

The Effect of “Ranked Income” on Mental Health: A Panel Data Approach

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Abstract

The effect of the relative rank of income has been recognised as a vital mechanism explaining the causality between wealth and mental health. Recently studies have explored the correlation between relative rank through linear models in panel data, but few interpretations about the effect of relative rank. By taking advantage of the large sample included in the Understanding Society data (Wave 1 to Wave 12), this study has generated asymmetric reference groups: individuals compare their income within different reference groups. To overcome the limitation of prediction associated with linear models that may produce probabilities higher than 1 or below 0, and fill the research gap; this paper tests the ranked income hypothesis, revealing that the existence of fixed-effects determines whether to reject the hypothesis. This paper estimated consistent average marginal effects of relative rank on the probability of being a high mental health status, which is around 0.06, and admits the small marginal effect cannot conclude an opinion about upward comparison. Being different from the literature, the violation of the parallel line assumption implies that there will be different estimates in different ranges of the latent variable. The introduction of generalised models confirms the robustness of fixed effect model estimation. These empirical results will shed light on the mechanism behind the causal effect between wealth and mental health and will contribute to policy implications towards welfare.

1. Introduction

In Apouey and Clark's study (2015), a set of lotteries and experiments confirmed the causality between income and mental health, making the discussion of potential mechanisms behind promising. Since last century, there have been conjectures about the rationale inducing the causality between income and mental health, where social status or income comparison between individuals is a convincing one. The most initial ranked income hypothesis provided direction to existing research, which suggested that level-term income would tend to be insignificant once ranked income was introduced in a regression (Parducci, 1965). This extreme hypothesis has been challenged by contemporary studies, which suggest that the relative rank captures some income effect on mental health, but not all of it (FitzRoy and Nolan, 2022). Furthermore, related studies have been ignoring the marginal effects of change in social status and the prediction of probability models. This paper examines the ranked income hypothesis by taking advantage of a long panel of Understanding Society data and computes the marginal effect of social status (University of Essex, 2022). The outcome of this paper yields policy implications related to well-being; by quantifying the effect of relative rank, policy reports can reasonably expect policy impact. Past research proposed several methods of measuring social status and mental health, this paper utilises the concept of subjectively rated life-satisfaction standing for the level of mental health and the relative rank of income (Boyce et al., 2010) representing social status, the latter is defined as follow:

$$R_{it} = \frac{absoluteRank - 1}{sizeOfComparisonGroup - 1}$$

Based on the generated relative rank, this paper supports the initial ranked income hypothesis in the fixed effect model but provides suspicion in the absence of the fixed effect. Secondly, this paper estimated the marginal effects of relative rank through multiple models, results suggested that the average marginal effect of being at a high mental health level for employed people is about 0.06, and a much lower absolute value of 0.015 is associated with a low level. The difference indicates that mental illness is induced by other complicated factors such as disability and other time-invariant effects. The surging pseudo-R-square in the fixed effect model confirmed that the individual effect contributed most to the explanation of mental health. To check robustness, the violation of the parallel line assumption motivates the introduction of a generalised model. The result of the generalised model, 0.053, does not suggest a large change but emphasises the balance effects on low-level and mid-level mental health.

Additionally, constructing a model using subjective income rank (Boyce et al., 2010), defined below, to find the best-fitted degree of upward comparison. When setting the η to 1.60, the fixed effect model reached the highest correctness of prediction; however, the differences between parameters are very small. Therefore, this paper could not conclude an opinion about upward comparison.

$$SR_{it} = 0.5 + \frac{(i - 1) - \eta(n - i)}{2[(i - 1) + \eta(n - i)]} 1$$

¹ η represents the degree of upward-comparison; i is the absolute rank within group; n is the size of comparison group

2. Literature Review

People aged 20 - 49 experience non-negligible mental health issues, and depression disorder becomes the main reason for healthy life loss (Abate et al., 2018). So far, researchers have consolidated the causality between income and mental health. Through randomised experiments design, the size of the lottery gain is positively associated with the causal effect on mental health (Apouey and Clark, 2015). However, a later study identified a smaller long-run effect of the lottery gains by restricting the comparison with individuals holding similar characteristics (Lindqvist et al., 2018). Except for income, other covariates contribute to determining the mental health status. The age effect on mental health follows a quadratic U-shape pattern; individuals aged around 50 are least mentally healthy, whereas adolescents and retired people have similar higher levels of mental health (Blanchflower, 2021); adding an age-squared variable better captures the age effect. And physical health is the strongest contributor to the indirect effect on mental health (Ohrnberger et al., 2017). It is worth noting that, a study focusing on a developing country used the exogenous impact of automation as an instrumental variable for income (Li et al., 2022). However, automation is not included in the Understanding Society dataset, and this IV could not be used to solve the endogeneity problem.

