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Anita Ratcliffe
Karl Taylor

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

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Department of Economics
University of Sheffield
9 Mappin Street
Sheffield
S1 4DT
United Kingdom
www.shef.ac.uk/economics

Who cares about stock market booms and busts? Evidence from data on mental wellbeing*

Anita Ratcliffe†
University of Sheffield

Karl Taylor‡
University of Sheffield and IZA

Abstract

This paper investigates the correlation between stock prices and mental wellbeing, exploiting the availability of interview dates in the British Household Panel Survey to match the level and changes in the FTSE 100 stock price index to respondents over the period 1991-2008. We present evidence that the level, 6 month and yearly changes in the price index are associated with better mental wellbeing while greater uncertainty, proxied by volatility in the price index, is associated with poorer mental wellbeing. Moreover, using several proxies of stockholder status, we find little evidence that this association is confined to holders of equity-based assets, which is inconsistent with a pure wealth effect.

Keywords: Share prices, Wealth, Economic conditions, Mental health

JEL classification: J26, D12

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†University of Sheffield, Department of Economics, 9 Mappin Street, Sheffield, S1 4DT. E-mail: `a.ratcliffe@sheffield.ac.uk`

‡University of Sheffield, Department of Economics, 9 Mappin Street, Sheffield, S1 4DT. E-mail: `k.b.taylor@sheffield.ac.uk`

1 Introduction

This paper aims to investigate the relationship between the stock market and mental wellbeing in Great Britain. One reason why stock market movements may correlate with mental wellbeing is that unexpected movements in stock prices have the potential to generate sizeable wealth shocks for stockholders. If the only implication of rapid increases/declines in stock prices is a change in the value of owned assets (and thus household wealth), a pure wealth mechanism emerges whereby the wellbeing of stockholders moves together with stock prices.

In addition to a pure wealth mechanism, the stock market may correlate with mental wellbeing because stock market activity is a key indicator of macroeconomic performance. This raises the possibility that stock market activity correlates with perceptions of economic prospects and/or uncertainty. Hence, stock market movements may correlate with the mental wellbeing of individuals regardless of stockholder status.

Finally, reverse causality may produce a correlation if social movements and mood influence stock market activity (Shiller, 1984; Prechter and Parker, 2007). To the extent that opinions and feelings spread throughout society, this possibility also implies that stock markets and wellbeing move together irrespective of tenure status.

To date there exists very little evidence on stock market performance and mental wellbeing, with most analyses confined to the aftermath of the recent financial crisis. These studies typically use time-series methods and/or short-term activity in stock markets. Our contribution in this paper is to use individual-level panel data over the period 1991-2008, matching stock market movements to respondents by interview date to shed light on the association between stock markets and mental wellbeing. In doing so, we are able to examine how various measures of stock market performance (i.e. levels and changes in the stock market index) correlate with general levels of wellbeing, and the wellbeing of different population groups. We also augment our analysis to include other performance measures, such as proxies of dividends and investment risk, and of market uncertainty.

To preview our results, we find evidence of a positive correlation between the daily level, 26 and 52 weekly changes in stock prices, and mental wellbeing. We find little evidence that this correlation differs across our proxies of stockholders and non-stockholders, or that performance measures, such as dividends and risk of investment return, correlate with the mental wellbeing of stockholders. In contrast, we find some evidence that volatility in the price index is associated with poorer mental health. We suggest this variable is likely to capture market uncertainty and/or gloominess. The remainder of this paper is structured as follows, the next section discusses the possible links between the stock market and mental wellbeing. Section 2 discusses potential links between stock prices and mental wellbeing in more detail, Section 3 discusses the empirical approach and our data, Section 4 discusses our results while Section 5 concludes.

2 Links between the stock market and mental wellbeing

2.1 A pure wealth effect

Fluctuations in stock prices in recent years have been large and are arguably predominantly unexpected. Hence, increases in stock prices may produce positive wealth shocks for stockholders, which suggests a positive correlation between stock prices and their wellbeing. Specifically, a pure wealth mechanism implies the only relevance of stock price movements for stockholder's wellbeing is through an effect on asset values and wealth levels. Moreover, since non-stockholders without plans to own equities are unaffected when stock prices rise, while non-stockholders aspiring to own equities may experience negative wealth shocks, a pure wealth mechanism suggests a negative, if any, correlation between the stock market and the wellbeing of non-stockholders.

A literature on the relation between economic resources and wellbeing suggests that material circumstances are important, and specifically that wealthier individuals report higher levels of wellbeing (see for example Heady and Wooden, 2004). However, few papers are able to exploit exogenous variations in economic resources, with notable exceptions using lottery winnings (Gardner and Oswald, 2007) and political changes (Frijters et al., 2004). A pure wealth mechanism suggests variations in stock prices may be tantamount to exogenous changes in the wealth of stockholders and aspiring stockholders, thus providing another avenue through which the effect of wealth on wellbeing can be analysed.

Existing analysis on the stock market and wellbeing provides mixed evidence of a pure wealth effect. For example, using repeated cross sections of Gallup Survey data, Deaton (2012) presents time-series plots of daily averages in satisfaction with living standards by household income level, which indicate a greater sensitivity of the satisfaction of non-stockholders (as proxied by low income households) to the recent financial crisis. However, using individual-level panel data from German Socio-Economic Panel, Falk and Jager (2011) provide some evidence of a greater sensitivity among stockholders to recent changes in stock prices (i.e. over the past 1-3 weeks), though this difference disappears after controlling for personal characteristics.

2.2 A barometer of economic prospects, social movements and social mood

In addition to possible wealth effects, other phenomena might induce a correlation between stock market activity and mental wellbeing. For example, stock prices may provide a barometer of economic prospects, social movements and social mood. A key feature of these scenarios is the suggestion of a positive association between stock prices and mental wellbeing that is independent of stockholder status. The following separates the discussion of economic prospects from social movements and mood, because they differ with respect to the direction of causality. In particular, the former suggests stock prices influence mental wellbeing whereas the latter suggests societal wellbeing influences stock prices. In practice, feedback effects are also likely to exist, for example, societal wellbeing may worsen in response to a bleak economic outlook and stock prices may decline following reduced societal wellbeing. Trying to separately identify these scenarios in an empirical context poses significant challenges that we are not able to fully address in this paper.

2.2.1 Economic prospects

The demand for a firm's stock by any investor is the outcome of a forward-looking assessment of that firm's prospects, and the stock market aggregates of these demands, such that the prevailing stock price provides a consensus view of that firm's future profitability. Stock market indices, such as the FTSE 100, provide similar summaries for groups of firms listed on the stock exchange. Hence, the stock market reflects concerns held by market participants about macroeconomic conditions and prospects, and as such, may shape individual perceptions of economic prospects and/or uncertainty. In particular, people may feel more confident about economic prospects and upwardly revise their income expectations during stock market booms or people may feel more uncertain about economic prospects as stock markets become more volatile. In turn, revisions to income expectations and uncertainty would influence consumption and leisure decisions, suggesting that any correlation between stock prices and wellbeing might disappear once changes in consumption and leisure are taken into account. However, existing research suggests that events that arguably influence confidence and/or uncertainty over economic prospects, such as job loss or long-term ill health, produce larger-than-warranted declines in reported financial wellbeing (Pudney, 2011). Di Tella et al. (2001, 2003) and Charles and DeCicca (2008) also document negative effects of increased risk of job loss, as measured via unemployment rates in national or local labour markets, and wellbeing. Since these authors control for personal economic circumstances in their analysis, their findings suggest that perceptions of economic confidence and/or uncertainty may directly affect wellbeing.

