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Anita Ratcliffe
Karl Taylor

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Anita Ratcliffe
University of Sheffield

Karl Taylor
University of Sheffield and IZA

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P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Who Cares about Stock Market Booms and Busts? Evidence from Data on Mental Health*

This paper investigates the relationship between share prices and mental health, exploiting the availability of interview dates in the British Household Panel Survey to match the level and changes in the FTSE All Share price index to respondents over the period 1991-2008. We present evidence that the level, 6 month and yearly changes in the share price index are associated with better mental health while greater uncertainty, as measured by index volatility, is associated with poorer mental well-being. Finally, using several proxies of investor status, we find little evidence that this relationship is confined to holders of equity based assets, suggesting that the observed relationship does not arise via wealth effects. Instead, it appears as though share prices matter to mental health because they perform the role of economic barometer.

JEL Classification: J26, D12

Keywords: share prices, economic conditions, mental health

Corresponding author:

Karl Taylor
Department of Economics
University of Sheffield
9 Mappin Street
Sheffield S1 4DT
United Kingdom
E-mail: k.b.taylor@sheffield.ac.uk

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1 Introduction

Data on well-being or mental health are increasingly used to complement traditional research methods in economics, and to inform public policy - particularly in the UK where the government has recently launched a program to measure national well-being. The aim of this paper is to complement existing research on the welfare effects of economic booms and busts by examining the relationship between the stock market performance and mental health. Existing studies typically focus on the effect of share price fluctuations on consumption and leisure patterns (see inter alia Banks et al., 2012; Disney et al., 2010, for UK evidence on the aged). While changing consumption and leisure patterns may underpin any association between economic cycles and well-being, focusing on mental well-being may reveal new insights if it transpires that economic conditions affect levels of distress independently from changes in personal economic circumstances. For example, Di Tella et al. (2001, 2003) find that macroeconomic conditions, as measured by unemployment rates, matter to happiness even after taking into account the effects of high unemployment on personal income and employment status. To explain this result, they suggest that unemployment rates are informative of economic prospects.

Researchers have recently begun to explore whether asset prices perform a similar role as an economic barometer (see for example Deaton (2012) for evidence on share prices and Ratcliffe (2012) for evidence on house prices). Asset prices may provide unique signals of economic prospects compared to unemployment rates if asset prices are more forward looking in that they reflect the net present value of future revenue streams. Asset markets may therefore aggregate the beliefs of many forward looking individuals and firms with respect to longer term economic prospects. A priori, however, one might expect any correlation between asset prices and mental health to reflect the effect of unexpected asset price fluctuations on personal wealth. The little evidence that exists linking stock markets to various measures of subjective well-being does not support a wealth mechanism. However, much of this evidence is visual in nature, with regression analysis confined to aggregate relationships between the stock market and well-being.

The current study makes several contributions to the literature. We are among the first to examine the relationship between share prices and mental well-being using individual level data, which is made possible by the availability of interview dates in the British Household Panel Survey. Hence, we can explore the existence of wealth effects versus an economic barometer mechanism by examining the relationship between share prices and mental health across various groups in the population, while taking into account detailed socio-economic and demographic information. Moreover, our analysis is not confined to the period of the recent crisis. Our data starts in 1991 and ends in 2008, and therefore covers the late 1990/early 2000 boom and bust as well as the onset of the financial crisis. Finally, this paper contributes to the wider literature on the effect of macroeconomic conditions, and in particular of asset prices, on mental health.

To preview our results, we find evidence of a positive correlation between changes in share prices and mental health. Conversely, our results suggest that greater uncertainty, as measured by increased volatility in the share price index, is associated with lower mental well-being. Finally, using several proxies of asset ownership, we find that both asset owners and non-owners are sensitive to fluctuations in share prices, suggesting that the observed relationship does not arise via wealth effects. Instead, it appears as though the share price index acts as a barometer of economic performance.

2 Literature

There is growing evidence that macroeconomic conditions affect mental health via an 'economic stress' mechanism (Catalano and Dooley, 1983). This posits that actual or anticipated job loss and associated financial insecurity are risk factors in illness. As the prospect of unemployment is greater when unemployment rates rise, much of this literature focuses on the effect of unemployment rates on well-being. Di Tella et al. (2001, 2003) present evidence of a negative relationship between national unemployment rates and happiness using cross country data, while Charles and DeCicca (2008) show that local labour markets have a similarly adverse effect on mental health. Since unemployment rates influence happiness or mental health even after taking into account the effect of high unemployment on personal income and labour market status, these findings are consistent with a psychological phenomena. In particular, Di Tella et al. (2001, 2003) suggest that high unemployment rates induce a 'fear of unemployment'.

More recently researchers have focussed attention on whether asset prices perform a similar role as an economic barometer. However, since rising asset prices makes asset owners wealthier, a positive relationship might exist between asset prices and the well-being of asset owners owing to wealth effects. To distinguish between wealth effects versus the role of economic barometer, it is necessary to consider the relationship between asset prices and well-being among non-asset owners. For example, the wealth of non-owners is unchanged (and lifetime wealth may even decline among aspiring asset owners) when asset prices unexpectedly rise, suggesting a negative, if any, relationship between asset prices and the well-being of non-asset owners. In contrast, if asset prices are viewed as an economic barometer, asset price movements are likely to matter to both asset owners and non-owners.

Using the Gallup daily random sample of 1000 Americans, Deaton (2012) presents time-series plots documenting a positive relationship between the daily share price index and daily averages of well-being, as measured by Cantril's Self-Anchoring Scale (Cantril's Ladder). Yet time-series plots of the proportion reporting satisfaction with their standard of living - closely correlated with the ladder - indicate that low income households, who are less likely to own shares, are most sensitive to the evolving crisis. This indicates that rather than providing a reflection of changes in financial resources, the share price index matters via a role as an economic barometer, or at least that the stock market and well-being are responding to the same stream of information. Regressions using daily and monthly averages of the share price index and Cantril's Ladder confirm a positive and statistically significant relationship that is robust to controlling for official measures of income and unemployment (albeit with 36 data points in the latter analysis).

Murgea and Reisz (2012) also use the Gallup survey to empirically investigate the relationship between monthly measures of the share price index, the Chicago Board Options Exchange Volatility Index (a measure of the expected stock market volatility over the next 30 days) and the Gallup healthways well-being index (a composite measure of life evaluation, emotional and physical health, healthy behaviour, work and local environment) between January 2008 and March 2011. In separate regressions, they find evidence of a positive relationship between the index and well-being, and a negative relationship between volatility and well-being. However, neither effect is statistically different from zero when both terms are simultaneously considered.

To date only one previous study investigates the relationship between the stock market and well-being using individual level data. Falk and Jager (2011) match stock market returns over 1, 2 and 3 weeks to individuals in the German Socio-Economic Panel via the interview date. However, given the primary focus of this analysis is to better understand investor utility, the sample is restricted to households containing only one household adult (investment in stock markets is collected at the household level), and in addition, to households completing interviews with the assistance of an interviewer. They do not find much evidence that average returns over short time periods are related to life satisfaction.[1]

Finally, in a related study investigating the relationship between asset prices and mental health, Ratcliffe (2012) presents evidence that local house prices are positively correlated with the mental health of homeowners and non-homeowners using the British Household Panel Survey. This correlation, which is inconsistent with wealth effects, is robust to controlling for proxies of local area amenities, and local unemployment and earnings, and suggests that house prices are a barometer of economic prospects.