Accompanying the research about the causal relationship between income and mental health, studies attempt to explain the mechanism behind such a relationship. The relative income hypothesis states that other people's wealth condition around an individual is more important than the individual's absolute income, attracts attention to social comparison (Duesenberry, 1949); while the ranked income hypothesis (Parducci, 1965) and reference income hypothesis (Clark and Oswald, 1996) emphasised importance of ranking within comparison group and of comparison with the norm. High social status has been considered as a protective function of physical and mental health (Roy et al., 2016). A panel study focusing on the effect between the relative rank of income and mental health initialised contemporary research on social status; through pooled OLS regression, significant coefficients of the relative rank of income within the comparison group (Boyce et al., 2010). Based on fixed and random effect probability models, in the same British Household Panel Survey data, significant results consolidated the importance of relative rank, but there was not much discussion about the marginal effect and the risk of violating the parallel line assumption (FitzRoy and Nolan, 2022). In the Norwegian Monitor dataset, the tax record became easily accessible online for everyone, the event-study analysis detected a negative structural break in mental health (Perez-Truglia, 2020).

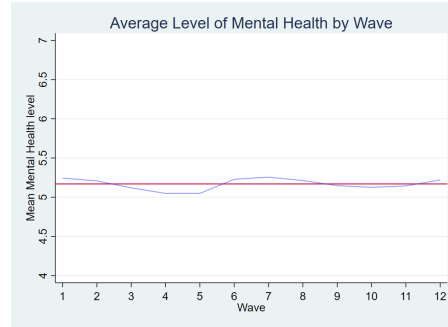
Moreover, people recognise upward comparisons outweigh the downward comparisons, and $\eta = 1.75$ was the best-fitted degree of upward comparison (Boyce et al., 2010). The unfavourable relative rank position would have a stronger impact than the favourable (Yu, 2019). However, a counter opinion suggested that lower social status around the neighbourhood may be a positive factor in mental health by inflating one's perception of oneself (Roy et al., 2016). Few papers analysed the marginal effect of the relative rank of income, either the average or at means, this paper will focus on filling these gaps with the latest panel dataset and fixed effect ordered logit models. Additionally, although the finding from the Norwegian case could be a potential explanation for the upward comparison, it is still worth checking the optimal value of the degree of upward

comparison introduced in Boyce’s study through FitzRoy and Nolan’s (2022) models.

3. Data

In the administrative data, income and mental health variables are recorded in different data sheets. To avoid potential individual identification mismatch problems raised, this paper applied a dataset generated from Wave 1 to Wave 12, from 2009 to 2021, of Understanding Society; Tabel 6 and Table 7 display the description of variables and summary statistics respectively. Multiple waves provided a large enough sample, more than 20000 individuals, to acquire accurate estimations. Although this appended dataset is unbalanced, the fixed effect ordered logit model method is still applicable (Baetschmann et al, 2020). Thus, this paper keeps the unbalanced data, since balancing the dataset eliminates 2/3 of the observation, which may cause selection bias.

The average level of mental health in all waves is almost constant around 5.2 out of 7, this little evidence of time variation reveals the sources of mental health variation are mainly cross-sectional. *fimngrs_dv* represents the total personal monthly income, by considering the small marginal effect of income, all models accommodate a *inc* variable, dividing the monthly income by 100. The health indicator reflects the existence of “long-term illness”, according to the definition of the dataset, it captures the “physical or mental impairment, illness or disability” that troubles the respondent “ over a period of at least 12 months or that is likely to trouble you over a period of at least 12 months” (University of Essex, 2022). This widely capturing indicator is by all means different to a severe and hard-to-recover concept of long-term disability, analyzing the marginal effect of health variables is comparable.



The dependent variable is *scfhsato*, a discrete variable with 7 levels about the self-rated satisfaction of overall well-being. The explanatory variable is the relative rank of income, a variable constructed as the within-group absolute rank of the income divided by the size of the comparison group. The *fimnnet_dv*, total net personal income of every individual, is ranked in the commensurate comparison group constituted by individuals in the same waves with identical gender, region, education level and one asymmetric age group indication. The asymmetric age groups imply that one only compares one’s income with people within an age group from 3 years younger to 6 years older. These criteria, without considering age group, generate 288 reference groups. In addition, small group size in some groups is not a problem: adding minimum group size restriction in estimation will not lead to astonishing change in estimated results. In this paper, the relative rank

variable *relrk1* expresses that the higher one's income within the reference group, the greater the value will be.

