13.866	3.751	3,723	13.309	3.782
Neuroticism	56,693	10.991	4.149	43,189	10.698	4.004	3,723	11.560	4.517
Openness	56,693	13.749	3.740	43,189	13.896	3.607	3,723	13.294	4.064

Table 2: Mental Distress, Life satisfaction and Unemployment Propensity

Pooled Sample	(1) RE	(2) FE	(3) RE	(4) FE	(5) IV	(6) IV
GHQ12-Likert	0.0109*** (0.00134)	0.00442*** (0.00156)			0.0200*** (0.00354)	
Life satisfaction			-0.00880*** (0.00114)	-0.00140 (0.00131)		-0.0287*** (0.00563)
Male	0.0213*** (0.00301)	0.00769 (0.00522)	0.0201*** (0.00301)	0.00255 (0.00322)	0.0224*** (0.00213)	0.0191*** (0.00219)
Age	-0.00288** (0.00130)	-0.00228 (0.00454)	-0.00290** (0.00129)	-0.00222 (0.00454)	-0.00328*** (0.000999)	-0.00384*** (0.00102)
Age Squared/ 100	0.00338** (0.00156)	0.00416 (0.00459)	0.00341** (0.00156)	0.00393 (0.00459)	0.00390*** (0.00120)	0.00449*** (0.00122)
Household Income	-0.00948*** (0.00103)	0.00768*** (0.00139)	-0.00933*** (0.00103)	0.00763*** (0.00139)	-0.0184*** (0.000925)	-0.0168*** (0.00104)
Having diploma or higher	-0.0353*** (0.00252)	0.00260 (0.00777)	-0.0348*** (0.00253)	0.00193 (0.00772)	-0.0282*** (0.00186)	-0.0259*** (0.00191)
Non-British	0.0252*** (0.00387)	-0.0124 (0.00806)	0.0242*** (0.00388)	-0.0120 (0.00801)	0.0222*** (0.00284)	0.0181*** (0.00297)
Married/ Civil partner	-0.0426*** (0.00295)	-0.00175 (0.00677)	-0.0422*** (0.00295)	-0.00189 (0.00678)	-0.0425*** (0.00225)	-0.0388*** (0.00247)
Separated	-0.0213*** (0.00788)	-0.00739 (0.0120)	-0.0207*** (0.00789)	-0.00690 (0.0120)	-0.0193*** (0.00690)	-0.0197*** (0.00696)

Number of children in the household	0.00232	-0.00125	0.00242*	-0.00126	0.00342***	0.00345***
	(0.00142)	(0.00294)	(0.00143)	(0.00294)	(0.00116)	(0.00116)
Having children aged 0-5 in household	-0.00118	0.00101	-0.00108	0.00105	-0.00415	-0.00340
	(0.00248)	(0.00290)	(0.00249)	(0.00290)	(0.00282)	(0.00285)
Having children aged 6-15 in household	-0.00254	-0.00230	-0.00272	-0.00237	-0.00311	-0.00359
	(0.00184)	(0.00196)	(0.00184)	(0.00196)	(0.00222)	(0.00223)
Not having long-standing illness or disability	-0.0118***	-0.00192	-0.0130***	-0.00235	-0.0140***	-0.0131***
	(0.00249)	(0.00320)	(0.00250)	(0.00320)	(0.00259)	(0.00282)
Agreeableness	0.00230		0.00251		0.00219*	0.00288**
	(0.00158)		(0.00159)		(0.00112)	(0.00113)
Conscientiousness	-0.00941***		-0.00960***		-0.00851***	-0.00792***
	(0.00162)		(0.00161)		(0.00120)	(0.00124)
Extraversion	-0.000466		-0.000272		0.000196	0.00115
	(0.00149)		(0.00149)		(0.00106)	(0.00109)
Neuroticism	0.00288*		0.00498***		-0.00158	-0.000256
	(0.00160)		(0.00157)		(0.00157)	(0.00152)
Openness	0.000603		0.000687		0.000123	0.000402
	(0.00160)		(0.00160)		(0.00112)	(0.00113)
Regional dummy	yes	yes	yes	yes	yes	yes
Wave dummy	yes	yes	yes	yes	yes	yes
Constant	0.167***	0.0753	0.168***	0.0783	0.171***	0.182***
	(0.0259)	(0.129)	(0.0258)	(0.129)	(0.0200)	(0.0202)
F-statistic on the excluded instruments					166.15	27.16
Observations	56693	56693	56693	56693	56693	56693

Note: *** p<0.001, ** p<0.05 and * p<0.1. RE = random effects model. FE = fixed effects model. IV = instrumental variable model. Robust standard errors are in parenthesis. GHQ12-Likert, life satisfaction, household income, age and scores for each of the Big Five personality traits are standardized. All independent variables are taken at time t-1.

