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# The impact of automatic enrolment on the mental health gap in pension participation: Evidence from the UK☆

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ABSTRACT

A large body of evidence shows that individuals with poor mental health have lower income over the lifespan but a dearth of evidence exists on how poor mental health affects savings behaviour. In this paper, we provide novel evidence of a mental health gap in pension participation in the UK using nationally representative longitudinal data from Understanding Society (UKHLS). Beginning in 2012, the UK government introduced automatic enrolment enabling us to assess the impact of one of the largest pension policy reforms in the world on this mental health gap. We measure mental health using the General Health Questionnaire (GHQ-12) which is a commonly used tool for measuring psychological distress. Prior to automatic enrolment, we find that male private sector employees with poor mental health are 3.7 percentage points less likely to participate in a workplace pension scheme while female private sector employees with poor mental health are 2.9 percentage points less likely to participate after controlling for key observables including age, education, race, marital status, number of children, occupation type, industry type, presence of a physical health condition and cognitive ability. The implementation of automatic enrolment removes the mental health gap in pension participation, equalising the pension participation rates of individuals with and without poor mental health in the private sector.

## 1. Introduction

In the UK, 1 out of 6 people have at least one common mental health condition (IMHE, 2018).[1] These conditions are often accompanied by high levels of emotional distress that interfere with the ability to participate effectively in daily activities (for e.g.,

☆ Understanding Society, which is the source of the data used here, is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by NatCen Social Research and Kantar Public. The research data are distributed by the UK Data Service. Neither the original collectors of the data nor the archive bears any responsibility for the analyses or interpretations presented here.

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[1] Common mental health disorders include depression, generalized anxiety disorder (GAD), panic disorder, phobias, social anxiety disorder, obsessive-compulsive disorder (OCD) and post-traumatic stress disorder.

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McManus et al., 2016). Despite being less damaging than major psychiatric conditions (e.g., schizophrenia, bipolar disorder), the higher incidence of common mental health conditions entails enormous economic costs (Bloom et al., 2012; Knapp and Wong, 2020; McManus et al., 2016).[2] These costs include direct health care costs as well as indirect costs incurred via the labour market due to higher unemployment and lower productivity amongst employees with poor mental health (OECD, 2018). There is also significant evidence that poor mental health leads to a range of adverse economic outcomes. For example, individuals with poor mental health are more likely to have lower educational attainment (e.g., Cornaglia et al., 2015), fewer employment opportunities (e.g., Egan et al., 2015, 2016; Mousteri et al., 2019) and lower earnings (e.g., Smith and Smith, 2010). These effects tend to be large and persistent over the lifespan (e.g., Goodman et al., 2011). Further, these economic costs are exacerbated by the pervasiveness of common mental health conditions amongst the working population (Layard, 2013).

In this paper, we investigate the effect of poor mental health on pension participation, one of the most important decisions a person makes regarding the quality of their later life. As individuals with poor mental health earn less income over their working lives and experience greater unemployment, they are particularly at risk of retirement poverty. This is exacerbated if they are also less likely to participate in workplace pension schemes. Individuals with mental health issues may be less likely to participate either by not taking an active decision to participate or not having access to these plans through their employers. Three main behavioural barriers to pension participation include cognitive burden, procrastination and self-control failures (Thaler and Benartzi, 2004). Evidence shows that individuals with common mental health conditions such as anxiety and depression are more likely to experience cognitive burden due to poorer concentration, memory, psychomotor speed, visual learning, flexible learning and self-control (for e.g., Cella et al., 2010; Maloney et al., 2014). Several studies have also found that these individuals tend to focus on smaller immediate rewards as opposed to larger later rewards (present bias) (Pulcu et al., 2014; Xia et al., 2017; Zhao et al., 2015) which may increase their tendency to procrastinate on decisions and struggle with self-control failures. As behavioural barriers to saving for retirement are more pronounced amongst those with poor mental health, we hypothesize that individuals with poor mental health are less likely to participate in a workplace pension scheme. The mental health gap in pension participation may also be affected by the selection of individuals with poor mental health into occupations or firms that are less likely to provide access to a workplace pension scheme.

By employing a nationally representative panel dataset, we provide novel evidence of a mental health gap in pension participation that is robust to key predictors of pension participation amongst male and female private sector employees in the UK. We also exploit one of the largest pension policy reforms in the world to assess how this mental health gap changes in response to automatic pension enrolment. We find that the mental health disparity in pension participation disappears amongst both male and female employees in the private sector after the implementation of automatic enrolment. Our findings contribute to the mental health and economics literature by documenting an important economic outcome that is affected by poor mental health. The lower probability of individuals with poor mental health participating in a workplace pension scheme has potentially deleterious effects on the financial security of these individuals and their families when they retire. Importantly, we show that in addition to reducing the pension participation gap amongst female and low income employees, automatic enrolment in the UK closed the pension participation gap between employees with and without poor mental health.

The rest of the paper is organised as follows. Section 2 discusses the pathways through which poor mental health might affect pension participation, the role of automatic enrolment in encouraging pension participation amongst employees with poor mental health, and provides details of the automatic enrolment policy introduced in the UK in 2012. Section 3 details the data used in the study, provides information on the main measures used in the analysis and outlines the econometric methodology applied. Section 4 presents descriptives, the main results and robustness checks. Section 5 concludes.

## 2. Theoretical background and literature

### 2.1. Poor mental health and workplace pension participation

Three of the main behavioural factors that affect pension participation are cognitive overload, self-control failures and procrastination (Thaler and Benartzi, 2004). The decision to participate in a workplace pension scheme is highly complex with individuals having to work out projected earnings and expenses, inflation and discounting rates before deciding on a plan and the specific contribution rate in the absence of a default process (Lusardi and Mitchell, 2007). Individuals may not possess sufficient financial literacy or experience to make these decisions optimally (Lusardi and Mitchell, 2011). Further, signing up for a workplace pension scheme requires self-control in that individuals have to forgo consumption now for benefits in the future. Given the complexity of the task and willpower required to commit to a pension plan, individuals may keep delaying the decision to participate in a workplace pension scheme. Individuals with poor mental health may also experience unsteady employment and work for employers that are less likely to offer access to a workplace pension scheme. In the next few paragraphs, we discuss in further detail why cognitive overload, present bias and employee sorting are likely to affect the pension participation of individuals with poor mental health. We focus

[2] An example of major psychiatric disorders are bipolar disorders and psychotic disorders such as schizophrenia.

specifically on the evidence for depressive and anxiety disorders which are the most commonly experienced mental health issues in the UK (IMHE, 2018).[3,4]

#### 2.1.1. Cognitive burden

Individuals experiencing mental health conditions face greater cognitive difficulties through impaired executive functioning (Cella et al., 2010; Maloney et al., 2014). These cognitive difficulties are worse amongst individuals who have experienced psychological distress over longer periods of time or more frequent episodes of psychological distress (Fossati et al., 2004). These symptoms are likely to affect the ability of individuals with mental health issues to navigate the complexity of pension decisions.

#### 2.1.2. Present bias and procrastination

There is evidence in both psychology and economics that individuals with poor mental health are more present-biased.[5] Discounting rates for future rewards amongst depressed individuals are higher and tend to increase with the severity of depression (Bayer et al., 2019; Pulcu et al., 2014). As for anxiety, studies have shown that high trait and state anxiety are associated with higher rates of future discounting (Rounds et al., 2007; Xia et al., 2017; Zhao et al., 2015).[6] Pessimism (Pulcu et al., 2014) and uncertainty (Xia et al., 2017) about future events have been put forward as key factors in depression and anxiety respectively that may influence how individuals perceive benefits far into the future for actions taken now. If the future seems bleak, smaller rewards now may seem more attractive. The greater tendency for present bias amongst individuals with poor mental health can lead to more procrastination and self-control failures which could further increase their propensity to delay the decision to participate in a workplace pension scheme.