To confirm the variable is computed correctly, one simple linear regression is implemented, in Table 1 nominal income (being divided by 100) is considered as the dependent variable, and independent variables include relative rank, reference group ignoring the asymmetric age group, and one constant. The significant evidence of a positive correlation between the relative rank and income indicates the relative rank is generated correctly, meanwhile showing a generally large gap between the top income and bottom personal income: 3677 pounds per month. Here, the *group_m1* is only a categorical variable indicating the status of education level, wave of survey, region and gender.

Control variables are obtained from a similar study: age, squared age, education, sex, health status, region, year of survey, marital status, employment status, household size, number of children, and time dummies (FitzRoy and Nolan, 2022). However, the reference group size variable is not included in this paper. When using an unbalanced long panel, the absence of some individuals in some waves causes a decrease in the group size; an individual not being interviewed does not mean one is excluded from the reference group in one wave and returned in another. Taking account of such unreasonable variation, the models do not include the group size.

Table 1: Linear Regression of income and relative rank

	(1) inc
relrk1	36.770*** (0.05)
group_m1	-0.026*** (0.00)
_cons	3.581*** (0.04)
<i>N</i>	313137

4. Econometric Specification

This analysis of this study is based on logit models, which are different to linear models and could produce insane probabilities such as greater than 1 or less than 0, the cumulative density function of the logit model is defined from 0 to 1, this nature of reasonable probability nature could provide an advantage in finding the best-fitted degree of upward comparison. Taking account of the ordinal nature of the dependent variable, mental health status, ordered probability models raise as opportune choices. This study implements logistic distribution-based models and reduces calculation difficulty by taking advantage of the calculation-friendly nature of the probability distribution function of the logistic distribution. This paper uses fixed effects, allowing models to capture the

cross-sectional heterogeneity. Compared to simple ordered logit models, fixed effect logit models add individual effects to the linear combination of explanatory variables and their coefficients, namely latent variables. There is another set of parameters, threshold parameters, in fixed effect ordered logit models, connecting the unobserved latent variable Y_{it}^* to observable ordered variable Y_{it} through the channel described below:

$$\begin{aligned}
Y_{it}^* &= \hat{Y}_{it}^* + \epsilon_{it} \\
&= \mathbf{X}_{it}'\beta + \alpha_i + \epsilon_{it}
\end{aligned}$$

$$\hat{Y}_i = \begin{cases} 1 & \text{if } Y_i^* \leq \tau_1 \\ 2 & \text{if } \tau_1 < Y_i^* \leq \tau_2 \\ 3 & \text{if } \tau_2 < Y_i^* \leq \tau_3 \\ 4 & \text{if } \tau_3 < Y_i^* \leq \tau_4 \\ 5 & \text{if } \tau_4 < Y_i^* \leq \tau_5 \\ 6 & \text{if } \tau_5 < Y_i^* \leq \tau_6 \\ 7 & \text{if } \tau_6 < Y_i^* \end{cases}$$

\mathbf{X}_{it} includes interested variables, income, reference income, relative rank and control variables². Meanwhile, logit models assume the residual ϵ_{it} independently and identically follows a logistic distribution, indicating the cumulative distribution function and the probability of the dependent ordered variable:

$$\begin{aligned}
\Lambda(\epsilon_{it}) &= [(1 + \exp(-\epsilon_{it}))]^{-1} \\
\Pr(Y_{it} = j) &= \Lambda(\tau_j - \mathbf{X}_{it}'\beta) - \Lambda(\tau_{j-1} - \mathbf{X}_{it}'\beta)
\end{aligned}$$

The analysis of the fixed effect ordered logit model relies on the *feologit* command in Stata. This approach implements blow-up and cluster- τ (BUC- τ) estimator, an estimating approach based on conditional maximum likelihood estimation (CML). Before the CML estimation, the BUC method replaces every observation with $7 - 1 = 6$ copies of its own and then converts them to binary variables by different cutoff points. However, in later analysis, this paper collapses the dependent variable to 3 levels; therefore, 2 copies are replicated. Based on this blow-up approach, estimating the standard error takes account of individual clustering. This method relieves the risk of convergence problems, and the cost of efficiency loss is tiny (Baetschmann et al, 2020). To estimate the threshold parameters and compute marginal effects, an assumption about identical threshold parameters is introduced: $\tau_{ik} = \tau_{jk} = \tau_k$ for $i \neq j$.

