Analysing the Relationship Between Mental and Physical Health, and Employment

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Abstract

This study aims to provide an updated and comprehensive analysis of the impact of physical and mental health on employment outcomes, by gender. Disability wage gaps are prominent, and there are benefits to understanding whether these gaps affect men and women differently, considering the different challenges they face in the labour market. This study uses the UK Household Longitudinal Study to isolate and compare the impacts of different measures of health on labour market outcomes between men and women. Using cross-sectional and panel data a variety of models have been used to attempt to overcome well-known challenges in this research area. The findings indicate a significant positive relationship between good health and wage for both men and women, with physical health having a significantly larger impact in males. Findings also indicate that this relationship is exacerbated for individuals with more severe health issues, highlighting the importance of supporting individuals with disabilities and illnesses in the workplace.

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1) Introduction and Motivation

There is a well-established understanding of the disability wage gap in the UK. The Office for National Statistics (2022) found a 13.8% gap between median pay of disabled and non-disabled employees. A recent survey found that one in eight disabled workers were concerned their disability affected their chance of promotion, and how their performance would be assessed by management (TUC, 2021). Around the same time, the National Disability Strategy (Gov.uk, 2022) was implemented, committing the Government to improve opportunities and outcomes for people with disabilities.

Similar surveys have also explored the impact of mental health impact on labour market outcomes. A UK charity (Money and Mental Health Policy Institute, n.d.) also found that people with anxiety and depression earn £8,400 per annum less than those without, and that even acute episodes of mental health problems can interrupt earnings. However, there is less intervention aimed at improving or understanding labour market outcomes for those with mental health problems.

Although there is a wealth of research to analyse the impacts of either mental or physical health, the impacts of both mental and physical health are rarely analysed together. The motivation of this paper is to provide an updated understanding of the isolated impacts of both physical and mental health on labour market outcomes in the UK, and to answer the following question:

What effect does physical and mental health have on labour market outcomes?

In addition to exploring the impacts of both physical and mental health, this paper will aim to improve understanding around the different impacts of health on males and females. It is well understood that males and females face different challenges in the labour market (Lu, et al., 2009) but females are also three times more likely to experience mental health issues than men (Mental Health Foundation, 2017) and account for a larger majority of individuals with disabilities in England (18.7% v 16.5%) (Office for National Statistics, 2023). Therefore, it is important to examine the impacts and relationships of each gender carefully.

A mixture of cross-section and panel estimators have been employed to do this, to test the null hypothesis *'health does not impact wage, for men or women'*.

This document will go on to review and evaluate relevant theoretical and empirical literature, explain challenges in this research area, introduce the data and a methodology, then discuss the results and limitations of this research.

2) Literature Review

2.1) Economic Theory

Most researchers reference human capital theory as the explanation behind the relationship between health and employment outcomes. Human capital is the set of characteristics, skills or experiences that contribute to, or influence a worker's productivity. Becker (1962) was key in refining this theory and argues that a greater investment in human capital returns a rise in earnings. Becker (1962) says that schooling, training, and medical care are amongst the ways to improve the an individual's physical and mental ability, raising income prospects.

Schultz (1961) was also key in refining this theory, agreeing that productivity can be enhanced through investments to human capital. Schultz (1961) attributed differences in earnings to differences in health and education, examining differences between farm workers they found more educated and healthier workers to earn more. More recently, Bloom & Canning (2003) have similarly argued that health indirectly influences productivity, and that returns on productivity and wage may be higher for healthier workers. Specifically focusing on Health Capital, Grossman (1972) similarly construct a model for the demand of "good health" and the positive impact it can have on wage.

In modern research, Economists have begun to specifically link mental health with human capital and productivity. Exploring the importance of social skills in the labour market, Deming (2017) references a modified human capital model where production function of a task is defined by: cognitive skill, multiplied by task-specific productivity, multiplied by labour supplied to the task. Following these theories, people with health problems would be more likely to have lower productivity, and therefore less likely to be employed and more likely to earn less. Health may impact productivity through ability to focus on tasks, communication or teamwork skills, attendance, or motivation in the workplace for example.

An alternative theory that could explain the relationship between poor health and employment outcomes is discrimination. As explained by Aigner & Cain (1977) in relation to racial and gender discrimination, employer uncertainty about worker productivity could lead to workers with the same productivity receiving different wages. This could extend to individuals with health problems, particularly those with visible physical disabilities.

2.2) Empirical Evidence

The physical health wage gap is well established whilst mental health as an area for economic research and analysis is still relatively new. However, there is a growing amount of research on both topics, particularly with the rise in mental health awareness and de-stigmatisation in society today. Although research has varied across measurements of health, groups of people studied, and the economic impacts, there is a consensus that there is a strong correlation between health and labour market outcomes in empirical evidence.

Many researchers focus their attention on the impact of health on specific labour market outcomes, such as employment propensity, wages, or hours worked. In their US paper Kessler *et al*. (2008) investigated the relationship between mental disorders and earnings at an individual and societal level. Using the National Comorbidity Survey and testing the impact of short term serious mental illness (SMI) and lifetime disorders on yearly earnings, Kessler *et al*. (2008) found that 12-month serious mental illnesses significantly reduced earnings by $16,306.

Other researchers find similar results. In their paper Ettner *et al*. (1997) use a two-stage instrumental variable (IV) model with US data to examine the impact of mental illness and substance use disorders on employment propensity, work hours, and income. They find strong evidence that recent disorders reduce employment rates by at least 11%, and a significant drop in conditional income, for both men and women. However, Ettner *et al*. (1997) found a small decrease in conditional working hours for males only, leading to the conclusion that health impacts wage through productivity, rather than a drop in hours worked. They also did not find big differences in the impact of psychiatric disorders between genders.

Investigating labour market outcomes in China, Lu *et al*. (2009) use the same empirical approach and similarly finds a significant reduction in both employment rate and income when average mental health declines at the population level. Using a two-stage model, as Ettner *et al*. (1997) and Lu *et al*. (2009) have, is a widely used approach to deal with reverse causality, which is a common empirical challenge when dealing with mental health variables.

Gilleskie & Hoffman (2014) use a dynamic modelling strategy with various models such as Logit and Ordinary Least Squares (OLS) to quantify the different avenues in which health can explain wage variation. Specifically, they focus on the roles of human and health capital in males with physical disabilities. Using this strategy, they find after changing job, men with moderate disabilities experience a $0.30 decline in hourly wages.

