Is wealth inequality associated with a Double Malnutrition burden in Pakistan?: A Multilevel analysis

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Abstract:

Background: Pakistan's progression through the demographic and epidemiological transition has been accompanied by a dual burden of under-nutrition and over-nutrition. Although higher income inequality has been found to be a risk factor for adverse nutritional conditions in many different settings using ecological study designs, few have looked at the potentially more pronounced effects of *wealth* inequality. In this study we examine whether wealth inequality is a risk factor for a double burden of malnutrition amongst reproductive aged women in Pakistan.

Methods: Using Pakistan Demographic and Health Survey (DHS) data, a three level random intercept multilevel model examined the effects of an increase in district level wealth inequality on three nutritional outcomes for women aged 15-49. Inequality was measured using the Gini index for 121 districts. A continuous measure of Body Mass Index was collected for 4,908 women and was split into nutritional status categories as per the WHO recommendations for South Asian populations. Findings were adjusted for a number of demographic, social and geographic covariates. The robustness of findings were verified using the 90/10 ratio of percentiles as an alternative measure of inequality. Evidence of interaction by education was also examined.

Results: Wealth inequality was found to be a risk factor for under-nutrition (OR 1.201; 95%CI 1.029–1.376; p=0.007) after controlling for demographic, social and geographical variables. Contrary to expectations, negligible effects of wealth inequality was found on the odds of overweight or obesity, after controlling for household wealth, for both women who had and had not received education. Findings were robust to the inequality measure used.

Conclusion: Policies focusing on improving the distribution of wealth and provision of social safety nets are recommended to reduce risk of under-nutrition among reproductive aged women. Specific aims should include reducing uncertainty around consumption and provide barriers to economic shocks such as food security or price inflation. Emphasis on nutrition education is advised to accelerate the weakening of the gradient between wealth and over-nutrition.

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Introduction

Pakistan's rapid progression through the demographic and epidemiological transition has been accompanied by a dual burden of both under-nutrition and over-nutrition (DBM).

Approximately a quarter of Pakistan's population are classified obese as per the WHO's Body Mass Index (BMI) guidelines for South Asian populations, and is particularly associated with being female, living in an urban areas, being literate and having a high socioeconomic status (Sherin 2013). Obesity is a "global epidemic and an important risk factor for developing cardiovascular diseases" (Sowers 2003; Amin et al 2015 p1), which itself can be a cause of premature death. The growing prevalence of obesity is evidence of Pakistan's path through the nutrition transition, where higher consumption of processed foods and an increasingly sedentary lifestyle (Popkin et al 2012) coincide with the stage of rising chronic diseases in the epidemiological transition.

At the same time however, according to the Demographic and Health Survey (DHS) collected in 2012-13, 13.9% of Pakistan's 84 million female population (United Nations 2015) is undernourished, which is itself associated with a number of adverse health consequences, including reduced immunity to infectious diseases (Calder and Jackson 2000).

Several risk factors for the existence of under or over-nutrition in various environments have been reported in the existing literature, including standard of living (Uustialo, Pietinen and Puska 2002; Ramachandran 2006), education level (Grabner 2008) and urban or rural residence (Ramachandran 2006). This paper aims to investigate the effect of wealth inequality as a risk factor for a DBM in Pakistan.

Literature review

Investigations into the role of economic inequality as a risk factor for a number of adverse health outcomes was prompted by the publication of Rodger's influential 1979 paper in *Population Studies.* Using aggregated data for developing countries, he concluded that people in countries with a relatively equal distribution of income could expect to live up to ten years longer than a counterpart in a relatively unequal country (Rodgers 1979; Rodgers 2002; Lynch and Smith 2002).

Different studies have aimed to explore the effects of economic inequality in a number of societies, using a wide range of health outcomes and study designs. Using an ecological study design, Kennedy et al (1996) reported a ‘statistically significant’ increase in total mortality, infant mortality, homicide, coronary heart disease and cancer as inequality increased, after adjustment for poverty and age. Kaplan et al (1996) used a similar study design to find a strong positive correlation between state income inequality and age specific all-cause mortality in the USA between 1980 and 1990, after adjusting for median state income.

Ecological studies are however limited by the inability to control for individual level confounders, including education and social status (Morgenstern 1982; Kennedy et al 1996), and the ecological fallacy of extrapolating findings to generate individual level implications. For instance, the main finding of Rogers (1979) could have been confounded by inequality in access to healthcare, social services and education (Lynch & Smith 2002).

This limitation has prompted alternative specifications of models to control for individual level confounders. Chiavegatto Filho et al (2012), using Bayesian multilevel logistic regression analysis, report a positive association between district income inequality (measured as the Gini coefficient) and poor self-reported health in Sao Paulo, Brazil, after controlling for age, individual income and education. Structural equation modelling was used to determine that income inequality affects self-reported health through the pathway of increased district level violence. As a result, levels of physical exercise decreased and caused an increased probability of poor self-reported health.

Logistic regression analysis has also been used in a number of studies investigating the association between economic inequality and nutritional outcomes. Using data from the United States, Kahn et al (1998) found that the household income inequality index (HII) is associated with a 1.04 times higher odds of weight gain at the waist for males, after controlling for age, BMI and ethnicity. The authors speculated that this was due to a biological explanation of “chronic stimulation of the stress pathway” (Marin and Bjorntorp 1993; Kahn et al 1998 p5), which in turn increases fat accumulation through the interaction of cortisol with insulin and lipoprotein lipase (Bjorntorp 1996; Kahn et al 1998 p5). No association was found for females, perhaps due to females using psychosocial support from family and friends more effectively than males (Kahn et al 1998). Subramanian et al (2007) also find, using India DHS data from 1998-99 and a multilevel logistic regression model, an increased odds of underweight and obesity of 19 per cent and 21per cent respectively, relative to normal BMI, for every standard deviation increase in state level Gini index among women 15-49, after controlling for a range of behavioural, social and demographic characteristics.

Research in the field varies with respect to the geographical level at which inequality is measured, with analysis at the level of the state being most common (Kennedy et al. 1996; Subramanian et al 2007; Shi and Starfield 2000). Evidence from Chang and Christakis (2005) suggests however that the hypothesised pathways through which inequality affects weight should be the primary factor in determining the level of geographical aggregation. Directions of association may be affected by this decision, as contrary to papers using state level exposures, they found lower odds of over-nutrition for women in metropolitan areas with higher income inequality.

Throughout the literature, many potential pathways have been proposed through which inequality could affect nutritional or health status: lower social and public service investment, due to the balance of power laying in the hands of a rich few who promote taxation levels favourable to themselves, (Kawachi and Kennedy 1999); inequality being linked to lower social cohesion which in turn leads to a lack of a social security net, in particular food security (Subramanian et al 2007; Martin et al 2004; Townsend et al 2001); psychosocial pathways, where "relative deprivation and diminished social capital invoke, implicitly or explicitly, some process of individual comparisons" (Chang and Christakis 2005 p85); or the fact that more unequal societies spend proportionately less on community level education or healthcare, have lower education levels and have relatively fewer people medically insured (Kaplan et al 1996; Diez-Roux 2000 p684).

The uniformity in the literature in only considering effects of income inequality, instead of other measures of disparities, has been criticised by Nowatzki (2012). Using a bivariate cross sectional study design, she found a strong significant negative association between wealth inequality and population health, after adjusting for state level per capita GDP. Nowatzki argues that the exclusive focus on income inequality in the existing literature has led to underestimation of the effects economic inequality has on health. This is due to the fact that use of "health promoting resources" and the balance of "political power" (two potentially mediating factors through which wealth inequality could affect nutritional status or population health) are more strongly associated with wealth than income. This negative association led Nowatzki to favour a more progressive tax on wealth and the general promotion of wealth redistribution.