The main contribution of this study is the computation of marginal effects, including average marginal effects (AME) and marginal effects at means (MEM), the concept of marginal effect

²“age, squared age, education, sex, health status, region, year of survey, marital status, employment status, household size, number of children, and time dummies (similar setup to FitzRoy and Nolan 2022)”

is the change of probability of observing $Y_{it} = k$ if an explanatory variable experiences a small change. The below equation shows the marginal effect of an individual i when d th variable in \mathbf{X} , and β_d represents the estimated coefficient of the changed variable.

$$\begin{aligned}\text{Marginal Effect}_{itkd} &= \frac{\delta \Pr(Y_{it} = k | \mathbf{X}_{it}, \alpha_i)}{\delta \mathbf{X}_{itd}} \\ &= \frac{\delta \Pr(Y_{it} \leq k | \mathbf{X}_{it}, \alpha_i)}{\delta \mathbf{X}_{itd}} - \frac{\delta \Pr(Y_{it} \leq k-1 | \mathbf{X}_{it}, \alpha_i)}{\delta \mathbf{X}_{itd}} \\ &= \{\Lambda(\tau_{k+1} - \hat{Y}_{it}^*)[1 - \Lambda(\tau_{k+1} - \hat{Y}_{it}^*)] - \Lambda(\tau_k - \hat{Y}_{it}^*)[1 - \Lambda(\tau_k - \hat{Y}_{it}^*)]\}\beta_d\end{aligned}$$

One limitation of *feologit* command is that it does not support the test about parallel line assumption; therefore, simple *ologit* (ordered logit model) is used for this test, the violation of this assumption does not mean the *feologit* model must violate this assumption as well but still reveal a positive probability. This paper introduced another set of generalised ordered logit models, *gologit2* (Williams, 2006), to relax this assumption. In this case, the fixed effect is not included due to the limitation of command, but this absence of individual effects still allows this model shed some light to the marginal effect in different mental health statuses. In the generalised ordered logit model, the different β s across different dependent variable values, the probability of the dependent variable is greater than a certain value k is computed below.

$$\Pr(Y_{it} > k) = (1 + \exp(-\alpha_k - \mathbf{X}_{it}'\beta_k))^{-1}, \quad k = 1, 2, \dots, 6^3$$

5. Results

5.1. Preliminary Model

Since the ordered models have more than two values in the dependent variable, the coefficient could only tell the sign of the effect on the probability of being top and bottom level. The following analysis mainly focuses on the marginal effects. The preliminary model suggests that marginal effects of relative rank on mental health have some similarity between groups: an increase in relative rank increases the probability of mental health being level 6 and 7; marginal effect on being the first two categories are similar. Taking account of the BUC method “blows up” every observation to $k-1$ copies, collapsing the number of categories to three, namely “low” “middle” and “high” levels of mental health, is a time-saving approach. Moreover, the mental health variable in this paper is the subjective rank so without commonly acknowledged criteria, eliminating several boundaries can still provide insightful intuition. In Table 2, being consistent with the initial ranked income hypothesis (Parducci, 1965), once the relative rank is introduced, the nominal income turns out not to be a factor that affects mental health. When the model only includes the nominal income, such a variable significantly affects mental health, particularly the probability being the highest level of mental health. To test the reference income hypothesis, another model considers both reference income, the mean nominal income of the reference group, and the nominal income. The

³k=1,2 after collapsing dependent variable into 3 levels

result does not provide any evidence for the purest reference income hypothesis but still highlights the role of reference income. The marginal effect at means of reference income to the highest mental health level at -0.0000917, reflects the change in probability of being the level 3 after 1 pound increase in reference income. Compared to the marginal effect of level-term income, 0.000564 is the effect of a 100 GBP increase in personal monthly income, the 100 GBP increase in reference income will induce a greater reduction in the probability of being at a high mental health status.

In the comprehensive model that involves all income-related variables, the income variable turns out to be insignificant; reference income and relative rank capture most of the income effects: confirming that social status is the mechanism behind the causal effect between income and mental health. It is worth noting that health condition is one non-negligible factor in modelling mental health, and it has greater marginal effects (both AME and MEM) than all three income-related variables. Therefore, the result confirms the vital role of physical health in mental health (Ohrnberger et al., 2017); the later prospective analysis of marginal effects includes the health effects additionally.

Although current models confirm the importance of reference income and relative rank, there exists a specification potentially diluting the effect of interested variables: intuitively unemployed people and people who do not participate in the labour force market are less likely to compare their income with others, even if they possess similar characteristics. The hypothesis raises that once the model only estimates based on self-employed and paid-employed individuals, there will be greater marginal effects for those income variables, and according to FitzRoy and Nolan (2022), a higher level of income will significantly improve the probability of being high mental health level. Meanwhile, by replacing the relative rank with subjective rank, the model produced the best prediction when the degree of upward comparison is set to 1.6, confirming Boyce's (2010) result. However, the difference in the correct percentage of prediction is marginal, because the size of the marginal effect of relative rank is small, and the fixed effect can capture about 30% of the variation; therefore, the following analysis will not focus on the upward comparison.