According to the efficient market hypothesis, stock prices reflect 'all available information' relevant to firm performance and profitability and hence stock market movements are unpredictable. This implies that, if it were possible to construct and control for 'all available information' in our analysis, stock prices would have no effect on mental wellbeing. This need not diminish the role of the stock market given that stock prices are likely to be the most readily accessible source of information for most people, with the FTSE 100 stock price index reported daily in television news bulletins, in newspapers and online. On the other hand, a correlation may still be observed even if we could take into account 'all available information'. For example, media reporting of stock prices may induce focusing effects (see for example Kahneman et al., 2006), with exposure to news of economic performance increasing the salience of economic conditions in evaluations of wellbeing. A recent crop of papers also suggest that expectations over future stock market performance are shaped by recent history (Hurd et al., 2011; Hurd and Rohwedder, 2012), which raises the possibility that how people process and interpret stock market activity may differ from rationality. For example, feedback effects - from which high prices generate enthusiasm and raise expectations of even higher prices - might operate (Shiller, 2003), or people may believe that stock markets convey unique signals of economic prospects.

Finally, at any point in time stock prices may not reflect ‘fundamental values’, with cognitive biases often invoked to explain market anomalies (Subrahmanyam, 2008). If stock prices matter only insofar as they convey information on ‘fundamental values’ the existence of market anomalies simply creates measurement error and biases estimates of this correlation towards zero. If focusing effects or extrapolative expectations matter, stock prices may influence wellbeing irrespective of whether they provide an accurate reflection of ‘fundamental values’ on any particular day.

Murgea and Reisz (2012) estimate an aggregate relationship between the stock market and well-being using US data since 2008. Specifically, they take monthly averages of the Gallup Healthways Wellbeing Index (a composite measure of life evaluation, emotional and physical health, healthy behaviour, work and local environment) and the value of the stock price index, the Chicago Board Options Exchange Volatility Index (VIX) on the first day of the month. Since stock options are more valuable when the future is more uncertain, the latter measure is frequently used as a proxy of uncertainty. In separate regressions, they find evidence of a positive relationship between the index and wellbeing, and a negative relationship between the VIX and wellbeing, suggesting that stock market activity may matter by shaping perceptions of economic confidence and uncertainty. However, neither effect is statistically different from zero when both terms are simultaneously considered.

2.2.2 Social movements and moods

Given the difficulty in valuing speculative assets, it is often argued that stock prices may be subject to ‘social movements’ (Shiller, 1984) or ‘social mood’ (Prechter and Parker, 2007). When investors lack definitive evidence on the value of stocks, their own appraisals may be influenced by the opinion of others. The spread of opinions, via human contact and to a lesser extent other media, generate social movements that are manifested in stock market activity. Similarly, psychological evidence suggests that emotions and mood matter in decision-making, particularly for complex decisions involving risk and uncertainty (see Nofsinger, 2005; Olsen, 2006, for reviews). The social mood hypothesis suggests that, when faced with uncertainty, people unconsciously herd so that social mood (i.e. feelings of optimism and pessimism) may spread via herding behaviour and influence stock market activity (Prechter and Parker, 2007). In summary, stock market activity may provide a reflection of how people feel rather than stock markets having an effect on how people feel.

What drives the formation and changes in opinion and mood? While these may be tied to a particular event they may also arise spontaneously (Shiller, 1984; Olsen, 2006). This suggests that stock markets may react to feelings of economic insecurity, and in addition, a plethora of circumstances unrelated to economic conditions.

3 Methods and Data

3.1 Empirical Model

We begin by providing a general description of how stock prices correlate with mental wellbeing, and later expand our analysis to consider possible heterogeneity, and additional measures of stock market performance to shed light on the possible drivers of this correlation. Therefore we initially estimate the following equation:

$$\mathrm{H_{idwt}} = \alpha_1 \mathrm{FTSE_{id_{-1}wt}} + \beta' \mathrm{z_{idwt}} + \theta_\mathrm{d} + \theta_\mathrm{w} + \theta_\mathrm{t} + \mathrm{v_{idwt}} \tag{1}$$

where $\mathrm{H_{idwt}}$ is a measure of the mental wellbeing of individual i, on a particular interview day d, in a given survey week w and year t, hence dwt is the specific interview date, and $\mathrm{FTSE_{id_{-1}wt}}$ measures the closing price of the FTSE 100 stock price index on the day prior to individual i being interviewed. For individuals interviewed at the weekend (just over 10% of the sample), we match the same values to respondents interviewed on the Friday preceding the weekend to respondents interviewed on the Saturday and Sunday. By matching stock prices measured prior to the interview date to respondents, our specification rules out the possibility that levels of mental wellbeing on the date of interview affect our stock price measure. This is our preferred specification although we also explore different lags (d-2) and leads (d+1, d+2) in stock market activity.

Initially we explore the influence of the (natural log of the) daily stock price index level (denoted ln FTSE (daily)), and high (1 day, 1 week and 4 weekly) and low frequency (26 and 52 weekly) percent changes in this index (respectively denoted % Δ FTSE (1 day), % Δ FTSE (1 week), % Δ FTSE (4 week), % Δ FTSE (26 week) and % Δ FTSE (52 week)) on mental wellbeing. This specification allows for diminishing marginal returns to wealth, and would also imply that reducing uncertainty at low uncertainty levels (as proxied by high stock prices) matters less than reducing uncertainty at high uncertainty levels.

We consider high and low frequency changes in the stock price index for two reasons. First, it is interesting in its own right to examine whether percent changes in the stock prices over various periods are correlated with mental wellbeing, and second, from an econometric viewpoint, the stock price index is likely to be I(1), which could result in a spurious correlation between stock prices and mental wellbeing. We consider whether the mental wellbeing, ln FTSE (daily), and high through to low frequency changes in the stock price index are stationary in Appendix A1. The findings reveal evidence that ln FTSE (daily) is a non-stationary process while low and high frequency changes in the stock price index and mental health do not contain a unit root.

The vector z initially contains plausibly exogenous demographic characteristics such as age, household composition, education level and region of residence. Personal circumstances that may be correlated with wealth shocks and economic conditions, such as labour market status and household income and wealth, are taken into account in robustness analysis. All specifications include dummy variables to capture the day of the week (θ_d), the survey week (θ_w) and the survey year (θ_t). Finally, v_{idwt} is a random error term, clustered by individual and date of interview. Twoway clustering of the standard errors is important because we match daily price movements to the date that the individual is interviewed and therefore need to take into account possible clustering at the level of aggregation of our explanatory variable i.e. date of interview (dwt in terms of equation 1) in addition to individual-level clustering.