Although a small number of papers claim to demonstrate limited evidence of an association between population health and inequality when using aggregated data (Gravelle et al 2002), and after having controlled for individual level factors (Mackenbach 2002) the literature is generally supportive of an association between economic inequality and population health or nutritional status.

The following paper aims to add to the existing wealth of literature by using the most up to date DHS data set on Pakistan, to investigate the association between district level wealth inequalities and a DBM among women 15-49 years. Analysis was restricted to women as the DHS is a female focused survey and equivalent data on males was unavailable.

This study aims to overcome the problems associated with ecological studies in this field by controlling for individual level confounders; an improvement considered as vital by a number of researchers (Wagstaff and van Doorslaer 2000; Wolfson et al 1999; Deaton 2001; Lynch and Smith 2002 p550). Moreover, the study will use two separate measures of inequality to observe whether associations are robust to the inequality measure used.

Finally, unlike previous studies, this investigation will measure the effects of *wealth* inequality, rather than income inequality, on the probability of under and over-nutrition. Advantages of looking at wealth inequality include the fact that it "is able to better capture the structural and relational aspects of inequality because it more accurately reflects differences in power", which is able to be used by the rich to "create social arrangements most likely to sustain and expand their existing bases of power and influence" (Oliver and Shapiro 2006; Nowatzki 2012 p405).

Aims and Objectives

For this investigation, I hypothesise the following:

1. Irrespective of socioeconomic status, women residing in more equal districts are less likely to be underweight, overweight and obese. The association between inequality and a DBM is expected to hold due to the association working through a number of other pathways outlined in Figure 1.
2. The effect of wealth inequality is stronger if a woman has no education. Women with no education are likely to be "more exposed to the psychosocial or material consequences of living in an unequal society" (Diez-Roux 2000 p674).

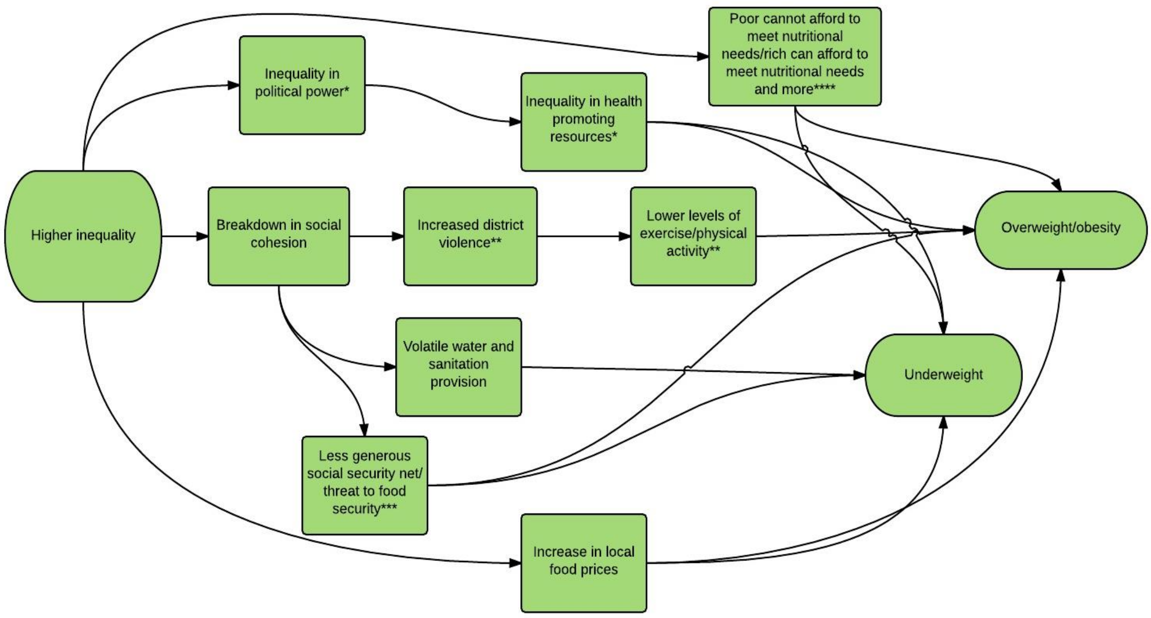

Figure 1. Association between inequality and nutritional status: proposed pathways
** Nowatzki (2012)*
*** Chiavegatto Filho (2012)*
**** Martin et al (2004); Townsend et al (2001);* Subramanian et al (2007)
***** Subramanian et al (2007)*

Data and Methods

The 2012-13 Pakistan Demographic and Health Survey (DHS) is a household survey collected and funded by the Pakistan Planning and Development Division and the United States Agency for International Development (USAID) respectively. The cross sectional survey was carried out in order to "provide reliable estimates of key fertility, family planning, maternal, and child health indicators at the national, provincial, and urban and rural levels" (NIPS & ICF International 2013, p4). It was designed to be representative of the populations of all of Pakistan except for the provinces of Azad Jammu and Kashmir, FATA and other restricted areas.

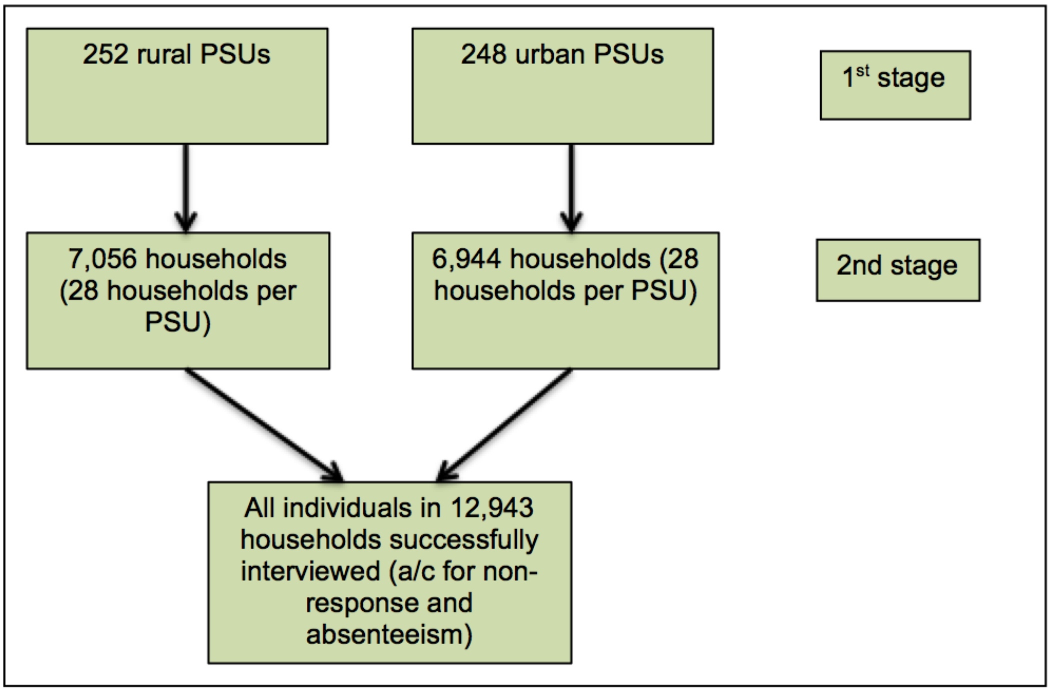

Figure 2. Two-stage stratified sampling in collection of DHS Pakistan 2012-13

**Primary sampling unit*

In order to generate the required estimate precision, a sample size of 14,000 households were chosen from 248 urban areas and 252 rural primary sampling units (PSU) using a two-stage stratified sampling approach (Figure 1). PSUs represented villages and enumeration blocks in rural and urban areas respectively, and were chosen with a probability proportional to size. Using a systematic sampling approach, with a starting point determined at random, 28 households from each PSU were chosen, and data on every available household member collected. Sampling weights were provided in the data to account for the oversampling of urban areas, and Baluchistan and Khyber Pakhtunkhwa (relatively smaller provinces) (Janjua et al 2015).