5.2. *Employed Group Model*

Table 8 records the estimated coefficients of the employed group. The main model results provide some validation and violation of previous literature. In the control variables, age squared *age* has a significant positive coefficient, indicating that the expected mental health conditional on age is a U-shaped curve, corresponding to Blanchflower's paper (2021) that mental health status decreases initially as age decreases then increases after age about 50. The insignificant coefficient on the female dummy does not provide any evidence of sex effect on mental health, or the effect is small so a fixed effect once introduced in the model may capture this. This fixed effect capture could be used to explain the insignificance of region and education level, in an unbalanced dataset this could reasonably happen. Although insignificant, there are negative coefficients on mid and high-education levels, which suggests that people who left school later may be less mentally healthy. The negative significant coefficients on marital status emphasised the role of a healthy long-term relationship in improving mental health reinforcing Grover and Helliwell (2019): both not married

Table 2: Marginal Effect at means Preliminary Model

	(1)	(2)	(3)
<hr/>			
inc			
1	-0.000178** (-3.05)	-0.000232*** (-3.93)	0.0000484 (0.46)
2	-0.000385** (-3.05)	-0.000501*** (-3.93)	0.000105 (0.46)
3	0.000564** (3.05)	0.000733*** (3.93)	-0.000153 (-0.46)
<hr/>			
2.edu3			
1	-0.00619 (-0.42)	-0.0236 (-1.57)	-0.0235 (-1.57)
<hr/>			
2.health			
1	-0.0183*** (-15.35)	-0.0183*** (-15.29)	-0.0183*** (-15.32)
2	-0.0397*** (-15.35)	-0.0395*** (-15.29)	-0.0396*** (-15.32)
3	0.0580*** (15.35)	0.0577*** (15.29)	0.0579*** (15.32)
<hr/>			
refinc			
1		0.0000290*** (7.71)	0.0000261*** (6.73)
2		0.0000627*** (7.71)	0.0000564*** (6.73)
3		-0.0000917*** (-7.71)	-0.0000825*** (-6.73)
<hr/>			
relrk1			
1			-0.0139** (-3.19)
2			-0.0300** (-3.19)
3			0.0439** (3.19)
<hr/>			
N	243762	243762	243762
<hr/>			

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

people and people who culminated marriage for some reason have lower mental health levels than married couples. In this model, there is no evidence of any existing mental health gap between self-employed and paid-employed people, which indicates this subgroup estimation is properly selected.

In Table 3, as the model only includes the nominal income, the marginal effect at means for the probability of being high mental health is 0.00108, meaning the 1000 GBP increase in nominal income results in a 1.08 percentage point increase in the probability of being high-level mental health for an individual with average income and age. This effect is almost two-fold of the marginal effects mentioned in the former part, confirming that employed individuals, no matter whether paid or self-employed, care more about the nominal income. The second model includes both nominal income and reference income, it is surprising that the introduction of reference income does not capture much of the nominal income effect in this case, indicating that the reference income effect in this setup is negligible. This prominent insignificance (t statistics = -0.28) violates FitzRoy and Nolan's (2022) estimation, they discovered reference income is weakly significant for groups with age less than 45; in the Understanding Society dataset, there is a huge overlap between ages less than 45 and employed people: approximately 10/13 people under age 45 are employed. The role of reference income will be discussed further in the robustness check part.

In the last model including all three income-related variables, both nominal and reference income turns insignificant, being similar to previous models that based on all job status samples, relative rank captures the majority effect of nominal income, supporting the ranked income hypothesis. Meanwhile, the marginal effect to the highest level of mental health at means is 0.0697 compared to the former 0.0439; supporting that the employed group cares more about their social status.

Through comparing the marginal effect at means of health status on three setups of two sets of models, the income variable does not capture much effect of health status. At mean income and age, one individual not tolerating long-term illness is 5.8% or 4.6% more likely to have high mental health. The higher effects in the former model imply that unemployed people, 3/4 proportion of these people are over 45 years old, receive more welfare after curing the long-term illness. Particularly, in the preliminary model the recovery of long-term illness outweighs the entire effect of the relative rank; in the employed model it also represents a large shock that is equivalent to a 66 percentage point increase in relative rank for an individual with average characteristics.

6. Robustness check and further results

FitzRoy and Nolan (2022) used sets of ordered logit models in elucidating the significant role of nominal income, and weakly significant reference income variable in modelling mental health. This paper utilised a similar ordered logit model to check the estimated result in the last section; Table 5 includes the average marginal effects, the average effect of all individuals induced by a small change in a specific variable, of interested variables. Without fixed effect, more time-invariant variables turn out to be significant; to dispel suspicion about the effect of education level and examine the effect of being healthy, *edu3* and *health* variables are included as well.