This study focuses on the relationship between share price fluctuations and mental health in Great Britain. Our main contribution to the literature is a detailed analysis of this relationship using individual level data but we are also the first to look at this issue with British data. Few Britons are invested in shares, either directly or indirectly through pension schemes, with asset portfolios dominated by housing wealth (Banks et al., 2004). As a result, share price fluctuations may register to a lesser extent with the British public. On the other hand, fluctuations in the FTSE 100 are reported on a daily basis in the media such that movements in share prices are quickly transmitted to the public. If frequency of information is an important characteristic of any indicator assuming the role of economic barometer, as the most frequently published indicator, the share price index may nevertheless shape mental health outcomes.

[1]They do, however, find evidence supporting behavioural theories, a discussion of which is beyond the scope of this paper.

3 Methodology

3.1 Empirical Model

We estimate the following regression specification:

$$\mathrm{H_{it}} = \alpha_1 \mathrm{FTSE_{it}} + \beta' \mathrm{z_{it}} + \theta_{\mathrm{t_1}} + \theta_{\mathrm{t_2}} + \theta_{\mathrm{t_3}} + \mathrm{v_{it}} \tag{1}$$

where $\mathrm{H_{it}}$ is a measure of the mental health of individual i at time t and $\mathrm{FTSE_{it}}$ measures the FTSE All Share price index on the date that individual i is interviewed. Initially we explore the influence of index levels, and high (1 day, 1 week and 1 month) and low frequency (6 months, 1 year) changes in the index on mental health. The vector z contains demographic characteristics such as age, household composition, education level, labour market status, monthly household income and region of residence. We also include dummy variables to capture the day of the week (θ_{t_1}), the survey week (θ_{t_2}) and the survey year (θ_{t_3}). Finally, $\mathrm{v_{it}}$ is a random error term, clustered at the individual level.

3.2 Data

Data are taken from the British Household Panel Survey[2] (BHPS) between 1991 and 2008. The BHPS is a nationally representative survey of 5 500 households[3] (over 10 000 individuals) that collects wide ranging socio-economic and demographic information on household members.

BHPS interviews begin on the 1st September each year with around 85% of interviews completed by early November, and crucially for this study, interview dates are publicly available. The BHPS contains a standard measure of mental well-being, the General Health Questionnaire (GHQ), which is frequently used to assess psychological health (see inter alia Clark, 2003; Gardner and Oswald, 2007; Roberts et al., 2011) and appears as part of the self-completed questionnaire administered to all household adults. The version of the GHQ in the BHPS has twelve questions, which focus on positive and negative emotions and answers to these questions are aggregated to produce a 0-36 point Likert index of mental well-being that is recoded so that higher scores reflect better psychological health.[4]

[2]University of Essex. Institute for Social and Economic Research, British Household Panel Survey: Waves 1-18, 1991-2009 [computer file]. 7th Edition. Colchester, Essex: UK Data Archive [distributor], July 2010. SN: 5151.

[3]To maintain representativeness of the British population, sample members are followed over time even as they move address and/or form new households. If sample members form new households, all adults in these households are also interviewed. Furthermore, children of household members are interviewed once aged 16. Note that booster samples for Scotland and Wales are added in 1999 and in 2001 for Northern Ireland but we restrict attention to original sample members.

[4]Respondents are asked *'Here are some questions regarding the way you have been feeling over the past few weeks. For each question please ring the number next to the answer that best suits the way you have felt. Have you recently...'* Question (a) *'been able to concentrate on what you are doing?'* with answers *'Better than usual...1'*, *'Same as usual...2'*, *'Less than usual...3'* and *'Much less than usual...4'*, Questions (b) *'lost sleep over worry?'*, (e) *'felt constantly under strain?'*, (f) *'felt you couldn't overcome your difficulties?'*, (i) *'been feeling unhappy or*

Levels and growth rates in the FTSE All Share price index are matched to respondents via the interview date,[5] thus providing variation in this aggregate index across respondents within each survey wave. These data are taken from Thomson Reuters Datastream, and have been adjusted for inflation using the retail price index. We concentrate on the FTSE All Share price index as opposed to the FTSE 100 in our analysis because the latter is an index of the 100 largest companies listed on the London Stock Exchange whereas the former combines the FTSE 100, the FTSE 250 (the next 250 largest companies after the FTSE 100) and the FTSE SmallCap (smaller companies). Compared to the FTSE 100, the FTSE All Share price index therefore provides a broader reflection of economic activity. In practice, however, both series produce similar results, which we discuss further in robustness analysis. Figure 1 plots the evolution of levels and the annual percent change in the index over the past year for the period analysed, which covers two boom and bust phases (late 1990/early 2000 and mid 2000/late 2000) in the stock market.

By using interview dates to create variation in the share price index across respondents within each survey year, we desire that interview dates are random, such that variation in share prices is exogenous to observed and unobserved characteristics that influence mental health. However, when we look at the distribution of characteristics of people interviewed across different weeks of the BHPS survey period, there is some evidence that people interviewed in the first two weeks of September are different to others. Table 1 reports normalised differences in the characteristics of people interviewed in each of the first 5 weeks of the BHPS survey period compared to the characteristics of people interviewed afterwards.[6] The normalised difference is calculated as $\frac{\overline{x}_1-\overline{x}_0}{\sqrt{s_0^2+s_1^2}}$ where $\overline{x}_0$ is the mean characteristic of people interviewed in week t and $\overline{x}_1$ is mean characteristic of people interviewed in weeks t+1 to T (where T is the final week in which interviews occur), and where s^2 is the variance of the relevant sample. It is evident that early interviewees are more likely to be older and retired, and hence to work fewer hours and have lower income, compared to others. This is perhaps unsurprising given the retired have fewer demands on their time and as such are more likely to be available for interview. In terms of the empirical analysis, this feature may be problematic for two reasons. Firstly, share prices are fairly persistent suggesting that people interviewed later in the year may be subject to higher/lower values or larger positive/negative changes

depressed?', (j) *'losing confidence in yourself?'*, (k) *'been thinking of yourself as a worthless person?'* with answers *'Not at all...1'*, *'No more than usual...2'*, *'Rather more than usual...3'* and *'Much more than usual...4'* and Questions (c) *'felt that you were playing a useful part in things?'*, (d) *'felt capable of making decisions about things?'*, (g) *'been able to enjoy your day-to-day activities?'*, (h) *'been able to face up to your problems?'*, (l) 'been feeling reasonably happy, all things considered?' with answers *'More than usual...1'*, *'Same as usual...2'*, *'Less so than usual...3'*, *'Much less than usual...4'*. The Likert scale (36-point) aggregation incorporates the severity of symptoms experienced by subtracting one from each response score (i.e. 1=0,2=1,3=2,4=3) and summing. The Likert scale is reversed so that higher scores reflect better mental well-being.

