The Invisible Cost: Understanding the Impact of Mental Health on Wages in the UK Economy

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Abstract

Analysing data from the UK Household Longitudinal Study, using both cross-sectional and panel data, this paper examines the impact of mental health on the net wages of individuals employed. Utilising econometric estimations across cross-sectional data, this study found evidence of a significant negative relationship between poorer mental health and earnings. Furthermore, the study investigated threshold effects and found empirical evidence of a significant net wage disparity associated with individuals experiencing symptoms indicative of a depressive disorders. These findings highlight the in-work costs of mental illness and highlight the need for interventions aimed at those already employed.

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Introduction

Physical health and its relationship with labour market outcomes has been a well-established focus of economic research, with better physical health often associated with higher employment rates, earnings, and productivity (Currie & Madrian, 1999).[1] In contrast, this same attention has not been afforded to the effects of mental health in economics, which have often been neglected and left unexplored.

This is despite mental health issues being one of the primary contributors to overall disease burden worldwide and in the United Kingdom (UK), with a staggering 1 in 4 people experiencing a mental health problem each year.[23] Rates of mental illness in England have been steadily rising, with COVID-19 only accelerating this upward trend. In 2021, mental health services in England received a record 4.6m referrals, up 22% from 2019.[4] A wealth of anecdotal evidence also exists to show how the current cost-of-living crisis is exacerbating this with a further increase in the volume and severity of mental health incidences (RCPSYCH, 2023).[5] In short, there has never been a more important time to investigate the effects of mental health. Despite its prevalence, the economic considerations of the UK's current mental health epidemic, particularly on individuals' productivity and labour market prospects, remains vastly under-developed.

With that said, there is a growing body of international literature that is recognising the importance of mental health's impact on productivity and exploring how mental health burdens affect individual's labour outcomes. This is driven by increased social spotlight and the increasing availability of large datasets that include explicit measures of mental health.

This increasing body of research consistently finds mental health to be an important determinant of labour market outcomes, with evidence suggesting that mental illness can significantly reduce an individuals' earnings potential and ability to participate in the labour market (Fritjers et al, 2010).[6] For instance, the incidence of psychiatric disorders has been found to reduce conditional income by around 13% in men and 18% in women (Ettner et al, 1997).[7] However, predominantly this research has been conducted in the US or other countries outside the UK.

Motivation and Objectives

This study builds upon the existing literature by quantifying the impacts of mental health on the UK labour market, this attempts to help fill the aforementioned research gap in UK-based studies.

This paper will focus specifically on the impact of mental health on earnings/wages, for those already employed. The reason for this is two-fold. Firstly, the majority of the existing international literature addresses labour market participation, therefore further research is needed to explore the influence of mental health on those already employed. Secondly, it will allow for the investigation of not only the threshold effects of those suffering from severe mental health disorders, but also the more incremental costs of declining mental health on a broader range of individuals. This approach should provide a more nuanced understanding.

A broad-stroke approach to examining the impact of mental health on wages will be taken, rather than investigating heterogeneities across specific demographics. This approach is justified because it allows scope for the proper exploration of both threshold and incremental effects, and it also enables general findings more widely applicable for policy use.

This area of research is important as understanding the impact of mental health can offer economic justification for increasing the allocation of resources towards mental health services that are available to working individuals. Moreover, it underscores the importance of addressing and managing mental illness in society to avoid incurring economic costs.

This research aims to utilise a large UK-level longitudinal dataset, which includes explicit information on current mental health status and individual earnings, to explore the causal relationship between mental health and wages. The main challenge of the study is overcoming empirical challenges well cited in this area of research, in particular endogeneity arising from simultaneity bias, unobserved heterogeneity, and measurement error.

Economic Theory on Mental Health as a Labour Market Determinant

Human Capital Theory

While the analysis of mental health on the labour market is contemporary, the basis for the discussion is founded in human capital theory, originally expounded by Gary Becker (1964).[8] Human capital theory suggests that the intrinsic stock of skills and characteristics possessed by an individual determines their productivity and therefore their earning potential (Schultz, 1961).[9]

Economic research identifies that health is a key component of human capital, as well as a complementary input into producing other forms of human capital (Bleakly, 2010).[10] There is a wealth of empirical evidence that productivity and wage remuneration are positively linked to human capital, primarily; innate ability, investment in education/training and the accruement of job experience (Schultz, 1971; Lopes, 2012; Azariades and Drazen 1990).[11] [12] [13] These returns are likely to be significantly reduced for those with poor health, as they experience potential increases in absenteeism, decreases in workplace productivity and health conditions that inhibit their opportunities for education and experience. There are numerous empirical studies providing evidence that wage rates decline substantially for workers who experience adverse health events, even for those who can remain in employment (Lenhart, 2019).[14]

However, historically economic research has been primarily focused on physical health, particularly on individuals with physical disabilities. On the other hand, the impact of mental health conditions, such as depression or anxiety, on the accumulation of human capital has received less attention.

Mental health can influence labour markets outcomes through the same mechanisms as physical health. For example, individuals suffering from depression may struggle to focus or concentrate on tasks, suffer from increased fatigue, find it more difficult to pursue new skills, or may be less likely to actively search for new job opportunities (Beck et al, 2011).[15] Declining mental health may lead to skill degradation, limited human capital formation and result in reduced employability or inhibited career progression. This is recognised in a growing library of literature that finds that psychiatric disorders significantly reduce employment, conditional hours of work and relative income of both men and women (Ettner, 1997).

Discrimination Theory

Alternative theories, notably discrimination theory, may also explain differences in relative wage outcomes for individuals with mental health conditions. Labour market discrimination has been well addressed in economic literature (Becker, 1957) but has tended to focus primarily on gender and ethnicity.[16] When it comes to understanding potential discrimination, through the lens of mental health, there are several schools of thought.