Other researchers narrow their studies to particular groups. For example, Hessels *et al*. (2020) use panel data to compare the relationship between health and earnings, between employees and self-employed workers. Unlike many other papers, Hessels *et al*. (2020) measures health using a multi-item variable from the Short Form Health Survey (SF-36) which measures not only general health, but also physical and mental health. Using this approach reveals a significantly positive relationship between health and earnings, which is stronger for those in self-employment. It is key to note, that Hessels *et al*. (2020) does not use an IV approach like many of the papers above. They instead use a Fixed Effects model with future earnings to control for within-person variation and deal with possible reverse causality bias.

However, not all studies find statistically significant relationships between health and labour market outcomes. Jäckle & Himmler (2010) use FE Two Stage and selection correction models and find a significant positive impact of health on wages for men, but no significant effect for women using. Testing both IV and AET (Altonji, et al., 2005) approaches, Chatterji *et al*. (2011) similarly find a significant relationship between mental disorders and employment, but no causal effect on earnings or hours worked.

Examining the evidence in this area, there is a lack of isolated gender analysis which forms a strong part of the motivation for this study. It is well established that males and females face different challenges in the UK labour market, therefore examining each gender separately could bring big benefits to the robustness and interpretation of this study (Lu, et al., 2009).

Additionally, this paper aims to fill a gap in literature by providing an up-to-date analysis of the impacts of both mental and physical health problems on UK labour market outcomes. Some researchers such as Hessels *et al*. (2020) use both physical and mental health to provide a comprehensive overview of the impact of poor health, however much of the recent work in this area focus on only one measure.

2.3) Empirical Challenges

a) Measuring Health

One empirical challenge is deciding on the most suitable measurement of health. Most health literature is divided between using self-reported measures, and clinically diagnosed disorders, which ranges significantly by severity.

A popular approach is to use an index created from a multitude of subjective health survey questions. Frijters *et al*. (2014) use survey questions such as whether the respondent felt full of life, whether they've been nervous, whether they've felt calm and peaceful, and whether they have been happy to construct a mean-based index. An alternative approach is to use binary variables to represent clinically diagnosed mental health problems. Paul & Moser (2009) use this approach in their analysis of unemployment on mental health, looking at a variety of indicator variables of mental health including depression and anxiety, alongside subjective measures.

b) Reverse Causality

Another challenge is the potential reverse causality and endogeneity in the relationship between mental health and the labour market outcome, wage. There is potentially a two-way relationship between these variables which can make it difficult to establish causality. It is assumed that poor mental health impacts wage. However, there is a possibility that poor wage could cause a bad mental health. The existence of this problem is well documented, and it is therefore important to understand the direction of causality in this relationship. The main approach taken in literature is using an IV to establish direction. Commonly used instruments in literature include: social support (Ojeda, et al., 2010), the death of a close friend (Frijters, et al., 2010), calmness (Pacheco, et al., 2014), religiosity (Chatterji, et al., 2007), and childhood mental health disorders (Ettner, et al., 1997). Although this is a common approach used in literature as demonstrated above, in reality this can be difficult to robustly implement, and the limitations of this approach will be discussed later.

3) Data

The data used in this study comes from Understanding Society: The UK Household Longitudinal Study. This study started in 2009 and continuously interviews a clustered and stratified sample of approximately 40,000 households across the UK. This data was selected because of its large size, and variety of variables. Participants are asked about all aspects of life, including family life, income, employment, education, health, and civic participation (Understanding Society, 2024).

3.1) Sample

To study this relationship, only working age, full-time, employed individuals have been included in the sample.[1] To ensure robust and consistent modelling, the wage variable has been restricted to remove outliers[2] and all other missing and outlier values have been removed from the sample using Python software.[3] For cross section modelling, only individuals who responded to the most recent wave (2021/22) have been included, and for panel modelling the sample has been restricted to keep only participants who responded to every wave in the last five years (2017-22) to ensure a full panel. Although more waves of the survey were available for this panel, it has been restricted to the last five years. This is due to longer panels being more subject to responder drop out and survey attrition, which impacts sample sizes once those individuals have been cleaned from the data. The final cross-section sample size is 6577 (3070 female and 3507 male), and the final panel sample size is 9655.

3.2) Variables

a) Independent variable

As discussed earlier in this paper, a key challenge in this research area is measuring health. Following the lead of Frijters *et al*. (2014) and Hessels *et al*. (2020), subjective, short-term illness measures have been used, namely SF-12 Mental Component Summary (MCS) and SF-12 Physical Component Summary (PCS). These variables were created by weighting and

[1] Self-employed individuals have not been included in this sample due to the lack of quality data.
[2] A graphical inspection of the data has led to the inclusion of wages between 100 and 8000.
[3] Thorough quality assurance was undertaken to check the robustness of the Python code.

aggregating answers to 12 different wellbeing questions, to create mental and physical functioning scores between 0 and 100 (low to high functioning). The score is formed of questions such as how often the respondent feels calm and peaceful, and how much does health limit the respondent when climbing multiple flights of stairs. The full set of questions from the SF12 Survey can be found in the appendix. These scores have been automatically generated in the Understanding Society study, and the guidance document 'How to Score Version 2 of the SF-12 Health Survey' (Ware, et al., 2002) provides additional information on how this scale is produced.

b) Dependent variable

Individuals in this study were also asked to report various labour market outcomes, including employment status, wages, and hours worked. Due to availability of data, this paper will focus on the earnings aspect of labour market outcomes. As a result of inadequate hourly pay data, the variable 'total monthly labour income gross' (referred to as 'Wage' in this paper) has been used as the dependent variable. This variable is well answered, captures the impact of hours worked per month and ignores the impact of varying amounts of tax and other deductions.

c) Sociodemographic variables

Various sociodemographic variables have been identified to help isolate the impact of health on wages, minimise the presence of heterogeneity and reduce omitted variable bias. These control variables have been selected due to their possible relationship with health and wage, and their popular use in existing literature (Lu, et al., 2009). In addition to splitting the models by gender, the control variables include respondents age, ethnicity, household size, marital status, the region they live, highest qualification, experience in current job and profession. The survey responses have been converted into either binary or continuous variables for modelling.