[5]For individuals interviewed at the weekend (just over 10% of the sample), we match the level and change of the index as measured on the Friday preceding the weekend to these respondents. This does mean that share prices are measured with a lag for some respondents but we obtain similar results if we exclude respondents interviewed at the weekend from our analysis.

[6]We focus on the first 5 weeks because differences in the composition of the sample occur in the first couple of weeks.

in share prices, which increases the likelihood that share prices are correlated with observed and unobserved characteristics. Even though it is possible to control for observed characteristics via regression methods, Imbens and Wooldridge (2009) suggest - as a rule of thumb - that normalised differences exceeding 0.25 make regression estimates of the effect of interest sensitive to the specification when the linearity approximation is not accurate globally. Moreover, we cannot control for unobserved time-varying characteristics, although we can take into account unobserved time invariant characteristics via individual fixed effects. Secondly, if there are heterogenous effects across different groups in the population and these groups experience levels and changes in share prices of different magnitudes as a result of when they are interviewed, we would not be able to identify the effect of interest. However, in robustness analysis we show that, in practice, this feature of the sample has little influence on our estimates.

Summary statistics for the sample used in analysis are presented in Table 2. For GHQ, FTSE levels, and high and low frequency changes, we consider whether each process contains a unit root or whether they are stationary. This is important in order to avoid potential spurious correlations between share prices and mental health. Throughout we find that each data series are stationary processes (see the Appendix for further details).

4 Results

4.1 The association between share prices and mental health

Table 3 presents various estimation results on the effect of share prices and mental health. For brevity we report only the estimated coefficient on the share price terms but a selection of extended results are available in Table 10 in the Appendix. For all estimates reported we multiply coefficients and standard errors by 100. Column 1 reports the estimated effect of daily share price index level on mental health. This result suggests that a 100 point increase in the share price index increases mental well-being by 0.04 units, equivalent to a 0.16% change of the mean GHQ score. However, high frequency changes in the share price index have no discernable effect on mental health despite widespread reporting of daily changes in the FTSE 100 in the media. On the other hand low frequency changes do matter. Columns 5 and 6 indicate that a one percentage point increase in half yearly and yearly growth rates increase mental well-being by 0.0081-0.0089. Given the average annual change in the share price index is 3.87 percent, share price fluctuations would typically generate a 0.13% change of the mean GHQ score.

In all specifications we take into account household income, indicators for the amount of dividend/payments received in the past year and labour market status. Hence, it appears as though the share price index matters to mental health after taking into account the effect of a booming stock market on current economic outcomes. However, it remains possible that the observed relationship arises because we are unable to effectively capture financial resources and hence consumption patterns. For example, it may be the case that people are simply adjusting their consumption in response to new information concerning economic prospects, so that unmeasured changes in consumption - as opposed to mental distress over future outcomes - drive the observed relationship. We cannot include further measures of financial resources or consumption but we have tried including self-assessments of current financial situation and the change in financial situation over the past year.[7] These measures may capture unobserved fluctuations in financial resources although it is likely that there is some reverse causality between financial self-assessments and mental health, which is why we do not use these variables in our main analysis. While there is a robust correlation between financial self-assessments and mental health, we still find evidence of a very similar relationship between share prices and mental health (for example the estimated coefficient on the annual change in share prices is 0.0094 with standard error 0.0032). We would argue this finding further supports the argument that fluctuations in share prices do not reflect unmeasured financial or economic circumstances.

Finally in column 7 we present results estimating the model in column 6 including individual fixed effects, since it is possible that systematic differences exist across respondents interviewed at different time points, and as a result facing different values of share prices. While we control for several observed characteristics of each respondent it may still be the case that unmeasured characteristics drive our results. The results presented in column 7 control for time-invariant unmeasured characteristics through individual fixed effects. The estimated coefficient is reasonably similar and remains statistically significant at conventional levels. For the daily share price index, the estimated coefficient is reduced by around 40% but remains statistically significant at conventional levels (the estimated coefficient is 0.0025 with standard error 0.0015). In the remaining analysis, we focus on changes in share prices.

One reason why high frequency changes in share prices have such little influence on mental health outcomes is that they are generally too small to have any significant impact on economic outcomes or perceptions of future economic outcomes. Furthermore, low frequency changes are volatile and any changes in stock prices over short periods are readily reversed. If this is the case, we might expect to observe a correlation between high frequency stock market movements and mental health once we measure the degree to which changes in share prices are perceived as temporary. We use the standard deviation in share prices to measure the extent to which share prices are fluctuating, and therefore the degree to which movements in share prices may be perceived as temporary. Of course there are other reasons to expect the volatility of share prices to matter. For example, it is well known from portfolio theory that investors are not only concerned with the mean returns but also

[7] For a measure of financial situation respondents are asked *'How well would you say you yourself are managing financially these days? Would you say you are'* with responses *'Living comfortably'*, *'Doing alright'*, *'Just about getting by'*, *'Finding it quite difficult'* and *'Finding it very difficult'*. For a measure of financial change respondents are asked *'Would you say that you yourself are better off or worse off financially than you were a year ago?'* with responses *'better'*, *'about the same'* and *'worse off'*. For a measure of financial expectations respondents are asked *'Looking ahead, how do you think you yourself will be financially a year from now, will you be'* where respondents can select *'Better than now'*, *'Worse than now'*, *'About the same'*. We introduce these measures as continuous variables.

the risk associated with investments i.e. the spread of returns around the mean (see Elton et al., 2007). Share price volatility increases the uncertainty of investor returns but it is also a reflection of greater uncertainty about the future. This would imply a negative relationship between volatility and mental health. Table 4 presents results where we add the standard deviation in share prices over the period in which the change in share prices is calculated. Clearly, this is only possible where the change is share prices is calculated over the past week or longer. For the most part, adding the standard deviation of share prices to the analysis makes very little difference to previously reported results. The standard deviation is generally negative and in column 4 it is statistically different from zero. The 1 year standard deviation is also of similar magnitude and statistically different from zero when included alongside changes in share prices measured over shorter horizons (not reported for reasons of space). In column 5, we add individual fixed effects to the model estimated in column 4. Adding the standard deviation slightly reduces the estimated magnitude of changes in share prices on mental health compared with Table 3 but the effect is remains statistically significant. Interestingly, the estimated standard deviation is barely changed in column 5 when we add individual fixed effects.

4.2 Evidence of wealth effects?

Thus far we document a positive association between changes in share prices and mental health, and conversely a negative association between stock market volatility and mental health. However, there are two competing explanations as to why these associations emerge. The first explanation suggests that these relationships are driven by people with investments in stock markets who experience unexpected wealth shocks in booming or tumbling stock markets, and who would likely care most about stock market volatility given the difficulty that uncertainty presents in identifying the best investment strategies. The second explanation suggests that, by aggregating the beliefs of many forward looking individuals/firms, the stock market may be a barometer of economic prospects. The key difference between these explanations is that the latter suggests people without stock market investments would also care about share price fluctuations.

