

Exploring Whether Place Shapes the Poverty-Health Relationship in England

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Executive Summary

This dissertation examines the poverty-health relationship in England drawing on data from the UK Household Longitudinal Study (UKHLS), with a particular focus on neighbourhood deprivation. Households are classified as low income when their equivalised net household income drops to less than 60% of the England median per wave. Low income is shown to be significantly negatively associated with self-rated health and mental health. Most importantly, the income-health penalty varies between the neighbourhood deprivation quintiles. In the most deprived areas, the income-health penalty is indistinguishable from zero statistically and regains statistical relevance in less deprived quintiles. Neighbourhood conditions precede personal income in establishing an individual's health outcomes. The current health returns to income support are based on the individual's local environment, so anti-poverty policies that are blind to place risk dismissing the conditions at the neighbourhood-level. Individual income transfers thus fall short in closing the health gap in those areas.

AI Statement

I confirm that generative AI was not used during the research or drafting of this paper.

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Introduction

Health inequality stands as a deeply persistent challenge confronting contemporary societies. In England, the life expectancy differential between individuals at opposite ends of the deprivation range, spans nineteen years, with the more deprived individuals reporting consistently worse physical and mental health outcomes throughout their lives (Bennet et al., 2024).

Labour market participation is weakened by poor health, with public expenditure on health and social care rising. Human capital accumulation constrains across the generations. A central question in health economics calls for the understanding of the determinants of current health inequality, beyond solely a public health concern.

Extensive empirical research documents the income-health gradient in question as strong and persistent. Worse self-rated health is reported continually by individuals in lower income groups, creating the low income-health gradient, followed by poorer mental health and an increased prevalence of chronic illness to higher-income individuals (Stronks et al., 1998; Benzeval et al., 2000). After introducing controls for employed, demographic characteristics, and education, the gradient remains robust, but questions remain surrounding its mechanisms, and more crucially if it is uniform in all contexts or if it changes depending on an individual's environment.

Income is embedded across social and spatial contexts. Fitzpatrick and LaGory (2003) write that neighbourhoods are “mosaics of risk and protection”, alluding that local environments mould outcomes to health independently of an individual's income. They are shaped by environmental hazards and access to services and organisations of which individuals have different levels of exposure.

Yen and Syme's (1999) findings show health outcomes are still predicted by neighbourhood socioeconomic conditions after controlling for individual income. Do's (2006) use of multi-level models reveals worse-self rated health is independently associated with neighbourhood poverty. Furthermore, Yang and Kanavos (2012) and Iqbal and Nawaz (2017) document spatial context differences cause income-linked health inequalities to vary significantly.

While this evidence is useful, income effects and place effects are analysed separately, without examining how they interact. Particularly with England as context and with the use

of longitudinal data that can address reverse causality. This dissertation aims to directly investigate this gap.

The principal research question is: does place shape the poverty-health relationship in England? Building from the research set out by Akanni et al. (2022) who use UKHLS data to analyse income trajectories and health, and Benzeval and Judge (2001) who lay out the necessity of longitudinal methods for determining the income-health effects, this dissertation assesses whether the income-health gradient differs across the levels of neighbourhood deprivation, as captured by the Index of Multiple Deprivation (IMD) 2019 variable. The hypothesis is congruent to the literature on area effects, that the differences in place amongst the poor are not fully compositional. The income-health penalty across the deprivation distribution varies in a way that is meaningful theoretically.

This dissertation adds three contributions to the existing literature. Firstly, the use of fifteen waves of the UKHLS data (2009-2024) provides updated longitudinal evidence on the income-health gradient, which seeks to extend the study of Benzeval and Judge (2001) through having a larger sample and longer time period. In addition, the interaction between poverty at the individual level and neighbourhood deprivation is modelled, which provides an England longitudinal evidence perspective on whether IMD quintiles cause the income-health gradient to vary. Lastly, effects on self-rated health and mental health are identified separately, allowing for the distinction between deprivation that is material and the stress-induced pathways that consequently lead to poverty affecting health (Gravelle and Sutton, 2008; Lende, 2012).

Literature Review

Income, Health, and Deprivation

Research has shown that income influences health through material and psychosocial pathways, and that the relative position within local social hierarchies plays a significant role. Local environments also shape exposure to stressors and access to resources, meaning the health effects of low income are likely to vary across geographical contexts. The following section explores these frameworks and reviews the empirical evidence on health trajectories from income dynamics.

Within social epidemiology, health as a product goes beyond biological or individual behaviours, encompassing broader social and environmental factors. In a literature survey, Yen and Syme (1999) argue that research must move beyond individual risk factors to consider the social environment, including neighbourhood socioeconomic status, local institutions, and social relationships, as these factors systematically influence morbidity and mortality.

UK policy frameworks have since incorporated this multi-layered perspective. In particular, the Marmot Review (Marmot et al., 2010) created a social determinants framework that tackled the present health inequalities in England. They argued that action spread across employment, income, education, and place is necessary to bridge the health gap. Studies such as Diderichsen et al. (2001) and Yen and Syme (1999) develop social stratification frameworks that link social position to unequal exposure to risk, differential vulnerability to the risks, and unequal consequences of illness. Income is understood to affect health through direct material pathways, such as housing, diet, working conditions, and indirect pathways, including the ability to navigate complex systems such as welfare and healthcare (Benzeval et al., 2000; Gravelle and Sutton, 2008; Lende, 2012). These mechanisms may reinforce cycles of disadvantage over time, inadvertently sustaining health inequalities that resist short-term interventions (Marmot et al., 2020).