#### 2.1.3. Employee sorting

Another mechanism that could influence workplace pension participation is selection into occupations and firms. Individuals with poor mental health may be more likely to self-select into specific types of jobs, companies and industries that are less likely to provide access to a workplace pension scheme. Given that these individuals typically have lower educational attainment (e.g., Fletcher, 2010), they may be more likely to work in low skilled occupations. They may also experience more unemployment (e.g., Butterworth et al., 2012; Egan et al., 2015; Mousteri et al., 2019) which reduces their chances of participating in a workplace pension scheme as they are simply spending less time in employment or accepting jobs with employers that are less likely to provide access to workplace pension schemes. Evidence on this specific mechanism; however, is lacking in the literature.

The introduction of pensions automatic enrolment in the UK presents a unique opportunity to study the consequences of such policies on the pension participation rates of individuals with poor mental health. The design and implementation of automatic enrolment simplifies the decision making process and expands access to a workplace pension plan for a large proportion of employees. Hence, we hypothesise that automatic enrolment reduces the pension participation gap between employees with and without poor mental health.

### 2.2. Automatic enrolment in the UK

Automatic enrolment in a workplace pension scheme was legislated in the Pensions Act 2008 due to concerns of falling pension savings by employees in the UK's private sector. The legislation requires employers to automatically enrol employees who meet the eligibility criteria into a workplace pension scheme with at least a minimum level of employee and employer contributions as

[3] Depressive disorders include disruptive mood dysregulation disorder, major depressive disorder (including major depressive episode), persistent depressive disorder (dysthymia), premenstrual dysphoric disorder, substance/medication-induced depressive disorder, depressive disorder due to another medical condition, other specific disorder and unspecific depressive disorder. The common feature of all these disorders is the presence of sad, empty or irritable mood, accompanied by somatic and cognitive changes that significantly affect the individual's capacity to function (American Psychiatric Association 2013).

[4] Anxiety disorders include disorders that share features of excessive fear and anxiety and related behavioural disturbances. Fear is the emotional response to real or perceived imminent threat whereas anxiety is anticipation of future threat. These two states overlap with fear more often associated with surges of autonomic arousal necessary for fight or flight, thoughts of immediate danger, and escape behaviour and anxiety more often associated with muscle tension and vigilance in preparation for future danger and cautious or avoidant behaviours. Anxiety disorders differ from one another in the types of objects or situations that induce fear, anxiety or avoidance behaviour and the associated cognitive ideation (American Psychiatric Association 2013).

[5] A related strand of literature in economics that provides further support to how poor mental health can affect the evaluation of risk and rewards over time is that on the effect of emotions on decision-making. These effects of emotions on decisions may be useful in understanding how poor mental health affects economic decisions as strong and prolonged negative affect is a crucial diagnostic feature of poor mental health (American Psychiatric Association 2013). Lab experiments find that induced affective states lead to decisions that are different when made in the opposite or neutral affective states. For example, inducing sadness leads participants to focus on present smaller rewards (Lerner, Li, and Weber 2013). Positive affect may impact time preferences by broadening focus and attention, promoting openness to information and enabling improved integration of information which contribute to greater cognitive flexibility (Pyone and Isen 2011). This improvement in cognitive flexibility encourages a more thorough evaluation of long-term rewards. Positive affect can also operate by increasing motivation among individuals so that they are willing to wait for delayed rewards (Erez and Isen 2002).

[6] Trait anxiety is defined as an individual's predisposition to respond, and state anxiety is defined as a transitory emotion characterized by physiological arousal and consciously perceived feelings of apprehension, dread, and tension (Spielberger 1966).

stipulated by the government. The Pensions Regulator was established as part of the Department for Work and Pensions (DWP) to ensure that employers are aware of and comply with their enrolment obligations. Compliance monitoring was high, with strict fines being imposed on employers who failed to enrol employees by the assigned timelines.

Employees are eligible for automatic enrolment if they are between 21 years old and the state pension age, earn above an earnings threshold and normally work in the UK under a contract of employment. Up to and including March 2018, the minimum total contribution level started at 2 per cent (at least 1 per cent contributed by the employer) of qualifying earnings. This level increased to 5 per cent (at least 2 per cent contributed by the employer) in April 2018 and 8 per cent (at least 3 per cent contributed by the employer) in April 2019. Employers can choose to automatically enrol their employees into pension schemes with higher contribution rates.[7] The earnings threshold is set at £10,000 per annum.[8] It has been documented in a number of studies that individuals with poor mental health earn less than individuals without poor mental health (e.g., Smith and Smith, 2010), therefore, we also provide descriptive evidence on whether individuals with poor mental health are less likely to meet the income threshold of £10,000 per annum to qualify for automatic enrolment.

The implementation of the policy began in October 2012 and was carried out over a period of five-and-a-half years. The staging dates for employers were allocated based on the number of employees the firm employed in April 2012, as captured by the number of employees on its Pay-As-You-Earn (PAYE) scheme so that larger companies auto-enrolled their employees first followed by smaller companies.[9,10] In addition to the *eligible* group of employees who are automatically enrolled, the *non-eligible* and *entitled* group of employees can choose to opt in to a workplace pension scheme. The non-eligible group consists of employees who are aged between 16 and 21 years or over the state pension age but earn at least £10,000 per annum or who are aged between 21 years and the state pension age and earn between £5,824 and £10,000 per annum. If they choose to opt into a pension scheme, the employer has to make a minimum contribution. The entitled group consists of employees who earn below £5,824 per annum. The employer does not have to contribute if this group chooses to opt into the pension scheme.

As of April 2019, 10 million workers have been automatically enrolled into a workplace scheme (DWP, 2019). 84 per cent of eligible employees were participating in a workplace pension with an opt-out rate of nine per cent at the end of 2017. This opt-out rate is driven by older employees (DWP, 2018). Using employer provided data up to April 2015, Emmerson and Cribb (2016) find that automatic enrolment resulted in a 37 percentage point increase in the probability of participating in a workplace pension plan amongst eligible private sector employees. The largest effects on pension participation were observed for employees in their 20s, in lower paid jobs and those who joined their employer more recently. Large gains were also recorded for female employees with automatic enrolment reducing the gender gap in pension participation (DWP, 2018).

The design and implementation of pensions automatic enrolment in the UK allows us to observe the sole effect of the policy on the mental health gap in pension participation which is challenging to do in other countries with auto-enrolment. This is largely because automatic enrolment is typically implemented partially or with other changes such as one-off government contributions.[11] Studies from the US largely focus on the impact of pensions automatic enrolment in specific companies (e.g., Beshears et al., 2009; Thaler and Benartzi, 2004). These employers are likely different from other employers since they have chosen to implement these schemes. In the UK, automatic enrolment was implemented nationwide, forbade employers from opting-out and was not implemented with any other initiatives to boost savings. Although more generous employer contributions could have made participation in pension plans more attractive, employer contributions greater than the minimum level set by the government were more likely in high paying industries

[7] Employers are not permitted to set the employee contribution rates too high as to encourage employees to opt out.

[8] The earnings threshold is pro-rated so that actual earnings threshold amounts will differ if employees are paid monthly, 4 weekly, fortnightly or weekly. For example, an employee will meet the earnings threshold if monthly and weekly earnings reach at least £833 and £192 respectively.