Since 1992 the BHPS asks respondents whether they have contributed to a personal pension scheme, and the year they began making contributions. We use this information to identify people with defined contribution pension arrangements, who are indirectly invested in the stock market via their pension scheme.[8] In 1995, 2000 and 2005, detailed information is available on financial assets. We use ownership of investment trusts, personal equity plans, shares and company stocks to measure who is directly invested in stock markets, matching this information to other years using an imputation procedure described in the Appendix. By combining information on DC pension and

[8]We assume the retired annuitize DC pension wealth upon retirement. Note also that there is a separate question relating to employer pension schemes, which over the period analysed are typically defined benefit pension arrangements.

equity investments, we are able to create a proxy of investor status.[9] Results of separate regressions by investor status are presented in the first two columns of Table 5. There is little evidence that investors are more sensitive to share price movements compared to others. Estimated effects are similar across both groups even if insignificantly different from zero owing to smaller sample sizes.[10]

Our measure of investor status is far from ideal as this information is solicited in some, but not all, waves. As an alternative proxy of investor status we split the sample by education level (where high education refers to degree level or similar qualifications). Individuals with higher education are more likely to be invested in stock markets and have more valuable assets conditional on investment (see Guiso et al., 2008). However, we again observe similar effects across high and low educated individuals. One issue with this proxy of investor status is the large expansion in higher qualifications over the period observed, although we also find similar results when we restrict our higher education measure to degree level qualifications, which expanded less dramatically.

As a third proxy of investor status, we split the sample by age (<35, 35-49 and 50+). Using information on the investment patterns in 1995, 2000 and 2005, 13% of those aged <35, 27% of those aged 35-49 and 32% of those aged 50+ are invested in stock markets via the financial assets listed above, with the value of these investments also increasing monotonically by age. A slightly different picture emerges for indirect investments via pension schemes where we measure 22% of those aged <35, 41% of those aged 35-49 and 35% of those aged 50+ to have DC pension arrangements. Overall, we would argue that younger persons would be less affected by wealth considerations given a lower propensity to be invested in stock markets. However, the evidence presented in the final three columns of Table 5 provides no indication that younger persons are any less affected by share price movements than others.

4.3 Robustness analysis

In this paper we provide evidence that changes and volatility of share prices affect mental health outcomes, and moreover, that the relationship observed is inconsistent with wealth effects. An alternative explanation that share prices are informative of economic prospects is better supported by the evidence. In this section we present various sensitivity analyses focusing first on the estimated magnitude of the share price effect followed by an investigation of alternative methods to estimate the standard error.

In this analysis, we have used the date of interview to create variation in share prices across respondents interviewed in the same survey year. However, as noted earlier, there is some evidence of systematic differences among respondents interviewed in the first two weeks of September compared to those interviewed later. We pursue a number of strategies in order to investigate whether our

[9] Note this information is missing for some sample members.

[10] We also check whether the magnitude of the stock market effect varies across children with parents who are/are not invested in the stock market. We find little evidence that intergenerational wealth transfers can explain the association between share prices and mental health among those who are not personally invested in stock markets. However, the sample sizes in this analysis are small (results available upon request).

results are sensitive to this feature of our sample. Firstly, we re-estimate our model excluding individuals interviewed in these first two weeks (7% of the sample). The estimated coefficients remain similar, for example the coefficient on the annual change in share prices is estimated to be 0.0065 with estimated standard error 0.0034, and the coefficient on the standard deviation of annual changes over the previous year is -0.0021 with standard error 0.001. Secondly, we drop the retired from our sample because the differences in age, employment and income variables are largely driven by the retired are being interviewed earlier than others. Again we find similar effects of annual changes in share prices (coefficient 0.0075 with standard error 0.0036) and the standard deviation term (coefficient -0.0022 with standard error 0.001). Thirdly, we split the sample according to labour market status, since differences in characteristics across those interviewed earlier and later in September can, for the most part, be attributed to differences in labour market activity. Table 6 presents normalised differences in the characteristics of people interviewed in weeks 1 and 2 compared with later weeks for the employed, self-employed, unemployed, family carers, students, long-term sick and the retired. There are no discernable differences in the characteristics of the employed, although there is some evidence that the self-employed interviewed in earlier weeks are less wealthy than those interviewed later, and that the unemployed and the long term sick interviewed in earlier weeks are less likely to be the household head.[11] There are other reasons to split the sample by labour market status. For example, if share prices are informative of economic prospects, we might expect that employees care about personal economic outcomes and the outcomes of close family members whereas those staying at home to look after family might only care about the economic outcomes of significant others. Results are presented in Table 7. Among employees the estimated effect of share prices is similar to previous estimates presented in Table 3 and Table 4 but the magnitude and precision of the share price effect varies considerably among others, highlighting the difficulty in estimating relevant effects without very large samples. Interestingly, we consistently find that the effect of increased volatility is larger for employees, the young or samples that exclude the retired, although it is not possible to say that these effects are larger from a statistical viewpoint. However, across each of the sub-samples split by labour market status we are unable to reject the null hypothesis that the parameter estimates associated with both the change in the FTSE and the volatility of share prices are equal to those estimated for the full sample (reported in column 4 of Table 4).

Fluctuations in share prices are clearly correlated with macroeconomic activity, and it may be the case that changes in share prices simply reflect the effect of general economic conditions on mental health. Since it is well documented that unemployment rates affect mental health, we augment our specification to include seasonally adjusted International Labour Organsiation (ILO) male regional unemployment rates (there are 11 regions in the BHPS sample). These data are taken from the Labour Force Survey (LFS) and are available on a quarterly basis from 1992 through the

[11]Note we set labour market hours to zero for those who do not report their economic activity as employed or self-employed.

Office for National Statistics (ONS).[12] Results presented in the first column of Table 8 suggest share prices have an independent influence on mental health outcomes. Following Di Tella et al. (2003) we also control for other macro economic indicators - explicitly quarterly GDP per capita, monthly industrial production and the monthly inflation rate as mesured by the rate of change in consumer prices (data are from the OECD national data base). The results are shown in columns two through to four respectively of Table 8 and reveal that the influence of share prices remains over and above macro economic indicators. Indeed, the results show that macro economic indicators such as GDP per capita have an insignificant effect on mental health, consistent with Di Tella et al. (2003), only regional unemployment rates matter in addtion to share prices.

In this paper we document the relationship between share prices and mental health but it is possible that the general mood in the population affects share prices rather than the converse. Since lagged stock market outcomes are correlated with current stock market values but we can be more confident that current mental health does not influence changes in share prices in the past, we replace contemporaneous values with lagged values from the previous week. Results reported in column 1 of Table 9 confirms a relationship exists when using lagged changes of the share price index. We also replace the FTSE All Share price index with the FTSE 100 price index. As discussed earlier, the former is a broader measure of economic activity whereas the latter is more widely reported in the media. In practice both series exhibit a correlation of 98% so it is perhaps not surprising that the FTSE 100 is also correlated with mental health (see column 2 of Table 9). Moreover, both series have almost identical effects when variables are standardised. However, there are some instances, particularly when using a fixed effects estimator, where the statistical precision associated with the FTSE 100 is lower.