Firstly, those with mental health conditions could be discriminated against in the labour market because of social stigma and prejudice (taste-based discrimination). Research examining attitudes towards various types of disabilities has revealed that individuals with mental illness encounter significant levels of intolerance, even more so than physical disabilities (Longhi et Al, 2012).[17] Some studies have found that the extent to which employees feel ‘stigmatised or discriminated against’ adversely affects income (Link, 1987; Baldwin and Marcus, 2006).[18]

Linked to this, Aigner and Cain’s (1977) statistical theory of discrimination suggests that when employers have insufficient knowledge about the productivity of minority-group workers they tend to rely on observable characteristics to estimate their productivity.[19] In this case, workers with mental health conditions may be paid less based on perceptions of lower expected productivity, often a result of dangerous stereotypes that those with mental health are in some way ‘lazy’ or part of a ‘snowflake generation’.

However, taste-based discrimination is only applicable in cases where individual workers disclose their mental health or in cases where mental health status is observable. Since workers tend to only reveal their true mental health status in safe, open, and non-discriminatory settings, the chances of taste-based discrimination are reduced. Thus, discrimination on the basis of mental health is less likely to act as an economic determinant of wages compared factors like gender or race.

Taste-based discrimination is notoriously hard to evaluate directly. Therefore, isolating the roles of human capital accumulation and discrimination can be difficult. While most studies conclude that the effects of productivity far outweigh that of discrimination, there is some evidence to suggest that in the context of mental health, “wage discrimination potentially remains a live issue” (Longhi et al, 2012).[20] For instance, Longhi et al (2012) found among ‘mentally disabled individuals’ with standard levels of productivity, a wage disparity remained. The authors concluded that discrimination could be attributed to this unexplained portion of the wage gap, about 2.3% at the mean, among individuals with a mental disability. This matched earlier findings from DeLieire (2001) who found that discrimination only accounted for 3.7% of the earnings gap among health impaired workers (physical health). [21]

With evidence to suggest that taste-based discrimination is a relatively smaller driver of the negative relationship between mental ill-health and wages, this study will focus its discussion on the impact of mental health on productivity, using a human capital theory approach.

Literature Review

Mental health, much like physical health, operates across a diverse spectrum. Even among clinically recognised mental disorders; diagnoses are extremely wide-ranging, encompassing anything from prevalent anxiety and mild mood disorders to more serious psychotic disorders like schizophrenia. While the mechanisms of effect may differ slightly, there is a broad collection of multidisciplinary research illustrating that mental health is strongly correlated with a number of adverse social and economic outcomes (Bartel, 1979; Tabuman, 1986).[22] [23]

This has led to many attempts to estimate the societal cost of mental illness across economies, including Greenberg et al. (2021)[24] who valued the cost of depression in the US to be \$326bn and more recently McDaid & A-La Park (LSE, 2022)[25] who valued the total burden of mental health on the UK economy at staggering £118bn per year, approximately 5% of GDP.[a] While figures vary significantly across studies, a commonly observed trend among estimates is that the reduced work productivity due to mental illness constitutes a particularly high proportion of overall societal costs, for example 61% in the case of Greenberg et al. In most cases this is greater than the direct costs borne by health services (Thomas & Morris, 2003).[26] This is one

[a] Note: this did not monetise in-work productivity losses (based on 2019 values).

of the factors that forms the motivation for this paper and its focus on labour market outcomes specifically.

These work-related costs, also discussed previously, include factors such as reduced labour market mobility among those with mental illness, lower rates of skills attainment, higher rates of absenteeism, and decreased presenteeism (e.g., Jacob & Hampson, 2020).[27]

These impacts have been studied across a range of literature, both in isolation and as part of research examining labour market productivity more broadly. For instance, Stewart et al. (2003) concluded that depression among US workers led to a greater 'lost productivity time' per week (5.6 hours) relative to workers not suffering from depression (around 1.5 hours).[28] Likewise, in the UK, Almond & Healey (2003) found that depression/anxiety constitutes the single most important causes of workplace absenteeism, with the proportion of workers reporting sick around four times higher for those with mental health conditions.[29] Some studies have found that anxiety leads to greater risk aversion (Giorgeta et al, 2012; Maner et al, 2007), which may influence decisions to pursue promotions or apply for new jobs.[30] [31]Moreover, Oliveria et al (2022) recently concluded a critical review of current literature and found clear evidence that poor mental health was associated with lost productivity, through a range of channels, across at least 38 studies.[32]

Other papers examine the causal link between mental health and labour market outcomes more broadly. They consider these individual mechanisms (alongside others) by virtue of exploring the end-effects of mental ill-health on an individual's key labour market outcomes, primarily the probability of employment and level of earnings (Marcotte & Willcox-Gok, 2001; Germinario et al, 2022).[33][34]

One of the seminal papers on the relationship between mental health and labour market outcomes is *"The Impact of Psychiatric Disorders on Labor Market Outcomes"* by Ettner et Al (1997). The authors of this US paper, using data from the National Comorbidity Survey, found that psychiatric disorders significantly reduced employment rates by around 11% among both men and women. More importantly for this study, they found psychiatric disorders led to a substantial reduction in wages (conditional on employment), consistent with the literature on the impact of psychiatric disorder on workplace productivity discussed previously. The annual reduction in wages conditional on employment ranged across specifications but was around 14% for men (~$4000) and 27% ($4500) for women.

Similar findings are present in Marcotte & Willcox-Gok (2001) and Kessler et al (2008) who updated previous studies and concluded individuals with mental illnesses earned an average of $3500-6000 and $14,000 (-43%) less (annually) than those without such conditions, respectively.[35] Similar correlations can be found in a host of other economic literature around the world, including China (Lu et Al, 2009), Australia (Fritjers et Al, 2010) and across Europe (Curran et Al, 2009).[36]

However, not all research finds a negative relationship between mental ill-health and wages. Chatterji et al. (2011)[37] did not discover any detrimental impacts on earnings, in contrast with papers such as Ettner et al. (1997). Likewise, Peng et al. (2016) revealed depression was associated with a 2.6 percentage point decrease in the likelihood of being employed but had no impact on conditional earnings.[38] However these studies represent the minority, most papers infer some kind of significant relationship between mental health and wages, although to varying magnitudes.