Table 3: Marginal Effect at Means of Employed Group

	(1)	(2)	(3)
<hr/>			
inc			
1	-0.000283*** (-4.72)	-0.000285*** (-4.74)	0.0000453 (0.39)
2	-0.000795*** (-4.72)	-0.000802*** (-4.74)	0.000127 (0.39)
3	0.00108*** (4.72)	0.00109*** (4.74)	-0.000173 (-0.39)
<hr/>			
2.health			
1	-0.0121*** (-9.19)	-0.0121*** (-9.19)	-0.0121*** (-9.18)
2	-0.0340*** (-9.19)	-0.0340*** (-9.19)	-0.0340*** (-9.18)
3	0.0461*** (9.19)	0.0461*** (9.19)	0.0461*** (9.18)
<hr/>			
refinc			
1		0.00000237 (0.51)	-0.00000132 (-0.28)
2		0.00000665 (0.51)	-0.00000372 (-0.28)
3		-0.00000902 (-0.51)	0.00000505 (0.28)
<hr/>			
relrk1			
1			-0.0183*** (-3.35)
2			-0.0514*** (-3.35)
3			0.0697*** (3.35)
<hr/>			
N	139736	139736	139736
<hr/>			

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In the ordered logit model, the result revealed strong significance in level-term income and weak significance of reference income at 10% significance level. Although based on a different BUC- τ method, and in a much longer panel dataset, the results are in line with FitzRoy and Nolan (2022), confirming the effect of reference income is smaller than relative rank. Since there is wage inflation, income follows an increasing trend, whereas the relative rank does not take into account inflation. The fixed effect model capturing more unobserved characteristics should be considered as a better model.

To examine the AME of relative rank, the main interested variable, the AMEs in ordered logit model to the probability of being high mental health is 0.0598: 10 percentage point increase in relative rank will induce about 0.6 average percentage point increase in such probability. Compared to the AME recorded in Table 9, 0.0616, the fixed effect, time-invariant variables, does not capture much relative rank effect; but it suspects the unidentified time-variant variables may impose negative effects on the relative rank effect. Whereas the AME for nominal income and reference income surged when ruling out the fixed effect, meaning that to estimate the effects of these two variables, more control variables need to be included. These differences in the changes of AME reveal that the AME and MEM of relative rank calculated in the Result section are robust. To compare the effect between nominal income and relative rank, the computed average change of relative rank once an individual experienced a 100 GBP increase is 0.034. Therefore, a positive 100 GBP shock in terms of relative rank leads to an AME of $0.034 \times 0.0598 = 0.00203$; even with the absence of a fixed effect, the relative rank effect still outweighs the nominal income AME (0.0017). One explanation is the nominal income increases with inflation, so the same effect of a 100 GBP increase in real income needs to be achieved by far more nominal income growth. Unfortunately, without the price level data for accurate city and time, it is hard to compute the real income variable.

Due to the diagnose check commands are not applicable after *feologit* command, diagnose tests associated with *oparallel* command are implemented after ordered logit regression, and the results of the tests are displayed in Table 4. The significance of all parallel line assumption tests rejects the null hypothesis that estimated coefficients are identical across two dichotomous regressions. The rejection of this jeopardises the explanation power of the marginal effects of relative rank. By testing the parallel line assumption with respect to interested variables separately, there is significant evidence proving that all of the income-related variables and health indicators violate the parallel line assumption. Although the formal Brant test is not implemented after fixed effect models, the similar marginal effect between the fixed effect models and models without fixed effect motivates nervousness that the fixed effect ordered logit models violate the parallel line assumption as well. Therefore, generalised models that relax such assumptions need to be introduced.

Table 10 includes the average marginal effect of the employed group under a generalised ordered logit model. Through comparison, the ordered logit model underestimated the effect of relative rank on the lowest level of mental health, indicating the negative parts of the AMEs are evenly distributed. The positive marginal effect on the high-level mental health is 0.0533, this unsurprising result confirmed the previous marginal effects estimation is robust.

Table 4: Diagnose tests results

(a) 'Oparallel' results				(b) Brant test detailed results			
	Chi2	df	P>Chi2		Chi2	df	P>Chi2
Wolfe Gould	1217	31	0.000	All	1162.38	31	0.000
Brant	1162	31	0.000	relrk1	8.25	1	0.004
score	1203	31	0.000	inc	7.35	1	0.007
likelihood ratio	1174	31	0.000	refinc	15.62	1	0.000
Wald	1204	31	0.000	2.health	121.64	1	0.000