In terms of employing alternative estimators for the standard errors, we consider explicitly modelling an AR(1) process in the error term in a fixed effects model following Baltagi and Wu (1999) and twoway clustering of standard errors following Cameron et al. (2011). The former approach may be relevant if unobserved shocks during the current period influence future outcomes. The latter approach may be relevant because we match daily price movements to the date that the individual is interviewed and we therefore may need to take into account possible clustering at the level of aggregation of our explanatory variable i.e. date of interview in addition to individual level clustering. However, in both cases, we generally find that the results are largely unaffected both in terms of economic magnitude and statistical significance (see columns 3 and 4 of Table 9).

5 Conclusion

In this paper we have investigated the relationship between psychological health and share prices, as measured by the FTSE All Share price index, in the UK over a relatively long time period which

[12] Quarterly unemployment rates are available from the second quarter of 1992. We therefore take the average unemployment rate across quarters two, three and four, for each year.

encapsulates both economic boom and bust. As far as we are aware this is the first paper for the UK to match daily share price fluctuations to dates of interview in a panel data set. Our empirical findings are robust to a number of alternative estimation strategies and reveal that the daily level of FTSE index and low frequency changes, specifically six monthly and annual, are positively correlated with mental health, while annual volatility in share prices reduces mental health. We investigate whether this relationship arises via a wealth effect by splitting the data into a variety of sub samples where a priori it might expected that wealth effects would be apparent e.g. by investor status (which we proxy by age, education and also whether individuals report they are invested in the stock market). Interestingly, throughout there is no strong evidence found in support of a wealth mechanism. Consequently, we would argue that the association between share prices and mental health is due to the possibility that the stock market is revealing additional information about the prevailing economic climate, where this 'economic barometer' effect exists after controlling for day, week and year fixed effects (in order to control for unobserved macro shocks) as well as conditioning upon unemployment rates and other macro economic indicators.

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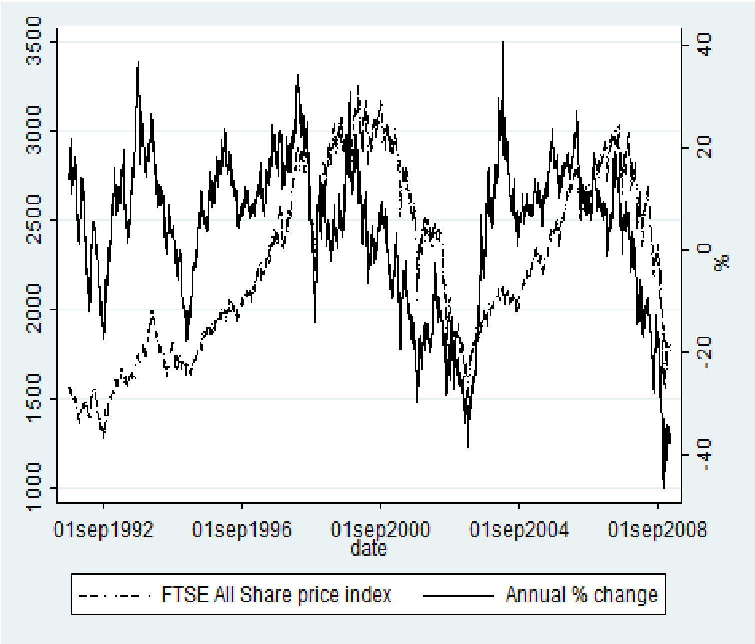
Tables and figures

Figure 1: FTSE level and changes



Source: Thompsom Reuters Datastream

Table 1: Normalised differences across interview weeks (full sample)

	1	2	3	4	5
household head	-0.10	-0.07	-0.04	-0.02	-0.01
female	-0.03	-0.04	-0.03	-0.04	-0.02
age	-0.38	-0.32	-0.26	-0.20	-0.15
partner	0.10	0.07	0.03	0.00	-0.02
divorced/separated	-0.02	-0.04	-0.01	-0.01	-0.00
single	0.01	0.05	0.05	0.06	0.06
widowed (base category)	-0.17	-0.16	-0.12	-0.09	-0.07
2 adults	0.03	0.04	0.01	-0.01	0.00
3 adults	0.09	0.05	0.03	0.02	-0.01
4+ adults	0.08	0.05	0.03	0.03	0.03
1 adult (base category)	-0.19	-0.14	-0.08	-0.05	-0.02
1 child	0.13	0.06	0.04	0.01	0.01
2 children	0.07	0.08	0.03	0.00	-0.01
3+ children	0.04	0.04	0.01	0.01	-0.00
kids aged 0-4	0.11	0.09	0.05	0.02	0.01
kids aged 5-11	0.11	0.08	0.03	0.00	-0.01
kids aged 12-15	0.04	0.04	0.01	0.01	-0.00
no children (base category)	-0.16	-0.11	-0.06	-0.02	-0.00
self employed	0.10	0.07	0.04	0.03	0.03
employed	0.32	0.25	0.19	0.13	0.08
unemployed	0.04	0.03	0.01	0.01	0.01
retired	-0.37	-0.32	-0.24	-0.19	-0.13
student	0.03	0.06	0.03	0.04	0.05
long-term sick	-0.13	-0.08	-0.04	-0.05	-0.04
family care (base category)	-0.01	-0.01	-0.02	-0.02	-0.02
ln(weekly work hours+1)	0.37	0.29	0.22	0.16	0.11
ln(household monthly income)	0.26	0.18	0.13	0.11	0.06
dividend < £100	0.05	0.12	0.07	0.05	0.03
dividend £100-£999	-0.06	-0.04	-0.03	-0.04	-0.03
dividend >= £1000	-0.04	-0.06	-0.05	-0.03	-0.03
no dividend (base category)	0.03	-0.02	-0.00	0.01	0.02
high ed	0.15	0.12	0.09	0.07	0.06
medium ed	0.04	0.04	0.03	0.02	0.01
low ed (base category)	-0.20	-0.16	-0.13	-0.10	-0.07
homeowner	0.07	0.04	0.01	-0.02	-0.04

The normalised difference is calculated as $\frac{\overline{x}_1-\overline{x}_0}{\sqrt{s_0^2+s_1^2}}$ where $\overline{x}_0$ is the mean characteristic of people interviewed in week t and $\overline{x}_1$ is mean characteristic of people interviewed in weeks t+1 to T (where T is the final week in which interviews occur), and where s^2 is the variance of the relevant sample.