Ethical approval

DHS data was downloaded with all names or personal identifiers already removed. Ethical approval to use this data was obtained on 14/04/2015 by the London School of Hygiene and Tropical Medicine (Ref: 9603).

Variables

The Pakistan DHS 2012-13 Individual Recode, containing information on 13,558 women aged 15-49, was used for my investigation.

Outcomes

The three key outcomes used in the analysis were derived from a continuous measure of Body Mass Index (BMI). The variable excluded pregnant women and women who had had given birth two months prior to the collection (NIPS & ICF International 2013). Anthropometric measures were collected for women in every third household, yielding a total study population of 4,908.

Body Mass Index, measured in kg/m^2, was grouped into 3 separate dummy variables, based on the WHO's recommendations of BMI cut-offs for South Asian populations [1] (Subramanian et al 2007; WHO 2004). The variables were grouped as follows:

- *'Underweight'* – equal to 1 if BMI was less than 18.5kg/m^2
- *'Overweight'* – equal to 1 if BMI was between 25.0 and 29.9kg/m^2
- *'Obese'* – equal to 1 if BMI was greater than 30kg/m^2

Each of the outcome variables equalled zero if the respondent was classified as having a normal BMI (between 18.5 and 24.9kg/m^2).

[1] Different BMI cut-offs for South Asian populations are necessary as they present a higher risk of chronic diseases at lower BMI scores. One possible reason is the "effect of poverty and resultant malnutrition during intrauterine and early childhood years, coupled with relative overnutrition in later years" (Jafar et al 2006 p1071; Bhargava et al 2004).

The original continuous variable was inspected for missing data and outliers. No recorded responses were identified as extreme outliers; however, flagged cases (22 of the 4908 responses) and non-responses (210) were reclassified as missing as no other appropriate recoding option was available. Measurement error of BMI, including differences in between observers or by the same observer, was not expected to be considerable as measures were objective.

Key exposure

The key exposure measuring district level wealth inequality was the Gini coefficient (Figure 3)[2]; widely considered as the Gold Standard of inequality measures (Galbraith 2014). The coefficient is obtained by comparing the Lorenz curve of wealth distribution (blue line) against a line of perfect equality of wealth distribution (red colour line) for each district independently. It is calculated as the ratio of the area between the blue and red line to the area enclosed by the red line and the line of perfect inequality (Kennedy et al 1996 p1007). The coefficient is equal to one if there is perfect inequality and zero if there is perfect wealth equality. The GINI coefficient was calculated for 121 districts in the data set. Figure 3 graphically shows the larger deviation of the Lorenz curve from the line of perfect equality compared to the district in Figure 4, thus creating a higher Gini score.

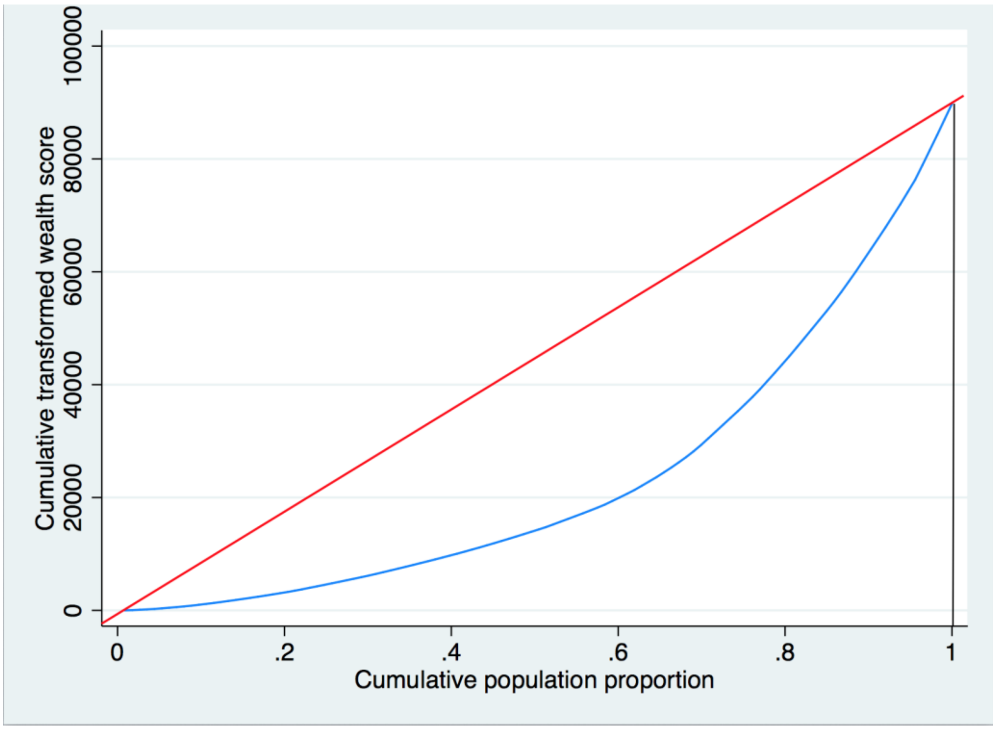

Figure 3. Lorenz curve of district 201 in Sindh (Gini 50.66)

[2] Lorenz curve created using the 'glcurve' command created by Phillipe van Kerm and Stephen Jenkins

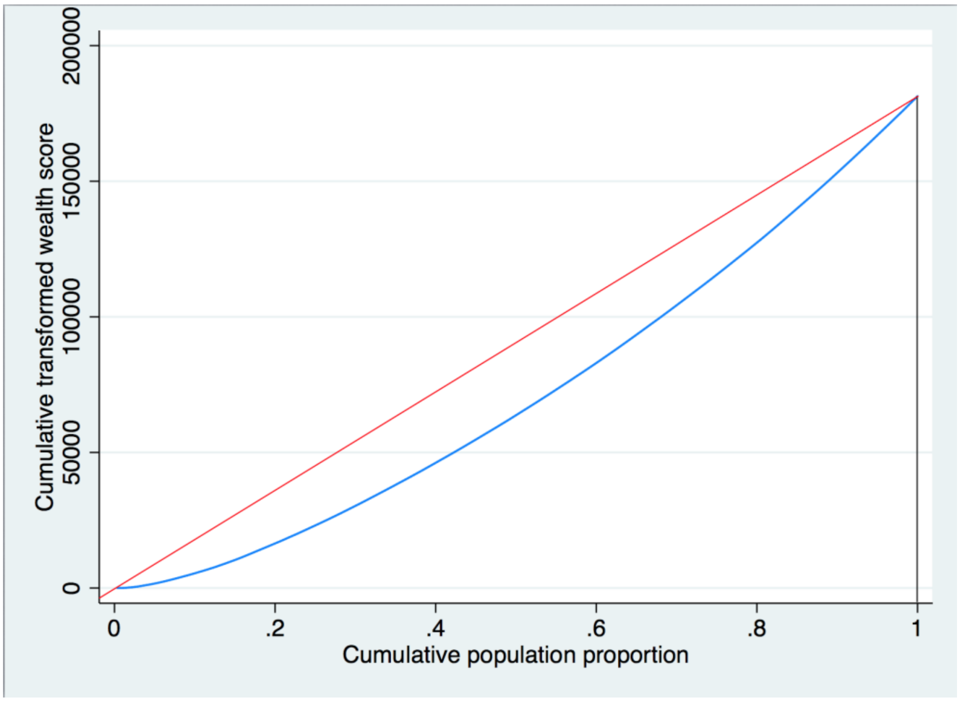

Figure 4. Lorenz curve of district 117 in Punjab (Gini 17.43)

The wealth index in the data set, used to generate the Gini coefficients, was created using a three-step process where initially, household wealth scores are created using indicators of wealth relevant in both urban and rural settings, before creating separate scores for urban and rural households. The third step involves adjusting scores in the second step using scores collected in the first (NIPS & ICF International 2013). The index is formed as a combination of binary variables relating to household possessions, construction and utilities to represent socioeconomic position (Janjua et al 2015).