A key contribution to this literature is the evidence on the social gradient in health from The Whitehall Studies, which include a set of studies spanning from 1967 to the present day originally led by Sir Michael Marmot (Marmot et al., 1984). The first study found a steep link between the employment level and mortality attributable to various factors, with worse health outcomes at each step down the hierarchy. Men in the lowest employment grades experienced a threefold increased likelihood of coronary heart disease versus their counterparts in senior positions (Marmot et al., 1984). The second Whitehall study with a new cohort (10,314 civil servants) reiterated that the same gradient had not diminished, confirming a persistent negative association between employment level and morbidity (Marmot et al., 1991). Both studies found that the standard risk factors such as cholesterol and smoking were unable to explain past one third of the gradient, therefore differences in health behaviours are not an overwhelming influence. Later work highlights the role of psychosocial mechanisms, particularly stress, perceived status, and lack of control (Marmot, 2004). An overarching result throughout the studies is the inverse relationship (Marmot et al., 1984;1991;2004).

Relative deprivation theory extends this argument by shifting the focus from absolute income to social comparisons, first formalised by (Runciman, 1962). Individuals with lower relative socioeconomic status experience poorer health outcomes, namely worse self-rated health, higher mortality, and greater engagement in harmful lifestyles such as tobacco use and alcohol misuse (Eibner and Evans, 2005; Balsa et al., 2014). These effects are explained through psychosocial pathways, including stress and perceived injustice, as well as behavioural responses such as “positional spending” on visible goods, often at the expense of health-related consumption (Chen, 2015).

A key challenge in this strand of literature is identifying appropriate reference groups. Evidence suggests that these vary across contexts, for example between rural and urban settings, and are increasingly fluid in modern societies (Mangyo and Park, 2011). In England, composite measures, notably the Index of Multiple Deprivation (IMD¹) are often used as proxies for local relative deprivation, although they may not fully capture subjective comparisons key to Runciman’s (1966) theory (Noble et al., 2006). Micro-level approaches, such as those developed by Stronks et al. (1998), distinguish between material deprivation and social exclusion, capturing both basic needs and participation in society.

Salutogenesis provides a complementary perspective by focusing on how individuals maintain health despite adversity. Antonovsky (1987) argues that individuals draw on generalised resistance resources, including material assets, social support, and personal capabilities, alongside a sense of coherence. Empirical studies suggest that strong social networks and coping mechanisms can counter the damaging consequences of poverty (Makoge and Maat, 2023), although this approach is less commonly applied in large-scale quantitative research where data is rarely available. Therefore, this study is able to capture neighbourhood deprivation’s consequences on health but is not able to measure the buffering role of local social capital directly. Future researchers using mixed methods would be well placed to address this limitation.

Research consistently shows that income shapes health in ways that unfold over time in place of functioning as a single time-point. Benzeval and Judge (2001) demonstrate that persistent

¹ The IMD serves as the primary tool for capturing relative deprivation in England, managed by the Ministry of Housing, Communities and Local Government. It shows how areas compare to each other, rather than using absolute measures. 39 weighted indicators are grouped into seven domains which include income, employment, education, health, crime, housing, and living environment. They are examined at the Lower Super Output Area level, comprising approximately 1,500 residents per area (Ministry of Housing, Communities and Local Government (2019)).

low income and downward income mobility are particularly detrimental to health. Using longitudinal data, they show that long-term income measures have a stronger bearing on overall health and chronic illness than single-year income, highlighting the importance of both the duration and depth of poverty.

More recent work reinforces these findings. Using the UKHLS survey, Akanni et al. (2022) studies how health is related to current income, average income, and income volatility differently. Their results show that higher and more stable income tends to produce improved personal health outcomes, while income volatility is linked to poorer mental health and life satisfaction. Persistent low income remains particularly harmful even after accounting for time-varying characteristics.

Consistent with a life-course perspective where cumulative exposure to disadvantage shapes health outcomes, Stronks et al. (1998) find a steep gradient in chronic illness and perceived health across income groups using data from the Netherlands. Their analysis shows that both material and social deprivation explain part of this gradient, suggesting that additional mechanisms are involved.

Recent UK evidence highlights the persistence of these inequalities. The Marmot Review 10 Years On is a follow-up assessment of the original 2010 review that examines the progress of health inequalities in the England using synthesised national mortality and life expectancy data amongst many demographic trends. It documents a strong and continuing relationship between deprivation and health outcomes, with stalled improvements in life expectancy and widening inequalities in more deprived areas (Marmot et al., 2020).

Income trajectories, including persistence and volatility, are closely linked to health outcomes. However, income alone does not fully explain observed inequalities, suggesting the importance of considering additional contextual factors.

Spatial Inequalities, Neighbourhood Deprivation, and Health

A parallel literature investigates how neighbourhood conditions impact individual health and wellbeing. Yen and Syme (1999) identify consistent associations between neighbourhood characteristics and health, although studies in this literature such as Yang and Kanavos (2012) and Iqbal and Nawaz (2017) are often limited by cross-sectional designs and crude measures of area characteristics, restricting causal inference.

More recent research provides stronger evidence of independent neighbourhood effects. Drawing on Whitehall II, Stafford and Marmot (2003) find that neighbourhood deprivation independently compromises health, remaining a significant predictor even once individual socioeconomic status is accounted for. These effects are attributed to both access to local resources and the influence of relative position within the neighbourhood.

Later studies further show that cumulative exposure to disadvantaged areas worsens health over time. Do (2008), using data from the Americans' Changing Lives longitudinal survey finds that sustained exposure to high-poverty neighbourhoods leads to worse self-reported health, even when controlling for personal factors. Evidence from the UK also suggests that long-term area deprivation has persistent effects on health outcomes (Lloyd et al., 2023).