Table 2: Summary statistics

	Mean	Std Dev	Min	Max	N
GHQ	24.88	5.36	0	36	145702
FTSE	2174	476	1291	3242	145702
1 day % Δ FTSE	-0.01	1.32	-8.34	9.21	145702
1 week % Δ FTSE	-0.15	2.79	-20.19	18.52	145702
1 month % Δ FTSE	-0.66	5.39	-26.69	17.46	145702
6 month % Δ FTSE	-1.04	11.32	-39.62	31.40	145702
1 year % Δ FTSE	3.87	14.92	-46.70	34.96	145702
1 week standard deviation	23.23	18.22	0.82	140	145702
1 month standard deviation	41.30	30.71	7.63	189	145702
6 month standard deviation	90.09	55.67	28.2	276	145702
1 year standard deviation	118.36	59.39	38.7	365	145702
household head	0.51	0.50	0	1	145702
female	0.54	0.50	0	1	145702
age	44.14	17.63	16	84	145702
partner	0.67	0.47	0	1	145702
divorced/separated	0.07	0.25	0	1	145702
single	0.20	0.40	0	1	145702
2 adults	0.56	0.50	0	1	145702
3 adults	0.18	0.38	0	1	145702
4+ adults	0.11	0.32	0	1	145702
1 child	0.12	0.33	0	1	145702
2 children	0.12	0.32	0	1	145702
3+ children	0.04	0.20	0	1	145702
kids aged 0-4	0.13	0.34	0	1	145702
kids aged 5-11	0.15	0.36	0	1	145702
kids aged 12-15	0.09	0.29	0	1	145702
high ed	0.48	0.50	0	1	145702
medium ed	0.25	0.43	0	1	145702
homeowner	0.75	0.43	0	1	145702
self employed	0.07	0.26	0	1	145702
employed	0.54	0.50	0	1	145702
unemployed	0.04	0.19	0	1	145702
student	0.06	0.23	0	1	145702
long-term sick	0.03	0.18	0	1	145702
ln(weekly work hours+1)	2.12	1.76	0	5	145702
ln(household monthly income)	7.56	0.78	0	11	145702
dividend $<$ £100	0.20	0.40	0	1	145702
dividend £100-£999	0.21	0.41	0	1	145702
dividend $>=$ £1000	0.07	0.26	0	1	145702
weekday (Monday=1)	3.16	1.69	1	7	145702
survey week	7	4	1	40	145702
year	1999	5	1991	2008	145702
investor	0.43	0.49	0	1	144995
regional unemployment rate	7.43	2.92	3.20	17.00	136419

Table 3: Levels, high and low frequency changes in share prices and mental health

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) FE
FTSE	0.04**						
	(0.02)						
1 day % Δ FTSE		-0.30					
		(1.03)					
1 week % Δ FTSE			0.11				
			(0.51)				
1 month % Δ FTSE				0.34			
				(0.33)			
6 month % Δ FTSE					0.89***		
					(0.34)		
1 year % Δ FTSE						0.81**	0.59**
						(0.33)	(0.29)
N	145702	145702	145702	145702	145702	145702	145702

*p<0.1, **p<0.05, ***p<0.01. Standard errors clustered by individual.
Dependent variable: GHQ score (0=very poor mental health, 36=excellent mental health).
All estimated effects are multiplied by 100 for presentation.
OLS and FE respectively denote Ordinary Least Squares and Fixed Effects results.
See Equation 1 for details of empirical specification.

Table 4: Changes in share prices, volatility of share prices and mental health

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE
1 week % Δ FTSE	0.11				
	(0.52)				
1 week standard deviation	-0.00				
	(0.12)				
1 month % Δ FTSE		0.21			
		(0.35)			
1 month standard deviation		-0.07			
		(0.09)			
6 month % Δ FTSE			0.93***		
			(0.35)		
6 month standard deviation			0.04		
			(0.08)		
1 year % Δ FTSE				0.79**	0.57**
				(0.33)	(0.29)
1 year standard deviation				-0.15*	-0.15*
				(0.09)	(0.08)
N	145702	145702	145702	145702	145702

See notes to Table 3.

Table 5: Testing for wealth effects

	Investor		Education		Age		
	=1	=0	high=1	high=0	< 35	35-49	50+
1 year % Δ FTSE	0.79	0.67	0.82*	0.84*	0.97*	0.55	1.15**
	(0.49)	(0.44)	(0.47)	(0.45)	(0.53)	(0.64)	(0.55)
1 year standard deviation	-0.18	-0.13	-0.21	-0.07	-0.35**	-0.07	0.01
	(0.14)	(0.12)	(0.13)	(0.13)	(0.15)	(0.18)	(0.16)
N	61678	83317	69532	76170	50632	41690	53380

See notes to Table 3. Investor refers to invested in stock markets and/or private pension arrangements. High education refers to degree or similar qualifications.

Table 6: Normalised differences in weeks 1 and 2 (disaggregated labour market status)

	Employed		Self-employed		Unemployed		Family care		Student		LT sick		Retired	
	1	2	1	2	1	2	1	2	1	2	1	2	1	2
household head	-0.05	-0.02	0.05	0.12	0.28	0.06	-0.09	-0.05	0.20	0.18	-0.28	-0.05	-0.03	-0.03
female	0.00	-0.02	-0.04	-0.09	0.13	-0.01	-0.00	0.06	0.09	-0.00	0.06	-0.02	-0.02	-0.02
age	-0.12	-0.13	-0.12	-0.16	0.08	-0.05	-0.22	-0.08	0.01	0.12	-0.16	-0.12	-0.17	-0.14
partner	0.05	0.04	0.12	0.09	0.21	0.12	0.00	0.05	0.12	0.05	0.23	0.11	0.06	0.07
divorced/separated	-0.03	-0.03	-0.13	-0.08	-0.08	0.03	0.13	-0.03	0.10	-0.01	-0.07	-0.05	0.02	-0.03
single	-0.02	-0.01	-0.07	-0.03	-0.17	-0.13	-0.07	-0.09	-0.14	-0.05	-0.09	-0.08	-0.09	-0.01
widowed (base category)	-0.05	-0.05	0.11	-0.04	0.10	-0.04	-0.04	0.05	0.03	0.03	-0.19	-0.03	-0.02	-0.05
2 adults	0.06	0.06	-0.01	-0.03	0.27	0.09	-0.02	0.06	-0.14	-0.03	0.01	0.06	0.02	0.05
3 adults	0.02	-0.03	0.05	0.03	-0.25	0.01	-0.12	-0.05	0.06	-0.01	0.21	0.04	0.11	0.07
4+ adults	-0.05	-0.03	0.05	0.07	-0.04	-0.07	0.18	-0.02	0.01	-0.02	0.25	-0.03	0.08	0.03
1 adult (base category)	-0.06	-0.03	-0.08	-0.04	0.00	-0.06	0.05	-0.00	0.09	0.12	-0.30	-0.09	-0.10	-0.10
1 child	0.04	-0.02	0.04	0.03	0.07	0.03	0.12	-0.01	0.01	-0.05	0.12	0.01	0.05	0.04
2 children	-0.03	0.02	0.02	-0.00	0.07	0.04	0.11	0.07	-0.02	0.08	-0.18	0.02	-0.01	0.00
3+ children	-0.00	-0.00	0.04	0.02	-0.07	0.10	0.02	0.03	0.08	0.04	0.09	0.07	0.02	0.03
kids aged 0-4	0.04	0.03	0.07	0.04	0.11	0.06	0.13	0.08	0.01	0.01	-0.04	0.06	-0.03	0.03
kids aged 5-11	0.01	-0.00	-0.02	0.05	-0.08	0.04	0.12	0.05	0.02	0.05	-0.01	0.04	0.05	0.02
kids aged 12-15	-0.06	-0.03	0.07	0.02	0.02	0.10	-0.04	-0.03	0.12	0.02	-0.02	0.01	0.00	0.03
no children (base category)	-0.01	0.01	-0.06	-0.03	-0.06	-0.09	-0.20	-0.07	-0.01	-0.01	0.02	-0.05	-0.03	-0.04
ln(weekly work hours+1)	0.08	0.06	0.05	0.09	.	.	.	.	.	.	.	.	.	.
ln(household monthly income)	0.08	0.04	-0.00	0.03	-0.20	-0.04	-0.03	0.01	-0.24	-0.12	0.31	0.02	0.08	0.01
dividend < £100	-0.04	0.11	0.13	0.06	0.13	0.08	0.18	0.11	-0.10	0.14	0.05	0.04	0.04	0.07
dividend £100-£999	0.05	0.00	-0.01	-0.02	-0.25	-0.13	-0.00	0.06	-0.07	-0.00	-0.04	-0.05	-0.05	-0.02
dividend >= £1000	-0.02	-0.02	0.26	-0.02	-0.04	0.02	-0.11	-0.02	0.10	0.03	0.19	-0.02	0.05	0.03
no dividend (base category)	-0.00	-0.08	-0.22	-0.01	0.13	0.03	-0.05	-0.12	0.13	-0.13	-0.07	0.01	-0.02	-0.05
high ed	0.01	0.01	0.00	-0.02	-0.19	0.01	0.10	0.01	-0.10	0.10	0.00	0.01	0.08	0.04
medium ed	-0.04	0.01	-0.01	0.02	0.17	-0.01	-0.08	-0.02	0.09	-0.06	0.05	-0.00	0.01	-0.01
low ed (base category)	0.02	-0.02	0.01	0.01	0.09	0.02	-0.02	0.01	-0.00	-0.08	-0.05	-0.00	-0.08	-0.03
homeowner	0.00	-0.01	0.11	-0.03	0.00	-0.06	0.08	0.07	-0.28	-0.15	0.15	0.01	0.06	0.05