Meanwhile in the UK while some supporting studies can be found, there is limited recent research dedicated to exploring the effect of mental health on individual earnings. The majority of supporting literature comes in the form of more general research examining the relationship between health and the labour market (e.g., Blundell & Costa-Diaz, 2020)[39] or studies isolating the effect of mental health on particular channels of productivity, like absenteeism (e.g., Almond & Healey, 2003). One notable exception is Rice & Contoyannis (2000), which examined longitudinal data from the 'British Household Survey'.[40] Their findings supported the hypothesis of a negative correlation between adverse psychological health and wage levels.

This absence of literature in the UK setting forms part of the motivation for this paper. It is hoped this paper can help fill this gap by providing an up-to-date view of the effects mental illness can have on an individual's earnings in the UK.

Literature Review: Empirical Challenges

The aforementioned papers make-up a growing body of global literature that supports the strong correlation between mental health and individual labour market outcomes. However, the challenge many of these studies face is progressing beyond the point correlation and proving a causal link between poor mental health and adverse wage effects. This is particularly important for actionable policy change but is widely accepted to be a particularly complex challenge in this area of research. (Blundell et al, 2020; Dor & Umapathi, 2014).[41] This is due to two widely recognised obstacles, relating to endogeneity of mental health; unobserved individual heterogeneity and reverse causation.

Firstly, studies must address unobserved characteristics that may jointly determine both mental health and wage renumeration. Ignoring unobserved heterogeneity in this context can lead to omitted variable bias, where an important factor that affects both variables is not included in the analysis. This is important as it can lead to spurious regressions which give misleading statistical evidence, including the over or under estimation of the mental health coefficient.

Secondly, numerous studies have illustrated that adverse employment, such as poor working conditions, can also have detrimental effects on mental well-being health (Cygan-Rehm et al., 2017; Latsou & Geitona, 2018; Belloni et al., 2022).[424344] It is also possible that higher income levels can yield better mental health outcomes, with those earning more able to access better healthcare services or pursue healthier lives (Grossman, 1972).[45] This underscores the significant impact that employment or wages can have on mental health. The implication of a bi-directional relationship between mental health and wage levels creates empirical challenges for interpreting results and drawing causal conclusions.

Economists and academics engaging in health-based research have utilised a range of econometric tools and model specifications to help them explore the causal impact of poor physical and mental health on labour market outcomes (Jackle & Himmler, 2007).[46] These come with varying degrees of success and few studies have effectively controlled for the two-way causality or the existence of unobserved individual characteristics. With that said, the literature can be distilled into three broad categories of approach.

'Control Variables'

The most basic method in dealing with unobserved heterogeneity is to utilise a range of control variables that capture or attempt to proxy the relevant unobserved characteristics or differences between individuals. In this context this may include controls for educational attainment, age, family size, geography (Lu et Al, 2009) and other 'sociodemographic variables' (Kessler et Al, 2008). Many studies also stress the importance of 'controlling' for physical health as a means of identifying the effect of mental health on work-place productivity independently of co-existing health issues. (Almond & Healey, 2003 and Verhaak et al 2005).[47] However, this may still be ineffective as some of those unobserved heterogeneities may not be captured by the data.

Fixed Effects Models

As the availability of high-quality longitudinal health data grows year-on-year, an increasing number of studies are using panel datasets to address endogeneity. Panel data allows for the 'differencing out' of fixed individual characteristics to eliminate unobserved time-invariant heterogeneity (Woolridge, 2010).[48] Past studies have typically utilised fixed effects (FE) models to observe the effect of changes in mental health on labour market outcomes in set time periods (Fritjers et Al, 2014, Rice & Contoyannis 2000 and Peng et al. 2016). Blundell et al. (2020) found that the use of panel methods to study changes in health can reduce health coefficients by half compared to cross-sectional methods. They observed that these results are in line with overcoming the issue of reverse causality bias.

Instrumental Variables

Despite attempts to overcome issues, such methods still struggle to properly address the non-trivial issue of reverse causality (or 'simultaneity bias). To address this, a common approach has been the use of an instrumental variable (IV) - a variable strongly associated with mental health but not labour market outcomes directly (only through mental health). By exploiting the exogenous variation of the instrument, an IV can provide more accurate estimation of the causal effect. Furthermore, it can also help mitigate issues such as omitted variable bias and measurement error. Issues around measurement error are touched on later in this paper.

The choice of instrumental variables has been wide-ranging and innovative with previous studies using average mental health by geographic area (Lu et al, 2009), parental mental health (Marcotte et al, 2000), death of a close friend (Fritjers et al,2014), social support (Ojeda et al. 2010), and childhood mental health and religiosity (Chatterji et al, 2007).[49] The majority of papers have found a detrimental effect of mental illness on labour market outcomes, although the magnitude of effect varies widely. Typically, studies using IV estimators show larger effects than those implementing fixed-effects specifications.

Nonetheless, none of these studies can convincingly satisfy the 'exclusion restriction' assumption that these instruments do not have a direct effect on labour market outcomes. When the outcome of interest is income-related, it becomes more probable that the area of effect for these variables will include direct effects on wages. As an example, the exclusion restriction assumption may be violated in the case of adolescent mental health, as research has shown a link between poor mental health during childhood and lower educational attainment (Fletcher, 2008).[50] Additionally, most instrumental variables are constant over time, neglecting the potential reverse causality effects of varying mental health throughout adulthood. While these issues may be inherent in the econometric analysis of health and the labour market, this paper will aim to, where possible, address these issues and clearly outline limitations of empirical analysis.