Table 3: Mental Distress, Life satisfaction and Unemployment Entry in Waves 2-5

Working or Self-employed in Wave 1	(1) RE	(2) FE	(3) RE	(4) FE	(5) IV	(6) IV
GHQ12-Likert	0.00747***	0.00302**			0.0154***	
	(0.00111)	(0.00126)			(0.00311)	
Life satisfaction			-0.00434***	-0.000285		-0.0101**
			(0.000914)	(0.00109)		(0.00454)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.102***	0.228**	0.102***	0.231**	0.0906***	0.0927***
	(0.0207)	(0.108)	(0.0207)	(0.108)	(0.0170)	(0.0172)
F-statistic on the excluded instruments					89.89	16.56
Observations	43189	43189	43189	43189	43189	43189

Note: *** p<0.001, ** p<0.05 and * p<0.1. RE = random effects model. FE = fixed effects model. IV = instrumental variable model. Robust standard errors are in parenthesis. GHQ12-Likert and life satisfaction are standardized. Control variables include standardized household income, standardized age, standardized age squared/ 100, standardized scores for each of the Big Five personality traits, number of children living in the household, and dummy variables indicating educational attainment, marital status, male, being non-British, having children aged 0-5 living in the household, having children age 6-15 living in the household, having long-standing illness or disability, demographic areas, and time. All independent variables are taken at time t-1.

Table 4: Mental Distress, Life satisfaction and Unemployment Exit in Waves 2-5

Unemployed in Wave 1	(1) RE	(2) FE	(3) RE	(4) FE	(5) IV	(6) IV
GHQ12-Likert	0.0144	0.0173			-0.00754	
	(0.00895)	(0.0109)			(0.0232)	
Life satisfaction			-0.0228***	-0.0170*		-0.0237
			(0.00810)	(0.00979)		(0.0407)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.337**	0.209	0.350**	0.257	0.380***	0.406***
	(0.149)	(0.856)	(0.149)	(0.854)	(0.116)	(0.121)
F-statistic on the excluded instruments					11.04	1.80+
Observations	3723	3723	3723	3723	3723	3723

Note: *** p<0.001, ** p<0.05 and * p<0.1. RE = random effects model. FE = fixed effects model. IV = instrumental variable model. Robust standard errors are in parenthesis. GHQ12-Likert and life satisfaction are standardized. Control variables include standardized household income, standardized age, standardized age squared/ 100, standardized scores for each of the Big Five personality traits, number of children living in the household, and dummy variables indicating educational attainment, marital status, male, being non-British, having children aged 0-5 living in the household, having children age 6-15 living in the household, having long-standing illness or disability, demographic areas, and time. All independent variables are taken at time t-1.

+ F (31, 3660) = 1.80, with Prob > F = 0.0044.

Table 5: Mental Distress, Life satisfaction and Unemployment by Gender: Instrumental Variable Model

	Pooled Sample				Working or self-employed in Wave 1			
	Males		Females		Males		Females	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GHQ12-Likert	0.0268***		0.0184***		0.0210***		0.0144***	
	(0.00601)		(0.00447)		(0.00546)		(0.00388)	
Life satisfaction		-0.0418***		-0.0248***		-0.0179**		-0.00794
		(0.0102)		(0.00654)		(0.00737)		(0.00535)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.249***	0.260***	0.134***	0.142***	0.137***	0.135***	0.0617***	0.0643***
	(0.0350)	(0.0352)	(0.0239)	(0.0242)	(0.0283)	(0.0282)	(0.0207)	(0.0210)
F-statistic on the excluded instruments	72.84	11.42	99.60	18.03	38.04	7.98^{+}	52.82	9.99^{++}
Observations	23193	23193	33500	33500	19414	19414	23775	23775

Note: *** p<0.001, ** p<0.05 and * p<0.1. Robust standard errors are in parenthesis. GHQ12-Likert and life satisfaction are standardized. Control variables include standardized household income, standardized age, standardized age squared/ 100, standardized scores for each of the Big Five personality traits, number of children living in the household, and dummy variables indicating educational attainment, marital status, being non-British, having children aged 0-5 living in the household, having children age 6-15 living in the household, having long-standing illness or disability, demographic areas, and time. All independent variables are taken at time t-1.