In order to use the index for the creation of the Gini coefficient, the scores were transformed from an index with a mean of 0 and standard deviation of 1 into a continuous measure. This was done by adding the minimum wealth score in each district to each of the individual wealth scores, as per recommendations by the DHS team.[3] Gini coefficients were calculated by running the *'inequal7'*[4] command on STATA separately for each district.

A measure of 90/10 ratio of percentiles (ROP) was also calculated separately for each district, in order to observe the extent to which findings were dependent on the measure of inequality chosen. This measure is derived by dividing the transformed wealth score at the

[3] Recommendations were provided by a senior member of the DHS team under the forum thread "Gini-Income inequality". See References section for link.
[4] '*inequal7'* command was developed by Phillipe van Kerm

90th percentile by the score at the 10th percentile[5] (Galbraith 2014). The Theil and Robin Hood indices were also considered for further analysis however they were too strongly correlated with the Gini coefficient (r=0.99 and 0.97 respectively), therefore their analysis would have been of little value. The correlation coefficient for the 90/10 ratio of percentiles with the Gini coefficient was 0.83.

<u>Covariates</u>

The choice of explanatory variables, to control for confounding of the association between inequality and the outcomes, was informed by literature and through independent analysis of the dataset (reasoning that they are not on the causal pathway between wealth inequality and nutritional status; that they are associated with wealth inequality; and that they are a risk factor for the outcome). Correlation coefficients were used to observe the association between continuous variables and the Gini index, linear regression was were used to observe the associations between categorical variables and the continuous Gini index, and cross tabulations with row percentages used to identify associations between two categorical variables. Continuous variables correlated with the primary exposure with a correlation coefficient greater than r=|0.7| were also omitted from inclusion to avoid collinearity (Dormann et al 2013). The following demographic, social, and geographical variables were used in the analysis:

Age – Age was included as an *a priori* covariate. It was collected by the DHS and included as a continuous variable.

Household size – Household size varies from 1 to 48 in the dataset. The variable was grouped into 4 categories – 1-2 members; 3-4 members; 5-9 members; and 10+ members. The larger groupings in the last two categories were done due to the smaller marginal effect of additional members at higher household sizes.

Marital status – Marital status was grouped as 1 for married women; 2 if widowed; 3 if divorced; and 4 if separated.

Ethnicity – Ethnicity was grouped into several groups: Punjabi, Sindhi, Urdu, Balochi, Pushto, Saraiki and other. The 'other' category was created to group smaller ethnic groups.

[5] 90/10 ratio of percentiles was calculated using the '*ineqdeco'* command created by Stephen Jenkins at the London School of Economics

Respondent's occupation **–** Three categories were created relating to occupation – 'manual labour', 'non-manual labour', and 'not working'. 'Manual labour' included professions such as tailors or blacksmiths, 'non-manual' included women working as teachers or clerical workers, and the 'not working' category included both housewives and unemployed women. This grouping was undertaken to avoid problems relating to sparse data as more than fifty different professions were listed in the original variable.

Respondent's education **–** For ease of interpretation, a dummy variable equal to 1 if the respondent had at least primary education, and 0 if the respondent had no education, was created.

Urban/rural residence **–** Residence was set equal to 1 if the woman resides in an urban area and 0 if she resides in a rural area.

Individual wealth quintile **–** Wealth quintiles are provided in the DHS data and are derived by ranking individual members of the population by household wealth score and splitting the population into five equally sized quintiles.

Median district wealth **–** This measure of wealth, aggregated at the district level, was obtained by taking ranking the population, by wealth score, in each district separately and selecting the middle wealth score. As this variable was highly correlated to the GINI index (r=-0.730), I decided not to include it in the models in order to avoid multi-collinearity.

<u>Statistical analysis</u>

As the explicit aim of this paper was the investigation of the effect of a district level indicator on an individual level binary outcome, and in order to model the unobserved heterogeneity in the outcome between subjects at a particular level after controlling for confounders in the hierarchical dataset, a three-level random intercept multilevel logistic regression model was adopted (Nguyen et al 2014; Subramanian et al 2007; Rabe-Hesketh and Skrondal 2006). Multilevel modelling enabled me to account for the clustered nature of the data and to avoid underestimation of standard errors. As within cluster variation is smaller than between cluster variation, this can cause Type I errors (Steele 2008; Osorio 2013). A multilevel model with a random slope was not chosen, as no *a priori* assumptions about variations in the association of interest between clusters was made.

The Stata 13 command '*gllamm*'[6] was used to fit the multilevel model as it allowed the inclusion of sampling weights. With the specific aim of investigating the first hypothesis, the following regression was used, which measures the effect of wealth inequality on the log odds of the three outcomes specified in the previous section:

$$log(\pi/1-\pi)_{i,j,k} = \beta_0 + (\beta_1 gini_k + \beta_2 \theta) + (\varphi_{j,k} + \omega_k)$$

β0 refers to the constant term, and *β1,* the effect of a unit increase in the Gini coefficient on the log odds of the three outcomes relative to a normal BMI for woman *i,* nested in PSU *j,* nested in district *k*. If the distribution of the exposure was found to be relatively symmetrical, results were expressed in terms of a one standard deviation increase in the exposure. For ease of interpretation, coefficients were transformed into odds ratios (OR) using the exponentiation function. The notation *β2* represents the coefficients on the covariates and interaction terms, and the φ and ω terms represent the PSU level and state level random effects respectively. The random effects are assumed to follow a normal distribution.

The complex survey design and heterogeneous selection probabilities in the data were accounted for by including sampling weights. The *'gllamm'* command requires weights to be specified at each level in the analysis. Therefore, using the formula below, first expressed in Goldstein (1999) and also used by Osorio et al (2013 p9), weights at the PSU level were derived from the total design weights included in the data:

$$w_j = (\Sigma_j w_{ij} / n_j) \; / \; (\Sigma_j (\Sigma_j w_{ij} / n_j)) \; / \; J$$

Where, wj refers to the inverse probability of a PSU being chosen; wij represents the total individual level weight in the DHS; nj, the number of individuals in PSU j; and J, the total number of PSUs. Following recommendations in Pfefferman et al (1998); Asparouhov (2006); Carle (2009); and Osorio et al (2013), individual level weights were rescaled to sum up to the cluster sample size (Method A in Chantala et al (2011)). The *'gllamm'* command further requires rescaling of weights if they pertain to levels lower than the highest level (Jeon 2012). Secondary rescaling, using the same method to account for the three tier structure of the model was undertaken, using original sampling weights of 1 for the districts as all districts in the sampled provinces were selected.

[6] 'Gllamm' was created by Sophia Rabe-Hesketh of UC Berkeley.

Modelling approach

A forward stepwise approach was adopted in the final statistical analysis, where covariates were added incrementally to observe the changes in the measure of effect of the Gini coefficient (Pearce 2015). This was done in order to incorporate a form of causal modelling into the analysis. Rather than focusing explicitly on p-values of added covariates, if the measure of effect of the inequality measure changed by five per cent or more[7], the covariate was kept in the model. Confounders may be of public health importance but not yield 'statistically significant' Wald test statistics if it is not highly variable across the study population (Pearce 2015). This procedure was repeated for each of the three binary outcomes.