[9] Automatic enrolment started with companies who employed 250 and more employees. These employers enrolled employees between October 2012 and February 2014. Companies who employed 50 to 249 employees enrolled their employees between April 2014 and April 2015. Employers with 30 to 49 employees enrolled their employees between August 2015 and October 2015. Employers with 30 or fewer employees began automatic enrolment between January 2016 and April 2017. A test tranche for employers with less than 30 employees were also conducted from January 2016 to April 2017. Employers who took on their first employees between 2012 and 2017 were required to complete automatic enrolment by February 2018.

[10] Employers could postpone automatic enrolment up to three months from the assigned staging date and enrol their employees earlier but had to inform The Pensions Regulator in advance. Employees can opt out of their employer pension scheme at any point by completing an opt-out form which will be provided by and should be returned to the employer. Employees would receive a full refund of their contributions if they opt out within one month of being automatically enrolled by the employer. Employers are required to re-enrol eligible employees who have opted out of the pension scheme 3 years after the employer's staging date. Employers are also required to inform their employees in advance before re-enrolling them into a pension scheme.

[11] Various forms of pensions auto-enrolment mandates are also present in Canada, Germany, Italy, Lithuania, Poland, Turkey and New Zealand. Auto-enrolment in Canada was implemented differently across provinces. As of 2019 in Germany, there was no evidence that auto-enrolment contracts were actually implemented. In Poland, auto-enrolment was complemented with a government welcome contribution and fixed payment per year. In Turkey, the government matches 25% of an employee's contributions and makes an additional one-time contribution for those who do not opt within the first two months. Auto-enrolment in Lithuania was also supported with government contributions for both employees and self-employed workers. In Italy, auto-enrolment was implemented on employment severance pay; whether employees would like a lump sum payment upon retirement or redundancy or have it to into a private pension fund (OECD, 2019). New Zealand introduced automatic enrolment in 2007 with other financial incentives such as a one-time government contribution upon enrolment and housing subsidies (John and Levine, 2009).

which were much more likely to have had higher pension membership rates prior to automatic enrolment (Emmerson and Cribb, 2016).

## 3. Data and empirical strategy

### 3.1. Description of the data

#### 3.1.1. Participants

We use data from the United Kingdom Household Longitudinal Study (UKHLS) also known as Understanding Society (University of Essex, 2020) which collects high quality longitudinal information on socioeconomic characteristics, health behaviours and attitudes, primarily from individuals aged 16 and over. It is a survey of respondents from approximately 40,000 households from across the UK (England, Scotland, Wales and Northern Ireland).[12] One of the largest surveys of its kind, the UKHLS is representative of the UK population and is designed to ensure that ethnic minorities are adequately represented. Beginning in 2009 to 2010 (Wave 1), households have been visited every year to capture changes in circumstances over time. Interviews are carried out face-to-face in respondents' homes by trained interviewers or through an online self-completion survey. Everyone in the household is surveyed and transitions out of the household and into the household are tracked.

#### 3.1.2. Key Measures

Respondents are asked whether their employer runs a pension scheme if they are currently employed and subsequently whether they belong to their employer's pension scheme.[13] This question is asked in Wave 1 (2009 to 2010), Wave 2 (2010 to 2011), Wave 4 (2012 to 2013), Wave 6 (2014 to 2015) and Wave 8 (2016 to 2017).[14] This question is asked only to individuals whose present employer provides a pension scheme or superannuation scheme for which they are eligible.[15] If respondents answer that their present employer does not provide a pension scheme or superannuation scheme for which they are eligible, we assume that they are not at that moment participating in a workplace pension scheme, provided that they are currently employed in the private sector. We also capture those who answer "don't know" to this question as not participating given that they are also employed in the private sector.[16] This treatment of responses will more accurately capture the impact of automatic enrolment since the goal of automatic enrolment was to make it mandatory for employers to provide a workplace pension scheme for their employees, and to put pension schemes in place where they were not previously available. We also provide descriptive evidence on how likely it is that individuals with poor mental health work for employers who provide a pension scheme for which they are eligible prior to the implementation of automatic enrolment.

#### 3.1.3. Independent variable of interest: Poor mental health as captured by the General Health Questionnaire-12 (GHQ-12)

Respondents completed the 12-item version of the GHQ, used to detect psychiatric cases in the general population by comparing the respondent's current state with their usual state, in every wave of the survey.[17] The GHQ-12 is a short yet well validated scale often used as a screening tool for assessing psychological distress. The score is highly correlated with standardised clinical interviews assessing the presence of a clinical mental health condition. In a review of six validity studies of the GHQ-12, Goldberg and Williams (1988) reported sensitivity rates (proportion of cases correctly identified) of between 71 and 91 per cent. Due to its brevity and effectiveness, the GHQ-12 is widely used in clinical practice, epidemiological research and psychological research (Goldberg et al., 1997; Sweeting et al., 2009; Thomas et al., 2005). It is also commonly used in economics research as a measure of mental health (e.g., Cornaglia et al., 2015; Egan et al., 2015, 2016) and well-being (e.g., Clark et al., 2001; Gardner and Oswald, 2007).

In the GHQ-12, respondents are asked to rate questions about their general happiness, confidence and their capacity to face problems, overcome difficulties, make decisions and enjoy normal day to day activities using a 4-item scale (where 1 = more so than usual, 2 = about the same as usual, 3 = less so than usual and 4 = much less than usual). These measures are then converted to a single scale by recoding 1 and 2 values on individual variables to 0, and 3 and 4 values to 1, and then summing, giving a scale running from 0 (the least distressed) to 12 (the most distressed). In line with accepted convention, respondents with a score of 3 or more are termed as achieving "psychiatric caseness" which means that they are likely to present with psychiatric disorder (Goldberg et al., 1997). For our analysis, we capture poor mental health as responses scoring 3 and above on this 0 to 12 point scale.

[12] The UKHLS sample is made up of three main components: a general population sample which consists of about 28,000 households, a continuation of the former British Household Panel Survey sample which consists of about 6,400 households and an ethnic minority booster sample which consists of about 4,200 minority households.

[13] Private pension participation is only captured for those aged 45 and older.

[14] We exclude Waves 3, 5 and 7 in the analyses. The absence of the pension participation question in these waves is not an issue as we are still able to sufficiently capture pension participation before and after automatic enrolment.

[15] This question was asked to respondents who were currently employed in both the public and private sector.

[16] These responses are coded as 0 (instead of missing) in the pension participation variable.

[17] The specific questions asked on the GHQ-12 are available in the Supplementary Materials.

### 3.2. Empirical strategy

We employ linear probability models with a post policy and mental health interaction term, and a host of individual controls to estimate the relationship between baseline psychological distress captured in Wave 1 and pension participation in a private sector workplace scheme before and after automatic enrolment. Baseline psychological distress (2009 and 2010) is used to obtain a measure of mental health that is uncontaminated by any effects that the policy which was implemented in 2012 may have had on mental health. The use of the baseline measure is justified due to the stability of GHQ-12 scores across waves.[18]

The individual controls include age, education, race, marital status, income, number of children, occupation type, industry classification, presence of at least one physical health condition, and cognitive ability. These controls are included on a wave basis as opposed to a baseline level. Occupation type is categorized as professional, managerial or technical, skilled non-manual, skilled manual, partly skilled, and unskilled. All the control variables with the exception of physical health conditions and cognitive ability are available in each wave. Physical health conditions were first asked in Wave 1 and then only to new entrants in Wave 3 onwards. To address the issue of missing values, we impute the values for Wave 2 based on Wave 1 and 3 responses. Cognitive ability is captured using several variables measuring word recall, delayed word recall, basic math skills, and verbal fluency. As these variables were only collected in Wave 3, we apply the responses in Wave 3 across the other waves of the data due to the stability of cognitive ability in adulthood (Friedman et al., 2016). We further use the sample mean value of the cognitive ability variables to impute any missing values in Wave 3. We limit the sample to the working age population (those aged 22 to 65) who are currently employed in the private sector. Our sample includes both part time and full time employees since automatic enrolment applied to both groups.