International evidence supports these findings. Yang and Kanavos (2012) show that income-related health inequalities vary across regions in China, particularly between urban and rural areas. Similarly, Iqbal and Nawaz (2017) demonstrate substantial spatial variation in health deprivation in Pakistan using a multidimensional index. These findings align with UK policy analysis, which emphasises the importance of place-based approaches. Measures such as the IMD are used to identify areas where deprivation and poor health are concentrated, supporting targeted interventions (Ministry of Housing, Communities and Local Government, 2019; Noble et al., 2006). Neighbourhood deprivation influences health independently of individual income, where the effects accumulate over time. However, most studies focus on average effects, with less attention given to variation within income groups.

Research Gap

While existing research shows that income and neighbourhood levels both matter for health, there is limited evidence on how these factors interact. In particular, few UK studies examine whether the health impact of low income varies systematically across levels of local deprivation. While the Whitehall Studies (Marmot et al., 1984) research how health outcomes differ between employment levels, and Benzeval and Judge (2001), Akanni et al. (2022) use UKHLS data to assess how health over time relates to income trajectories, neither set of these studies specifies whether the health consequence of low income differs across levels of area deprivation.

Some related work using the Millenium Cohort Study used income and IMD quintiles combined to predict child health outcomes (Skarda et al., 2025). Separately, Ghaly and Jivraj (2022) use the same UKHLS from waves 8-10 to moderate self-rated health using

neighbourhood income inequality. Neither use a relative poverty threshold interacted with the IMD quintiles in an adult panel sample, thus the evidence is limited.

To overcome the gap, longitudinal income data is combined with local deprivation measures. Then, the UKHLS survey linked to IMD quintiles is used to test whether the relationship between income and health outcomes varies across local contexts. The central hypothesis is that low income is associated with poorer health, but that this relationship is stronger in more deprived areas.

Data

The data source for this study is the UK Household Longitudinal Study (UKHLS), commonly referred to as Understanding Society. By following approximately 40,000 households and tracking more than 100,000 individuals across time, the UKHLS is the largest longitudinal household panel study in the United Kingdom. The study encompasses a broad selection of indicators, health outcomes, income, employment, housing, and many socio-economic demographics. The data collection is annual, with wave 1 beginning in 2009-10 and the most recent wave (wave 15) covering 2023-24.

The selection of this data is grounded in the theoretical framework of this dissertation. First, the longitudinal structure allows the separation of within-person income changes from between-person differences. This aims to address the endogeneity concern mentioned by Benzeval and Judge (2001), where the causality between income and health is thought to be conflated with the reverse pathway from ill health to less earnings. Second, this survey collects detailed income data and substantiated health measures (self-rated health, mental component summary score) which were identified in the literature as the primary channels of which poverty affects health. This strengthens the analysis of health across general and psychosocial dimensions. Last, the addition of IMD 2019 at the neighbourhood level from wave 12 onwards establishes a unique possibility to test the central hypothesis regarding the idea that place moderates the poverty-health relationship. IMD 2019 is England's tool for quantifying deprivation (Ministry of Housing, Communities, and Local Government, 2019). This edition is the latest release, and its methodology remains consistent with prior editions. The analysis on place heterogeneity is restricted to waves 12-15 with the subsample size having 92,528 observations. This test would be impossible with cross-sectional data or studies that do not include neighbourhood identifiers.

The dataset has been cleaned extensively to improve the modelling results accuracy. The analysis is restricted to England to be consistent with the IMD 2019 measure, which is specific to England with no direct comparability to the rest of the United Kingdom. Other types of cleaning include restricting the sample to respondents aged 16 and above; removing individuals with values missing on key variables; following the associated User Guide on recoding negative values as missing; reversing the self-rated health scale so the higher values correspond to better health; and recalculating the income poverty threshold in each wave for the England-specific sample. This recalculation was done to ensure that the 60% median threshold is an accurate representation of the contemporary living standards and price levels in each period, aiming to capture relative poverty rather than absolute.

The England only 2009-2024 sample covers all available waves, 1-15 yielding an unbalanced panel of 450,874 person-wave observations from 76,334 unique individuals. The individuals are observed between 1 and 15 waves, with a median of 4 waves. Only 6,236 individuals (8.2%) are present in all 15 waves. For the main pooled OLS models, all observations are kept. For the individual fixed effects robustness model checks, the sample is restricted to the balanced panel of 6,236 individuals, to avoid differential attrition stemming from composition changes.

Table 1: Summary Statistics for Key Variables

Variable	Description	Distribution				N
Self-rated health (SRH)	SF-1 global health question reversed; 5=Excellent, 1=Poor. Used as primary health outcome.	Poor: 6.3% / Fair: 15.7% / Good: 31.5% / Very good: 33.1% / Excellent: 13.4%				450,871
Low income (0/1)	1 if equivalised income below 60% of wave-specific England median – DWP relative poverty threshold.	=0: 84.6% / =1: 15.4%				450,871
IMD Quintile (1-5)	IMD 2019 England neighbourhood deprivation quintile. 1=most deprived, 5=least deprived. Wave 12+ only.	Q1: 19.3% / Q2: 19.6% / Q3:19.7% / Q4:20.7% / Q5:20.7%				92,528
Variable	Description	Mean	Median	Std. Dev	Min-Max	N
Equivalised HH income (£/month)	Net monthly household income from all sources, equivalised using modified OECD scale to adjust for household size.	1,882.15	1,596.99	2,079.38	-25,985.76 - 389,337.38	450,874
Age (years)	Age at interview	48.19	48.00	18.59	16.00-104.00	450,874
MCS-12 score (0-100)	SF-12 Mental Component Summary Score. Standardised index of psychological wellbeing, 0=lowest to 100=highest functioning.	48.67	51.24	10.38	0.00-78.08	403,009

Equivalised household income deflated using OECD modified equivalisation scale. Negative minimum income reflects self-employment losses (n=161, 0.04% of sample); these observations are excluded when constructing log income. MCS-12 has a lower sample size due to non-response to the self-completion questionnaire.