3.3) Summary statistics tables

Table 1 - Full table of variables

Name in model	Definition
Wage	Monthly gross wage (£)
MCS	Mental component score
PCS	Physical component score
Age	Age of respondent
Ethnic minority	= 1 if part of ethnic minority, = 0 if otherwise
Household size	Number of people living in household
Married	= 1 if married, = 0 otherwise
Degree	= 1 if highest qualification is degree or higher, =0 otherwise
Experience	Number of years in current job
Region	Government office region

Table 2 - Summary statistics of continuous variables in latest wave[4]

	Mean	SD	Min	Max
Wage	2990.65	1398.42	119.17	7999
MCS	47.14	10.21	2.47	73.98
PCS	53.11	7.56	9.24	71.19
Age	43.02	11.84	19	65
Household size	2.97	1.38	1	13
Experience	8.68	8.18	1	48

[4] Where applicable, numbers in this study have been rounded to either 2 or 3, or the next most appropriate rounding value.

Table 3 - Summary statistics of binary variables in latest wave

	= 1/Yes (%)	= 0/No (%)
Female	46.68%	53.32%
Ethnic minority	18.23%	81.77%
Married	52.85%	47.15%
Degree	62.17%	37.83%

4) Methodology

4.1) Cross section

A series of OLS regressions were conducted to establish a relationship between the dependent and independent variables and evaluate the model specification and significance of controls (Gilleskie & Hoffman, 2014).

Separate models have been conducted for both mental (MCS) and physical (PCS) variables. This decision has been made to isolate and examine the separate effects of each variable. However, as a robustness check, part of the empirical strategy was to repeat all models with both variables included and compare the magnitude and direction of these coefficients. Each model has also been split by gender, to isolate the impact of health on males and females separately as discussed earlier.

The first stage of the empirical strategy was to test the significance of a basic relationship between wage and the health variables and provide a base for more complex models. Consistent with literature on wage regressions (Lee, 1982), the wage variable was logged[5] in all models due to its skewed nature.

$$Ln(Wage) = \beta_0 + \beta_1 X1 + \varepsilon_i \qquad (1)$$

Where β_0 represents the intercept, $X1$ denotes the MCS/PCS variable of interest, and ε_i captures the error term.

Next, a series of sociodemographic control variables were introduced to minimise heterogeneity and omitted variable bias. During testing, the inclusion of control variables was staggered to examine the impact different controls had on the health coefficients.

[5] Natural log denoted as Ln.

$$Ln(Wage) = \beta_0 + \beta_1 X1 + \beta_2 X_i + \varepsilon_i \quad (2)$$

Where the additional term X_i denotes a set of sociodemographic control variables.

An important part of the empirical strategy for all models was to test different functional forms and variations of key variables, the outcome of which would provide guidance towards the preferred model specification.

Following on from the OLS regressions, and after establishing well-specified models, an IV regression using a Two Stage Least Squares (TSLS) model was conducted with the MCS variable.[6] Using a two-stage model is a common approach to efficiently estimate an equation which includes an endogenous variable and identify a causal relationship (Lu, et al., 2009). Using the preferred model specification for MCS above, estimated values of mental health using an IV were calculated, then applied in a second stage regression to estimate wage:

$$First\ stage\text{: MCS} = \beta_0 + \beta_1 Z + \beta_2 X_i + \varepsilon_i$$

$$Second\ stage\text{: Ln(Wage)} = \beta_0 + \beta_1 \hat{X} + \beta_2 X_i + \varepsilon_i \quad (3)$$

Where Z represents the IV, and $\hat{X}$ represents the fitted values of MCS in the first stage equation.

4.2) Panel

Various panel data models were also tested to examine the effect of time in the relationship between wage and health. After cleaning the data, splitting the sample into female and male workers did not provide an adequate amount of data to run robust regressions. Therefore, the panel models presented in this paper act as a supplement to the cross-section models, to provide a more general overview of the impact of poor health on earnings over time.

The first step of this part of the empirical strategy was to test basic pooled OLS models, with the same specifications as the cross-sectional OLS models above for both PCS and MCS variables:

$$Ln(Wage)_{it} = \beta_0 + \beta_1 X1_{it} + \beta_2 X_{it} + \varepsilon_{it} \quad (4)$$

[6] Due to the nature of the elements comprising the physical health variable reverse causality with wage is assumed to not be a concern. This assumption was tested using a TSLS but results showed that the model was not appropriate and therefore the model has not been used for PCS.

Additionally, for both variables a Fixed Effects model was tested (Hessels, et al., 2020). Fixed Effects models importantly allow for the control of individual time-invariant effects, accounting for individual heterogeneity. In other words, capturing individual characteristics that could influence wage but cannot be directly controlled through variables. This is important as wage can be influenced by a lot of factors, many of which are not available or reliable in the data used in this study. Some examples of time-invariant effects that these models could pick up and cannot be easily measured are parental education, or quality of education before joining the workforce. Relevant time-invariant controls from earlier models were also included and tested:[7]

$$Ln(Wage)_{it} = \beta_1 X1_{it} + Individual\,Effects + Time\,Effects + \varepsilon_{it} \qquad (5)$$

Finally, as an extra measure to control for the reverse causality between MCS and wage, a Fixed Effects TSLS (6) has been conducted using the preferred specifications of the pooled and Fixed Effects models above. This strategy allows for a combination of the benefits of a Fixed Effects models while using an IV to control for reverse causality and endogeneity (Milner, et al., 2017).

4.3) Instrumental Variables

Various IVs were tested in line with the literature and availability in the data. These included death of a family member (Frijters, et al., 2010) and religiosity (Chatterji, et al., 2007). Theoretically, experiencing grief or losing a loved one would be a particularly good instrument for mental health. However, early tests on these instruments proved them not to be statistically strong, or predictive of MCS in this sample.

A set of social capital variables did prove to be statistically correlated with mental health and strong in testing. Similar to the social support variables used in the literature (Ojeda, et al., 2010) (Hamilton, et al., 1997) (Alexandre & French, 2001) respondents were asked a series of questions, including how often they feel a lack of companionship, how often they feel left out, how often they feel isolated from others, and how often they feel lonely. Responses to the questions in this module were given in a categorical form, ranging from 'hardly ever or never' to 'often', and an average numerical score for social support/capital between 1 and 3

[7] After examining the data, household size, marital status, and job hours are the only time-varying controls available, and therefore the only controls included in the Fixed Effects models.

has been calculated for each respondent. A low score would indicate a lack of social support, and a high score would indicate a high level of social support.