If it was hypothesised from the outset that the measure of effect varies by the level of a third variable (effect modification), OR specific to each stratum of the third variable were derived using the *'mhodds'* command (Hypothesis 2). The null hypothesis of no difference in the odds ratios after stratification was tested to confirm whether evidence of effect modification was present. Due to the low power of the test[8], only *a priori* effect modifiers were considered, and the relatively high p-value cut-off of $p<0.1$ was used when deciding if evidence of interaction was present. This was accounted for in the model by generating interaction terms, and presenting stratum-specific odds ratios, rather than summary measures.

A null model was run for each of the outcomes, wherein no explanatory variables were included. Variance at each level was represented by the random effects generated and was used to provide reasoning for the multilevel approach as opposed to a single level analysis (Nguyen et al 2014). Further to this, five models for each outcome were created: Model 1, the bivariate model, included just the district level Gini index in order to observe the unadjusted crude effect of inequality on the odds of the binary nutritional responses; Model 2 contained adjustment for the *a priori* covariate, age; Model 3 included the remaining demographic variables household size, marital status and ethnicity; Model 4 included additional variables relating to the respondents social or geographical characteristics; and Model 5 further included a measure of socioeconomic status, the wealth index quintile.

[7] The choice of a five per cent cut-off is somewhat arbitrary. It is lower than the 10 per cent cut-off recommended by Pearce (2015) in order to be as inclusive as possible when covariates only marginally change the measure of effect of interest.

[8] The test for homogeneity in odds ratios is often poorly powered, thus increasing the chances of accepting homogeneity when OR may in fact be different (Rothman et al 2008; Breslow and Day 1980).

Summary p-values for categorical variables were provided, using the *testparm* command, rather than p-values for each category for ease of interpretation.

Any considerable changes to the standard error of the Gini coefficient was inspected after covariates were added and omitted if the standard error changed my more than a half in order to avoid multi-collinearity. It was also ensured that the number of events per variable remained above 10 in order to avoid biased odds ratios, as per recommendations in Peduzzi et al (1996).

Results

Initial cross tabulations of the outcomes with the covariates were conducted to gain an understanding of what under and over-nutrition is associated with in the data. While just under a half of Pakistan's reproductive aged female population has a normal BMI score, 14.21 per cent (95%CI 12.66-15.93) were classified as obese and 12.98 (CI 11.35-14.80) classified as underweight. Table 1 also shows that women with some education, women living in urban areas, widowed women and women living in households with between 1 to 2 people are more likely to be overweight or obese than underweight.

	Underweight % (95%CI)	Normal % (95%CI)	Overweight % (95%CI)	Obese % (95%CI)
Education				
No education	15.67	51.25	22.13	10.94
	(13.58-18.02)	(48.61-53.89)	(19.78-24.68)	(9.18-13.00)
Some education	9.44	43.14	28.91	18.51
	(7.74-11.47)	(40.12-46.21)	(26.13-31.85)	(16.13-21.16)
Residence				
Rural	15.83	52.14	21.46	10.57
	(13.62-18.33)	(49.64-54.63)	(19.14-23.98)	(8.70-12.78)
Urban	7.23	38.9	32.32	21.55
	(5.69-9.14)	(36.07-41.80)	(29.32-35.47)	(19.23-24.07)
Region				
Punjab	12.86	45.53	25.16	16.45
	(10.51-15.64)	(42.69-48.40)	(22.30-28.26)	(14.09-19.12)
Sindh	18.51	53.31	19.29	8.88
	(15.53-21.92)	(49.21-57.37)	(16.24-22.76)	(7.04-11.15)
Khyber Pakhtunkhwa	6.06	44.5	33.48	15.95
	(4.13-8.82)	40.79-48.29)	(29.73-37.45)	(12.63-19.95)
Baluchistan	8.31	54.93	29.86	6.90
	(5.14-13.17)	(46.79-62.81)	(21.62-39.64)	(3.65-12.69)
Gilgit Baltistan	5.26	80.9	11.21	2.63
	(2.63-10.25)	(74.12-86.24)	(7.71-16.02)	(1.20-5.68)
Islamabad	6.87	36.46	32.06	24.61
	(4.34-10.70)	(30.57-2.79)	(26.75-37.87)	(20.46-29.30)
Wealth Index				
Poorest	24.42	59.28	12.23	4.06
	(19.54-30.06)	(54.50-63.90)	(9012-16.22)	(2.45-6.67)
Poorer	16.5	58.08	18.79	6.63
	(13.27-20.32)	(54.16-61.91)	(15.89-22.08)	(4.91-8.91)
Middle	13.17	48.92	24.54	13.37
	(10.57-16.29)	(44.36-53.50)	(20.75-28.76)	(10.74-16.54)
Richer	8.38	39.83	31.80	20.00
	(6.07-11.45)	(35.77-44.03)	(28.02-35.82)	(16.7-23.76)

Richest	4.12	35.06	35.76	25.06
	(2.78-6.06)	(31.43-38.87)	(31.55-40.21)	(21.58-28.89)
Marital Status				
Married	12.75	48.37	24.75	14.13
	(11.10-14.61)	(46.35-50.39)	(22.79-26.82)	(12.56-15.86)
Widowed	11.74	35.65	32.74	19.87
	(6.66-19.87)	(26.67-45.77)	(23.71-43.26)	(12.65-29.79)
Divorced	35.69	15.19	37.96	11.16
	(15.74-62.25)	(4.53-40.33)	(17.27-64.21)	(2.72-36.05)
Separate	24.19	48.64	21.07	6.10
	(10.49-46.48)	(28.08-69.67)	(7.80-45.74)	(8.40-33.22)
Household size				
1 to 2	8.81	46.79	25.27	19.13
	(3.20-22.01)	(33.87-60.16)	(14.93-39.46)	(10.20-33.01)
3 to 4	13.21	45.45	27.35	13.99
	(9.56-17.97)	(40.02-50.98)	(22.89-32.31)	(10.60-18.25)
5 to 9	12.87	45.67	25.80	15.67
	(11.02-14.97)	(42.99-48.37)	(23.52-28.21)	(13.70-17.86)
10+	13.38	53.2	22.44	10.98
	(10.67-16.66)	(49.51-56.85)	(19.05-26.23)	(8.49-14.09)
Total	12.98	47.75	25.06	14.21
	(11.35-14.80)	(45.73-49.77)	(23.11-27.12)	(12.66-15.93)

Table 1. Proportion of women in the four BMI categories (n=4676) (2dp)

**Cross tabulations calculated after using 'svy' prefix to account for complex survey design*

The Gini measure of inequality followed an approximately normal distribution (Figure 5) and ranged from 14.67 to 59.13 across the 121 districts for which the index was calculated in Pakistan. The mean Gini coefficient was 35.53, with a standard deviation of 9.87. Table 2 shows the variation in the Gini coefficient by province. Inequality is highest in Sindh and lowest in Islamabad.