Participants were asked questions on some demographic and socio-economic characteristics, where categorical variables were derived. Many of these variables are correlated with income and health and have been included as controls to lower omitted variable bias, with an aim to isolate the income-health relationship. A summary is provided in Table 2 and 3.

Table 2: Control variables

Variables		=0(%)	=1(%)	N
Female		48.5	51.5	450,874
Married/civil partner		50.4	49.6	450,061
White British		14.8	85.2	449,520
Urban		21.1	78.9	450,874
Long-standing illness		63.9	36.1	450,196
Education (no qualification)		88.7	11.3	450,874
Employment Status – Total N: 450,871				
Category	Employed	Self-employed	Unemployed	Economically inactive
%	47.5	7.6	4.8	40.1

Proportions are survey-weighted using cross-sectional individual weight with Primary Sampling Unit (PSU) and strata declared. N varies across variables due to item non-response.

Methodology

Ordinary Least Squares (OLS)

To determine how low income shapes health outcomes in England, two diagnostic models using log equivalised income were estimated, using natural logarithms per the literature from Gravelle and Sutton (2008), due to its highly skewed distribution nature (skewness = 55.4). These confirm the income-health gradient is positive and significant, with a coefficient of 0.184. The coefficient remained unchanged when age was added and age squared was found to be statistically insignificant, with R^2 not improving. Age squared was excluded from all further models.

Instead of employing the continuous equivalised net household income variable, the binary low-income indicator is used as the primary variable. It is set to equal to one if the equivalised household income falls to less than 60% of the wave-specific England median, 0 otherwise. The relative poverty concept central to the research question is able to be captured with this direct threshold, remaining consistent with the UK's government official poverty definition. This follows Townsend's (1979) principal argument that deprivation should not be understood through an absolute monetary threshold lens, rather relative to prevailing social standards, a seemingly more robust variable to measurement error than self-reported income.

Model 1 below estimates self-rated health on the derived low-income indicator, with wave fixed effects only. For each individual i observed at wave t , in household h . By establishing

the unconditional binary gradient, this first model produces the basis foundation prior to the addition of controls in the subsequent models.

$$1. \quad SRH_{it} = \alpha + \beta_1(LowIncome_{ht}) + \sum \lambda_t(Wave_t) + \varepsilon_{it}$$

Where, $\sum \lambda_t$ denotes wave fixed effects across the fifteen waves, wave 1 as reference. ε_{it} is the error term for individual i at wave t clustered at the individual level.

Model 2 adds age as a control variable. Age and health outcomes across the life course have a well-established relationship in the literature (Benzeval and Judge, 2001; Marmot et al., 1991). The inclusion of age ensures the income-health penalty net of the income groups' age differences is captured by the low-income coefficient.

$$2. \quad SRH_{it} = \alpha + \beta_1(Lowincome_{ht}) + \beta_2(Age_{it}) + \sum \lambda_t(Wave_t) + \varepsilon_{it}$$

Model 3 below is the main specification built, adding the complete vector of individual and place controls in addition to region fixed effects. This is built by including various socio-demographic characteristics, marital status, sex, employment status, ethnicity, education, and urban location. The inclusion of these controls aids in the account for potential confounding effects they have on the poverty-health relationship. Household size and presence of children as controls were included initially as household level controls (δH) in the baseline, but their results were statistically insignificant. They were removed from the final specification to maintain parsimony.

The baseline equation is:

$$SRH_{it} = \alpha + \beta_1(Lowincome_{ht}) + \gamma X_{it} + \delta H_{ht} + \sum \mu_r(Region_r) + \sum \lambda_t(Wave_t) + \varepsilon_{it}$$

Where γX_{it} is the vector of individual-level controls for person i at wave t . The controls comprise of age, sex, marital status, employment status², ethnicity, geography, and educational attainment. The $\sum \mu_r$ represents the region fixed effects across the nine Government Office Regions in England, with Northeast as reference category. The full expanded equation for Model 3 is:

² Employment status is included in the controls as a set of three binary indicators: employed, self-employed, and unemployed. Economically inactive is the reference category, which includes individuals who are retired, disabled or long-term health condition, and those in full-time study.

$$3. SRH_{it} = \alpha + \beta_1(Lowincome_{it}) + \beta_2(Age_{it}) + \beta_3(Female_{it}) + \beta_4(Married_{it}) + \beta_5(Employed_{it}) + \beta_6(Unemployed_{it}) + \beta_7(Selfemp_{it}) + \beta_8(Whitebritish_{it}) + \beta_9(Urban_{it}) + \beta_{10}(Noqual_{it}) + \sum \mu_r(Region_r) + \sum \lambda_t(Wave_t) + \varepsilon_{it}$$

β_1 is the coefficient of interest, capturing the conditional income-health penalty, and β_2 - β_{11} are the individual control coefficients. This specification is replicated with MCS-12 as the dependent variable to test separately the mental health dimensions of the poverty-health gradient, given the evidence from Gravelle and Sutton (2008) that income affects mental and physical health through distinct pathways.

Place Heterogeneity

To test the central hypothesis, that place shapes the poverty-health relationship, two further specifications are estimated on the subsample from wave 12 onwards, where IMD data is available. The first one adds the IMD quintile dummies to Model 3, looking for independent area deprivation effects on health that go beyond individual income. Where q represents the neighbourhood deprivation quintile, $q=1$ denotes the area most deprived, and $q=5$ least deprived.

$$4. SRH_{it} = \alpha + \beta_1(Lowincome_{it}) + \sum \theta_q(IMDquintile_q) + \gamma X_{it} + \sum \lambda_t(Wave_t) + \varepsilon_{it}$$

The second test embodies the complete heterogeneity test from the baseline, using the categorical interaction term created between IMD quintiles and low income. This estimates the income-health penalty separately for each deprivation quintile.

$$5. SRH_{it} = \alpha + \sum \theta_q(IMDquintile_q) + \sum \phi_q(IMQquintile_q \times Lowincome_{it}) + \gamma X_{it} + \sum \lambda_t(Wave_t) + \varepsilon_{it}$$

The θ_q coefficient represents the main area deprivation effect and ϕ_q captures the additional income-health penalty specific to the quintile, all of which are relative to quintile 1 (most deprived, reference). A value of $\phi_q = 0$ indicates that the gradient in quintile q is indifferent from that in the most deprived areas. This specification directly tests the claim that place differences among the disadvantaged are not purely compositional.