Data

The primary data source used for this study is derived from the UK Household Longitudinal Study (UKHLS), this dataset is the largest longitudinal household panel study in the UK. The study follows around 40,000 households over time and collects a wide range of indicators: including education, employment, health, economic outcomes and socio-economic demographics. The latest wave of the data collected in 2020-21 (wave 12) covers around 30,000 individuals.

This dataset was selected due to its large sample size and because it asked participants several questions specifically around their mental health and labour market outcomes, as well as several socio-economic demographics which allow for rigorous statistical modelling.

Primary Variables: Mental Health Index and Wages

The main health variable of interest for this paper is 'SF-12 Mental Component Summary' (MCS-12)- a self-reported outcome measure assessing the impact of mental health on an individual's everyday life. The standardised index used across the world is formed from responses to a number of well-being related self-assessment questions which converts valid answers into a single mental functioning score, resulting in a continuous scale with a range of 0 (low functioning) to 100 (high functioning). The self-assessment survey included questions such as:

- *"How much of the time during the past week - have you felt calm and peaceful?"*
- *"How much of the time during the past week - have you felt downhearted and blue?"*

Furthermore, individuals were also asked to report their current economic status (employed or unemployed) and their net monthly income derived from labour (net of taxes and national insurance contributions), allowing for direct analysis of the effect of mental health on key labour market outcomes without the need for proxies. Although hourly wages are typically used in wage equations, the UKHLS data on the number of hours worked is of insufficient quality, with many observations reporting negative or sub-minimum wage hourly rates. As an alternative, monthly wages may provide more reliable estimates and can also capture the effects of mental health on the number of hours worked.

Table 1: Summary Statistics for Key Variables

	Mean	**Median**	**Min-Max**	**Std. Deviation**
NET WAGE	£1810.50	£1670.00	£100.00 - £4993.00	£888.04
MCS-12	46.850	48.870	1.590 - 70.990	10.192

Physical health

In line with the literature and to explore mental health independently from co-existing physical conditions (Verhaak et al., 2005), the analysis incorporates the SF-12 Physical Component Survey (PCS-12). The PCS-12 is a self-reported outcome measure assessing the impact of physical health on an individual's life and well-being.

Socio-Economic Variables

Participants were also asked questions on several socio-economic characteristics and demographics, such as gender, marital status, level of qualifications, for which continuous or dummy variables have been derived. Many of these are likely to be correlated with mental health and wages. In absence of meaningful data on experience, *'age'* and *'if in paid employment in previous wave'* have been used as proxies. A summary of these variables can be found in table two. These are used to control for intervening factors, in an attempt to isolate the impact of mental health on earnings, allowing for robust econometric modelling.

Table 2: Summary Statistics for 'Control' Variables

	=0 (%)		=1 (%)	
SEX	Female (0) – 56%		Male (1) – 44%	
MARRIED	Not Married (0) – 45%		Married (1)- 55%	
URBAN	Rural (0) – 33%		Urban (1) – 77%	
EXPERIENCE	Otherwise (0) -15%		In employment in previous wave (1)-95%	
NO EDUCATION	Otherwise (0) – 88%		No Formal Qualifications (1) – 12%	
LOW EDUCATION	Otherwise (0) – 67%		L3 Qualification or Lower[b] (1) – 33%	
HIGH EDUCATION	Otherwise (0) – 53%		Degree (or equivalent) (1) – 47%	
	Mean	**Median**	**Min-Max**	**Std. Deviation**
PCS-12	53.090	55.130	10.780 – 74.000	7.815
AGE	42.691	44.000	18.000 – 65.000	12.447

Instrumental Variable

Parts of the model specification also utilise an IV which takes the form of the 'Buckner's Neighbourhood Cohesion' – a self-reported instrument designed to assess levels of neighbourhood cohesion. The index, ranging from 1 (low cohesion) to 5 (high cohesion), is formed from several questions relating to 'attraction to neighbourhood', 'neighbouring' and 'sense of community'.

Sample

This study utilises both cross-sectional and panel data models. The cross-sectional model uses data from the most recent wave of UKHLS (2020-21) and contains data from 10,458 participants. The panel data models are made up of data from 5511 individuals consistent across the last five consecutive waves of the UKHLS (2015-21). The panel data also only includes respondents who have participated in all five waves. This is beneficial as it helps to avoid attrition bias, which can arise when there is differential drop-out across waves.

In addition, both datasets have been extensively cleaned to improve the accuracy of modelling results, including removing individuals with missing data points, refining samples to those of working age (18-65), removing participants with outlier or zero-wage wage observations and other sensible practices.[c]

Empirical Strategy

Ordinary Least Squares (OLS)

To determine the relationship between mental health condition and earnings, a series of OLS regression models were conducted, utilising cross-sectional data. The econometric starting point was an OLS model (model 1), whereby log net monthly wages is regressed on mental health index (MCS-12). In line with the literature, the natural logarithm was applied to income due to its skewed distribution (Harwood et al). This first model serves as a foundation for more complex econometric analyses and helps establish a baseline before additional controls are included in subsequent models.

1. $\ln(wages) = \alpha + \beta_1(Mental\ Health) + \varepsilon_i$

[b] This would include A-Levels, AS levels, GCSE's or other schooling certifications

[c] NOTE: Wages data was trimmed to only capture those earning a minimum of £100 and maximum of £5000 (net) per month after examining the distribution of raw data.

This is then built upon by including measures for human capital and socio-demographic characteristics, including marital status, age (squared), location, sex, education level and physical health (Model 2 and 3). These controls help to account for the potential confounding effects of these variables on the relationship between mental health and earnings, aiming to minimise unobserved heterogeneity and reduce omitted variable bias.

2. $\ln(wages) = \alpha + \beta_1(Mental\ Health) + \beta_2 X_i + \varepsilon_i$

$* X_i = denotes\ set\ of\ control\ variables, made\ up\ of\ socio-economic\ charactertistics$

The inclusion of these 'control variables' has been phased. This is because some, principally educational attainment, directly capture the link between mental health and human capital accumulation (Smith et al, 2017), impacting wages. These are then added to explore the effects of mental health on wages with and without the mediating effects of education.