Province	No. districts	Mean Gini	Standard deviation
Punjab	36	31.51	8.55
Sindh	27	40.13	12.28
Khyber Pakhtunkhwa	24	35.99	6.93
Baluchistan	26	37.01	9.08
Gilgit Baltistan	7	34.24	8.07
Islamabad	1	15.58	.
Pakistan	121	35.53	9.86

Table 2. Mean and standard deviation of Gini coefficient by province (2dp)

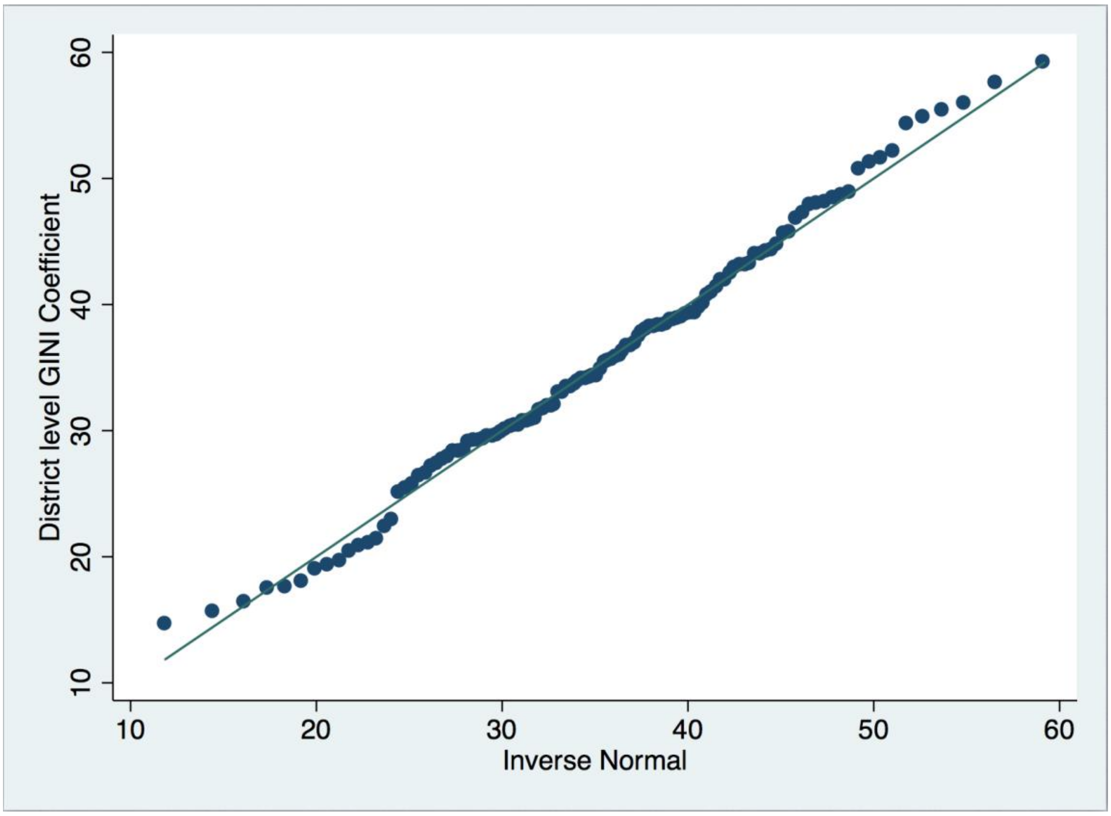

Figure 5. Distribution of the GINI coefficient (points lying close to the 45 degree line indicate an approximately normal distribution)

Regression Analysis

Using the methodology outlined in the previous section, separate multilevel analyses were run for the three binary outcomes. The null models, including just the constant term and the random intercepts at the PSU and district levels, provided evidence of variation in each of the outcomes across PSUs and districts. The p-values for each likelihood ratio test, testing the null hypothesis that between PSU and between districts variance in the logged outcome is zero, indicate that these results are unlikely to be due to chance (Table 3). Figures 6 and 7 provide graphical representation of PSU and district residuals, with 95 per cent confidence intervals, for obesity, providing justification of the use of the multilevel model.

	Variance PSU (p-value*)	**Variance District (p-value)**
Underweight	0.090 ($p<0.001$)	0.497 ($p<0.001$)
Overweight	0.298 ($p<0.001$)	0.368 ($p<0.001$)
Obese	0.705 ($p<0.001$)	0.843 ($p<0.001$)

Table 3. Between cluster variance for each outcome in the null models (3dp)