3.2 Data

Data are taken from the British Household Panel Survey[1] (BHPS) between 1991 and 2008. The BHPS is a nationally representative survey of 5 500 households[2] (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. The BHPS contains a standard measure of mental wellbeing, 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 wellbeing that is recoded so that higher scores reflect better psychological health (see Appendix A2). Figure 1 shows the distribution of the mental health measure for the individuals in the sample revealing a slight skew to the right, i.e. over the period on average people are happier.

Data on the FTSE 100 stock price index are obtained from Thomson Reuters Datastream, and have been adjusted for inflation using the OECD's consumer price index (CPI). We also calculate changes in the index across trading weeks (see Appendix A3). Figure 2 plots the stock price index, and its annual changes, over the period analysed, which covers two boom and bust phases (late 1990/early 2000 and mid 2000/late 2000) in the stock market. Summary statistics for our sample are presented in Table 1.

By using interview dates to create variation in the stock price index across respondents within each survey year, we desire that interview dates are random, such that variation in stock prices is exogenous to observed and unobserved characteristics that influence mental wellbeing. However, an inspection of the characteristics of people interviewed across different weeks of the BHPS survey period suggests some differences between those interviewed earlier and later. Table 2 presents the

[1] 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.

[2] 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.

normalised difference in the means of characteristics of those interviewed in each of the first 5 weeks of the BHPS survey period and those interviewed in later weeks. 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 the mean characteristic of people interviewed in weeks t+1 to T, and where s^2 is the variance of the relevant sample. The larger the normalised difference, the larger the imbalance in the distribution of characteristics of people interviewed at different dates. Imbens and Wooldridge (2009) suggest - as a rule of thumb - that normalised differences exceeding 0.25 make linear regression methods sensitive to model specification. 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.

Since stock prices are fairly persistent, people interviewed later in the survey year may be subject to larger (smaller) values of the stock market index or larger (smaller) changes in the index, and may have different personal characteristics to others. However, using regression methods to control for differences in personal characteristics is problematic where imbalance exists. Figure 3, which plots the average of variables showing evidence of imbalance against annual changes in the FTSE 100, does not, however, indicate a systematic correlation between those days that are characterised by a particular stock market outcome and the characteristics of people interviewed on those days.

4 Results

4.1 The correlation between stock prices and mental wellbeing

Table 3 presents various estimation results documenting the correlation between the stock price index and mental wellbeing. For brevity we report only the estimated coefficient on stock price terms (a selection of extended results are available in Table 10 in Appendix A4), and we multiply coefficients/standard errors relating to index changes by 100 for presentation. Column 1 reports the estimated correlation between the (natural log of the) daily stock price index and mental wellbeing. This result approximately suggests that a 1 percent increase in the stock price index increases mental wellbeing by 0.0078 units, equivalent to a 0.03% change of the mean GHQ score. However, there is no discernible correlation between high frequency changes in the stock price index and mental wellbeing despite widespread reporting of daily changes in the FTSE 100 stock price index in the media. On the other hand, low frequency changes correlate with mental wellbeing. Columns 5 and 6 indicate that a one percentage point increase in half yearly and yearly percent changes in the stock price index are associated with 0.0074 and 0.0054 unit increases in GHQ scores respectively. A larger point estimate for half year percent changes is suggestive of greater saliency of more recent changes although confidence intervals associated with these point estimates clearly overlap.

In Table 4 we explore how this observed correlation changes across different lags and leads in stock market activity. For example, if stock prices generate wealth shocks or provide signals of economic prospects we might expect past and current values of stock prices to correlate with mental wellbeing. If, on the other hand, stock prices are a reflection of social movements and mood, we expect current and future values of stock prices to correlate with mental wellbeing given these explanations suggest that changes in wellbeing precede stock market movements. We therefore match stock prices two days prior to interview (d-2), stock prices on the day (d), and stock prices one and two days after the interview (d+1 and d+2 respectively) to respondents, in addition to our preferred specification (d-1) to investigate timing effects. Our results presented in Table 4 provide suggestive evidence of a stronger correlation between stock market values measured prior to the interview date, since the point estimates and levels of statistical significance decline when moving from stock prices measured prior to the interview date to those measured afterwards. For the stock price index, we also find evidence of a positive and statistically significant correlation when stock prices are measured after the interview, which is consistent with the notion that social movements and mood influence stock prices. Based upon the unit root tests undertaken (see Appendix A1), however, it is also likely that empirical analysis using ln FTSE (daily) produces spurious regression results. As we cannot distinguish between these possibilities, in the remaining analysis we focus on the association between the annual percent change in the FTSE and mental health.

4.2 Evidence of wealth effects?

Our analysis documents a positive association between levels and low-frequency changes in stock prices and mental wellbeing. The preceding discussion suggests that a correlation may arise via a pure wealth mechanism and also because the stock market may be a barometer of economic prospects, social movements and social mood. To shed light on the possible sources of this correlation, we create several proxies of stockholder status, and analyse the correlation between stock prices and mental wellbeing across people with and without stock market investments. For example, if a pure wealth mechanism operates, then we ought to observe a positive correlation between our proxies of investor status and the wellbeing of stockholders, with little or even a negative correlation observed among non-stockholders.

We construct three proxies of stockholder status based on respondents' reported investment behaviour, their education level and their age. 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 (DC) pension arrangements, who are indirectly invested in the stock market via their pension scheme.[3] 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,

[3] 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.

matching this information to other years using an imputation procedure described in Appendix A5. By combining information on DC pension and equity investments, we are able to create a proxy of investor status (albeit with this information missing for just under 700 observations).

We also proxy stockholder status using the education and age of the respondent as two arguably exogenous proxies of stockholder status. For education level, we identify high education respondents as having a degree or similar qualification. Individuals with high education are more likely to be invested in stock markets and have more valuable assets conditional on investment (see Guiso et al., 2008). However, owing to a rapid expansion in UK higher education since the 1980s, the proportion of respondents with high education increases over time, with likely composition effects. We therefore also use the respondent's age to proxy stockholder status, given that older respondents are more likely to own stocks. For example, using the information on investment patterns available in 1995, 2000 and 2005, we find that 17% of those aged <40 while 33% of those aged 40 plus are invested in stock markets via the financial assets listed above, with the value of these investments also increasing with age. In contrast, a similar proportion of both age groups (just over 25%) have pensions invested in stock markets, as might be expected given a trend towards DC pension schemes.

Turning to our results, which are presented in Panel A of Table 5 where column 1 includes all individuals and columns 2-7 split the sample by our three alternative proxies of stockholder status. We estimate a larger correlation between stock market activity and the mental health of stockholders, as proxied by self-reported investment behaviour (column 2), compared to non-stockholders (column 3) but this correlation is statistically insignificant and confidence intervals for these groups overlap. When we proxy stockholder status by education (columns 4-5) and age (columns 6-7), we find little evidence that stockholders are more sensitive to stock market movements. Indeed, we estimate a correlation that is both larger and statistically significant among younger individuals who are least likely to own stocks, but again confidence intervals for these point estimates overlap. Overall, the results shown in Panel A of Table 5 provide little support for a pure wealth mechanism.