Main specification:-

$$y_{i(wave\ 1-8)} = \alpha_i + \beta_{pre}(MH_i)_{wave\ 1} + \beta_{post}\left((MH_i)_{wave\ 1} * POST_{(wave4-8)}\right) + \phi POST_{wave4-8} + \delta X_{it} + \varepsilon_{it}$$

$y_{i(wave\ 1-8)}$ denotes participation in a workplace pension plan. $(MH_i)_{wave\ 1}$ is baseline mental health. To assess the effect of automatic enrolment on the pension participation rates of employees with and without poor baseline mental health, a post policy and baseline mental health interaction term, $(MH_i)_{wave\ 1} * POST_{(wave4-8)})$, is employed. The coefficient on the interaction term can be interpreted as the additional effect of automatic enrolment for those with poor baseline mental health compared to those with good baseline mental health. We include a post policy time dummy, $POST_{wave4-8}$, as part of the interaction model but we omit specific wave dummies as the policy was implemented over several waves. POST is a dummy equal 0 for Waves 1–2 and equal 1 for Waves 4–8. $X_{it}$ refers to the controls. We do not use contemporaneous measures of psychological distress in our main specification as it is possible that automatic enrolment had an effect on mental health so the use of contemporaneous measures may introduce endogeneity. Secondly, estimations using contemporaneous measures imply that year on year changes in mental health are associated with year on year changes in pension participation which is misleading. It is more realistic to think of mental health as an initial condition that affects pension participation over a period of time as opposed to having sharp yearly effects on pension participation that is relatively inert over the life course.

Standard errors are clustered at the individual level. The use of a standard fixed effects estimator is not feasible as the mental health measure is only captured in one period. To better understand the role of the control variables in explaining the association between baseline mental health and pension participation in a workplace plan, we also estimate decompositions based on the Gelbach approach. The advantage of this approach is that it estimates the contribution of the control variables in a way that is not affected by the ordering of the variables and enables the grouping of sets of variables (Gelbach, 2016).

## 4. Results

### 4.1. Descriptive analysis

Fig. 1 shows the pension participation rates amongst public and private sector employees in the UK using UKHLS data which are consistent with pension participation trends reported by The Department for Work and Pensions.[19] Although the pension participation rates of employees in the public sector have been historically high, there is a slight increase after the introduction of automatic enrolment in 2012. There is a major increase in the pension participation rates of employees who were eligible for automatic enrolment in the private sector from about 65 per cent to almost 90 per cent after automatic enrolment was implemented. There is also a significant increase in the pension participation rates of employees in the private sector who were not eligible for automatic enrolment but could opt into the scheme. This particular trend is consistent with results from Cribb and Emerson (2016).[20]

[18] The average GHQ-12 caseness scores by each wave for male and female respondents in UKHLS are provided in Table S1 in the Supplementary Materials.

[19] Trends in pension participation for 2008 to 2018 by The Department for Work and Pensions can be found here https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/806513/workplace-pension-participation-and-saving-trends-2008-2018.pdf and is also available in the Supplementary Materials.

[20] Cribb and Emerson (2016) also find increases in pension participation for employees who were not eligible for automatic enrolment but could opt in using employer reported data from the Annual Survey of Hours and Earnings. The authors suggest that this increase could be driven by peer effects in the workplace or the initiative of employers who are automatically enrolling their employees who earn less than the set income threshold of £10,000 per annum.

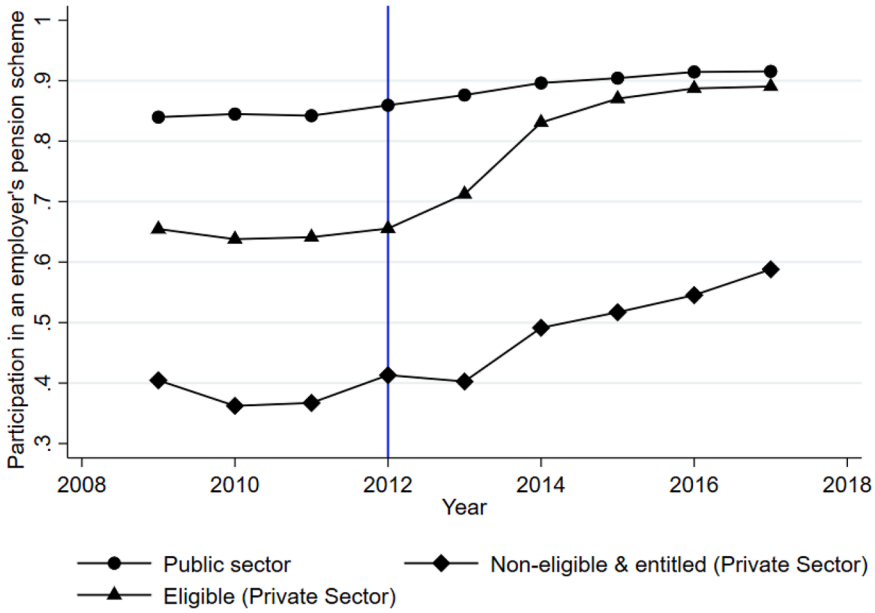


**Fig. 1.** Pension participation rates amongst public sector and private sector (eligible and non-eligible) employees in the UK
Notes: The sample covers private and public sector employees aged 22 to 65 years old.

Since the interviews for one wave in UKHLS is conducted over a period of 2 years, we have yearly estimates of the pension participation rate in every year. Fig. 2 plots pension participation rates in each year by the baseline measure of psychological distress. There is a 4.4 percentage point difference, which is significant at the 0.1% level, between individuals with and without poor baseline mental health in the private sector across all years. Once pensions automatic enrolment is introduced in 2012, there is a large increase

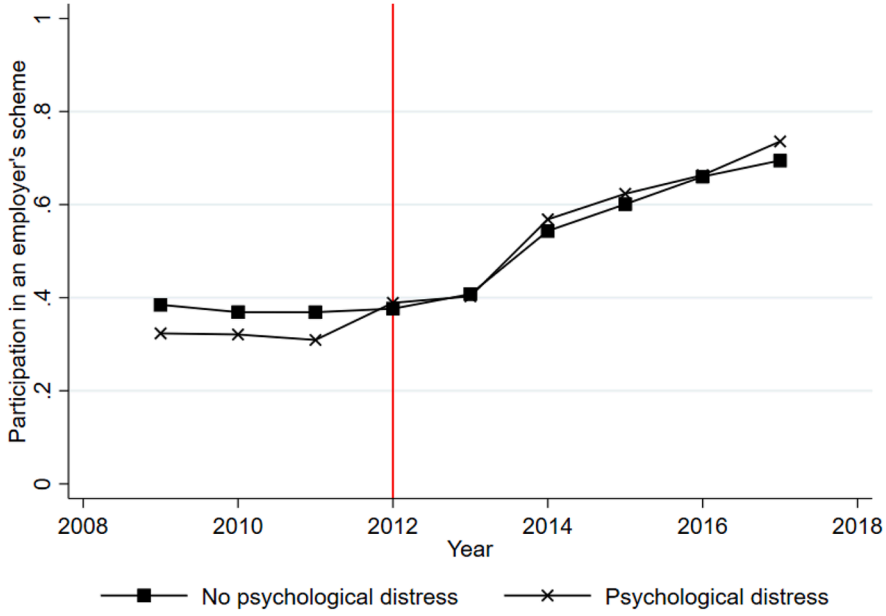


**Fig. 2.** Pension participation rates by baseline psychological distress in Wave 1 (2009–2010) amongst private sector employees
Notes: The sample covers private employees aged 22 to 65 years old. Baseline psychological distress refers to individuals scoring 3 and above and no psychological distress refers to individuals scoring below 3 on the GHQ-12 scale in Wave 1 (2009–2010). The analysis employs pension participation information in Wave 2, 4, 6 and 8. We capture those who respond "don't know" to whether their employer provides a scheme for which they are eligible and those who respond that their employer does not provide a scheme for which they are eligible as not participating in a workplace pension scheme.