The difficulty of identifying good instruments for mental health is well discussed and understood in the literature (Chatterji, et al., 2007) (Frijters, et al., 2014). In relation to many of the assumptions for good IVs, social support is a good fit. The IV is statistically strongly associated with mental health, whereby low levels of social support worsen mental health. A good instrument should also only impact the dependent variable through the independent variable. It is unlikely that social support alone impacts a person's wages. Instead, it is more likely that social support impact wages primarily through the impact on mental health. However, this assumption is difficult to satisfy particularly in labour market and wage equations.

Finally, as with many of the commonly used mental health IVs, a limitation is that this IV is based on personal characteristics (Ojeda, et al., 2010). Therefore, there is a possibility that this IV is not completely exogenous. It is likely that lacking friends or companionship would worsen mental wellbeing, however it may be possible that someone with an existing poor mental health may struggle making friends, or simply perceive their social support to be lower. It is therefore very important to note that while these limitations are common in this area of literature (Ojeda, et al., 2010), this study uses this IV in an attempt to control for possible endogeneity and will discuss the limitations of the results.

5) Results

5.1) Cross section

In accordance with the empirical strategy, several OLS and TSLS regressions were run. Running basic OLS models confirmed the significance of a relationship between health and wages. Control variables were then gradually added, and robustness checks carried out.

To check the robustness of each model, a set of statistical tests were performed. This included the Ramsey RESET test which tests functional form. Initially, failed RESET tests revealed a non-linear relationship for wage (as expected), and experience. After logging wage and introducing the square of experience, the RESET test indicated the correct functional form was being used and this provided guidance towards the final model specifications in table 4 and 5. For ease of interpretation, logged independent variables were also tested and proved significant in the model specification. Additional robustness checks included an examination of Variation Inflation Factors (VIF) which confirmed the model did not show any signs of collinearity.

Part of the empirical strategy was to also control for differences in profession. However, statistical tests revealed that this variable caused problems for the model specification and did not significantly impact the size of the MCS or PCS variables, so was not included in the final models.

This specification was then extended to a TSLS regression for MCS. Hausman tests on the TSLS model confirmed that this model specification was appropriate over OLS, however not significantly for both models, therefore both OLS and TSLS models have been shown and discussed below. Finally, a weak instrument test showed that the chosen IV, social support, was statistically strong in all models.

The presence of non-normal errors and heteroskedasticity was exposed by White and Brusch-Pagan tests in some models. Various steps were taken to reduce these issues which included cleaning of outliers and re-specification of models. In addition to taking these steps, to ensure robust modelling, each model was replicated using heteroskedastic robust standard errors, which have been presented in the final model specifications below.

Additionally, as a robustness check in accordance with the empirical strategy, all models were repeated using both MCS and PCS variables in the same regression. The magnitude and direction of coefficients were in line with the separated regression models, which provided confidence in the final preferred models. The p-value results of all robustness and statistical checks can be found in the appendix.

5.2) Panel

Following the empirical strategy, supplementary panel models were also conducted. Again, statistical checks were performed to check robustness and guide development of each model. As with the cross-section models, due to the presence of some heteroskedasticity, heteroskedasticity- and autocorrelation-consistent (HAC) standard errors have been applied to all models. Statistical tests revealed no signs of autocorrelation, the F-stat on a joint test of named regressors revealed that a Fixed Effects model was appropriate over pooled OLS for both MCS and PCS variables, and a Wald joint test on time dummies indicated that time effects were significant in all models. Together these checks led to the selection of the preferred models below, which are similar to the approaches taken in empirical literature for models of this type (Hessels, et al., 2020).

As an additional test, a Random Effects model was explored, but the Hausman test indicated that it was not statistically appropriate for this model, despite returning significant coefficients on both MCS and PCS. Finally, to control for reverse causality in the mental health variable, a Fixed Effects model with the same IV as discussed earlier has been applied. Again, the details of the results of all statistical tests can be found in the appendix.

6) Discussion

6.1) Cross section

Positive coefficients on all physical and mental health variables suggest a positive and significant relationship between good health on earnings, which is in line with existing empirical evidence. This supports the hypothesis that wages are higher for individuals without health conditions or illnesses. These coefficients are smaller than many in the empirical evidence that was examined for this research, however this is likely because many researchers chose to analyse the impact of long-term or diagnosed illnesses that likely have a larger impact on wage, than general mental and physical wellbeing.

Examining mental health in table 4, the magnitude of the coefficients in the male and female regressions are notably similar. Across both female models, the mental health coefficient ranges from 0.074 to 0.248. This would indicate a 1% increase in MCS leads to between a 0.07% and 0.25% increase in wage for females when holding controls fixed. In the male models, these coefficients range from 0.091 to 0.186 for the controlled OLS and TSLS models. Similarly, a 1% increase in MCS leads to between a 0.09% and 0.19% increase in wage for males.

Table 4 - Regression results on MCS variable[8]

*P-Value <0.1 *, <0.05 **, <0.01 ****

Dependent variable: Ln(Wage)				
	Female		Male	
	OLS (2)[9]	**TSLS (3)**	**OLS (2)**	**TSLS (3)**
Constant	7.059***	6.414***	7.079***	6.719***
	(0.122)	(0.230)	(0.115)	(0.219)
Ln(MCS)	0.074**	0.248***	0.091***	0.186***
	(0.029)	(0.060)	(0.028)	(0.057)
Age	0.004***	0.004***	0.004***	0.004***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Ethnic minority	−0.060**	−0.062***	−0.137***	−0.135***
	(0.023	(0.023)	(0.022)	(0.022)
Household size	−0.027***	−0.027***	0.002	0.0006
	(0.006)	(0.006)	(0.006)	(0.006)
Married	0.127***	0.116***	0.162***	0.160***
	(0.018)	(0.018)	(0.017)	(0.017)
Degree	0.296***	0.297***	0.309***	0.312***
	(0.017)	(0.017)	(0.015)	(0.015)
Experience	0.004	0.005	0.005**	0.005**
	(0.003)	(0.003)	(0.003)	(0.003)
Experience-squared	−0.0002*	−0.0002**	−0.0002**	−0.0002**
	(0.000)	(0.000)	(0.000)	(0.000)
Dummy Controls for region[10]	Yes	Yes	Yes	Yes
R-squared	0.168	0.158	0.191	0.189
Adjusted R-squared	0.163	0.153	0.187	0.184
F-stat	31.381	30.889	42.536	42.474

[8] Throughout this paper coefficients and p-values are provided in each result table, with standard errors below in parentheses.
[9] Model number in reference to the methodology
[10] Refer to appendix for regional coefficients.