In addition to examining whether heterogeneity exists in the observed correlation between the stock price index and wellbeing, we augment our analysis to include other measures of stock market performance of interest to stockholders. For example, portfolio theory suggests stockholders care about the total return on their investments (i.e. the price change and dividend payment relative to the original price), and in addition, the risk associated with these investments (i.e. the spread of returns around the mean) (see Elton et al., 2007). We therefore add a proxy of the dividend return over the past year i.e. the dividend as a percentage of the original price (denoted dividend return (52 week)) and proxy the risk faced by investors on their investments using the dispersion of annual returns over the past year (denoted SD(% Δ FTSE (52 week))). Further details of the construction of these proxies can be found in Appendix A3. Results are presented in Panel B of Table 5, where the column structure is the same as in Panel A and all three measures of stock market performance are included simultaneously in each regression. There is no evidence that either of these proxies of risk and return matter to the mental wellbeing of stockholders.

4.3 A barometer of economic prospects?

Our aim in Panels A and B of Table 6 is to include additional measures of stock market activity that may proxy uncertainty levels. In particular, it may be the case that changes in the index proxy changes in economic prospects while stock market volatility proxies changes in uncertainty with respect to those prospects. We consider two measures of stock market volatility in our analysis. First, we consider the standard deviation of daily returns over a 4 week period (denoted SD(% Δ FTSE (1 day))), which is used to measure volatility in Schwert (1989) among others. His analysis suggests that this measure of stock price volatility increases during periods of recessions. Moreover, SD(% Δ FTSE (1 day)) is also highly correlated with the FTSE 100 Implied Volatility Index (FTSE IVI), which is the UK counterpart of the VIX. While measures based on stock options, such as the VIX and FTSE IVI are typically used as proxies of uncertainty (see Murgea and Reisz, 2012), the FTSE IVI is only available from 2000. Figure 4 shows how SD(% Δ FTSE (1 day) and FTSE IVI compare with each other and how they relate to the overall level of the stock market index. For ease of comparison, we demean and normalise each series by its standard deviation, so plotted values reflect the number of standard deviations away from the mean for any realisation of SD(% Δ FTSE (1 day)) or FTSE IVI. We refer to values exceeding two standard deviations from the mean as spikes in activity. Both series spike following sharp declines in the stock price index, with spikes observed in late 1998, late 2001, mid-to-late 2002/early 2003 and late 2008/early 2009. Sharper spikes are also observed for SD(% Δ FTSE (1 day)) compared to FTSE IVI. Panel A of Table 6 reports results that include the raw values of SD(% Δ FTSE (1 day)) alongside annual changes in the index. While correlations between this measure of stock price volatility and wellbeing are generally negative, as might be expected for any proxy of uncertainty, these correlations are neither statistically significant nor present any discernible pattern of findings across the alternative proxies of stockholder status.

In Panel B, we consider another proxy of uncertainty, which may also capture market gloominess. Specifically, we construct the standard deviation of the stock price index over the past year (denoted SD(FTSE)). Figure 4 indicates that spikes in SD(FTSE) are less frequently observed, occurring in late 2002/early 2003 and late 2008/early 2009, and in general this series exhibits a greater correlation with SD(% Δ FTSE (1 day)) from 2002 onwards. The spike in late 2002/2003 occurs towards the end of a pro-longed stock market decline, where uncertainty and/or gloominess about the future are likely to have been high. The spike in late 2008/early 2009 coincides with extreme levels of uncertainty experienced at the onset of the recent financial crisis. Hence the SD(FTSE) appears to capture unusual periods in stock market activity. Results in Panel B of Table 6 suggest that this proxy of economic uncertainty exhibits a negative and statistically significant correlation with wellbeing. One reason why we find a statistically significant association with SD(FTSE) but not with SD(% Δ FTSE (1 day)) may be that the latter is more volatile, spikes more frequently and therefore may reflect events of less gravity. SD(% Δ FTSE (1 day)) may also provide a proxy of uncertainty over shorter horizons or it may be the case that notable activity in SD(% Δ FTSE (1 day)) (i.e. mid 2002) falls outside of the BHPS survey period. Finally, spikes in SD(FTSE) may just coincide with heightened media focus on stock market performance.

In addition to a general correlation between the SD(FTSE) and wellbeing, we also find evidence of a large and statistically significant correlation for persons aged less than 40. While we cannot say that the difference in point estimates across younger and older individuals is statistically significant, this finding is in line with Crossley et al. (2013) who find that weak economic conditions hit the young hardest insofar as their expenditures appear to be most to recessions. We explore how controlling for personal economic circumstances influences our results in Section 4.4 below.

4.4 Sensitivity analysis

4.4.1 Controlling for personal and macroeconomic circumstances

In this paper we provide evidence that stock market activity is correlated with mental wellbeing. So far, we document this correlation controlling only for plausibly exogenous characteristics, such as gender, age, family composition and education. In Table 7, we consider to what extent our main findings change when we take into account personal economic circumstances, and also macroeconomic variables, that may be changing at the same time as stock prices. To facilitate this comparison, we repeat our key finding in column 1. In column 2 we control for labour market status and number of hours worked in employment while in column 3 we control for monthly household income, interest/dividend payments from investments and home ownership status. Somewhat surprisingly, taking into account personal circumstances increases the correlation between stock market activity and wellbeing. We also find these correlations further increase in size when we include self-reported financial circumstances and expectations for the year ahead (results available upon request).[4]

In column 3 we include macroeconomic variables, such as annual changes in quarterly GDP per capita, and annual changes in monthly industrial production, inflation and consumer confidence,[5] which are available from the OECD and in column 4 we include male regional unemployment rates available from the Office for National Statistics (ONS) since the latter is only available from 1992 onwards. Full results in Table 10 in Appendix A4 show that these macroeconomic indicators have little effect on mental wellbeing while increases in regional unemployment rates reduce wellbeing, which is consistent with Charles and DeCicca (2008). The results shown in the final two columns

[4] Self-reported financial situation and expectations may capture unobserved fluctuations in financial resources and capabilities (Pudney, 2011). Notwithstanding a smaller sample owing to missing observations in self-reported financial circumstances, we find these financial variables correlate with wellbeing (although reverse causality may be an issue) and that a statistically significant correlation remains between stock prices and mental wellbeing. Since these variables have little influence on our results we omit them from our main analysis.

[5] The consumer confidence indicator which we use is based upon an assessment of the economic situation. The question asked for the compilation of this indicator is 'How do you expect the general economic situation in this country to develop over the next 12 months? It will (++) get a lot better (+) get a little better (=) stay the same (-) get a little worse (–) get a lot worse (N) don't know.' The confidence indicator is expressed as the balance of positive over negative results.

reveal that the influence of share price movements upon mental wellbeing remains even after controlling for proxies of economic activity.