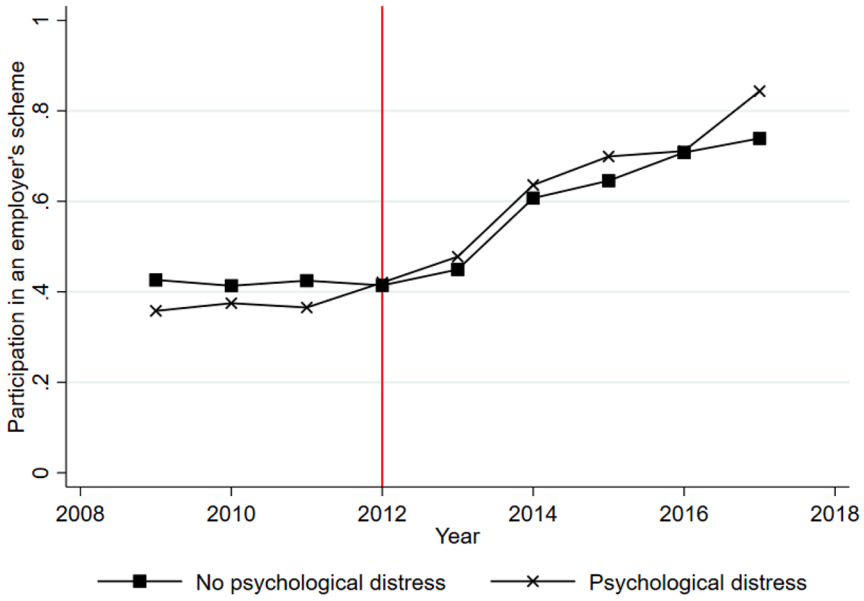


**Fig. 3.** Pension participation rates by baseline psychological distress in Wave 1 (2009–2010) for male employees in the private sector
Notes: The sample covers male private employees aged 22 to 65 years old. Baseline psychological distress refers to individuals scoring 3 and above and no psychological distress refers to individuals scoring below 3 on the GHQ-12 scale in Wave 1 (2009–2010). The analysis employs pension participation information in Wave 2, 4, 6 and 8. We capture those who respond "don't know" to whether their employer provides a scheme for which they are eligible and those who respond that their employer does not provide a scheme for which they are eligible as not participating in a workplace pension scheme.

in pension participation for both groups with pension participation converging over time. Before automatic enrolment, the difference in pension participation between individuals with and without baseline psychological distress is 5.4 percentage points, significant at the 0.1% level. In the post policy periods, the difference in pension participation is no longer significant.

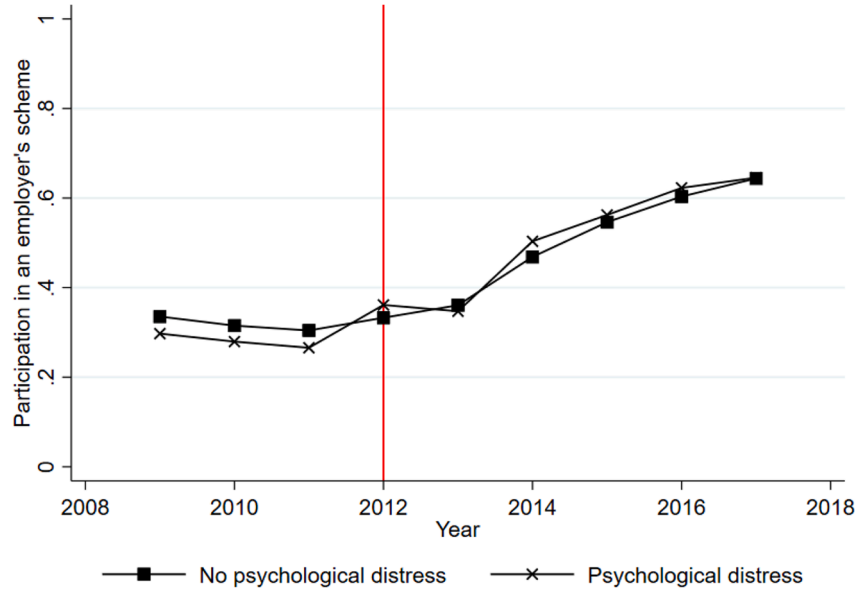


**Fig. 4.** Pension participation rates by baseline psychological distress for female employees in the private sector,
Notes: The sample covers female private employees aged 22 to 65 years old. Baseline psychological distress refers to individuals scoring 3 and above and no psychological distress refers to individuals scoring below 3 on the GHQ-12 scale in Wave 1 (2009–2010). The analysis employs pension participation information in Wave 2, 4, 6 and 8. We capture those who respond "don't know" to whether their employer provides a scheme for which they are eligible and those who respond that their employer does not provide a scheme for which they are eligible as not participating in a workplace pension scheme.

Prior to the implementation of automatic enrolment, male private sector employees with baseline psychological distress are 5.1 percentage points (significant at the 0.1 per cent level) less likely to participate in an employer's pension scheme. In the post policy periods, the difference is no longer significant. Before automatic enrolment, female employees with baseline psychological distress are 3.5 percentage points (significant at the 1 per cent level) less likely to participate in an employer's pension scheme. This difference is also no longer significant post policy (Figs. 3 and 4).

Table 1 provides a comparison of individuals with and without baseline psychological distress in the sample of those employed and unemployed between the ages of 22 and 65 inclusive. Compared to individuals without poor mental health, individuals with poor mental health are more likely to be female (63.3 per cent vs. 55.8 per cent), are less likely to have higher education qualifications (39.2 per cent vs. 42.1 per cent), are more likely to spend time in unemployment (8.1 per cent vs. 5.3 per cent) and long-term sickness or disability absences (10.6 per cent vs. 3.3 per cent), earn on average less per month (£1203.62 vs. £1536.09) and are less likely to be married (51.7 per cent vs. 58.6 per cent). There are no large differences in occupational types between employees with and without psychological distress. Individuals with baseline psychological distress account for about 15 per cent of total observations in the data which is consistent with national prevalence estimates (McManus et al., 2009).