The normalised difference is calculated as $\frac{\overline{x}_1-\overline{x}_0}{\sqrt{s_0^2+s_1^2}}$ where $\overline{x}_0$ is the mean characteristic of people interviewed in week t and $\overline{x}_1$ is mean characteristic of people interviewed in weeks t+1 to T (where T is the final week in which interviews occur), and where s^2 is the variance of the relevant sample.

Table 7: Effects by personal labour market status

	(1) Emp	(2) Self-emp	(3) Unemp	(4) Family	(5) Student	(6) LT sick	(7) retired
1 year % Δ FTSE	0.68	0.18	2.13	0.62	1.35	1.44	1.13
	(0.43)	(1.16)	(2.13)	(1.34)	(1.26)	(2.69)	(0.82)
1 year standard deviation	-0.27**	0.47	0.08	-0.57	-0.53	-0.31	0.31
	(0.12)	(0.30)	(0.65)	(0.40)	(0.36)	(0.76)	(0.24)
N	78717	10754	5431	11640	8209	4955	25996

See notes to Table 3. Employee refers to working for a firm, Self-emp refers to working for oneself, Unemployed refers to not in employment but looking for work, Family refers to staying at home to provide care for family members, Student refers to full-time education, LT sick refers to long-term sick and retired refers to the retired.

Table 8: Adding unemployment rates, gdp per capita, industrial production and inflation

	(1) Unemployment	(2) GDP	(3) Ind. Prod.	(4) CPI inflation	(5) All
1 year % Δ FTSE	0.85**	0.80**	0.83**	0.88**	0.93**
	(0.34)	(0.33)	(0.33)	(0.33)	(0.35)
1 year standard deviation	-0.16*	-0.16*	-0.19*	-0.17*	-0.19**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
regional unemployment rate	-0.05**				-0.05**
	(0.02)				(0.03)
Δ GDP per capita		0.04			0.01
		(0.19)			(0.20)
Δ Industrial producton			-0.04		-0.04
			(0.03)		(0.03)
Δ CPI				-0.08	-0.06
				(0.05)	(0.06)
N	136419	145702	145702	145702	136419

See notes to Table 3. Columns 1 and 4 includes regional unemployment rates (available from 1992), column 2 includes quarterly gdp per capita, column 3 includes monthly industrial production, and column 4 uses the monthly consumer price index. Estimates in columns 1 to 5 are by OLS.

Table 9: Using lagged FTSE values, the FTSE 100, and applying alternative estimators for standard errors

	(1) OLS	(2) OLS	(3) AR(1) s.e.	(4) Twoway s.e.
1 year % Δ FTSE (lagged 1 week)	0.71**			
	(0.32)			
1 year standard deviation (lagged 1 week)	-0.16*			
	(0.09)			
1 year % Δ FTSE 100		0.67**		
		(0.32)		
1 year standard deviation FTSE 100		-0.14		
		(0.09)		
1 year % Δ FTSE			0.23	0.80**
			(0.29)	(0.32)
1 year standard deviation FTSE			-0.18**	-0.17*
			(0.08)	(0.09)
N	145702	145702	128579	145702

See notes to Table 3. Column 1 uses share prices lagged 1 week, column 2 uses the FTSE 100 price index, column 3 imposes an AR(1) error structure and column 4 uses twoway clustering of standard errors.

Appendix

Identifying who is invested in the stock market

Firstly, whether the individual owns shares in 1991 is imputed by matching information in 1995 to 1991, making some adjustments to account for the fact that share ownership in 1991 was lower than in 1995 (Grout et al., 2009) and because matching information from older selves to younger selves leads to share ownership that is too high.[13] Secondly, the shares information is filled in between the years 1991, 1995, 2000 and 2005. For example, if someone is observed to own shares in both 1991 and 1995, 1995 and 2000, 2000 and 2005, it is assumed that they own shares in the intervening years (and likewise in the case of no shares). If someone is observed to switch share-ownership across any of these years, the year in which shares are sold (bought) is randomly assigned.[14]

[13] It is known that share ownership was 20% in 1991 and because the BHPS is a random sample of households in that year, it is assumed that 20% of the BHPS sample own shares. In 1995 just under 23% of the sample own shares so assuming that the age distribution of share ownership remains constant across these years (supporting this assumption the ratio of average share holdings by age-groups 15-34, 35-49, 50-65, and 66+ between 1995 and 2000 ranges from 0.77 to 0.82) it is possible to calculate the proportion of people by age-group who would own shares in 1991. For the age-group of interest, 50-69, the proportion that own shares in 1995 is 0.34 and taking into account the lower share ownership in 1991, it is calculated that 0.3 of this age-group would own shares in 1991. Which respondents then 'lose' shares is randomly determined. It is inevitable that some people will have owned shares in 1991 but have sold them by 1995, which is not captured by this approach.