$^{+}$ F (30, 19353) = 7.98, with Prob > F= 0.0000

$^{++}$ F (30, 23714) = 9.99, with Prob > F= 0.0000

Table 6: Mental Distress, Life satisfaction and Unemployment by Ethnic group (British vs Non-British): Instrumental Variable Model

	Pooled Sample				Working or self-employed in Wave 1			
	British		Non-British		British		Non-British	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GHQ12-Likert	0.0155***		0.0281***		0.0155***		0.0084	
	(0.00369)		(0.00909)		(0.00329)		(-0.00757)	
Life satisfaction		-0.0225***		-0.0395***		-0.0119**		0.00218
		(0.00597)		(0.0139)		0.00517		(-0.00869)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.152***	0.163***	0.236***	0.238***	0.0812***	0.0847***	0.121**	0.123**
	(0.0219)	(0.0222)	(0.0494)	(0.0494)	(0.0180)	(0.0183	-0.0494	-0.0492
F-statistic on the excluded instruments	143.25	22.08	30.71	6.51+	77.70	12.84	15.87	5.43++
Observations	45144	45144	11549	11549	35405	35405	7784	7784

Note: *** p<0.001, ** p<0.05 and * p<0.1. Robust standard errors are in parenthesis. GHQ12-Likert and life satisfaction are standardized. Control variables include standardized household income, standardized age, standardized age squared/ 100, standardized scores for each of the Big Five personality traits, number of children living in the household, and dummy variables indicating educational attainment, marital status, male, having children aged 0-5 living in the household, having children age 6-15 living in the household, having long-standing illness or disability, demographic areas, and time. All independent variables are taken at time t-1.

+ $F(30, 11488) = 6.51$, with Prob > F = 0.0000

++ $F(30, 7723) = 5.43$, with Prob > F = 0.0000

Table A1: Mental Distress, Life satisfaction and Unemployment using Independent Variables Lagged to t-2: Instrumental Variable Model

	Pooled Sample		Working or self-employed in Wave 1	
	(1)	(2)	(3)	(4)
GHQ12-Likert	0.00939**		0.00963***	
	(0.00417)		(0.00356)	
Life satisfaction		-0.0241***		-0.00923*
		(0.00649)		(0.00528)
Controls	yes	yes	yes	yes
Constant	0.154***	0.161***	0.0678***	0.0695***
	(0.0235)	(0.0235)	(0.0196)	(0.0196)
F-statistic on the excluded instruments	122.67	24.72	61.17	13.41
Observations	39122	39122	30001	30001

Note: *** p<0.001, ** p<0.05 and * p<0.1. Robust standard errors are in parenthesis. GHQ12-Likert and life satisfaction are standardized. Control variables include standardized household income, standardized age, standardized age squared/ 100, standardized scores for each of the Big Five personality traits, number of children living in the household, and dummy variables indicating educational attainment, marital status, being non-British, having children aged 0-5 living in the household, having children age 6-15 living in the household, having long-standing illness or disability, demographic areas, and time. All independent variables are taken at time t-2.

Table A2: Mental Distress, Life satisfaction and Unemployment with a Balanced Panel: Instrumental Variable Model

	Pooled Sample		Working or self-employed in Wave 1	
	(1)	(2)	(3)	(4)
GHQ12-Likert	0.0192***		0.0132***	
	(0.00423)		(0.00361)	
Life satisfaction		-0.0265***		-0.00991*
		(0.00650)		(0.00517)
Controls	yes	yes	yes	yes
Constant	0.167***	0.176***	0.0303	0.0327*
	(0.0251)	(0.0254)	(0.0185)	(0.0188)
F-statistic on the excluded instruments	104.41	20.63	55.13	12.77
Observations	36208	36208	28384	28384

Note: *** p<0.001, ** p<0.05 and * p<0.1. Robust standard errors are in parenthesis. GHQ12-Likert and life satisfaction are standardized. Control variables include standardized household income, standardized age, standardized age squared/ 100, standardized scores for each of the Big Five personality traits, number of children living in the household, and dummy variables indicating educational attainment, marital status, being non-British, having children aged 0-5 living in the household, having children age 6-15 living in the household, having long-standing illness or disability, demographic areas, and time. All independent variables are taken at time t-1.

Table A3: Mental Distress, Life satisfaction and Unemployment: Instrumental Variable Model Using GMM

	Pooled Sample		**Working or self-employed in Wave 1**	
	(1)	(2)	(3)	(4)
GHQ12-Likert	0.0165***		0.0122***	
	(0.00340)		(0.00292)	
Life satisfaction		-0.0195***		-0.00940**
		(0.00540)		(0.00430)
Controls	yes	yes	yes	yes
Constant	0.174***	0.178***	0.0861***	0.0910***
	(0.0198)	(0.0199)	(0.0166)	(0.0167)
F-statistic on the excluded instruments	166.15	27.16	89.89	16.56
Observations	56693	56693	43189	43189

Note: *** p<0.001, ** p<0.05 and * p<0.1. Robust standard errors are in parenthesis. GHQ12-Likert and life satisfaction are standardized. Control variables include standardized household income, standardized age, standardized age squared/ 100, standardized scores for each of the Big Five personality traits, number of children living in the household, and dummy variables indicating educational attainment, marital status, being non-British, having children aged 0-5 living in the household, having children age 6-15 living in the household, having long-standing illness or disability, demographic areas, and time. All independent variables are taken at time t-1.