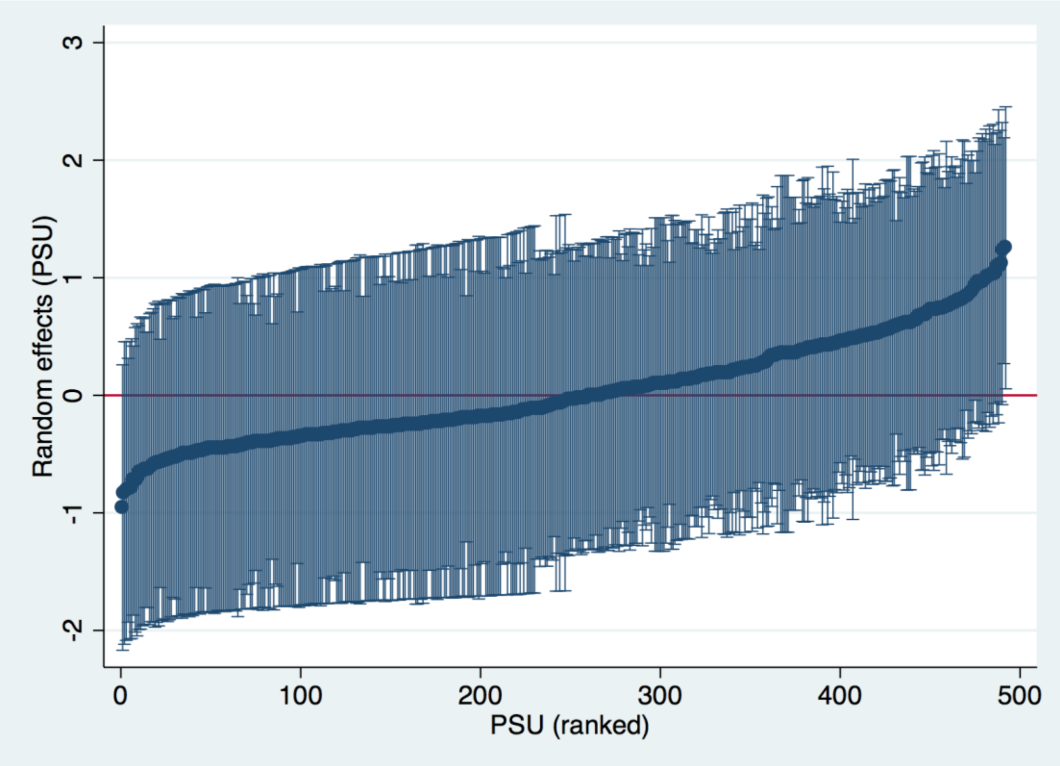

Figure 6. Between PSU variance in obesity, and 95% confidence intervals

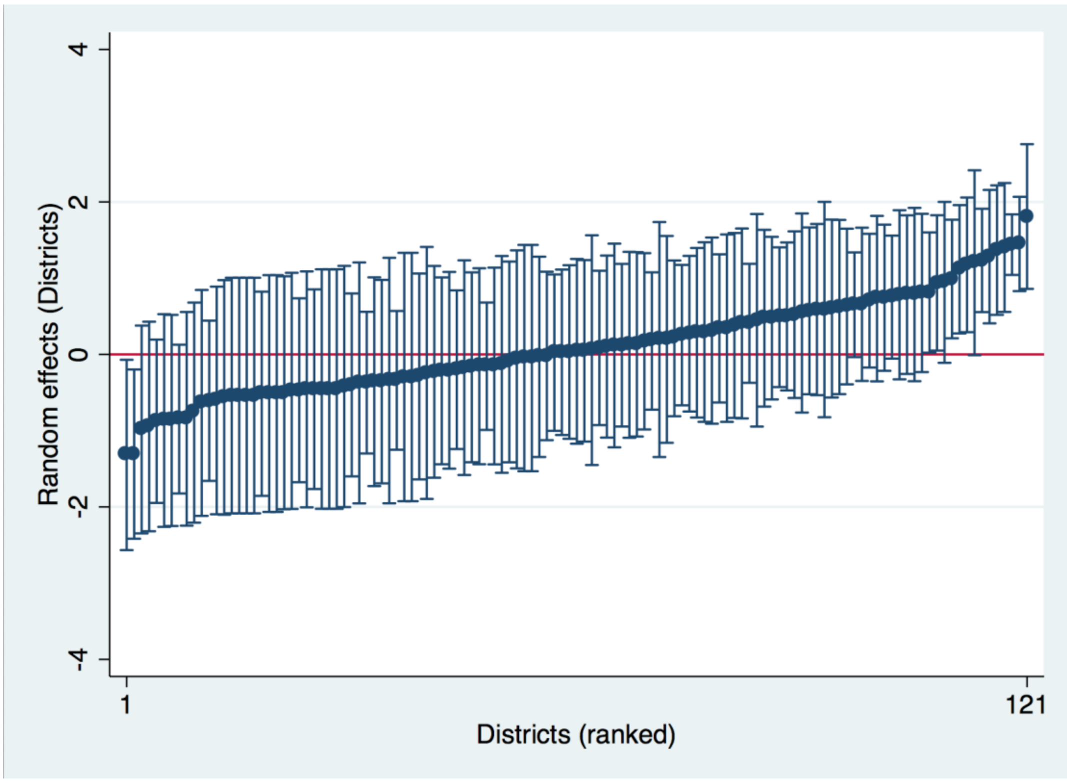

Figure 7. Between district variance in obesity, and 95% confidence intervals

Tables 5-7 show the forward stepwise regression output for the three outcome variables. Model 1, which includes exclusively the main exposure of interest, indicates that a one standard deviation increase in the district Gini index (approximately a 10 per cent increase) is associated with a 37.5 per cent (95%CI 1.236 - 1.516; p<0.001) increased risk of underweight, relative to the normal BMI category in a given cluster. Equivalent analysis for the two overweight variables suggest that a standard deviation increase in the Gini index is associated with 35.2 per cent (OR 0.648; 95%CI 0.496 – 0.803; p<0.001) lower risk of overweight compared to normal weight, and a 43.5 per cent (OR 0.565; 95%CI 0.384 - 0.750; p<0.001) lower risk of obesity.

The inclusion of age in the model, the only *a priori* covariate, had a negligible effect on the main measure of effect for all three outcomes (Model 2). Adjustment for household size had a minimal effect on the odds of underweight and overweight for an increase in the GINI coefficient, and was thus omitted from the models. The same was true when attempting to adjust for marital status in the obesity model.

When adjusting for a number of demographic variables in Model 3, the effect of a one standard deviation increase in the Gini index on the odds of underweight fell to 1.312 (95%CI 1.170 - 1.456; p<0.001). The odds of overweight and obesity also moved closer to one after the same adjustments, demonstrating some confounding effect of the demographic variables.

Model 4, additionally adjusting for the woman's education, her occupation, and geographical variables, led to a decrease in the effect of a one standard deviation increase in inequality on the odds of underweight, from 1.312 to 1.246 (95%CI 1.103 - 1.390; p=0.001). The direction of this relationship remained after controlling for standard of living, although the association was slightly weaker (OR 1.201; 95%CI 1.029 to 1.376; p=0.007). The results of the Wald hypothesis test indicated that a strength of association of this magnitude or larger could be expected to be found 7 in 1000 times, upon multiple repetitions of the sample (Model 5).

Stratification by the binary education variable indicated a stronger effect of the Gini index on the odds of overweight and obesity if a woman had received no education. The test of homogeneity, testing the null hypothesis of equivalent odds ratios for those with no education and those with some education, indicate that these differences were unlikely to be chance findings.

	Underweight	Overweight	Obese
No education	1.325 (1.187 - 1.453)	0.734 (0.645 - 0.832)	0.586 (0.458 - 0.714)
Some education	1.286 (1.128 - 1.453)	0.901 (0.803 - 1.000)	0.921 (0.813 - 1.039)
Test of homogeneity			
Chi2 value (1)	0.100	5.220	14.980
p-value	*0.751*	*0.023*	*<0.001*

Table 4. Stratification, by education, of the effect of a one standard deviation increase in Gini coefficient on odds of underweight, overweight and obesity (3dp)

Consequently, Models 4 and 5 for the outcomes overweight and obese present measures of effect stratified by education. Results of the stratification indicate that the summary measures previously presented masked the modifying effect of education. After controlling for social, demographic and geographical variables in Model 4, there is a negligible effect of a one standard deviation increase in inequality on the odds on overweight (OR 0.998; 95%CI 0.995 – 1.001; p=0.149) and some effect on the odds of obesity (OR 0.987; 95%CI 0.980 – 0.994; p<0.001) among women who have received at least some education, in a given cluster. Among women with no education, the equivalent increase in the Gini index was associated with 0.868 times the odds of overweight (95%CI 0.696 – 1.044; p=0.140) and 0.714 times the odds of obesity (95%CI 0.448 – 1.000; p=0.048). Hypothesis tests indicate that there is some evidence to reject the null hypothesis of no association between inequality and obesity, amongst women who had received no education, after controlling for the demographic and social variables. However the equivalent Wald test for the overweight outcome suggested that such a magnitude of effect or larger could expect to have been seen 14 per cent of the time upon repeated samples.

Model 5, in which standard of living quintile was added, showed that being in higher wealth quintiles was associated with higher odds of obesity and overweight. For instance, being in the richest quintile, compared to the poorest was associated with 6.181 times higher odds of obesity (95%CI 3.045 – 12.547; p<0.001). After adjusting for the effect of standard of living, there appeared to be no association between district level inequality and odds of overweight and obesity for neither women who hadn't received any education nor women who had received some education.

Results of the extended analysis aimed to assess whether the findings obtained were robust to alternative measures of wealth inequality. Tables 9-10 in Appendix A show a negative association between wealth inequality, as measured by the 90/10 ratio of percentiles, and overweight/obesity before adjusting for individual level standard of living, for women with no education. After adjustment for wealth quintile however, the association approaches the null, and any observable association is likely to be due to chance, as indicated by the Wald test statistics and corresponding p-values. These findings are consistent with what was found when using the Gini index as the inequality measure. Moreover, the positive relationship between inequality and the odds of underweight holds even before and after adjustment for wealth quintile; also consistent with findings of the main analysis.

UNDERWEIGHT	Model 1			Model 2			Model 3			Model 4			Model 5		
	OR* / *p-value*	**95% CI**		**OR* / *p-value***	**95% CI**		**OR* / *p-value***	**95% CI**		**OR* / *p-value***	**95% CI**		**OR* / *p-value***	**95% CI**	
Gini**	1.375	1.236	1.516	1.370	1.233	1.510	1.312	1.170	1.456	1.246	1.103	1.390	1.201	1.029	1.376
	<0.001			*<0.001*			*<0.001*			*0.001*			*0.007*		
Age				0.991	0.978	1.004	0.988	0.975	1.001	0.986	0.973	0.998	0.988	0.972	1.003
				0.172			*0.064*			*0.029*			*0.065*		
Marital Status															
Married							1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Widowed							1.494	0.804	2.775	1.482	0.776	2.829	1.462	0.707	3.025
Divorced							10.605	2.123	52.961	10.300	1.991	53.300	10.404	2.030	53.320
Separated							2.087	0.726	6.003	1.846	0.665	5.125	1.862	0.683	5.073
							0.008			*0.012*			*0.021*		
Ethnicity															
Urdu							1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Punjabi							1.133	0.710	1.807	0.834	0.495	1.406	0.756	0.440	1.300
Sindhi							1.486	0.883	2.499	1.282	0.722	2.278	1.148	0.623	2.117
Pushto							0.357	0.189	0.676	0.324	0.136	0.771	0.296	0.132	0.664
Balochi							1.491	0.834	2.666	1.181	0.631	2.212	1.043	0.528	2.060
Saraiki							0.999	0.613	1.629	0.734	0.423	1.274	0.666	0.370	1.197
Other							0.946	0.506	1.766	0.887	0.424	1.856	0.806	0.417	1.559
							<0.001			*<0.001*			*<0.001*		
Education															
No education										1.000	1.000	1.000	*1.000*	1.000	1.000
Some education										0.908	0.660	1.250	1.039	0.738	1.464
										0.555			*0.836*		
Respondent's Occupation															
Not working										1.000	1.000	1.000	1.000	1.000	1.000
Non-manual labour										0.667	0.282	1.582	0.694	0.278	1.731
Manual labour										1.347	1.007	1.801	1.294	0.974	1.720
										0.059			*0.118*		
Province															
Punjab										1.000	1.000	1.000	1.000	1.000	1.000