Panel Data and Reverse Causality

A principal methodological concern, which was identified and consistent with Benzeval and Judge (2001) is reverse causality. The notion that poorer health may lower labour market participation and reduce earnings, causing the lower income instead of resulting from it.

From the literature, unobserved heterogeneity can cause health to be correlated with the error term.

A Hausman test ($\chi^2(20) = 2,760.06$ $p < 0.001$) rejects the null hypothesis that random effects are consistent. Individual effects are correlated with the regressors, and the estimates would be biased. The main models use pooled OLS with standard errors, clustered at the individual level, correcting within-person serial correlation across waves.

Next, the current low income is replaced with lagged income, its value from the previous wave, to ensure the income measure predates the health outcome. This addresses the concern poor health reduces contemporaneous income as opposed to income affecting health.

$$6. SRH_{it} = \alpha + \beta_1(Lowincome_{h,t-1}) + \gamma X_{it} + \sum \lambda_t(Wave_t) + \varepsilon_{it}$$

Where the $Lowincome_{h,t-1}$ is the low-income status of the household h in the previous wave $t-1$, only the income measure is lagged. The other variables captured by the individual controls vector γX_{it} remain contemporaneous. Region fixed effects are excluded since the lagged income restricts the sample to waves 2-15. The control vector is the same as Model 3.

Finally, individual fixed effects are estimated on a balanced panel of 6,236 individuals observed in all 15 waves. Panel data fixed effects models use these individual fixed effects to account the unobserved stable heterogeneity often found with health, like genetic predisposition and childhood conditions, in order to mitigate endogeneity issues found in pooled OLS models.

$$7. SRH_{it} = \alpha + \beta_1(Lowincome_{it}) + \beta_2(Age_{it}) + \beta_3(Employed_{it}) + \beta_4(Unemployed_{it}) + \beta_5(Selfemp_{it}) + \beta_6(Urban_{it}) + FE_i + \sum \lambda_t(Wave_t) + \varepsilon_{it}$$

The FE_i is the individual fixed effect capturing all time-invariant unseen heterogeneity. Time invariant variables – sex, education, ethnicity – are removed automatically by the estimator. Long standing illness is included as a control in the FE specification; the aim is to directly address the imminent reverse causality of health and income. Exploring pooled OLS and fixed effects models enables a worthwhile comparison and acts as a robustness check.

Results and Discussion

Baseline Income-Health Gradient

Following the empirical strategy identified, a sequence of stepwise OLS regression models were estimated. The results are shown in Table 3.

Across all the specifications tested, low income was found to be negatively and significantly associated with SRH. This provides concrete support for the hypothesis that low income is linked with worse health outcomes. The unconditional gradient (Model 1) reveals low-income individuals report 0.271 points (1% significance level) less SRH on the 1-5 scale than those above the poverty line roughly one quarter of a standard deviation. Model 2 with the addition of Age remains with a virtually unchanged coefficient ($\beta = -0.268$), confirming a life course artefact is not what the gradient is.

The main specification (Model 3) sees the coefficient fall to -0.106 after the full set of controls. Correlated characteristics have part of the raw gradient operating through them. Low-income individuals are more likely to be less educated, not in employment, and living in urban areas, which all independently predict worse health. After controlling these observable factors, the income-health penalty still persists. With a statistical significance of 1%, this finding is consistent with the existing literature by Benzeval, Taylor, and Judge (2000) that low adult income is associated with worse health effects with demographic and characteristic controls. Akanni et al. (2022) used the same dataset and found that repeated low-income trajectories predict worse SRH.

The same specification estimated using the MCS-12 dependent variable yields a coefficient of -1.015 at the 1% significance level. Low-income individuals report worse mental health to those above the poverty line. This draws upon the psychosocial stress pathway mentioned by Gravelle and Sutton (2008) revealing health is not limited to absolute income, but also by relative income and social comparisons. Mental health is thus disproportionately affected by the chronic psychosocial stress. Lende (2012) furthers the analysis by arguing that biological and cognitive processes are affected by the chronic stress linked with poverty. To demonstrate, the average MCS score is 48.67 in the sample. A low-income individual would expect to have a score of 46.71. This deterioration signifies the greater psychological distress, where lower scores point to lower mental health.

Control Variables

In Model 3, the polarity of the coefficients is as expected. Alongside income, employment status is the largest predictor of health. Those with self-employed status report 0.335 points higher SRH than those economically inactive, those employed 0.263 points higher, whilst the unemployed see 0.142 points lower SRH, all significant at the 1% level.

Those without qualifications report 0.291 points less SRH than those with degrees ($p < 0.001$). This outcome is consistent with education seen as the driver of health improvements through health literacy and access to resources that promote health and wellbeing. Marital status also appears to be of benefit, as those married report significantly better health, reinforcing the protective advantages of the pooling of household resources and social support ($\beta = 0.135$, $p < 0.001$). Urban residents report worse health than their rural counterparts ($\beta = -0.135$, $p < 0.001$) in all specifications. Yang and Kanavos (2012) document worse health due to socioeconomic disadvantage is felt more strongly in urban environments. This suggests that the setting amplifies the exposure to health-related risks. Female sex is not significant after controlling for marital status and employment, this indicates that the gap in gender health in the raw data may reflect compositional differences as opposed to a direct sex effect.