7. Implication

According to previous results, all models identified the outweighed relative rank effect compared to either nominal income or reference income effects, consolidating the importance of social status in mental health. However, the marginal effect of relative rank is much smaller when facing the health effect; this result suggests that in terms of improving subjective welfare, focusing on individual health may be more effective than agonising over income equality. There are 1/4 of the individuals in the estimated sample and 1/3 of the total respondents suffering from long-term mental or physical illness. Further policy reports could explore the average cost of treatment, and determine one more efficient allocation to the budget. Meanwhile, the survey data may contain bias, there may be some unidentified characteristics related to mental health status in the not applicable individuals; further research based on administrative data, if available, will be more persuasive. In addition, one severe problem in this paper is the absence of real income; being influenced by inflation factors, the effect of purchasing power is underestimated in the nominal income variable. Further research computing a real income variable will be able to provide a more accurate estimation and more intuitive comparison between the purchasing power effect and social status effects. Furthermore, this paper does not provide strict proof of causality between relative rank and mental health through neither experiment design nor causal analysis, unobserved variables such as relative ability are causing the endogeneity problem. If one can access the Norwegian dataset mentioned in the previous paper (Perez-Truglia, 2020), the marginal effects will be estimated with support of causality.

8. Conclusion

In conclusion, this paper successfully estimates the marginal effects of relative rank, a measure of social status, the AME is about 0.062, whereas MEM has a higher effect of 0.07. Through quantifying the AME of relative rank in terms of nominal income, relative rank is more influential than the other two income variables even in the absence of a fixed effect, which could be explained by not capturing the inflation. The large positive effect of being healthy is emphasised through comparisons, yielding policy focuses toward healthy concerns. Without including the real income variable, this paper confirms the rank income hypothesis in fixed effect models and suspects the importance of comparison between social norms, represented by reference income. Although the

Table 5: Ordered Logit Model Average Marginal Effect

	(1)	(2)	(3)
inc			
1._predict	-0.000653*** (-30.21)	-0.000664*** (-30.45)	-0.000401*** (-8.56)
2._predict	-0.00212*** (-31.60)	-0.00216*** (-31.87)	-0.00130*** (-8.59)
3._predict	0.00277*** (31.59)	0.00282*** (31.87)	0.00170*** (8.59)
2.edu3			
1._predict	-0.00503*** (-9.06)	-0.00896*** (-8.32)	-0.00921*** (-8.55)
2._predict	-0.0166*** (-8.95)	-0.0298*** (-8.18)	-0.0307*** (-8.40)
3._predict	0.0216*** (8.98)	0.0388*** (8.22)	0.0399*** (8.44)
3.edu3			
1._predict	-0.000146 (-0.09)	-0.00267 (-1.59)	-0.00283 (-1.69)
2._predict	-0.000461 (-0.09)	-0.00839 (-1.57)	-0.00890 (-1.66)
3._predict	0.000606 (0.09)	0.0111 (1.57)	0.0117 (1.67)
2.health			
1._predict	-0.0328*** (-41.78)	-0.0328*** (-41.80)	-0.0328*** (-41.77)
2._predict	-0.0949*** (-50.30)	-0.0949*** (-50.33)	-0.0948*** (-50.28)
3._predict	0.128*** (49.08)	0.128*** (49.11)	0.128*** (49.06)
refinc			
1._predict		0.00000667*** (4.22)	0.00000404* (2.47)
2._predict		0.0000217*** (4.22)	0.0000131* (2.47)
3._predict		-0.0000284*** (-4.22)	-0.0000171* (-2.47)
relrk1			
1._predict			-0.0141*** (-6.28)
2._predict			-0.0457*** (-6.29)
3._predict			0.0598*** (6.29)
N	182522	182522	182522

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

best-fitted degree of upward comparison is 1.60, this cannot be strong evidence of either confirming or rejecting the theory of upward comparison, for the differences between parameters are extremely small.

Unfortunately, the surging of pseudo-R-square reveals that, in terms of modelling mental health, there are influential variables in the shadow and the models without fixed effect cannot capture many variations, achieving the consensus with FitzRoy and Nolan (2022). The violation of the parallel line assumption indicates that the ordered probability model is not a suitable type of model to estimate mental health, although the difference in the marginal effect of relative rank is small.

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Appendices

Table 6: Variable Information from Stata

Variable Name	Description
pidp	cross-wave person identifier (public release)
scfsato	Satisfaction with life overall
dvage	age for whole sample
fmngrs_dv	total monthly personal income gross
jbstat	Current economic activity
marstat_dv	Harmonised de facto marital status
health	long-standing illness or impairment
nchresp	number of children under 16
region4	Government Office Region
hhsz	Household size, including absent members
sex	sex
oprlg	whether belong to a religion
scend	school leaving age
wave	wave of survey
inc	$fmngrs_dv/100$
refinc	nominal income mean within reference group
relrk1	relative rank income