4.4.2 Other sensitivity analysis

In this section, we discuss but do not report additional sensitivity tests (results are available upon request). As discussed above, we find evidence that people interviewed in the first two weeks of September are different to those interviewed later, with older and retired persons more likely to be interviewed first. Among employees, however, there is little evidence that those interviewed earlier are different to those interviewed later and therefore we repeat our analysis restricting our attention to this group. As an alternative test, we also include individual fixed effects to control for unobserved and invariant characteristics that may differ across persons interviewed at different points in times. In both cases results remain similar to those presented elsewhere in the paper.

5 Conclusion

Subjective well-being data are increasingly used to inform public policy, particularly in the UK, where the government has launched a program to measure national well-being. In this paper we examine the association between the stock market and mental wellbeing in the UK over a relatively long time period which encapsulates both stock market boom and bust. Our empirical findings reveal that the FTSE 100 stock price index and low frequency changes (i.e. six monthly and annual) in this index are positively correlated with mental wellbeing, while annual volatility in the FTSE stock price index is associated with poorer mental wellbeing. We investigate whether this relationship arises via a pure wealth effect by splitting the data using proxies of stockholder status (i.e. reported investment behaviour, education and age). Interestingly, we find similar effects of stock market activity across these proxies of stockholders and non-stockholders, which is inconsistent with a pure wealth effect. Our results suggests that other phenomena, such as the role of the stock market in shaping perceptions of economic prospects, likely operate alongside potential wealth effects. Moreover, this ‘economic barometer’ effect exists after controlling for day, week and year fixed effects (in order to control for unobserved macroeconomic shocks) as well as conditioning upon observable macroeconomic controls that have been found to influence wellbeing in the literature.

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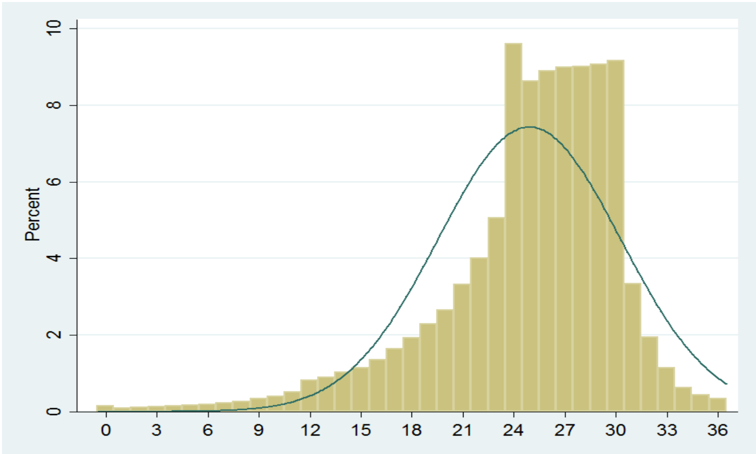
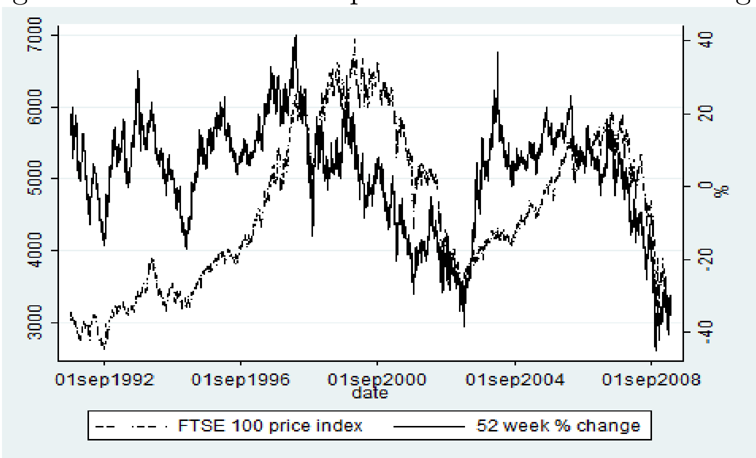
Tables and figures

Figure 1: Histogram of GHQ mental health scores



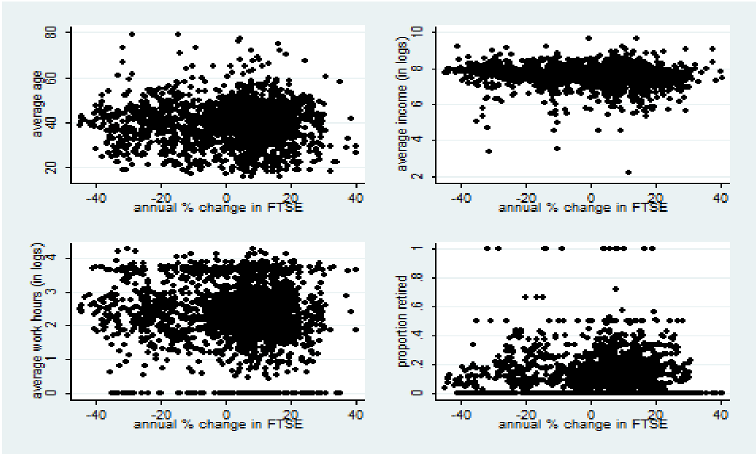
Source: BHPS

Figure 2: FTSE 100 stock price index and annual changes



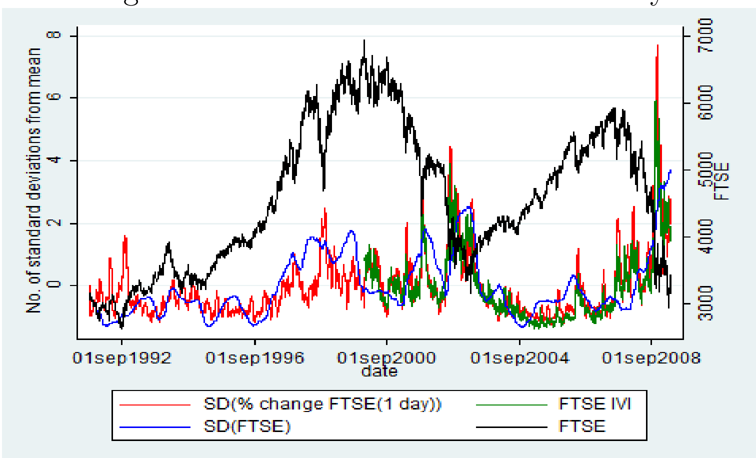
Source: Thompsom Reuters Datastream

Figure 3: Distribution of annual changes in FTSE and average age, income, employment and retired