Instrumental Variable

As highlighted by the literature, mental health may be correlated with the error term (endogeneity), due to the effects of reverse causality, measurement error and unobserved heterogeneity. Therefore, this study will re-estimate results utilising a two-stage instrumental variable model (model 4), using a neighbourhood cohesion index as an instrument for mental health, in a similar vein to studies like Ettner et al (1997).

Neighbourhood cohesion has been found to be strongly correlated with mental health levels in past literature (Williams et al, 2020; Urzura et al, 2019).[51][52] Social connectedness is likely to offer greater emotional support during times of adversity, reduce feelings of isolation and produce other forms of 'social capital' that may be determinants of mental health (Julien et al, 2012).[53] It is unlikely that community cohesion will impacts wages through any alternative mechanism, with an omission of studies linking social cohesion to wages directly. In addition, some prior studies have utilised indicators of community well-being as valid instruments (Lu et al., 2009), and the results of both the Hausman test and the Weak Instruments test provided supporting evidence. With neighbourhood cohesion significantly correlated with MCS-12 in the first-stage regression, and believed to satisfy the exclusionary restriction, it serves as a means of isolating the variation in mental health that is exogenous to earnings.

Operating under this assumption, the two-stage IV model allows for more robust and credible estimates of the causal effect of mental health on earnings.

3. $\ln(wages) = \alpha + \beta_1(IV\wedge) + \beta_2 X_i + \varepsilon_i$

$* IV = Buckner's\ Neighbourhood\ Cohesionis\ used\ as\ instrument\ for\ mental\ health$

Panel Data

This study also uses a fixed effects (FE) model, using panel data from the last five waves of the UKHLS, as a comparator specification. This follows previous studies such as Fritjers et al (2014) and Rice & Contoyannis (2000). This model uses a different sample selection to previous cross-sectional models, by virtue of only including participants who were present in all five collection periods (*n=5111*).

4. $\ln(wages) = \alpha + \beta_1(Mental\ Health) + \beta_2 X_i + FE_i + \varepsilon_i$

$* FEi\ represents\ the\ fixed\ effects\ for\ the\ i-th\ individual\ that\ captures\ the\ individual\ or\ entity-specific\ effects\ that\ are\ constant\ over\ time.$

Cross-sectional data, by nature, captures only a snapshot of individuals at a specific point in time and therefore has limitations. Panel data FE models, on the other hand, uses individual fixed effects to better control for unobserved time-invariant heterogeneity to mitigate issues of endogeneity (unobserved heterogeneity and reverse causality) present in cross-sectional data. Exploring both cross-sectional and panel data models will allow for comparison of results and act as a robustness checking exercise.

In addition, the utilisation of panel data models adds another element by allowing for analysis of dynamic marginal effects (changes) in mental health. This will provide a more nuanced understanding of the relationship between wages and mental health and allow for a broader set of conclusions.

Threshold Effect: Depressive Disorders

This research paper also establishes a binary variable to represent individuals experiencing symptoms indicative of clinical depressive disorders (or similarly severe mental disorders) based on the literature-defined threshold of scoring 42 or below on the SF-12 MCS index (Kosinski & Keller, 1995). By re-estimating models using this alternative variable instead of the continuous MCS index, it becomes possible to explore whether the effects of mental health on wages are larger at the threshold than on average across the distribution.[d]

Results and Discussion

Cross-Sectional Approach

A series of stepwise OLS regression models were run in accordance with the identified empirical strategy. These ranged from a simple OLS regression (model 1) to a final two-stage least squares model using an IV (Model 4). Results are shown in figure 1.

Mental Health

Across specifications, the mental health index had a positive and significant effect on earnings; providing support for the hypothesis that wages levels are statistically greater for those with better mental health (higher scores on the MCS-12). These findings are statistically significant at the 95% confidence level across all OLS results.

The co-efficient for mental health ranged between 0.002 and 0.003 (<1%) in non-instrumented OLS estimates. However, results from the final IV estimation (model 4) yielded greater estimates on the effect of the mental health index on wages than in previous models, with a 1-unit increase in the mental health index associated with a 0.9% increase in wages (0.009). This is roughly ten times larger in effect size compared to non-instrumented models. Similar studies conducted also yielded bigger estimates after using an IV approach (Yu et al, 2009)

This may indicate that the IV is successfully addressing endogeneity, and there could several reasons why the results obtained from the IV model are larger. Firstly, it may indicate the presence of omitted variables that have a negative association with either mental health or wages, such as environmental factors, that were not accounted for in the non-instrumented models. Secondly, the mental health index may suffer from measurement error, creating a 'attenuation bias towards zero, this is touched on later in the paper but is entirely possible given the index is made up of self-reported survey questions. Finally, the IV approach effectively captures the 'local treatment' effect by examining the impact on wages for only those whose mental health varies in conjunction with neighbourhood cohesion. This may only apply to a

[d] 28% of the total sample (3279 participants) were identified as suffering from depressive disorders.

particular sub-set of the overall sample used in previous models, resulting in different estimates of effect.

Control Variables

The polarity of the coefficients in the cross-sectional regressions are consistent with the anticipated direction based on human capital theory. Better physical health, much like mental health, positively affects wages which is consistent with expectations that those with poorer health are less productive. Age (proxy for experience), high levels of educational attainment, and being married also positively affect log wages, whereas being female was negatively associated with log wages. The magnitude of effect and significance of these control variables was quantitatively similar across models.

It is worth noting, the estimates presented across model two onwards are reflective of the 'direct' effects of mental health after controlling for mediating factors, such as age or marital status.