Looking to the physical health coefficients in table 5 indicates that a 1% increase in PCS leads to a 0.25% (0.245) increase in wage for females, while a 1% increase in PCS leads to a much larger 0.4% (0.403) increase in wage for males when controls are held constant.

Qualitatively comparing the male and female regression coefficients provides an interesting insight. The male and female coefficients in the mental health regressions are relatively similar, however here is quite a large difference in the physical health coefficients for males and females. This is similar to the findings of Jäckle & Himmler (2010) who only find a significant relationship between health and wage for men, but not for women.

This is also in line with recent disability employment statistics, The Office for National Statistics (2022) found that the wage gap between disabled and non-disabled males to be larger (12.4%) than the pay gap between disabled and non-disabled females (10.5%). One potential explanation for this may be the type of industries and occupations that males typically dominate. Males typically dominate more labour-intensive industries and therefore may experience even more detrimental impacts on productivity as a result of poor physical health (Evans, 2021). In a labour-intensive job, it can be assumed that someone with good physical health would be more productive than some with worse physical health (particularly as defined by the PCS variable: experiencing pain, trouble with daily activities). For both males and females, but particularly individuals in more labour-intensive jobs, this would likely have a significant impact on everyday tasks, therefore lowering productivity and wage.

Table 5 - Regression results on PCS variable

*P-Value <0.1 *, <0.05 **, <0.01 ****

Dependent variable: Ln(Wage)		
	Female (2)	**Male (2)**
Constant	6.329*** (0.174)	5.776*** (0.223)
Ln(PCS)	0.245*** (0.040)	0.403*** (0.053)
Age	0.005*** (0.0008)	0.005*** (0.0008)

Ethnic minority	−0.051** (0.023)	−0.125*** (0.021)
Household size	−0.027*** (0.006)	0.002 (0.006)
Married	0.131*** (0.017)	0.160*** (0.017)
Degree	0.289*** (0.017)	0.289*** (0.017)
Experience	0.004 (0.003)	0.006** (0.003)
Experience-squared	−0.0001* (0.000)	−0.0002** (0.000)
Dummy Controls for region[11]	Yes	Yes
R-squared	0.175	0.206
Adjusted R-squared	0.170	0.201
F-stat	32.880	44.873

Across both measures of health, the physical health coefficients are larger than their mental health counterparts. This is also found by Hessels *et al*. (2020), and it suggests that physical health has a larger impact on wage than mental health for both males and females. A potential explanation for this may be that poor physical health has a stronger impact on productivity. Experiencing pain, discomfort or health issues may have a bigger effect on an individual's ability to focus on work, do normal work activities, or even attend work. This is likely also a larger problem for more manual or active workers.

Comparing the OLS and TSLS estimates, the coefficients on instrumented mental wellbeing were significantly larger. In empirical work, researchers usually find TSLS estimates to be bigger than OLS. These findings are also consistent with literature in this area. Bright (2020) found an 8.1% difference between OLS and IV results when examining the impact of mental illness on earnings. There are various reasons for this phenomenon, and it may suggest that

[11] Refer to appendix for region coefficients.

the endogeneity has been successfully accounted for and causality has been established, but the IV exogeneity concerns discussed previously should not be shadowed and these results should be approached with caution. Despite this, these results still provide a good insight into the potential magnitude of this relationship.

It is also important to note that the direction and magnitude of the coefficients on the control variables were consistent with what would be expected based on theory, with age, experience, and having a degree positively impacting wage, whilst being an ethnic minority negatively impacting wage. Negative coefficients on experience-squared implies that experience in current job has a non-linear relationship with wage. This finding is to be expected, according to research hourly earnings was 6.6% higher for individuals who had changed job, compared to those who stayed in their current job (Office for National Statistics, 2022). Another interesting result is that household size has a significant negative impact on wage for females, but an insignificant positive impact for males. One explanation could be that females are more likely to take on the care responsibilities for additional children, or elderly family members in the household, leading them to work fewer hours or even step back from professional progression goals. This implies that there are indeed differing impacts on labour market outcomes between men and women, in line with the motivation for this study.

As an additional robustness check, and to test the thresholds of the MCS and PCS variables, each model above has been replicated using a binary variable representing severe physical and mental health problems. These variables were created from the original MCS and PCS variables, following the guidance of the authors of the SF12 Health Survey (Ware, et al., 2002). They recommend that a score of 50 or less in the PCS variable is indicative of a physical health condition, and a score of 42 or less in the MCS variable is indicative of clinical depression.

After the same statistical and robustness checks as the previous models, the results also supported the hypothesis that good health increases wages and support the findings from the models above. Across all models, for both males and females, the presence of a severe health condition has a negative impact on wage. This impact ranges from a 4.5% to 17.58% reduction in wage for those with clinical depression, and a reduction between 8.80% to 12.96% for those with physical conditions. The coefficients in these models are more similar to findings in empirical literature who have also analysed severe or long-term illnesses (Ettner, et al., 1997). More details on the results of this model can be found in the appendix.

6.2) Panel

Looking at the PCS coefficient, there is a statistically significant positive relationship between good physical health and wages (0.046) when controlling for individual and time fixed effects. This is expected from the cross-section models and existing empirical evidence. There is also a positive coefficient on mental health but, for both models the coefficient is no longer significant. This may indicate that the variation in mental health identified earlier was picked up by the time dummies, there is further underlying misspecification, omitted variables or endogeneity impacting the regression. Although these findings are different to many who do find a statistical relationship between mental health and wage, the findings are similar to those of Chatterji *et al*. (2011) who also do not find a causal effect between these variables.