Source: BHPS, Thompsom Reuters Datastream

Figure 4: Proxies of economic uncertainty



Source: Thompsom Reuters Datastream

Table 1: Summary statistics

	Mean	Std Dev	Min	Max	N
GHQ	24.90	5.37	0	36	142152
ln FTSE (daily)	377	23	327	424	142152
% Δ FTSE (1 day)	-0.02	1.45	-9.71	8.96	142152
% Δ FTSE (1 week)	-0.13	2.87	-21.05	18.27	142152
% Δ FTSE (4 week)	-0.50	5.44	-27.21	18.73	142152
% Δ FTSE (26 week)	-0.70	11.12	-38.79	34.99	142152
% Δ FTSE (52 week)	3.89	14.65	-45.00	40.29	142152
Dividend return (52 week)	6.93	1.22	4.14	9.93	142152
SD(% Δ FTSE (52 week))	7.40	2.30	2.36	16.84	142152
SD(% Δ FTSE (1 day))	1.12	0.75	0.33	5.21	142152
SD(FTSE)	239.53	129.41	75	716	142152
household head	0.50	0.50	0	1	142152
female	0.54	0.50	0	1	142152
age	43.20	16.80	16	79	142152
partner	0.68	0.47	0	1	142152
divorced/separated	0.07	0.25	0	1	142152
single	0.20	0.40	0	1	142152
2 adults	0.56	0.50	0	1	142152
3 adults	0.18	0.39	0	1	142152
4+ adults	0.12	0.32	0	1	142152
1 child	0.13	0.33	0	1	142152
2 children	0.12	0.32	0	1	142152
3+ children	0.04	0.20	0	1	142152
kids aged 0-4	0.13	0.34	0	1	142152
kids aged 5-11	0.15	0.36	0	1	142152
kids aged 12-15	0.10	0.29	0	1	142152
high ed	0.48	0.50	0	1	142152
medium ed	0.25	0.43	0	1	142152
homeowner	0.75	0.43	0	1	142152
self employed	0.08	0.26	0	1	142152
employed	0.55	0.50	0	1	142152
unemployed	0.04	0.19	0	1	142152
student	0.06	0.23	0	1	142152
long-term sick	0.03	0.18	0	1.00	142152
ln(weekly work hours+1)	2.17	1.75	0	4.61	142152
ln(household monthly income)	7.57	0.78	0	11	142152
dividend < £100	0.20	0.40	0	1	142152
dividend £100-£999	0.21	0.41	0	1	142152
dividend >= £1000	0.07	0.26	0	1	142152
homeowner	0.75	0.43	0	1	142152
weekday (Monday=1)	3	2	1	7	142152
survey week	7	4	1	39	142152
survey year	1999	5	1991	2008	142152
stockholder	0.43	0.50	0	1	141454
regional unemployment rate	7.44	2.93	3.20	17.00	133068

Table 2: Normalised differences across interview weeks (full sample)

	1	2	3	4	5
household head	-0.10	-0.05	-0.02	-0.01	-0.01
female	-0.02	-0.04	-0.03	-0.04	-0.02
age	-0.35	-0.30	-0.24	-0.18	-0.14
partner	0.10	0.06	0.02	-0.01	-0.02
divorced/separated	-0.03	-0.04	-0.02	-0.01	-0.00
single	0.00	0.04	0.04	0.06	0.06
widowed (base category)	-0.16	-0.13	-0.09	-0.08	-0.06
2 adults	0.03	0.03	0.01	-0.01	-0.00
3 adults	0.08	0.04	0.03	0.02	-0.02
4+ adults	0.07	0.04	0.02	0.03	0.03
1 adult (base category)	-0.18	-0.12	-0.06	-0.03	-0.01
1 child	0.12	0.05	0.04	0.01	0.01
2 children	0.06	0.07	0.03	-0.00	-0.01
3+ children	0.04	0.03	0.01	0.01	-0.00
kids aged 0-4	0.11	0.08	0.05	0.02	0.01
kids aged 5-11	0.10	0.07	0.03	-0.00	-0.01
kids aged 12-15	0.03	0.04	0.01	0.01	-0.01
no children (base category)	-0.15	-0.10	-0.05	-0.01	0.00
self employed	0.09	0.06	0.04	0.03	0.03
employed	0.30	0.23	0.18	0.12	0.07
unemployed	0.03	0.02	0.00	0.01	0.01
retired	-0.34	-0.29	-0.22	-0.17	-0.13
student	0.03	0.05	0.03	0.04	0.05
long-term sick	-0.14	-0.09	-0.05	-0.05	-0.04
family care (base category)	-0.01	-0.02	-0.03	-0.02	-0.02
ln(weekly work hours+1)	0.35	0.27	0.21	0.15	0.10
ln(household monthly income)	0.24	0.15	0.11	0.09	0.05
dividend < £100	0.06	0.12	0.07	0.05	0.03
dividend £100-£999	-0.05	-0.03	-0.02	-0.03	-0.03
dividend >= £1000	-0.05	-0.05	-0.05	-0.03	-0.03
no dividend (base category)	0.02	-0.03	-0.01	0.01	0.02
high ed	0.14	0.11	0.08	0.06	0.05
medium ed	0.03	0.03	0.03	0.02	0.01
low ed (base category)	-0.17	-0.15	-0.11	-0.09	-0.06
homeowner	0.08	0.03	0.00	-0.03	-0.05
region	0.03	0.07	0.05	0.03	0.02

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 3: FTSE 100 stock price index and mental wellbeing

	ln	% Δ				
	daily	1 day	1 week	4 week	26 week	52 week
	(1)	(2)	(3)	(4)	(5)	(6)
FTSE	0.78**	-0.41	0.09	0.26	0.74**	0.54*
	(0.38)	(1.02)	(0.55)	(0.35)	(0.34)	(0.32)
N	142152	142152	142152	142152	142152	142152

*p<0.1, **p<0.05, ***p<0.01. Standard errors clustered by individual and date of interview. Dependent variable: GHQ score (0=very poor mental health, 36=excellent mental health). Columns 2-6 are multiplied by 100 for presentation. See Section 3.1 for details of empirical specification.

Table 4: Past, present and future stock market values

	(1)	(2)	(3)	(4)	(5)
	d-2	d-1	d	d+1	d+2
ln FTSE (daily)	0.80**	0.78**	0.72*	0.70*	0.57
	(0.36)	(0.38)	(0.38)	(0.38)	(0.37)
%Δ FTSE (52 week)	0.57*	0.54*	0.53	0.37	0.35
	(0.32)	(0.32)	(0.33)	(0.33)	(0.33)
N	142152	142152	142152	142152	142152

See notes to Table 3. d-2,d-1,d,d+1 and d+2 define the date at which stock prices are matched to respondents interviewed on day d. For example, d means that stock prices at date d are matched to respondents at date d, d-1 means that stock prices at date d-1 are matched to respondents at date d and d+1 means that stock prices at date d+1 are matched to respondents at date d.

Table 5: Stock price index changes, dividend payments, and return risk, by proxies of stockholder status

		Stockholder		Education		Age	
	All	=1	=0	high=1	high=0	< 40	40+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
% Δ FTSE (52 week)	0.54*	0.76	0.31	0.56	0.59	0.74*	0.46
	(0.32)	(0.48)	(0.46)	(0.47)	(0.47)	(0.45)	(0.47)
Panel B							
% Δ FTSE (52 week)	0.61	0.75	0.48	0.46	0.89	0.72	0.60
	(0.40)	(0.58)	(0.56)	(0.56)	(0.58)	(0.54)	(0.57)
Dividend return (52 week)	-2.38	0.62	-6.50	4.40	-11.32	-0.14	-3.14
	(9.62)	(14.45)	(12.93)	(12.98)	(13.62)	(13.23)	(13.36)
SD(% Δ FTSE (52 week))	1.15	1.24	1.33	-0.04	2.11	-3.09	4.99
	(2.09)	(3.02)	(2.86)	(2.81)	(2.82)	(3.02)	(3.08)
N	142152	61044	80410	68896	73256	65344	76808

See notes to Table 3. Stockholder denotes those with equities and/or DC pension arrangements. High education denotes holds degree or similar qualification.