The specification tested with the addition of long-standing illness on low income (Table 3, Column 5) yields a significant result of $\beta = -0.117$. This result is virtually unchanged from Model 3, $\beta = -0.106$, whilst R^2 notably increased to 0.290 from 0.123. Reverse causality through the channel of illness-income is confirmed to not be driving the main result, in line with Benzeval and Judge (2001) who found that the income-health relationship maintained robustness after baseline health was controlled.

Regional Health Disparities

A North-South health gradient appears from the regional fixed effects, in line with Bennet et al.'s (2024) evidence of distinct regional health inequalities. All 8 government regions in England report significantly better SRH than the Northeast reference. However, the interaction term between low income and North is not significant, suggesting between North and South the income-health gradient does not differ. The regional health gap represents differentials in average health as opposed to poverty effects.

Table 3: Effects of low income on self-rated health and mental health

	Model 1 SRH OLS	Model 2 SRH + age	Model 3 + all controls	Model 3 MCS-12	Model 3 SRH + Illness
Low income	-0.271***	-0.268***	-0.106***	-1.015***	-0.117***
Age		-0.015***	-0.013***	0.101***	-0.006***
Female			-0.013	-2.058***	-0.001***
Married			0.135***	1.296***	0.076***
Employed			0.263***	0.908***	0.125***
Unemployed			-0.142***	-2.925***	-0.123***
Self-employed			0.335***	1.136***	0.192***
White British			0.026**	-0.483***	0.080***
Urban			-0.135***	-0.857***	-0.108***
No qualification			-0.291***	-1.035***	-0.234***
Long-standing illness					-0.990***
N	417,160	417,160	416,285	394,873	415,661
R-squared	0.018	0.085	0.123	0.083	0.290
F-statistic	162.9	505.0	304.8	207.2	957.7

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

Place and Health: IMD Deprivation

Table 4 presents the tested IMD place models using a sub sample from wave 12 onwards. The results find IMD quintiles to be a highly significant predictor of health for both outcomes. With the most deprived quintile (Q1) as the reference, progressively better self-rated health arises as the residents come from successively less deprived quintiles: Q2 (+0.169), Q3 (+0.258), Q4 (+0.315), and Q5 (+0.444), all significant at the 1% level. The 0.444 points gap between Q5 and Q1 is four times the low-income coefficient in the same model ($\beta=-0.055$), emphasising neighbourhood conditions have a dominant role in impacting health outcomes.

For MCS-12, residents in Q5 report mental health scores reaching 2.586 points higher than Q1 residents. This corresponds to Do (2006) who reveals that neighbourhood poverty is significantly related to worse self-rated health, irrespective of individual socioeconomic status. Bennet et al. (2024) also documents pronounced neighbourhood health inequalities that are closely tied to the deprivation patterns seen in England.

Most relevantly, low income remains a significant independent effect after controlling for IMD, $\beta=-0.055$, $p<0.001$ for SRH; $\beta=-0.322$, $p<0.10$ for MCS. This stipulates that neighbourhood-level deprivation and individual poverty exert distinct influences on health, operating through separate channels. The associated environmental conditions of neighbourhood deprivation and the material constrain of an individual's low income both predict worse health, independently. This remains consistent with the framework outlined by Fitzpatrick and Lagory (2003).

Table 4: Effects of low income and area deprivation on self-rated health and mental health

	Model 4 SRH	Model 4 MCS-12
Low income	-0.055***	-0.322*
IMD Q2	0.169***	0.933***
IMD Q3	0.258***	1.476***
IMD Q4	0.315***	1.887***
IMD Q5	0.444***	2.586***
Age	-0.043***	0.141***
Female	-0.043***	-2.437***
Married	0.142***	1.605***
Employed	0.225***	1.235***
Unemployed	-0.201***	-3.309***
Self-employed	0.304***	1.307***
White British	-0.046**	-1.134***
Urban	-0.053***	-0.497***
No qualifications	-0.179***	-0.101
N	91,030	89,512
R-squared	0.117	0.110
F-statistic	186.2	168.3
Comments	Individual-level clustered SEs. Wave FEs included but not reported. Reference: IMD Q1 non-low income. Wave 12+ subsample	

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

Place Heterogeneity: Does Place Shape the Poverty-Health Relationship?

Table 5 contains the central finding of the research question. It presents the full categorical interaction between IMD quintiles and low income, testing the specification hypothesis that differences in place amongst the poor are not fully compositional.

The results provide suggestive evidence. In the most deprived areas with Q1 as reference, the low-income coefficient is statistically indifferent to zero for both income measures (SRH: $\beta=0.001$, $p=0.984$ and MCS: $\beta=0.193$, $p=0.590$). However, in the less deprived quintiles, low income becomes associated with significantly worse health. For SRH, the Q2 and the Q5 interaction is slightly significant, $\beta=-0.087$ and $\beta=-0.086$ respectively. For MCS, the Q4 interaction is significant, $\beta = -1.169$.

These findings contribute to answering the research question of whether place shapes the poverty-health relationship. In severely deprived areas, the neighbourhood conditions' pervasive nature determines the health experiences and outcomes of all residents irrespective of personal income. Fitzpatrick and LaGory's (2003) framework extend this finding, where their view of cities is "mosaics of risk and protection". In neighbourhoods, the most deprived experience lack of services, environmental hazards, and social disorganisation which impose associated health costs on the residents no matter their individual income. This acts binding as their health outcomes dominate the possible income effect. Yen and Syme (1999) find that the socioeconomic conditions of neighbourhoods can predict health after considering individual income. The current findings extend this by observing that individual income in the most deprived areas is constrained by the neighbourhood effect, rendering their addition negligible.