Table 6 - Panel data regressions

*P-Value <0.1 *, <0.05 **, <0.01 ****

Dependent variable: Ln(Wage)			
	Individual Fixed Effects (5)		**Individual Fixed Effects with IV (6)**
Ln(PCS)	0.046** (0.020)		
Ln(MCS)		0.006 (0.011)	0.019 (0.041)
Controls for time varying sociodemographic characteristics	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
LSDV R-squared	0.871	0.871	
R-squared			0.117

With access to more granular regional data, cluster robust regional standard errors may be more appropriate and robust for these models. The error terms of these models may be correlated within regions in the UK, and this would need to be accounted for in further research. For example, local economic, environmental, or social influences may have a significant within cluster impact on mental health which cannot be accounted for here. Another limitation of these models is the lack of available time varying controls that may have a significant impact on these regressions. With access to more data, more controls could be included, and the sample size could be increased, which would help increase the robustness of modelling.

6.3) Limitations

As has been frequently discussed throughout this paper and in other literature in this area, there are various limitations that are crucial to be aware of when using and interpreting these results. Firstly, the implications of using self-reported measures of physical and mental health. Self-reported surveys are exposed to potential biases and limitations such as lack of honesty, poor introspective ability, and varying interpretation of questions (Very Well Mind, 2023). Despite this potential limitation, the SF-12 Survey is still widely used and accepted as a reliable measure of health, giving credit to its use in this research (Huo, et al., 2018) (Salyers, et al., 2000).

Another key limitation is the potential reverse causality between mental health and wage. Using a prominent instrument from published literature (Alexandre & French, 2001) (Hamilton, et al., 1997) (Ojeda, et al., 2010), this paper has taken steps to address this issue in this model. However, there is still the potential that there is remaining endogeneity for reasons discussed earlier, which could be causing some bias and inconsistency. Despite this, these results can be viewed as potentially high-bound estimate of the cost of poor health on wage. Using larger or different datasets may allow for the exploration of alternative instruments, and this should be a focus for future research. Alternatively, different empirical models could be tested such as the approach proposed by Altonji *et al*. (2005) which doesn't rely on identifying IVs.

7. Conclusion

Using OLS models, this paper finds evidence of a significant relationship between mental and physical health, and wage. For females, results indicate a 1% rise in mental health and physical health leads to a 0.07% and 0.25% rise in monthly gross wage respectively. For males, this leads to a 0.09% and 0.40% rise respectively.

In an effort to control for potential endogeneity, a series of TSLS IV models were also conducted. Results from these models found a larger impact on wage, compared to the OLS estimates. The elasticities of these coefficients rose from 0.07% to 0.25% for females, and from 0.09% to 0.19% for males. This is generally consistent with other empirical evidence (Bright, 2020), however the limitations of this approach as discussed previously mean that this could be due to overestimation. It's therefore important that some caution is taken when interpreting these findings.

Finally, as a supplement and robustness check of the main cross-sectional findings, a set of models using severe health problems as the independent variables, and a set of panel models was also conducted. In line with the earlier findings, the severe variable models show a negative and more prominent relationship between poor health and wage, whilst the panel model results found a significant and positive relationship between good physical health and wage over time. However, the results on the mental health variable over time were inconclusive, as the relationship between mental health and wage was no longer significant.

The findings in this paper are generally in line with other empirical evidence. Using very similar variables to represent mental and physical health and a similar empirical strategy, Hessels *et al*. (2020) also find a significant relationship between both measures of health and wages. In terms of answering the proposed research question for this paper, '*what effect does physical and mental health have on labour market outcomes?*', it's clear that there is a relationship between health and wage, particularly physical health. Although there are remaining concerns around reverse causality, these results may be viewed as a high estimate of the impact health can have on wage. Future research should focus on exploring the specific impact of this relationship in different UK sectors and trialling new experimental methods to control for endogeneity and reverse causality.

7.1) Policy Implications

Not only assessing the results of this study, but also the findings of other recent empirical evidence in this area, it is clear that more should be done to support individuals with disabilities, illnesses and health problems in the UK labour market to reduce health wage gaps. The differences in impacts between males and females should also be noted, particularly in regard to the large impact of poor physical health in males, on wage. More should be done to understand the causes of this relationship, whether it be due to differences in occupations or discrimination. It is therefore also recommended that targeted interventions or support schemes are provided based on gender, to make work environments more accessible.

8. References

Aigner, D. J. & Cain, G. G., (1977). Statistical Theories of Discrimination in Labor Markets. *ILR Review,* 30(2), pp. 175-187.

Alexandre, P. K. & French, M. T., (2001). Labor Supply of Poor Residents in Metropolitan Miami, Florida: The Role of Depression and the Co-Morbid Effects of Substance Use. *The Journal of Mental Health Policy and Economics,* 4(4), pp. 161-173.

Altonji, J. G., Elder , T. E. & Taber, C. R., (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy,* 113(1), pp. 151-184.

Becker, G. S., (1962). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy,* 70(5), pp. 9-49.

Bloom, D. & Canning, D., (2003). Health as Human Capital and its Impact on Economic Performance. *The Geneva Papers on Risk and Insurance. Issues and Practice,* 28(2), pp. 304-315.

Bright, M., (2020). *The Impacts of Mental Health Problems on Wages Using the Instrumental Variable Approach, Case of Selected Countries in the European Community Household Panel (ECHP) Data Set.* [Online]
Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3822674
[Accessed 2 May 2024].

Chatterji, P., Alegria, M., Lu, M. & Takeuchi, D., (2007). Psychiatric Disorders and Labor Market Outcomes: Evidence from the National Latino and Asian American Study. *Health Economics,* 16(10), pp. 1069-1090.

Chatterji, P., Alegria, M. & Takeuc, D., (2011). Psychiatric disorders and labor market outcomes: evidence from the National Comorbidity Survey-Replication. *J Health Econ,* 30(5), pp. 858-868.

Deming, D. J., (2017). The Growing Importance of Social Skills in the Labour Market. *The Quarterly Journal of Economics,* 132(4), pp. 1593-1640.

Ettner, S. L., Frank, R. G. & Kessler, R. C., (1997). The Impact of Psychiatric Disorders on Labour Market Outcomes. *Industrial and Labor Relations Review,* 51(1), pp. 64-81.

Evans, A., (2021). *Why is blue-collar work still male-dominated?.* [Online]
Available at: https://www.brookings.edu/articles/why-is-blue-collar-work-still-male-dominated/
[Accessed 5 May 2024].

Frijters, P., Johnston, D. W. & Shields, M. A., (2010). *Mental Health and Labour Market Participation: Evidence from IV Panel Data Models,* Bonn: The Institute for the Study of Labor.