Table 6: Stock price index changes and proxies of uncertainty, by proxies of stockholder status

		Stockholder		Education		Age	
	All	=1	=0	high=1	high=0	< 40	40+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
% Δ FTSE (52 week)	0.48	0.80	0.21	0.64	0.41	0.59	0.44
	(0.37)	(0.57)	(0.52)	(0.56)	(0.52)	(0.51)	(0.54)
SD(% Δ FTSE (1 day))	-1.46	1.15	-2.62	2.11	-4.94	-3.86	-0.28
	(4.71)	(7.12)	(6.49)	(7.00)	(6.67)	(7.17)	(6.11)
Panel B							
% Δ FTSE (52 week)	0.50	0.73	0.26	0.51	0.56	0.70	0.44
	(0.32)	(0.48)	(0.46)	(0.47)	(0.47)	(0.45)	(0.47)
SD(FTSE)	-0.09*	-0.07	-0.10	-0.09	-0.08	-0.16**	-0.03
	(0.05)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)
N	142152	61044	80410	68896	73256	65344	76808

See notes to Table 3 and Table 5.

Table 7: Including personal economic characteristics and macroeconomic variables

	(1)	(2)	(3)	(4)	(5)
% Δ FTSE (52 week)	0.50	0.58*	0.60*	0.67**	0.79**
	(0.32)	(0.31)	(0.31)	(0.32)	(0.35)
SD(FTSE)	-0.09*	-0.09*	-0.09*	-0.09*	-0.09*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
labour market variables:	no	yes	yes	yes	yes
economic resource variables:	no	no	yes	yes	yes
macroeconomic variables:	no	no	no	yes	yes
regional unemployment rates:	no	no	no	no	yes
N	142152	142152	142152	142152	133068

See notes to Table 3. Macroeconomic data from OECD statistics and the ONS.

Appendix

A1 Unit Toot Tests

We investigate whether the GHQ and stock prices are stationary processes. If both variables are non stationary and integrated to the same order (e.g. I(1)), 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.

We test whether ln FTSE (daily) (i.e. logged values of the daily stock price index) and high/low frequency changes in the index are stationary prior to matching into the BHPS sample. For this analysis we use traditional macro unit root tests such as Augmented Dickey Fuller (ADF), Phillips-Perron (PP) and KPSS tests. The results are shown in Panel A of Table 8 and reveal that the ADF and PP tests cannot reject the null hypothesis that ln FTSE (daily) is non stationary while this hypothesis is rejected for high and low frequency changes in the index. These results are confirmed by the KPSS test where the null hypothesis is reversed (i.e. a stationary series is hypothesised), and which is rejected at the 5 percent level for ln FTSE (daily).

We also investigate whether stock market prices contain a unit root after matching the aggregated data into the BHPS sample. 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 is 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).

Our panel is unbalanced with individuals observed between 1 and 18 years, and 13 years on average. Consequently in order to ensure white noise in the error term 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 5 periods (i.e. an unbalanced panel with NT=87,547 where T=5 years is the minimum requirement 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 panel with NT=43,056). For the unbalanced sample we use Fisher ADF, Fisher Phillips-Perron and IPS tests, while for the balanced panel we supplement our analysis with Levin-Lin-Chu (LCC), Harris-Tsavalis (HS), Breitung and Hadri tests (see Baltagi (2008) for further details). Results are shown in Panels B and C of Table 8 respectively. In unbalanced data, the null hypothesis of a unit root is usually rejected at the 1 percent level, implying stationary processes throughout, with the exception that the IPS test only rejects the null at the 10 percent level for ln FTSE (daily). Conversely once the data is balanced we find more evidence that ln FTSE (daily) contains a unit root. Given the mixed evidence on the stationarity of the stock price index and the asymptotic power of these panel tests relying on a large N (e.g. IPS) and/or a large T (e.g. ADF and PP) dimension we would cautiously conclude that ln FTSE is likely to be non stationary, as is commonly found in the literature (Elton et al., 2007).

Table 8: FTSE unit root tests

	ln	% Δ				
	daily (1)	1 day (2)	1 week (3)	4 week (4)	26 week (5)	52 week (6)
Panel A (macro)						
Macro ADF	p= 0.503	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Macro PP	p= 0.458	p=0.000	p=0.000	p=0.000	p=0.007	p=0.005
Macro KPSS	k= 0.673	k=0.185	k=0.149	k=0.107	k=0.095	k=0.094
N	4579	4579	4579	4579	4579	4579
Panel B (unbalanced)						
Panel ADF	p= 0.005	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Panel PP	p= 0.003	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Panel IPS	p= 0.070	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
NT	87518	87518	87518	87518	87518	87518
Panel C (balanced)						
Panel ADF	p= 0.370	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Panel PP	p= 0.410	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Panel IPS	p= 0.540	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Panel LLC	p= 0.170	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Panel HT	p= 0.075	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Panel Breitung	p= 0.090	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
Panel Hadri	p= 0.053	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
NT	43056	43056	43056	43056	43056	43056

In each test the null hypothesis is that the variable contains a unit root. The exception is for the KPSS test where the null hypothesis is that the variable is a stationary process. The optimal lag length is chosen by the AIC. p-values are reported throughout (in the macro tests these are based upon MacKinnon approximates) with the exception of the KPSS test where the test statistic is shown. For the KPSS test the critical value is 0.15 at the 5 percent level. For each test we also restrict the deterministic component to include a constant (i.e. drift term) only.

We also employ the same panel unit root tests to investigate whether the GHQ is a stationary process. The results are shown in Table 9. The first column of the table reports results for the

Table 9: Mental health panel unit root tests

	(1) Unbalanced	(2) Balanced
Panel ADF	p= 0.000	p= 0.000
Panel PP	p= 0.000	p= 0.000
Panel IPS	p= 0.000	p= 0.000
Panel LLC	-	p= 0.000
Panel HT	-	p= 0.000
Panel Breitung	-	p= 0.000
Panel Hadri	-	p= 0.000
NT	87518	43056

In each test the null hypothesis is that the series contains a unit root. The optimal lag length is chosen by the AIC. For each test we also restrict the deterministic component to include a constant only i.e. drift term.

unbalanced panel while the second column tests the GHQ for stationarity in the balanced data. Under both samples the battery of tests reveal that mental health is a mean reverting process.

A2 The General Health Questionnaire

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 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 wellbeing.

A3 Thomson Reuters Datastream Data

FTSE (daily)

The FTSE 100 stock price index is a market capitalisation weighted index. We extract this from Datastream where it is calculated as follows:

$$FTSE_d = FTSE_{d-1} * \frac{\sum_{i=1}^{n}(P_d * N_d)}{\sum_{i=1}^{n}(P_{d-1} * N_{d-1} * f_d)}$$

where $FTSE_d$ denotes the value of the FTSE 100 stock price index at day d, P_d is the unadjusted price on day d, N_d is the number of shares in issue on day d, f_d is an adjustment factor and n is the number of constituents in the index.