In the less deprived areas, there is some evidence that the effect of one's income reasserts its relevance on health outcomes, though this should be interpreted with caution as the pattern across quintiles is not uniform. This links to Makoge and Maat's (2023) research that argues the presence and provision of supportive environments and local resources contribute to mitigating the effect poverty has on negative health effects. Where local protection is absent, the consequences of low income on health are the most visible.

Looking at mental health, Q4 observes the largest income penalty. In moderately affluent areas, low income observes a 1.169-point decrease MCS score compared to the same quintile residents that aren't classified as low income. Gravelle and Sutton (2008) and Stronks et al. (1998) documented this very mechanism, relative deprivation. Being surrounded by relative

affluence, where social comparisons entrench the experience of feeling financially inadequate create a mental-emotional burden of poverty. Stronks et al. (1998) further remarks the inability to participate in social activities alludes to more of the income-health gap than simple material deprivation. This is mostly seen in moderately richer areas where low-income individuals find themselves exposed to this social comparison effect.

That being said, many interaction terms returned results that were not significant but equally as informative. The low income and urban-rural ($p=0.178$), low income and North of England ($p=0.497$), low income and continuous IMD ($p=0.229$), and low income and age ($p=0.268$) interactions imply that the observed place heterogeneity in this poverty-health relationship is distinct to a neighbourhood deprivation dimension. It does not extend beyond to a broader demography or geography. Iqbal and Nawaz (2017) support this through their work on spatial variation in health deprivation. For them, it operates at a localised level as opposed to through broad regional patterns.

Table 5: IMD x Low Income Interaction (Wave 12+) effect on self-rated health and mental health

	Model 5 SRH	Model 5 MCS-12
IMD Q2	0.192***	1.093***
IMD Q3	0.276***	1.646***
IMD Q4	0.333***	2.129***
IMD Q5	0.463***	2.736***
Low income – Q1	0.001	0.193
IMD Q2 * Low inc.	-0.087*	-0.554
IMD Q3 * Low inc.	-0.063	-0.614
IMD Q4 * Low inc.	-0.067	-1.169**
IMD Q5 * Low inc.	-0.086*	-0.508
Age	-0.013***	0.141***
Female	-0.043***	-2.435***
Married	0.141***	1.594***
Employed	0.225***	1.237***
Unemployed	-0.202***	-3.324***
N	91,030	89,512
R-squared	0.117	0.110
F-statistic	152.7	137.2

Comments	Individual-level clustered SEs. Wave FEs included but not reported. Reference: IMD Q1 non-low income. Wave 12+ subsample
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p-value * <0.10 , ** <0.05 , *** <0.01

Robustness Checks

Table 6 includes six robustness checks, all broadly consistent with the main result.

The lagged income model ($\beta = -0.125$, $p < 0.001$), shows the previous wave's poverty status predicts current health, coherent to a causal income to health pathway. The coefficient is larger than the contemporaneous one matching Benzeval and Judge's (2001) study that those continually exposed to low income tend to propagate cumulative health effects that surpass income measures of one period.

The most important test, testing for individual fixed effects (FE) yields a balanced panel ($\beta = -0.020$, $p < 0.05$, $N = 93,540$) confirms a within-person link. Once all time-invariant individual heterogeneity is removed, low income is still significantly associated with worse health. Indeed, the coefficient with FE is smaller relative to OLS ($\beta = -0.106$) suggesting that the stable unobserved individual differences make up part of the cross-sectional gradient, whilst a veritable within-person income-health relationship remains.

Restricting to the working ages 16-64 years ($\beta = -0.122$, $p < 0.001$) and excluding the COVID waves ($\beta = -0.107$, $p < 0.001$) show little difference from the main specification. The individual FE for MCS ($\beta = -0.269$, $p < 0.05$) confirms that within the same individual, mental health does deteriorate when income falls. Adding long-standing illness to the FE model ($\beta = -0.023$, $p < 0.01$) is the most demanding test of reverse causality. It confirms the survival of the within-person income-health relationship even when health status changes are controlled for directly.

For all six specifications the low-income coefficient is negative and significant, ranging from -0.020 (FE) to -0.125 (lagged income OLS), a plausible interval for the causal income effect. The apparent consistency between estimators, samples, and various specifications provides support that low income predicts worse health outcomes in England.

Table 6: Robustness checks on the effects of low income on self-rated health and mental health

	Model 6 Lagged	Model 7 SRH FE	Model 3 Working age	Model 3 No COVID waves	Model 3 MCS-12 FE	Model 7 SRH FE + Illness
Low income		-0.020**	-0.122***	-0.107***	-0.269**	-0.0228***
Low income lagged (t-1)	-0.125***					
Age	-0.011***	0.003	-0.019***	-0.013***	0.026	0.001
Female	-0.001		-0.023**	-0.011		
Employed	0.289***	0.020*	0.381***	0.269***	-0.892***	0.014
Unemployed	-0.137***	-0.035	-0.032**	-0.140***	-2.272***	-0.035*
Self-employed	0.353***	0.055***	0.473***	0.339***	-0.407**	0.048***
Urban	-0.132***	-0.019	-0.124***	-0.136***	-0.106	-0.025
Long-standing illness						-0.320***
N	331,086	93,540	321,165	371,862	90,880	93,437
R-squared	0.123	0.090	0.114	0.125	0.018	0.120
F-statistic	260.8	168.1	210.2	335.4	38.80	225.7
Comments	Pooled OLS with individual-level clustered Ses. FE: xtreg fe. Balanced panel individuals (6,236) observed all 15 waves. Wave and region FEs included but not reported.					

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

Limitations

Whilst the combination of lagged income, individual FE, and long-standing illness address reverse causality from different angles, there still remain unobserved time-varying factors.