Table 7: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
scfssato	313,329	5.169	1.469	1	7
dvage	313,280	49.818	17.405	16	102
fimngrs_dv	313,329	1,777.060	1,339.311	0.010	8,332.770
jbstat	313,232	3.488	6.622	1	97
marstat_dv	312,730	2.423	1.937	1	6
health	312,999	1.638	0.481	1	2
nchresp	313,329	0.312	0.755	0	10
hhsiz	313,329	2.801	1.443	1	16
sex	313,329	1.560	0.496	1	2
oprlg	110,859	1.466	0.499	1	2
wave	313,329	5.949	3.444	1	12
edu3	313,329	1.370	0.535	1	3
region4	313,329	1.307	0.769	1	4
age	313,329	55.686	35.996	0.020	208.080
group_m1	313,329	152.867	76.639	1	288
refinc	313,329	1,787.700	587.181	83.375	7,146.640
grpsize	313,280	812.132	527.891	1	2,345
absrk1	313,280	405.900	387.096	1.000	2,341.000
grpsize1	313,137	812.503	527.727	2	2,345
relrk1	313,137	0.495	0.290	0.000	1.000
inc	313,329	17.771	13.393	0.0001	83.328

Table 8: Fixed Effect Ordered Logit Coefficients for Employed Group

(Employed Model)		(continue.)	
	lsf		lsf
relrk1	0.280*** (3.35)	2.jbstat3	-0.00999 (-0.26)
inc	-0.000696 (-0.39)	1.marstat_dv	0 (.)
refinc	0.0000203 (0.28)	2.marstat_dv	0.0475 (1.19)
dvage	-0.0321 (-0.98)	3.marstat_dv	-0.556*** (-4.21)
age	0.0492*** (6.32)	4.marstat_dv	-0.356*** (-5.53)
1.sex	0 (.)	5.marstat_dv	-0.611*** (-8.66)
2.sex	-0.112 (-0.17)	6.marstat_dv	-0.297*** (-5.66)
1.region4	0 (.)	1.wave	0 (.)
2.region4	0.0224 (0.10)	2.wave	-0.105* (-2.55)
3.region4	-0.0275 (-0.13)	3.wave	-0.378*** (-5.54)
4.region4	1.038 (1.91)	4.wave	-0.518*** (-5.33)
1.edu3	0 (.)	5.wave	-0.621*** (-4.88)
2.edu3	-0.155 (-0.63)	6.wave	-0.379* (-2.40)
3.edu3	-0.140 (-0.32)	7.wave	-0.390* (-2.08)
hhsize	-0.0555*** (-4.68)	8.wave	-0.552* (-2.54)
nchresp	0.0502* (2.21)	9.wave	-0.789** (-3.18)
1.health	0 (.)	10.wave	-0.864** (-3.11)
2.health	0.185*** (9.18)	11.wave	-0.922** (-2.99)
1.jbstat3	0 (.)	12.wave	-0.861* (-2.54)
cut1	0 (.)		
cut2	3.181*** (159.27)		
<i>N</i>	1361629	<i>N</i>	1361629

Table 9: Average Marginal Effect of Employed Group in Fixed Effect Models

	(1)	(2)	(3)
<hr/>			
inc			
1	-0.0002404 (-1.09)	-0.0002426 (-1.09)	0.0000385 (0.37)
2	-0.0007149** (-2.39)	-0.0007207** (-2.40)	0.0001144 (0.39)
3	0.0009553*** (4.59)	0.0009633*** (4.60)	-0.0001529 (-0.39)
<hr/>			
2.health			
1	-0.0107034 (-1.12)	-0.0107054 (-1.13)	-0.0106892 (-1.12)
2	-0.0298454** (-2.38)	-0.0298247** (-2.40)	-0.0297728** (-2.40)
3	0.0405488*** (7.68)	0.0405301*** (7.71)	0.040462*** (7.73)
<hr/>			
refinc			
1		2.01e-06 (0.47)	-1.13e-06 (-0.27)
2		5.98e-06 (0.50)	-3.34e-06 (-0.28)
3		-7.99e-06 (-0.51)	4.47e-06 (0.28)
<hr/>			
relrk1			
1			-0.0155357 (-1.08)
2			-0.046139** (-2.09)
3			0.0616747 *** (3.26)
<hr/>			
N	139736	139736	139736
<hr/>			

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Average Marginal Effect of Employed Group in Generalised Model

	(1)
inc	
1	-0.0001439 (-1.40)
2	-0.0017043*** (-8.68)
3	0.0018482*** (4.78)
2.health	
1	-0.0189727*** (-13.77)
2	-0.1168628*** (-43.63)
3	0.1358355*** (50.40)
refinc	
1	0.0000107*** (-4.94)
2	0.0000376*** (6.64)
3	-0.0000269*** (-3.86)
relrk1	
1	-0.0270807*** (-5.76)
2	-0.0261759*** (-2.79)
3	0.0532566*** (5.52)
<i>N</i>	182,522

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$