Frijters, P., Johnston, D. W. & Shields, M. A., (2014). The Effect of Mental Health on Employment: Evidence From Australian Panel Data. *Health Economics,* 23(9), pp. 1058-1071.

Gilleskie, D. & Hoffman, D., (2014). Health Capital and Human Capital as Explanations for Health-Related Wage Disparities. *Journal of Human Capital,* 8(3), pp. 235-279.

Gov.uk, (2022). *National Disability Strategy.* [Online]
Available at: https://www.gov.uk/government/publications/national-disability-strategy
[Accessed 4 May 2024].

Grossman, M., (1972). On the Concept of Health Capital and the Demand for Health. *Journal of Political Economy,* 80(2), pp. 223-255.

Hamilton, V. H., Merrigan, P. & Dufres, É., (1997). Down and out: estimating the relationship between mental health and unemployment. *Health Economics,* 6(4), pp. 397-406.

Hessels, J., Rietveld, C. A. & van der Zwan, P., (2020). The Relation Between Health and Earnings in Self-Employment. *Frontiers in Psychology,* Volume 11.

Huo, T., Guo, Y., Shenkman, E. & Muller, K., (2018). *Assessing the reliability of the short form 12 (SF-12) health survey in adults with mental health conditions: a report from the wellness incentive and navigation (WIN) study,* Gainesville: Health and Quality of Life Outcomes.

Jäckle, R. & Himmler, O., (2010). Health and Wages: Panel Data Estimates Considering Selection and Endogeneity. *The Journal of Human Resources,* 45(2), pp. 364-406.

Kessler, R. C. et al., (2008). The individual-level and societal-level effects of mental disorders on earnings in the United States: Results from the National Comorbidity Survey Republican. *Am J Psychiatry,* 165(6), pp. 703-711.

Lee, L.-F., (1982). Health and Wage: A Simultaneous Equation Model with Multiple Discrete Indicators. *Interntaional Economic Review,* 23(1), pp. 199-221.

Lu, C., Frank, R. G., Liu, Y. & Shen, J., (2009). The Impact of Mental Health on Labour Market Outcomes in China. *The Journal of Mental Health Policy and Economics,* 12(3), pp. 157-166.

Mental Health Foundation, (2017). *Men and women: statistics.* [Online]
Available at: https://www.mentalhealth.org.uk/explore-mental-health/statistics/men-women-statistics
[Accessed 4 May 2024].

Milner, A. et al., (2017). Combining fixed effects and instrumental variable approaches. *Journal of Public Health,* 40(2), p. 426–434.

Money and Mental Health Policy Institute, n.d. *THE FACTS.* [Online]
Available at: https://www.moneyandmentalhealth.org/money-and-mental-health-facts/
[Accessed 20 April 2024].

Office for National Statistics, (2022). *Disability pay gaps in the UK: 2021.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/disability/articles/disabilitypaygapsintheuk/2021
[Accessed 30 April 2024].

Office for National Statistics, (2022). *Disability pay gaps in the UK: 2021.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/disability/articles/disabilitypaygapsintheuk/2021#:~:text=In%202021%2C%20median%20pay%20for%20disabled%20women%20(%C2%A311.51%20per,hour)%20(Figure%202).
[Accessed 4 May 2024].

Office for National Statistics, (2022). *Job changers and stayers, understanding earnings, UK: April 2012 to April 2021.* [Online]
Available at:
https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/articles/jobchangersandstayersunderstandingearningsukapril2012toapril2021/april2012toapril2021#:~:text=In%20April%202021%2C%20employees%20who,remained%20in%20the%

20same%
[Accessed 3 May 2024].

Office for National Statistics, (2023). *Disability by age, sex and deprivation, England and Wales: Census 2021.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/disability/articles/disabilitybyagesexanddeprivationenglandandwales/census2021#:~:text=Source%3A%20Office%20for%20National%20Statistics%20%E2%80%93%20Census%202021&text=.xlsx-,In%20En
[Accessed 4 May 2024].

Ojeda, V. D., Frank, R. G., McGuire, T. G. & Gilmer, T. P., (2010). Mental Illness, Nativity, Gender and Labor Supply. *Health Economics,* 19(4), p. 396–421.

Pacheco, G., Page, D. & Webber, D. J., (2014). Mental and physical health: re-assessing the relationship with employment propensity. *Work, Employment & Society,* 28(3), pp. 407-429.

Paul, K. I. & Moser, K., (2009). Unemployment impairs mental health: Meta-analyses. *Journal of Vocational Behaviour,* 74(3), pp. 264-282.

Salyers, M. P. P. et al., (2000). Reliability and Validity of the SF-12 Health Survey Among People With Severe Mental Illness. *Medical Care,* 38(11), pp. 1141-1150.

Schultz, T. W., (1961). Investment in Human Capital. *The American Economic Review,* 51(1), pp. 1-17.

TUC, (2021). *Nearly one in three disabled workers surveyed treated unfairly at work during the pandemic – new TUC polling.* [Online]
Available at: https://www.tuc.org.uk/news/nearly-one-three-disabled-workers-surveyed-treated-unfairly-work-during-pandemic-new-tuc
[Accessed 5 May 2024].

Understanding Society, (2024). *The UK Household Longitudinal Study.* [Online]
Available at: https://www.understandingsociety.ac.uk/
[Accessed 3 May 2024].

Very Well Mind, (2023). *The Use of Self-Report Data in Psychology.* [Online]
Available at: https://www.verywellmind.com/definition-of-self-report-

425267#:~:text=Disadvantages%20of%20Self%2DReport%20Data&text=Self%2Dreports%20are%20subject%20to,able%20to%20assess%20themselves%20accurately.
[Accessed 3 May 2024].

Ware, J. E., Kosinski, M., Turner-Bowker, D. M. & Gandek, B., (2002). *How to Score Version 2 of the SF-12 Health Survey,* Lincoln: Quality Metric Incorporated.