Figure 1: Effects of Mental Health on Earnings

*p-value *<0.10, ** <0.05, ***<0.01*

OLS (n=10,458) Dependent variable: LN_WAGE (Log of monthly net wages)				
	Model 1 (Single OLS)	**Model 2 (w/ controls)**	**Model 3 (w/controls inc. education)**	**Model 4 (2SLS-IV)**
MENTAL HEALTH (MCS-12)	**0.003*****	**0.002*****	**0.002*****	
NEIGHBOURHOOD COHESION				**0.009****
PHYSICAL HEALTH (PCS-12)		0.008***	0.007***	0.008***
AGE		0.079***	0.070***	0.070***
AGE^2		-0.000***	-0.001***	-0.001***
EXPERIENCE		0.198***	0.193***	0.235***
MARITAL STATUS		0.014	0.005	0.002
URBAN		0.006	- 0.002	0.008
SEX		0.300***	0.323***	0.305***
LOW EDUCATION			-0.000	−0.015
HIGH EDUCATION			0.283***	0.301***
R-SQUARED	0.003	0.172	0.233	0.179
F-STAT	36.323	265.500	313.556	276.224
COMMENTS		Social cohesion index used as IV for mental health. Weak Instruments Test (F-Stat=59) indicated strong instruments		

Educational attainment

Separate regressions were conducted to include or exclude dummy variables representing different levels of educational attainment. This is because economic theory would suggest that educational attainment is a mediator variable which would account for some of the transmission of the effect of mental health on earnings. For example, poor mental health, especially in adolescence, has been shown to result in lower rates of educational attainment (Smith et al, 2017) and therefore inhibit human capital accumulation.

Interestingly, the results show that the coefficient for mental health increases when education levels are included. This is inconsistent with economic theory as it would be expected the inclusion of education would explain some of the relationship between mental health and wages, resulting in a diminished (rather than amplified) effect. This could indicate a potential issue of multicollinearity where the relationship between mental health and the log of wages is influenced by education levels in a complex or non-linear way.

Indeed, one of the limitations of the survey data used is that it only queries respondents about their current mental health status, without delving into historical patterns. Theoretical considerations suggest that the impact of mental health on educational outcomes may be more pronounced during early stages of life when individuals are more likely to pursue formal qualifications, such as a degree. In later life, declining mental health is more likely to affect wages through the attainment of more informal education and/or experience. The limitations of this study's current data are that it fails to account for informal education or skill development.

Depression

Conducting further analysis, similar models were re-estimated using a binary variable for individuals experiencing symptoms indicative of clinical depressive disorders, instead of the mental health index. This allowed for the analysis and exploration of threshold effects in relation to the impact of mental ill-health on wages. These results are shown in figure 2.

As one would expect, the incidence of a depressive disorder had a negative and significant effect on wages across all model specifications. The magnitude of effect for the constructed depression variable on the log of net wages ranged from -0.075 (simple linear regression) to -0.037 and -0.034 (with education) for more robust regressions including control variables. This would indicate that individuals with a depressive disorder in the current period experience around a 3.5% reduction in wages compared to individuals without a depressive disorder. With much larger co-efficients than figure 1, this provides support for the hypothesis that impacts of mental ill-health wages are much larger at the threshold of mental illness.

The IV model (model 4) was also replicated using the binary depression variable, using the same instrument – neighboured cohesion index. Once again, this yielded much greater estimates with mental disorder negatively affecting wages by 28.4% (-0.250).[e] This result is broadly consistent with prior research, Ettner et al. (1997) also found that implementing an instrumental variable approach resulted in higher estimated effects and concluded the presence of a mental disorder reduced women's wages by 29%, from $19,800 to $14,100.

[e] *(exp(-0.250)-1)*100=28.4%*

Figure 2: Effects of Depression or other mental illness on Earnings *p-value *<0.10, ** <0.05, ***<0.01*

OLS (n=10,458) **Dependent variable: LN_WAGE (Log of monthly net wages)**				
	Model 1 (Single OLS)	**Model 2 (w/ controls)**	**Model 3 (w/controls inc. education)**	**Model 4 (2SLS-IV)**
DEPRESSION (1= DEPRESSED, MCS-12 < 42)	**-0.075*** **	**-0.037** **	**-0.034** **	
NEIGHBOURHOOD COHESION				**-0.250** **
PHYSICAL HEALTH (PCS-12		0.008***	0.007***	0.007***
AGE		0.079***	0.070***	0.070***
AGE^2		-0.001**	-0.001***	-0.001***
EXPERIENCE		0.197***	0.193***	0.231***
MARITAL STATUS		0.014	0.006	0.002
URBAN		0.007	−0.002	0.011
SEX		0.301***	0.323***	0.306***
LOW EDUCATION			-0.000	−0.015
HIGH EDUCATION			0.282***	0.297***
R-SQUARED	0.002	0.172	0.233	0.169
F-STAT	34.000	264.935	312.138	271.105
COMMENTS		Social cohesion index used as instrumental variable for depression.		

However, this study recognises the potential issue of using a continuous instrument for a binary variable. Utilising a continuous IV for a binary indicator is likely to may make it more prone to having a direct effect on wages, therefore potentially violating the exclusion restriction assumption.

It is worth noting, like previous iterations, the size and significance of the included control variables was similar across models. However, in contrast to figure 1, the depression coefficient decreased in size when education levels were included. This may indicate that the effects of mental health on formal education are slightly more pronounced at the threshold of mental illness, although the differential was relatively minor.

Heteroskedasticity

Robust standard errors are used in modelling due to the presence of heteroscedasticity, revealed by Brusch-Pagan and Halbert White tests. In addition, as an additional robustness check, all models were re-estimated using a Heteroskedasticity-corrected linear model which yielded very similar statistical results.

Panel Data Approach

As per the empirical strategy, a fixed effects (FE) model, using panel data, was also conducted as a robustness check, and to utilise the advantages of panel data in exploring the marginal effects of mental health on wages. Results for the FE model can be found in figure 3.