[14] Over the three years between 1992-1994 a third are imputed to sell (buy) shares in each year and between 1996-1999 and 2001-2004 respectively, a quarter are imputed to sell (buy) shares in each year. Share ownership in 2005 is matched to 2006-2008.

Selected results including demographic variables

Table 10: The relationship between the FTSE, demographic variables and mental health

	(1) OLS		(2) OLS		(3) OLS		(4) FE	
FTSE	0.04**	(0.02)						
1 year % Δ FTSE			0.81**	(0.33)	0.79**	(0.33)	0.57**	(0.29)
1 year standard deviation					-0.15*	(0.09)	-0.15*	(0.08)
household head	-0.38***	(0.08)	-0.38***	(0.08)	-0.38***	(0.08)	-0.16**	(0.07)
female	-1.47***	(0.08)	-1.47***	(0.08)	-1.47***	(0.08)		
partner	0.34**	(0.17)	0.34**	(0.17)	0.34**	(0.17)	1.29***	(0.17)
divorced/separated	-0.46**	(0.19)	-0.46**	(0.19)	-0.46**	(0.19)	0.51***	(0.19)
single	0.37**	(0.18)	0.37**	(0.18)	0.37**	(0.18)	1.21***	(0.18)
2 adults	-0.21*	(0.13)	-0.21*	(0.13)	-0.21*	(0.13)	-0.15	(0.11)
3 adults	-0.48***	(0.14)	-0.48***	(0.14)	-0.48***	(0.14)	-0.41***	(0.11)
4+ adults	-0.51***	(0.15)	-0.51***	(0.15)	-0.51***	(0.15)	-0.50***	(0.12)
1 child	-0.14	(0.12)	-0.14	(0.12)	-0.14	(0.12)	-0.22**	(0.09)
2 children	0.02	(0.16)	0.02	(0.16)	0.02	(0.16)	-0.37***	(0.12)
3+ children	-0.16	(0.21)	-0.16	(0.21)	-0.16	(0.21)	-0.57***	(0.18)
kids aged 0-4	-0.00	(0.10)	-0.00	(0.10)	-0.00	(0.10)	0.08	(0.08)
kids aged 5-11	0.12	(0.10)	0.12	(0.10)	0.12	(0.10)	0.40***	(0.08)
kids aged 12-15	-0.06	(0.10)	-0.06	(0.10)	-0.06	(0.10)	0.12	(0.08)
high ed	0.14	(0.09)	0.14	(0.09)	0.14	(0.09)		
medium ed	0.15	(0.10)	0.15	(0.10)	0.15	(0.10)		
homeowner	0.28***	(0.07)	0.28***	(0.07)	0.28***	(0.07)	-0.11	(0.07)
self employed	0.75***	(0.16)	0.74***	(0.16)	0.75***	(0.16)	0.56***	(0.13)
employed	0.77***	(0.14)	0.77***	(0.14)	0.77***	(0.14)	0.53***	(0.11)
unemployed	-1.12***	(0.14)	-1.12***	(0.14)	-1.12***	(0.14)	-1.34***	(0.12)
student	0.75***	(0.14)	0.75***	(0.14)	0.75***	(0.14)	0.57***	(0.12)
long-term sick	-4.06***	(0.22)	-4.06***	(0.22)	-4.06***	(0.22)	-2.68***	(0.17)
ln(weekly work hours+1)	-0.00	(0.04)	-0.00	(0.04)	-0.00	(0.04)	-0.02	(0.03)
ln(household monthly income)	0.28***	(0.04)	0.28***	(0.04)	0.28***	(0.04)	0.17***	(0.03)
dividend < £100	0.28***	(0.05)	0.28***	(0.05)	0.28***	(0.05)	0.16***	(0.04)
dividend £100-£999	0.46***	(0.06)	0.46***	(0.06)	0.46***	(0.06)	0.22***	(0.04)
dividend >= £1000	0.71***	(0.09)	0.71***	(0.09)	0.71***	(0.09)	0.33***	(0.07)
N	145702		145702		145702		145702	

See notes to Table 3. Column 1 replicates column 1 of Table 3, column 2 replicates column 6 of Table 3, column 3 replicates column 4 of Table 4 and column 4 replicates column 5 of Table 4.

Unit Toot Tests

Given that there is a relatively long time series dimension to the BHPS one possibility is that any significant correlation found between well being and share prices is potentially spurious. Hence we investigate whether the GHQ and share prices are stationary processes. If both variables are non stationary, i.e. not integrated to I(0), and integrated to the same order, e.g. I(1) so stationary after first differencing, then unless there is a cointegrating vector any correlation will be spurious. Conversely, if the two variables are integrated to different orders, e.g. I(0) and I(1), then regression analysis is meaningless as one variable has a constant mean whilst the other drifts over time. Since we have panel data the most flexible approach to testing for a unit root in a variable y across individuals i and time t is as follows based upon Im et al. (2003) (IPS) where the autoregressive parameter is not held constant across cross sectional units:

$$\Delta y_{it} = \alpha_i^{'} d_{it} + \rho_i y_{it-1} + \theta_0 \overline{y_{it-1}} + \sum_{j=0}^{p} \theta_{j+1} \Delta \overline{y_{t-j}} + \sum_{k=1}^{p} \phi_k \Delta y_{it-k} + u_{it} \tag{2}$$

where Δ denotes a first difference (by year), d is a vector of deterministic components e.g. constant and time trend, and u is a white noise error term. The null hypothesis is that the series is non stationary, i.e. $H_0 : \rho_i = 0 \forall_i$. For some of the tests that we implement the autoregressive parameter is assumed to be constant over cross sectional units, i.e. $\rho_i = \rho$. As in common in panel unit root testing we allow for cross sectional dependence, i.e. the error terms are not independent across cross sections, by including the lagged cross sectional average, $\overline{y}$, and its first difference, $\Delta \overline{y}$, following Pesaran (2007).

The data are unbalanced where the minimum time period an individual is in the data is 1 year through to a maximum of 18 years. Consequently in order to ensure white noise in the error terms u after including extra lagged terms of Δy we conduct the unit root tests on two sub samples: (i) for those individuals present for at least 6 periods NT=102,938 (T=6 years is the minimum in order to be able to include lags where the optimal lag length is chosen by the AIC); and (ii) a subset of individuals present for all periods, i.e. a balanced data set NT=28,764. For the unbalanced sub sample we use the IPS approach for unit roots and for the balanced sub sample the IPS, Fisher ADF, Fisher Phillips-Perron and Harris-Tsavalis tests. See Baltagi (2008) for further details. For each test we also restrict the deterministic component, d, to include a constant only i.e. drift term, and alternatively a constant and time trend. For the FTSE we focus on the level and also low frequency changes in the variable for stationarity (since we find no evidence that high frequency changes in the FTSE affect mental health). Each test is implemented across both sub samples, both including and excluding a time trend. The null hypothesis is always rejected at either the 1 or 5 per cent level which implies that the data are stationary for GHQ, FTSE level and FTSE low frequency changes.