Acute health shocks, sudden job losses, or family rupture are some examples that may simultaneously affect income and health in the observation period and cannot fully be captured by the fixed effects or lagged income models (Benzeval and Judge, 2001).

Comparing OLS ($\beta=-0.106$) and FE ($\beta=-0.020$) provides indicative bounds on the income-health effect but may still be subject to bias. Time-varying confounders are not accounted for in the fixed effects model, and the lagged income specification may capture persistence in one's health status instead of a purely causal income effect. Benzeval and Judge (2001) wrote that a significant income-health relationship remains from longitudinal data after the controls,

so the relationship is unlikely to fully result to reverse causation, but the precise magnitude is uncertain.

Secondly, attrition is not random. Low-income individuals are 1.8% more likely to leave the sample ($p < 0.001$) and those without qualifications 5.6% ($p < 0.001$) more likely to do so. This constricts the sample to healthier and stable individuals in the later waves. The estimates of the gradient are rendered conservative; the true gradient may in fact be larger than reported, supported by Akanni et al. (2022) that add panel data reliance can underestimate potential health impacts as the most disadvantaged are subject of selective attrition.

In addition, the place heterogeneity tests are restricted to wave 12 onwards ($n=92,528$) where the sample size and time period for the main interaction term is limited in the Table 5 results, hindering the precision of the interaction estimates. Some of the interaction coefficients that may be meaningful in magnitude may be unable to reach the significance thresholds. Plus, the IMD 2019 variable is a cross-sectional profile and fails to encompass neighbourhood changes between 2019 and 2024. Individuals who have moved between waves are assigned the latest deprivation score, potentially missing out the cumulative exposure. These estimates should be interpreted with some caution.

Lastly, the SRH variable is ordinal, but the OLS specification treats it as cardinal. This simplifying assumption applies to all the SRH specifications tested in Tables 3-6. Yet, the consistency of the results across SRH and the MCS-12 (continuous) offers some support that the assumption does not materially alter the findings. Also, this research looked at England and should not be generalised to other national contexts. The income-health relationship is likely to be shaped by institutional features pertaining to the country such as healthcare access and how deprivation is spatially distributed.

Conclusion and Policy Recommendations

This study aimed to examine if place shapes the poverty-health relationship in England. With the inclusion of fifteen waves of UKHLS data and pooled OLS estimation, there is strong and consistent evidence that low income is negatively associated to self-rated health and mental health in England, a finding that holds true against a number of robustness checks.

The main contribution of this dissertation is the finding that the income-health gradient changes significantly based on the level of neighbourhood deprivation. In the most deprived

areas, the penalty is found to be effectively zero. The neighbourhood conditions are pervasive to the extent that they determine the health outcomes of residents irrespective of their personal incomes, extending the literature on area effects by Fitzpatrick and LaGory (2003), Yen and Syme (1999), and Bennet et al. (2024) with longitudinal evidence. In more advantaged areas, the reassertion of personal income on health is seen, regaining its importance as is consistent with the absolute income hypothesis.

Mental health observes the largest income penalty in moderately affluent areas, linking to the Gravelle and Sutton's (2008) relative deprivation hypothesis. They iterate that being surrounded by visible relative affluence brings about a psychosocial burden of poverty. This study's finding adds a side of behavioural economics to the place heterogeneity result. The consequences of poverty on mental health are shaped by social comparison effects that are tied to the local income distribution. Place therefore matters in a specific, coherent way: poverty is not destiny, whether low income translates in poor health depends on the neighbourhood environment an individual belongs to.

Firstly, area-based investment must accompany individual income support. In areas the most deprived, conditions such as abysmal quality of housing, environmental pollution, poor access to healthcare encroach on health outcomes to the extent that interventions such as universal credit increases, tax credit extensions, and various other income transfers are unlikely to close the health gap. The Department for Levelling Up, Housing and Communities (2022)'s Levelling Up agenda includes area-based regeneration, empirically supported by these results. Sustained investment in the social and physical infrastructure in communities, not income transfers alone, is needed to reap sizable, improved health outcomes in the most disadvantaged communities.

Secondly, where mental health service commissioning is concerned, integrated care boards should not be exclusive to the most deprived areas. The income-health gradient there is the flattest. Rather, low-income individuals in these neighbourhoods that are not deprived may be less visible but experience a mental health disadvantage that is disproportionate. The mean MCS differential between higher and lower income individuals is the largest where material resources are seemingly more abundant. Community mental health services, debt counselling, social programmes should via means-tested access to residents in these populations is justified.

Finally, income support should be sustained instead of transient. The significant lagged income result of -0.125 and the broader findings by Benzeval and Judge (2001) and Akanni et al. (2022) confirm that persistent low income is more damaging to health than temporary income shortfalls. Policies in England such as the four-year benefits freeze and two-child limit create an entrenched income disadvantage that has the largest health costs (Machin, 2021; Barnard, 2019). The fixed effects result of -0.020 supports that transitions into low income induce measurable consequences on one's health. Policy that prevents income dropping below the poverty line can have observable benefits to health, including uprating benefits in line with earnings, instead of prices alone reducing persistent relative poverty exposure.

Further research on this should look to address the three limitations of this study. Firstly, the analysis of place was restricted to four waves, since the availability of the IMD data was from wave 12 onwards. The place heterogeneity analysis extended as future waves are released can welcome an estimation of the interaction effects that is much more precise. New research can include quasi-experimental variation in neighbourhood deprivation, examples like household demolition schemes may be able to provide clearer and cleaner causal identification. Lastly, the neighbourhood deprivation variable (IMD 2019) is treated as static. A longitudinal measurement of neighbourhood changes would open up the analysis to whether neighbourhood conditions that are improved reduce the penalty in areas most deprived, creating a working evaluation of the recommendations offered.

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