In this paper, we focus only on employed individuals in the private sector as this sector was the main target for automatic enrolment. Although individuals with poor mental health earn less than individuals without poor mental health, they are only slightly less likely to meet the threshold of £10,000 per year to qualify for automatic enrolment. Within the private sector, 82.4 per cent of individuals without poor mental health meet the cut-off, while 78.3 per cent of individuals with poor mental health do. While this difference is significant, the majority of individuals with poor mental health who work in the private sector also qualify for automatic enrolment. Amongst male employees, 92.9 per cent of individuals without poor mental health meet the cut off criteria while 90.5 per cent of individuals with poor mental health do. As for female employees, 69.6 per cent without poor mental health meet the cut off

**Table 1**
A comparison of individuals with and without baseline psychological distress by key individual characteristics.

| | No psychological distress | Psychological distress(GHQ-12 $\geq$ 3) | Test of Difference (p-value) |
|---|---|---|---|
| Mean age | 43.6 | 45 | 1.4 (0.00)*** |
| Gender | | | |
| Male | 44.3% | 36.8% | - 7.5% (0.00)*** |
| Female | 55.8% | 63.3% | 7.5% (0.00)*** |
| Race | | | |
| White | 83.6% | 82.8% | −0.8% (0.00)*** |
| Asian | 9.7% | 9.5% | −0.2% (0.32) |
| Black | 4.3% | 4.6% | 0.3% (0.01)** |
| Others | 2.5% | 3.2% | 0.7% (0.00)*** |
| Highest education | | | |
| GSCE/O Levels | 21.4% | 22.0% | 0.6% (0.02)* |
| A Levels/IB | 8.0% | 7.9% | 0.1% (0.46) |
| Degree/Diploma | 42.1% | 39.2% | −2.9% (0.00)*** |
| Employment Status | | | |
| Paid employment | 63.8% | 53.9% | −9.9% (0.00)*** |
| Unemployment | 5.3% | 8.1% | 5.3% (0.00)*** |
| Retired | 7.7% | 7.7% | 0.0% (0.20) |
| Self-employment | 9.5% | 8.1% | −1.4% (0.00)*** |
| Long term sick or disabled | 3.3% | 10.6% | 7.3% (0.00)*** |
| Sector | | | |
| Public | 37.9% | 40.8% | 2.9% (0.00)*** |
| Private | 62.1% | 59.2% | −2.9% (0.00)*** |
| Occupation Type | | | |
| Professional | 6.6% | 6.0% | −0.6% (0.001)** |
| Managerial and Technical | 38.3% | 37.9% | −0.4% (0.28) |
| Skilled non-manual | 20.3% | 22.1% | 1.8% (0.00)*** |
| Skilled manual | 18.5% | 16.6% | −1.9% (0.00)*** |
| Partly skilled | 13.1% | 13.6% | 0.5% (0.05) |
| Unskilled | 3.2% | 3.8% | 0.6% (0.00)*** |
| Mean monthly income | £1536.09 | £1203.62 | -£332.47 (0.00)*** |
| Cognitive ability | | | |
| Word recall | 6.5 | 6.4 | −0.1 (0.00)*** |
| Delayed word recall | 5.5 | 5.4 | −0.1 (0.00)*** |
| Basic math | 4.1 | 4.0 | −0.1 (0.00)*** |
| Verbal fluency | 22.5 | 22.3 | −0.3 (0.00)*** |
| Having at least one physical health condition | 13.8% | 24.5% | 10.7% (0.00)*** |
| Marital status | | | |
| Single | 29.7% | 29.9% | 0.2% (0.48) |
| Married/Civil Partnership | 58.6% | 51.7% | −6.9% (0.00)*** |
| Separated/Divorced | 11.7% | 18.4% | 6.7 (0.00)*** |
| Number of observations | 183,653 | 32,948 | |

Notes: Sample covers all available data. Baseline psychological distress refers to individuals scoring 3 and above and no psychological distress refers to individuals scoring below 3 on the GHQ-12 scale in Wave 1 (2009–2010). P values from a t-test are shown in parentheses. *, **, *** indicates significance at the 5, 1 and 0.1 per cent levels respectively.

criteria while 68.5 per cent with poor mental health do.

As the pension participation question is only asked of respondents who state that their present employer provides a pension scheme or superannuation scheme that they are eligible for, it is important to determine how likely it is for individuals with poor mental health to work for employers who provide these schemes and whether they are eligible for them.[21] For male private sector employees, 64.7 per cent of individuals without poor mental health work with employers who provide these schemes for which they are eligible compared to 61.3 per cent of individuals with poor mental health prior to automatic enrolment. This difference is significant at the 1 per cent level. There is no significant difference for female private sector employees. Although descriptive in nature, these statistics provide some support for the hypothesis that individuals with poor mental health are more likely to work for employers that are less likely to offer a workplace pension scheme prior to automatic enrolment, particularly for male employees.

### *4.2. The relationship between poor mental health and participation in a workplace pension scheme before and after automatic enrolment*

Table 2 reports the results of linear probability models based on the main specification. It shows that male employees with baseline psychological distress are 5.1 percentage points (significant at the 1 per cent level) less likely to participate in a workplace pension scheme before automatic enrolment in the uncontrolled specification. This coefficient reduces to 3.7 percentage points after the inclusion of controls and is significant at the 5 per cent level. Female employees with baseline psychological distress are 3.5 percentage points less likely (significant at the 5 per cent level) to participate before automatic enrolment in the uncontrolled specification. After accounting for the controls, this coefficient reduces to 2.9 percentage points and remains significant at the 5 per cent level.[22] Based on Gelbach decompositions, income and occupation type are particularly important in explaining the relationship between baseline psychological distress and workplace pension participation for male and female employees respectively, before automatic enrolment. The Gelbach decomposition results are available in Table S3 in the Supplementary Materials.

These negative associations are offset by the positive gains in pension participation for individuals with poor mental health after automatic enrolment which is captured by the coefficients on the interaction term. The positive effect of automatic enrolment on pension participation is stronger for male employees. In particular, the participation rates for male employees with poor baseline

**Table 2**
The relationship between baseline psychological distress captured in Wave 1 (2009 and 2010) and pension participation in a workplace scheme before and after automatic enrolment amongst employees in the private sector.

| | Male employees | | Female employees | |
|---|---|---|---|---|
| | Uncontrolled | Controlled | Uncontrolled | Controlled |
| Baseline psychological distress (1) | −0.051** | −0.037* | −0.035* | −0.029* |
| | (0.017) | (0.015) | (0.014) | (0.012) |
| Post policy dummy | 0.171*** | 0.157*** | 0.176*** | 0.161*** |
| | (0.007) | (0.006) | (0.007) | (0.007) |
| Post*Baseline psychological distress (3) | 0.077*** | 0.047** | 0.035* | 0.014 |
| | (0.018) | (0.017) | (0.016) | (0.015) |
| Age | | √ | | √ |
| Education | | √ | | √ |
| Race | | √ | | √ |
| Marital status | | √ | | √ |
| Number of children | | √ | | √ |
| Presence of a physical health condition | | √ | | √ |
| Income | | √ | | √ |
| Occupation type | | √ | | √ |
| Industry | | √ | | √ |
| Cognitive ability | | √ | | √ |
| Cons | 0.420*** | −0.011 | 0.316*** | −0.046 |
| | (0.007) | (0.038) | (0.007) | (0.040) |
| *(1) + (3)* | 0.026 | 0.010 | −0.000 | −0.016 |
| | [0.113] | [0.494] | [0.998] | [0.263] |
| N | 22,845 | 22,845 | 20,592 | 20,592 |
| R-squared | 0.033 | 0.188 | 0.035 | 0.227 |

Notes: These results are based on the sample of employees aged 22 to 65 years who are employed in the private sector.
The analysis employs baseline mental health captured in Wave 1 and contemporaneous pension participation in an employer's scheme. The analysis employs pension participation information in Wave 2, 4, 6 and 8. We capture those who respond "don't know" to whether their employer provides a scheme for which they are eligible and those who respond that their employer does not provide a scheme for which they are eligible as not participating in a workplace pension scheme.
Standard errors are clustered at the individual level and shown in parentheses. P-values obtained from an F-test of whether (1) + (3) = 0 are reported in square brackets. *, **, *** indicates significance at the 5, 1 and 0.1 per cent levels respectively.