% Δ FTSE

To calculate daily percent changes in the index we take the difference between closing values across adjacent days where the stock market is open (i.e. Monday-Friday). Hence we calculate:

$$\%\Delta\ FTSE\ (1\ day)_d = \frac{FTSE_{d_{cv}} - FTSE_{d-1_{cv}}}{FTSE_{d-1_{cv}}}$$

where $FTSE_{d_{cv}}$ is the closing value on day d and where $FTSE_{d-1_{cv}}$ is the closing value on day d-1. For example, if $FTSE_{d_{cv}}$ denotes the closing value on the Friday then $FTSE_{d-1_{cv}}$ is the closing value on the preceding Thursday.

To calculate percent changes across trading weeks (i.e. Monday-Friday) we subtract the opening value that week from the closing value that week. For example, for the change in the index across 1 week we calculate:

$$\%\Delta\ FTSE\ (1\ week)_d = \frac{FTSE_{d_{cv}} - FTSE_{d-4_{ov}}}{FTSE_{d-4_{ov}}}$$

where $FTSE_{d_{cv}}$ is the closing value on day d and $FTSE_{d-4_{ov}}$ is the opening value 4 days prior. For example, if $FTSE_{d_{cv}}$ denotes the closing value on the Friday then $FTSE_{d-4_{ov}}$ is the opening value on the preceding Monday. We make similar calculations for 4, 26 and 52 weeks. Note that for small changes in the FTSE, the log difference in the FTSE approximates the percent change.

Dividend return (52 week)

The total investment return is given by the change in the price of a stock, plus any dividend payment, relative to the original stock price (Elton et al., 2007). Datastream calculates the dividend yield as:

$$DY_d = \frac{\sum_{i=1}^{n}(D_d * N_d)}{MV_d} * 100$$

where D_d is the dividend per share on day d and MV_d is the market value on day d (where the latter is also available in Datastream). Re-arranging gives $\sum_{i=1}^{n}(D_d * N_d) = DY_d * \frac{MV_d}{100}$. We approximate the average dividend payment over the previous year relative to the original stock price by:

$$Dividend\ \ return\ \ (52\ \ week)_d = \frac{\frac{1}{260}\sum_{j=d-259}^{d}\sum_{i=1}^{n}(D_j * N_j)}{FTSE_{d-259_{cv}}}$$

where $\frac{1}{260}\sum_{j=d-259}^{d}\sum_{i=1}^{n}(D_j * N_j)$ is the average dividend paid over the preceding 52 weeks and $FTSE_{d-259_{cv}}$ is the closing value of the price index at the beginning of that trading period.

SD(% Δ FTSE (52 week))

To proxy investment return risk we take the standard deviation of annual percent changes in the index over the previous 52 weeks:

$$SD(\%\Delta\ \ FTSE\ \ (52\ \ week))_d = \frac{(\%\Delta\ \ FTSE\ \ (52\ \ week)_d - \overline{\%\Delta\ \ FTSE\ \ (52\ \ week)})^2}{260}$$

where $\overline{\%\Delta\ \ FTSE\ \ (52\ \ week)}$ is the average annual return over the preceding 52 weeks and 260 is the number of trading days in that 52 week period.

SD(1 day % Δ FTSE (1 day))

To proxy stock market volatility we take the standard deviation of daily percent changes in the index over the previous 4 weeks:

$$SD(\%\Delta\ \ FTSE\ \ (1\ \ day))_d = \frac{(\%\Delta\ \ FTSE\ \ (1\ \ day)_d - \overline{\%\Delta\ \ FTSE\ \ (1\ \ day)})^2}{20}$$

where $\overline{\%\Delta\ \ FTSE\ \ (1\ \ day)}$ is the average daily return over the preceding 4 weeks and 20 is the number of trading days in that 4 week period.

SD (FTSE)

To proxy stock market volatility we take the standard deviation of the index over the preceding 52 weeks:

$$SD(FTSE)_d = \frac{(FTSE_d - \overline{FTSE})^2}{260}$$

where $\overline{FTSE}$ is the average of the index the preceding 52 weeks and 260 is the number of trading days in that 52 week period.

A4 Additional analysis

Table 10: A selection of extended regression results

	(1)		(2)		(3)	
% Δ FTSE (52 week)	0.54*	(0.32)	0.50	(0.32)	0.79**	(0.35)
SD(FTSE)			-0.09*	(0.05)	-0.09*	(0.05)
household head	-0.39***	(0.08)	-0.39***	(0.08)	-0.38***	(0.08)
female	-1.49***	(0.08)	-1.49***	(0.08)	-1.51***	(0.08)
partner	0.37**	(0.18)	0.37**	(0.18)	0.42**	(0.19)
divorced/separated	-0.79***	(0.20)	-0.79***	(0.20)	-0.36*	(0.20)
single	0.27	(0.19)	0.27	(0.19)	0.44**	(0.19)
2 adults	0.13	(0.13)	0.13	(0.13)	-0.22	(0.14)
3 adults	-0.06	(0.14)	-0.06	(0.14)	-0.50***	(0.14)
4+ adults	-0.00	(0.14)	-0.01	(0.14)	-0.52***	(0.15)
1 child	-0.23*	(0.12)	-0.23*	(0.12)	-0.14	(0.12)
2 children	-0.06	(0.16)	-0.06	(0.16)	0.00	(0.17)
3+ children	-0.40*	(0.23)	-0.40*	(0.23)	-0.21	(0.23)
kids aged 0-4	-0.12	(0.11)	-0.12	(0.11)	0.02	(0.11)
kids aged 5-11	0.12	(0.11)	0.12	(0.11)	0.15	(0.11)
kids aged 12-15	-0.05	(0.11)	-0.05	(0.11)	-0.07	(0.11)
high ed	0.84***	(0.09)	0.84***	(0.09)	0.12	(0.09)
medium ed	0.68***	(0.10)	0.68***	(0.10)	0.15	(0.10)
self employed					0.76***	(0.17)
employed					0.77***	(0.14)
unemployed					-1.09***	(0.15)
student					0.82***	(0.14)
long-term sick					-4.08***	(0.23)
ln(weekly work hours+1)					-0.01	(0.04)
ln(household monthly income)					0.29***	(0.04)
dividend < £100					0.26***	(0.06)
dividend £100-£999					0.44***	(0.06)
dividend >= £1000					0.68***	(0.10)
homeowner					0.28***	(0.08)
regional unemployment rate					-0.06**	(0.03)
52 week Δ GDP per capita					-5.26	(3.25)
52 week Δ industrial production					-1.48	(2.28)
52week Δ Inflation					1.91	(8.63)
Δ Confidence					0.00	(0.01)
age dummies:	yes		yes		yes	
region dummies:	yes		yes		yes	
day, week and year dummies:	yes		yes		yes	
N	142152		142152		133068	

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 5 of Table 7.

A5 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.[6] 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.[7]

[6] 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.

[7] 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.