Figure 3: Effects of Mental Health on Earnings (Fixed-Effects Model using panel data)

*p-value *<0.10, ** <0.05, ***<0.01*

Fixed-effects (n=27,652, Includes **5511 cross-sectional units across 5 periods) Dependent variable: LN_WAGE (Log of monthly net wages)**				
	Model 1 (Simple FE Model)	**Model 2 (FE Model w/ controls)**	**Model 3 (Simple FE Model)**	**Model 4 (FE Model w/ controls)**
MENTAL HEALTH (MCS-12)	-0.001***	-0.001***		
DEPRESSION (1= DEPRESSED, MCS-12 < 42)			0.018**	0.019**
PHYSICAL HEALTH (PCS-12)		-0.001*		-0.000
MARITAL STATUS		0.059***		0.589***
URBAN		-0.011		-0.010
LOW EDUCATION		−0.141***		−0.142***
HIGH EDUCATION		0.147***		0.149***
LSDV R-SQUARED	0.858	0.859	0.858	0.858
COMMENTS	Arrellano Robust Standard Errors			

Mental Health

In contrast to previous results, results from the FE model established that the mental health index had a negative, yet significant, effect on the log of wages. This indicates that a 1-point improvement in an individual's mental health levels negatively affects their net wage by around -0.1% (-0.001). This finding was broadly consistent across several model variations using different variable combinations (e.g., including and excluding education levels). This implies declining mental health would result in increasing wage levels, contravening the expected theoretical prediction and previous results.

The FE model was also re-estimated using a binary variable for individuals experiencing depressive disorders, with similar counter-intuitive results.

Comparison of results and follow-up analysis

There could be several reasons for the counterintuitive findings present in the FE model. The most obvious are reverse causality and/or unobserved heterogeneity, a well-cited issue in the literature across this research area.

One possible hypothesis is that shifts or changes in employment, resulting in lower wages, may contribute to positive impacts on mental health through reduced workloads, less pressure or improved working environments. This works with the assumption that higher paid jobs tend to be more stressful and therefore have more detrimental effects on mental health. If this is the case, this may distort the relationship between mental health and wages.

This may be the case where marginal reductions in wages are associated with reduced levels of work-related stress but drops in income are not sufficient to lead to greater financial pressure, reduced investment in personal health or a fall living standards. Given this sample is made up entirely of employed persons who have held a job over the past five years and where mean wages are over £27,000 (this also includes part time work), this may very well be the case.[f] This phenomenon may have been further accentuated by the widespread re-evaluation of work/life priorities in the wake of the pandemic. It would be beneficial to explore this hypothesis by controlling for changes in employment using SOC codes. Unfortunately, a significant proportion of respondents have missing observations on occupation in the UKHLS, this limits the extent to which this theory can be analysed.

There are other potential reasons that may explain the results from the FE model, such as specific dynamics in the panel data. Time-variant socio-economic factors, such as labour market conditions, policy interventions, or other unobserved factors could impact the relationship between mental health and wages in unexpected ways. The Wald test for time dummies suggested that there is a significant time trend in the data that cannot be explained by the included variables or time-invariant unobserved heterogeneity. Initially, it was thought that the dataset may impacted by the COVID-19 pandemic, which had major impacts on the labour market and mental health landscape. However, after re-estimating the model using pre-COVID time periods there was little to no change. In this case, incorporating time dummies to capture time variation did not affect the coefficient's sign or magnitude and resulted in the insignificance of mental health.

Limitations

When discussing the results from this study, it is crucial to consider the challenges associated with utilising self-reported health measures. Self-reporting requires psychological introspection which may differ across individuals and time periods- individuals' perception of 'depression' are likely to differ and may be inconsistent with diagnoses in clinical settings (Jurges 2008).[54] This can result in reporting volatility and/or error which may lead to attenuation bias in the estimates of mental health effects (Blundell et al, 2020).

There is also the issue of 'justification bias'. While most applicable to non-working individuals, it may also apply to persons in employment who over-report their level of ill-health to justify sub-optimal career outcomes or underemployment (Black et al, 2017).[55]

An ideal variable would be a composite index of mental health, reflecting health in the context of "human capital stock", but such data is not available. Therefore, this study's approach may suffer from some degree of measurement error, leading to estimates which may be either upward or downward bias. With that said, there is a wealth of scientific literature preponing

[f] Mean gross annual wages for sample is equivalent to around ££27,435 per annum.

the validity of the MCS-12 and its use for detecting mental health disorders (Huo et al, 2018, Vilagut et al, 2013). [56] [57]

Conclusion

Mental health has been deteriorating across the UK, particularly in the wake of the pandemic (BMA, 2023), and this can have serious consequences for labour market outcomes.[58] This study focuses on one of the most important and under researched outcomes in the UK; an individual's wages from being employed.

Building on the existing literature, using OLS estimations, this study found evidence of a significant positive relationship between mental health and earnings, with a one-point increase in mental health levels leading to 0.2% to 0.3% increase in wages.

This study also used a constructed instrument for mental health in a 2SLS IV model, having contended that neighbourhood cohesion will only affect wages through its effect on mental health. Results from this IV approach showed a much larger magnitude of effect, with a one-point increase in instrumented mental health positively affecting wages by around 0.9%.

For illustration, altering the response to the question *"During the last week, have you felt downhearted and blue?"* from *'"None of the time"* to *"Most of the time"* would elicit an average of a 10-point reduction in the mental health index. This represents a 2-3% or 9% (using IV model) decrease in wage levels. For the average salary in the cross-sectional sample this would represent a net wage 'penalty' of between £435 and £650 per annum as a conservative estimate.[g] This would be as high as £1955 per year using the upper estimate from the IV model. This puts in context the importance of tackling mental health across a broad spectrum of individuals, not just those who are unable to participate in the labour market.

Building upon this, the study investigated threshold effects of suffering from a mental illness. There was empirical evidence of a significant negative relationship between the current incidence of depression (or similar mental illness) and wages, with results indicating that individuals suffering from depression earn 3.4% to 3.7% less than their non-depressed counterparts. For the average salary in the cross-sectional sample this would represent a net wage disparity of around £740-£805 per annum. Once again, estimates of the negative earnings disparity for those suffering from depression were much greater using an IV estimation at 28.4%, representing an average wage disparity as high as £6170 per year.