[21] At the overall level in the private sector, 61 per cent of employees without poor mental health work for employers who provide pension schemes while 58.4 per cent of employees with poor mental health do. This difference is significant at the 1 per cent level.
[22] Full results including coefficients on the control variables are available in Table S2 in the Supplementary Materials.

mental health increases by 7.7 percentage points in the uncontrolled model and 4.7 percentage points in the controlled model after automatic enrolment. Meanwhile, the participation rates for female employees with poor mental health increases by 3.5 percentage points in the uncontrolled model and 1.4 percentage points in the controlled model although the latter is not significant.

To quantify the relationship between baseline psychological distress and pension participation after automatic enrolment, we sum the coefficients in (1) and (3) and run F-tests to test the hypotheses of whether these sums are equal to zero across the uncontrolled and controlled models. We find that these sums are not significantly different than zero. Thus, there is no longer a relationship between baseline psychological distress and pension participation which demonstrates that automatic enrolment closed the mental health gap in pension participation amongst private sector employees in the UK.

### 4.3. Robustness

#### 4.3.1. How do the results change when a higher threshold is used on the GHQ-12?

We re-estimate the main specification by measuring psychological distress using an additional cut-off point of 8 and above on the GHQ-12 to denote severe psychological distress.[23] Results are available in Table S4 in the Supplementary Materials. Before automatic enrolment, the results show that male employees with more severe psychological distress (8–12 on the GHQ-12) are 6.1 percentage points less likely to participate in a workplace pension scheme based on the uncontrolled model, but this coefficient is not significant. It is possible that we do not have sufficient power to detect a significant association since only 4 per cent of male private sector employees classify as having severe psychological distress. The sample size of female private sector employees with severe psychological distress is twice the sample size for males. Female employees with more severe psychological distress (8–12 on the GHQ-12) are 5.6 percentage points less likely to participate in a workplace pension scheme in the model with no controls, and this coefficient is significant at the 5 per cent level. This coefficient reduces to 4 percentage points and is not significant after the inclusion of controls. The negative associations between poor baseline mental health and pension participation before automatic enrolment are offset by the gains in pension participation after auto-enrolment only for employees with less severe psychological distress.

#### 4.3.2. How do the results change when contemporaneous measures of psychological distress and pension participation are employed?

We repeat the main specification using contemporaneous measures of psychological distress and pension participation. Results are available in Table S5 in the Supplementary Materials. In the uncontrolled model, males are 5.0 percentage points (significant at the 0.1 per cent level) less likely to participate in a workplace pension in the same year that they report psychological distress. This coefficient reduces to 3.3 percentage points (significant at the 1 per cent level) after accounting for controls. Female employees with psychological distress are 2.4 percentage points (significant at the 5 per cent level) less likely to participate based on the uncontrolled specification. After the inclusion of controls, this coefficient reduces to 1.6 percentage points and is not significant. The mental health gap in pension participation in the uncontrolled models using contemporaneous measures of mental health reduces for male employees and disappears for female employees after automatic enrolment.

#### 4.3.3. How do the results change when employees without access to pension schemes are excluded from the data?

We re-estimate the main specification using the pension participation in an employer's scheme variable as it is in the data, excluding those who reported no access to a pension plan through their employer or did not know whether their employer provided access. Results are available in Table S6 in the Supplementary Materials. Based on the uncontrolled model, male employees with psychological distress are 6.2 percentage points less likely to participate (significant at the 1 per cent level) in a workplace pension before automatic enrolment. This coefficient reduces to 4.1 percentage points when key predictors of pension participation are controlled for. Female employees with psychological distress are 5.1 percentage points less likely to participate in a workplace pension scheme in the uncontrolled model, before automatic enrolment. This negative association reduces to 4.2 percentage points in the fully controlled model. The negative relationship between poor baseline mental health and pension participation disappears for male employees and is no longer significant for female employees after automatic enrolment.

#### 4.3.4. What is the relationship between workplace pension participation and overall savings amongst individuals with poor mental health?

The framing of the questions about savings in UKHLS does not rule out respondents from considering workplace pension participation as part of their savings especially as the pensions question is asked before the savings question in the questionnaire.[24] As we do not know whether respondents consider workplace pension plans as part of their savings, we test the associations between baseline mental health and savings separately for those who report and do not report workplace pension participation. Results are available in Table S7 in the Supplementary Materials.

Male and female employees with poor baseline mental health who participated in a workplace pension plan before automatic enrolment were significantly less likely to report participating in overall savings. If automatic enrolment into a pension plan led to

[23] Less severe and severe psychological distress is classified as those scoring 3-7 and 8-12 on the GHQ-12 respectively. The omitted group are those with no psychological distress scoring 0-2 on the GHQ-12

[24] In UKHLS, whether someone saves or not is captured via this question: Do you save any amount of your income, for example by putting something away now and then in a bank, building society, or Post Office account, other than to meet regular bills? Please include share purchase schemes and ISA's.Respondents are also asked about their monthly amount saved via this question: About how much on average do you personally manage to save a month?

decreases in overall savings for employees with poor mental health, potentially due to substitution away from other savings, we would expect the negative association between poor mental health and participation in overall savings to be larger post policy. Although there is still a negative association between poor baseline mental health and participation in overall savings after automatic enrolment, the coefficient for male and female employees are considerably smaller in magnitude. The amount saved by male employees with poor mental health also improve after automatic enrolment. However, there is a decrease in the amount saved for female employees with poor mental health who were affected by automatic enrolment.

*4.3.5. How does mental health compare to other characteristics in predicting pension participation before and after automatic enrolment?*

We implement the lasso procedure (Tibshirani, 1996) to understand the relative importance of mental health as a predictor of pension participation before automatic enrolment as well as the gains in participation from automatic enrolment compared to our control variables.[25] Although this procedure can provide insights on the relative importance of mental health in predicting pension participation, it does not account for potential mediation effects of mental health. For example, poor mental health is also associated with and can cause adverse outcomes such as lower educational attainment, lower earnings and poorer employment prospects that may subsequently affect pension participation rates.

The results of the lasso analysis are presented graphically in Figs. S3 and S4 in the Supplementary Materials for male and female employees respectively. The graphical results for the main variables and the interaction of these variables with the post auto-enrolment time period dummy are presented separately for ease of comparing how these characteristics (including poor mental health) predict pension participation before automatic enrolment and the gains in pension participation after automatic enrolment. Note, these coefficients are obtained from one model stratified by male and female employees. Figs. S3 and S4 show the coefficient path of the lasso model. Variables whose coefficients reach zero first as the regularization of the model (ln (lambda)) increases are considered less important in predicting pension participation.

Based on Fig. S3 (a), baseline psychological distress is less important than industry, cognitive ability, age, education, marital status, race, occupation, and income in predicting pension participation rates prior to automatic enrolment for male employees. This is not surprising as the importance of these other characteristics are established in the retirement savings literature. However, as shown in Fig. S3 (b), poor mental health is a stronger predictor of the gain in pension participation compared to non-White backgrounds, lower educational attainment, and absence of a spouse or partner. Note, income remains in the negative space as 1 is coded as earning below the threshold to be auto-enrolled and 0 otherwise. Based on Fig. S4 (a), baseline mental health is a much less important predictor compared to all the other characteristics except for the presence of a physical health condition for female employees prior to automatic enrolment. In Fig. S4 (b), poor mental health is the least important predictor of the gain in pension participation compared to all other characteristics except for the presence of a physical health condition which predicts lower participation after automatic enrolment.