9. Appendix

Table 7 - P-values for statistical tests: models in table 4

	Female		Male	
	OLS (2)	**TSLS (3)**	**OLS (2)**	**TSLS (3)**
RESET test	0.82		0.37	
White's/ Pesaran-Taylor test	0.001	0.18	0.22	0.87
Test for normality of residual	0.000	0.000	0.000	0.000
Hausman test		0.0004		0.06
Weak instrument test		568.39 (F-stat)		507.86 (F-stat)

Table 8 - P-values for statistical tests: models in table 5

	Female (2)	**Male (2)**
RESET test	0.90	0.40
White's test	0.002	0.19
Test for normality of residual	0.000	0.000

Table 9 - P-values for statistical tests: models in table 6

	Fixed Effects (PCS)	Fixed Effects (MCS)
Joint test on named regressors	0.000	0.000
Robust test for differing group intercepts	0.000	0.000
Wald joint test on time dummies	0.000	0.000
Distribution free Wald test for heteroskedasticity	0.000	0.000
Test for normality of residual	0.000	0.000
Wooldridge test for autocorrelation	0.44	0.45
Hausman test on Random Effects model	0.000	0.000

Table 10 - Regional control coefficients and std error in table 4

*P-Value <0.1 *, <0.05 **, <0.01 ****

	Female		Male	
	OLS (2)	**TSLS (3)**	**OLS (2)**	**TSLS (3)**
South East	0.158*** (0.041)	0.160*** (0.041)	0.156*** (0.033)	0.157*** (0.033)
West Midlands	0.055 (0.043)	0.061 (0.043)	0.074** (0.037)	0.081** (0.037)
North East	−0.002 (0.048)	0.007 (0.049)	0.062 (0.041)	0.064 (0.041)
Scotland	0.093** (0.041)	0.101** (0.042)	0.095*** (0.035)	0.097*** (0.035)
North West	0.042 (0.042)	0.044 (0.042)	0.044 (0.033)	0.046 (0.033)

Yorkshire and the Humber	0.089** (0.041)	0.096** (0.041)	0.061* (0.033)	0.061* (0.033)
East Midlands	0.084* (0.044)	0.086* (0.044)	0.088** (0.037)	0.091** (0.037)
London	0.287*** (0.041)	0.286*** (0.041)	0.257*** (0.035)	0.261*** (0.035)
South West	0.045 (0.043)	0.052 (0.043)	0.095*** (0.034)	0.099*** (0.034)
East of England	0.166*** (0.044)	0.179*** (0.044)	0.180*** (0.035)	0.184*** (0.035)
Wales	0.052 (0.043)	0.059 (0.044)	−0.003 (0.040)	0.0008 (0.040)

Table 11 - Regional control coefficients in table 5

*P-Value <0.1 *, <0.05 **, <0.01 ****

	Female (2)	**Male (2)**
South East	0.156*** (0.041)	0.159*** (0.033)
West Midlands	0.057 (0.043)	0.070* (0.037)
North East	0.0004 (0.047)	0.061 (0.040)
Scotland	0.088** (0.041)	0.0893105*** (0.034)
North West	0.043 (0.042)	0.044 (0.033)
Yorkshire and the Humber	0.081** (0.041)	0.060* (0.033)
East Midlands	0.081* (0.044)	0.086** (0.037)
London	0.287*** (0.041)	0.248*** (0.035)

South West	0.040 (0.043)	0.097*** (0.034)
East of England	0.155*** (0.044)	0.177*** (0.035)
Wales	0.057 (0.043)	−0.005 (0.040)

Table 12 - Severe mental health condition coefficients

*P-Value <0.1 *, <0.05 **, <0.01 ****

Dependent variable: Ln(Wage)				
	Female		**Male**	
	OLS (2)	**TSLS (3)**	**OLS (2)**	**TSLS (3)**
Constant	7.355*** (0.052)	7.415*** (0.055)	7.437*** (0.044)	7.462*** (0.045)
MCS <= 42	−0.045*** (0.017)	−0.176*** (0.042)	−0.053*** (0.017)	−0.129*** (0.039)
Age	0.004*** (0.0008)	0.004*** (0.0008)	0.004*** (0.0008)	0.004*** (0.0008)
Ethnic minority	−0.058** (0.023)	−0.055** (0.023)	−0.136*** (0.022)	−0.134*** (0.022)
Household size	−0.027*** (0.006)	−0.028*** (0.006)	0.002 (0.006)	0.001 (0.006)
Married	0.129*** (0.018)	0.120*** (0.018)	0.162*** (0.017)	0.160*** (0.017)
Degree	0.296*** (0.017)	0.296*** (0.017)	0.307*** (0.015)	0.310*** (0.015)
Experience	0.004 (0.003)	0.005 (0.003)	0.005** (0.003)	0.005** (0.003)
Experience-squared	−0.0002* (0.000)	−0.0002** (0.000)	−0.0002** (0.000)	−0.0002** (0.000)

Dummy Controls for region	Yes	Yes	Yes	Yes
R-squared	0.168	0.154	0.191	0.187
Adjusted R-squared	0.163	0.148	0.187	0.182
F-stat	31.774	30.711	42.554	42.234

Table 13 - Severe physical health condition coefficients

*P-Value <0.1 *, <0.05 **, <0.01 ****

Dependent variable: Ln(Wage)		
	Female (2)	**Male (2)**
Constant	7.332*** (0.052)	7.413*** (0.044)
PCS <= 50	−0.088*** (0.018)	−0.130*** (0.018)
Age	0.005*** (0.0007)	0.005*** (0.0008)
Ethnic minority	−0.052** (0.023)	−0.130*** (0.021)
Household size	−0.027*** (0.006)	0.003 (0.006)
Married	0.131*** (0.017)	0.159*** (0.017)
Degree	0.291*** (0.017)	0.293*** (0.015)
Experience	0.004 (0.003)	0.005** (0.003)
Experience-squared	−0.0001 (0.000)	−0.0002** (0.000)

Dummy Controls for region	Yes	Yes
R-squared	0.172	0.202
Adjusted R-squared	0.167	0.198
F-stat	32.357	45.604

Table 14 - SF12 Survey questions

Variable name	Description
Sf1	General health?
Sf2a	Does health limit typical moderate activities?
Sf2b	Does health limit climbing stairs?
Sf3a	How often does physical health mean you accomplished less than you would like?
Sf3b	How often does physical health limit the kind of work/daily activities you do?
Sf4a	How often do emotional problems mean accomplished less than you would like?
Sf4b	How often do emotional problems mean work/daily activities were done less carefully than usual?
Sf5	How often does pain interfere with normal work/housework?
Sf6a	How often have you felt calm and peaceful?
Sf6b	How often have a lot of energy?
Sf6c	How often have you felt downhearted and depressed?
Sf7	How often does your physical health or emotional problems interfere with social activities?