The results obtained using IV estimations, which indicate higher effect sizes, are largely in line with previous research (Ettner et al., 1997; Lu et al., 2009). However, while this may suggest that the original OLS specifications were underestimated due to endogeneity bias (e.g., reverse causality), there may also be other empirical explanations. Given the well-established challenges associated with identifying suitable IVs in wage equations, and some reservations regarding the excludability criteria, it is recommended that the findings be approached with a degree of caution (Blundell et al., 2020; Fritjers et al., 2014). There is some risk of overestimation. Nonetheless, these results could be viewed as representing the upper bound estimates of the potential cost of mental health on the wages of employees.

As part of a robustness check and to investigate the dynamic effects of mental health changes, panel data and a fixed-effect model were employed. However, even after accounting for time dummies, the results were counter-intuitive and inconclusive.

[g] Average salary in the cross-sectional sample= (£1810.50*12) *1%=£216

Although this study's overall findings are broadly consistent with the body of literature in this area, there are very few recent econometric studies analysing the effect of mental health on wages in the UK.

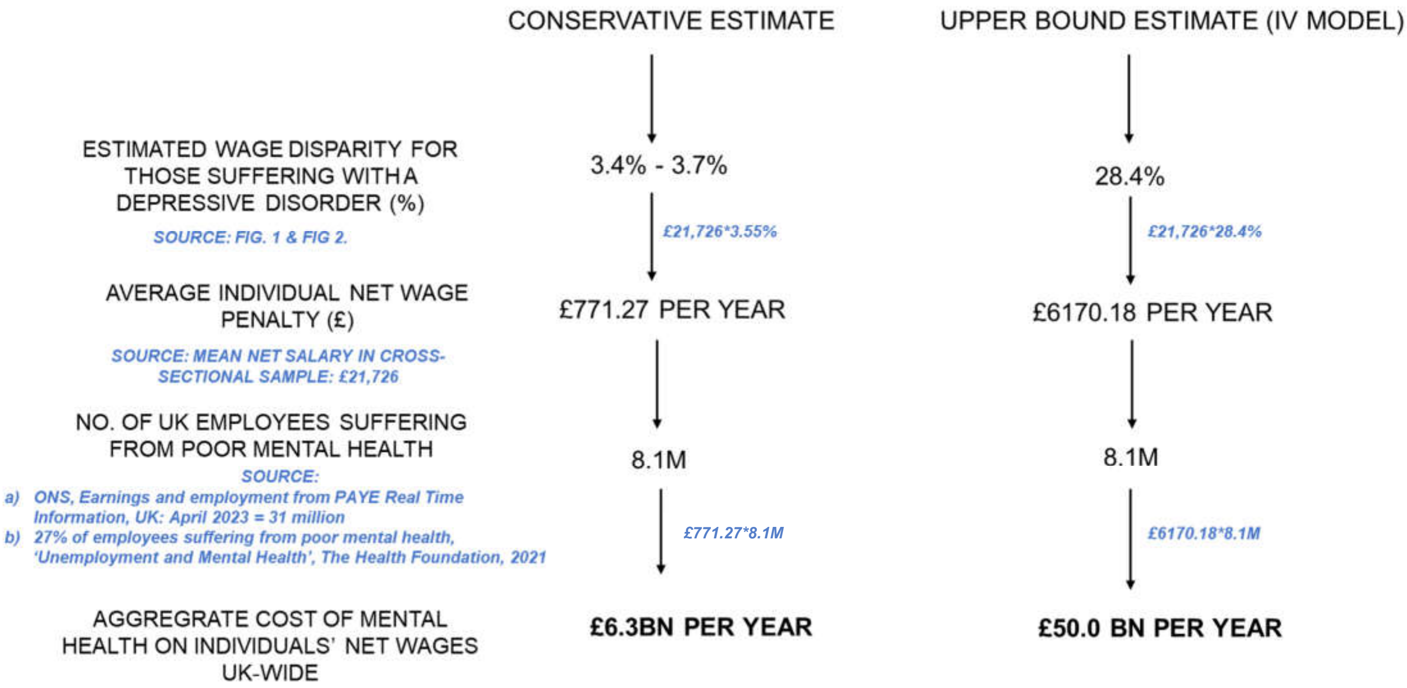
Policy Implications

Overall, these findings highlight the economic costs of mental health in the workplace, and the need for interventions aimed at reducing their negative impact on those already employed. Although assessing the aggregate cost of mental health on individuals' wages is not in scope of this study, findings indicate the wage penalty faced by those with mental illness may translate into substantial costs nation-wide, exceeding £6.3bn annually (net) (see fig. 4).

These findings have significant policy implications regarding both efficiency and equity. The negative impacts of mental health on employee's productivity, career outcomes and ability to remain (and progress) in the workforce lead to substantial efficiency losses. Moreover, those with poorer mental health face significant disadvantages, not only in terms of pay, but also the negative spill-over effects linked to wages. These may be addressed through effective interventions that better support employees suffering from mental health issues, such as subsidised physical activity or psychotherapy, supported employment initiatives, or flexible working practices.

The economic costs of mental illness are much larger than the wage penalty alone and call for a comprehensive set of policy interventions aimed at improving both the efficiency and equity of the labour market for those affected by mental illness. It is hoped this study will lend economic justification to the prevailing societal demand for increased allocation of resources towards mental health services in the UK.

Figure 4: Indicative diagram illustrating the aggregate costs of mental health on individual wages in the UK.



The advantage of this study is its broad stroke approach, however further research is needed to explore the potentially heterogenous effects of different mental health disorders on labour market outcomes. Different disorders, such as anxiety or OCD, may have distinct mechanisms and varying degrees of effects.

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