*4.3.6. How robust are the pre policy main specification results to omitted variable bias based on the Oster method?*

We use the Oster method (Oster, 2019) to assess the effect of possible omitted variable bias on the pre policy coefficients on poor baseline mental health.[26] The Oster method is implemented using the main specification. Following other papers, we use a range of values for the maximum R-squared value calculated based on the R-squared value of the controlled model to perform the test. Results are available in Table S8 in the Supplementary Materials. The identified set which contains the bias-adjusted coefficient and the coefficient from the fully controlled model excludes 0 (robust to omitted variable bias) at twice the R-squared value of the controlled model for both private sector male and female employees, with the assumption of equal selection between the observables and unobservables. This indicates a relatively high robustness to omitted variable bias.

[25] We convert the categorical variables into binary variables to simplify the interpretation of the results and ensure that large categories are treated in the same way as smaller categories. We also create binary variables for the continuous variables so that the interaction of these variables and the post automatic enrolment time dummy can be interpreted more concisely (e.g. Tibshirani et al., 2012). The recoding is done as follows: race is recoded to White vs. everyone else; education is recoded to having a college degree vs. no college degree; income is recoded as above or below the earnings threshold for automatic enrolment (£10,000 per year); number of children is recoded to having children vs. no children; age is recoded as 40 years and older vs. younger than 40 years old; marital status is recoded to married vs. not married; occupation is recoded to professional, managerial and technical vs. skilled non-manual, skilled manual, partly skilled and unskilled; and industry is recoded to services vs. goods industries. The four cognitive ability measures are summed up first to create a high (above the mean) vs. low cognitive score. Finally, all the binary variables are recoded so that the base category (0) is the category where we would expect respondents to have higher pension participation rates, to match how the baseline psychological distress measure is coded.The lasso procedure is implemented using lasso2 from the Stata package lassopack (Ahrens et al., 2020).

[26] The test is performed by calculating bounds for the results based on information on both the coefficient and R-squared movements due to the addition of controls to the regression. Assumptions are made about the coefficient of proportionality $\delta$ and the maximum R-squared value of the model if one could control for both observables and unobservables. The coefficient of proportionality $\delta$ measures how strongly the unobservable characteristics are correlated with the explanatory variable of interest relative to the unobservable characteristics. Oster argues that it is reasonable to assume that $\delta = 1$ such that unobservables are equally as important as observables in explaining the outcome variable. Setting the maximum R-squared value at 1 means that the outcome can be fully explained by the explanatory variable of interest and controls but this is not always the case due to measurement errors and idiosyncratic variation.

## 5. Discussion

This paper contributes to empirical evidence on the link between poor mental health and savings behaviour. In particular, we demonstrate the importance of poor mental health as a negative predictor of workplace pension participation in the private sector amongst male and female employees prior to automatic enrolment. The negative association between poor baseline mental health and workplace pension participation before the policy change is robust to most of the key predictors of pension participation including educational attainment, occupational type, industry, physical health condition, and cognitive ability. The mental health gap in pension participation closes after the introduction of automatic enrolment. This finding provides further support to automatic enrolment policies which have already been shown to reduce gaps in pension participation amongst financially vulnerable groups such as female and low income employees (Emmerson and Cribb, 2016; Department for Work and Pensions, 2018).

This paper has limitations. As mental health is not randomly assigned, the results of our study are observational. To get closer to a causal estimate, the earliest possible measure of mental health could be used, particularly prior to participation in the labour force. Recent studies in the mental health and economics literature has also explored the use of sibling fixed effects models (e.g., Currie and Stabile, 2006; Fletcher, 2010; Anderson et al., 2015; Egan et al., 2015; Mousteri et al., 2019) or genetic data (e.g., Fletcher et al., 2009; Ding et al., 2009) to address some of these issues. These methods could potentially be used to provide causal estimates of the effect of mental health on retirement savings participation where the relevant data is available.

Although we measure mental health using one of the most credible and commonly used screening tools through the GHQ-12, we are unable to identify specific mental health conditions. This is a potentially interesting area as the variation in symptoms across different mental health conditions may have different implications on how mental health relates to pension participation. Further, our measure of pension participation is self-reported and we lack objective data about whether and how much respondents save in a workplace pension plan. Future work could potentially address some of these limitations through administrative-data linkage to provide objective data on pension participation, including on contribution rates.

Individuals with poor mental health may also be less likely to opt-out of pension enrolment if they are more passive in their decision-making process even in circumstances where it will benefit them to do so. It is not possible to determine whether there is a differential opt-out rate for those who would benefit from opting out as the dataset lacks information on objective opt-out behaviour. In general, there is a large support for automatic enrolment amongst employees based on survey data. In particular, a survey conducted in the UK that investigates attitudes towards pension automatic enrolment, finds that most respondents acknowledged the importance of saving in a pension plan. Respondents also stated that they would have participated in a plan in the absence of automatic enrolment (Robertson-Rose, 2021).[27]

We could not use an event study design to estimate the causal effect of automatic enrolment on the mental health gap in pension participation due to a lack of accuracy on the variable required to determine when respondents were automatically enrolled. The staging date on which companies began automatically enroling their employees into a pension plan was based on number of employees in a company, so that larger companies were affected first. Although UKHLS asks respondents to provide the number of employees, this question is framed in the context of the respondent's workplace and not the overall company where they are employed. When workplace pension participation is plotted against this number of employees variable, we observe that respondents who report working in smaller firms (199 employees and less) experience huge increases in pension participation at the time when only large firms (200 and more employees) began automatic enrolment.[28] Based on reports by the Department for Work and Pensions, the majority of employers complied with their staging dates, so that there was no early implementation of the policy. Compared to data obtained from the UK's Business Population Estimates which collects information directly from employers, UKHLS data contains a much larger proportion of employees who report working in smaller firms.

To conclude, our study contributes to a deeper understanding of how poor mental health may affect lifelong financial wellbeing. If individuals with poor mental health are less likely to participate in a workplace pension plan, they will have less income and consequently less financial security in retirement. The implementation of automatic enrolment completely removes the mental health gap in pension participation, equalising the pension participation rates of individuals with and without poor mental health in the private sector. In designing retirement savings policies, governments ought to consider the interaction between mental health and outcomes of interest. For example, in automatic enrolment policies, the income threshold set for automatically enroling employees may systematically exclude those with mental health problems who earn less to begin with (Smith, 2009; Smith and Smith, 2010). As we show, most people with poor mental health in the private sector in the UK do meet this threshold although they are more at risk of falling below it. We also show that employees with poor mental health were more likely to work with employers who did not provide access to a workplace pension scheme before automatic enrolment. Policies that focus on expanding employee access to workplace pension plans or providing access to alternative pension plans that do not require a costly employer set-up, such as automatic enrolment into individual retirement savings accounts, could potentially address this disparity.

[27] Based on studies in the US, employees often acknowledge that they would like to save more in retirement savings plans but often do not act on these desires. Choi et al. (2002) combine a survey and administrative data linkage to understand how perceptions of savings adequacy translate into actual savings behaviour. They find that the majority of respondents who want to save more do not follow through.

[28] See Fig. S2 in the Appendix.

## CRediT authorship contribution statement

**Karen Arulsamy:** Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Visualization. **Liam Delaney:** Conceptualization, Methodology, Writing – review & editing, Supervision.

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jhealeco.2022.102673.

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