Sindh										0.849	0.635	1.135	0.845	0.601	1.187
Khyber Pakhtunkhwa										0.914	0.483	1.731	0.893	0.492	1.620
Baluchistan										0.504	0.259	0.979	0.495	0.284	0.864
Gilgit Balistan										0.241	0.106	0.544	0.212	0.088	0.509
Islamabad(ICT)										1.287	0.874	1.895	1.484	0.797	2.761
										<0.001			*<0.001*		
Residence															
Rural										1.000	1.000	1.000	1.000	1.000	1.000
Urban										0.788	0.575	1.080	0.950	0.660	1.370
										0.139			*0.785*		
Wealth Quintile															
Lowest quintile													1.000	1.000	1.000
2nd quintile													0.869	0.576	1.312
3rd quintile													0.882	0.564	1.378
4th quintile													0.721	0.408	1.274
Highest quintile													0.435	0.226	0.840
													0.169		
Constant	0.069	0.041	0.116	0.092	0.050	0.170	0.119	0.060	0.239	0.218	0.092	0.514	0.298	0.105	0.847
	<0.001			*<0.001*			*<0.001*			*0.001*			*0.009*		
Level 1 units	2804			2804			2804			2804			2804		
Level 2 units	480			480			480			480			480		
Level 3 units	121			121			121			121			121		

Table 5. Fixed effects from the multilevel model (outcome Underweight) (3dp)

**OR are conditional on PSU and district level random effects*

***Measures the effect of a one standard deviation increase in Gini index*

OVERWEIGHT	**Model 1**			**Model 2**			**Model 3**			**Model 4**			**Model 5**		
	OR* / *p*-*value*	**95% CI**		**OR* / *p*-*value***	**95% CI**		**OR* / *p*-*value***	**95% CI**		**OR* / *p*-*value***	**95% CI**		**OR* / *p*-*value***	**95% CI**	
Gini**	0.648	0.496	0.803	0.655	0.503	0.811	0.846	0.697	0.997						
	<0.001			*<0.001*			*0.045*								
Gini * Education Interaction															
No education										0.868	0.696	1.044	1.001	0.819	1.186
										0.140			*0.002*		
Some education										0.998	0.995	1.001	1.000	1.000	1.000
										0.149			*0.480*		
Age				1.048	1.035	1.060	1.046	1.034	1.058	1.051	1.039	1.064	1.047	1.035	1.060
				<0.001			*<0.001*			*<0.001*			*<0.001*		
Household size															
1 to 2							1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3 to 4							1.323	0.778	2.251	1.342	0.787	2.290	1.484	0.877	2.509
5 to 9							6.038	2.219	16.434	6.333	2.411	16.636	6.860	2.381	19.765
10 +							0.713	0.236	2.156	0.715	0.241	2.118	0.707	0.191	2.615
							0.001			*<0.001*			*<0.001*		
Ethnicity															
Urdu							1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Punjabi							0.735	0.507	1.067	0.870	0.596	1.271	0.913	0.626	1.334
Sindhi							0.400	0.247	0.647	0.641	0.388	1.059	0.722	0.440	1.185
Pushto							0.866	0.570	1.316	0.708	0.399	1.259	0.708	0.408	1.229
Balochi							0.096	0.033	0.274	0.129	0.049	0.340	0.148	0.060	0.365
Saraiki							0.331	0.211	0.517	0.473	0.313	0.716	0.517	0.353	0.759
Other							0.600	0.374	0.963	0.667	0.403	1.104	0.691	0.421	1.135
							<0.001			*<0.001*			*<0.001*		
Education															
No education										1.000	1.000	1.000	1.000	1.000	1.000
Some education										0.811	0.429	1.531	0.738	0.370	1.471
										0.518			*0.387*		
Respondent's Occupation															
Not working										1.000	1.000	1.000	1.000	1.000	1.000
Non-manual labour										0.996	0.585	1.698	0.997	0.585	1.697
Manual labour										0.811	0.589	1.117	0.940	0.673	1.312

										0.387			0.926		
Province															
Punjab										1.000	1.000	1.000	1.000	1.000	1.000
Sindh										0.679	0.460	1.000	0.734	0.481	1.120
Khyber Pakhtunkhwa										1.742	1.017	2.986	2.221	1.315	3.750
Baluchistan										1.562	0.861	2.835	1.999	1.011	3.951
Gilgit Balistan										0.288	0.136	0.609	0.493	0.230	1.056
Islamabad(ICT)										1.175	0.871	1.584	1.099	0.819	1.475
										<0.001			*<0.001*		
Residence															
Rural										1.000	1.000	1.000	1.000	1.000	1.000
Urban										1.706	1.336	2.178	1.167	0.852	1.599
										<0.001			0.336		
Wealth Quintile															
Lowest quintile													1.000	1.000	1.000
2nd quintile													1.129	0.796	1.601
3rd quintile													1.842	1.181	2.873
4th quintile													3.206	2.034	5.053
Highest quintile													3.911	2.262	6.762
													<0.001		
Constant	1.564	0.912	2.680	0.333	0.168	0.660	0.296	0.139	0.628	0.160	0.070	0.370	0.064	0.026	0.161
	0.104			*<0.001*			*0.002*			*<0.001*			*<0.001*		
Level 1 units	3551			3551			3551			3551			3551		
Level 2 units	493			493			493			493			493		
Level 3 units	121			121			121			121			121		

Table 6. Fixed effects from the multilevel model (outcome Overweight) (3dp)

**OR are conditional on PSU and district level random effects.*

***Measures the effect of a one standard deviation increase in Gini index*

OBESE	Model 1			Model 2			Model 3			Model 4			Model 5		
	OR* / *p-value*	95% CI		OR* / *p-value*	95% CI		OR* / *p-value*	95% CI		OR* / *p-value*	95% CI		OR* / *p-value*	95% CI	
Gini	0.565	0.384	0.750	0.589	0.401	0.780	0.720	0.511	0.934						
	<0.001			*<0.001*			*0.011*								
Gini * Education Interaction															
No education										0.714	0.448	1.000	0.921	0.665	1.177
										0.048			*0.528*		
Some education										0.987	0.980	0.994	1.000	1.000	1.000
										<0.001			*0.008*		
Age				1.077	1.062	1.093	1.074	1.059	1.089	1.083	1.067	1.099	1.076	1.060	1.092
				<0.001			*<0.001*			*<0.001*			*<0.001*		
Household size															
1 to 2							1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3 to 4							0.537	0.219	1.320	0.488	0.197	1.208	0.481	0.201	1.150
5 to 9							0.565	0.206	1.547	0.471	0.173	1.287	0.449	0.172	1.172
10 +							0.413	0.159	1.071	0.354	0.138	0.908	0.285	0.112	0.723
							0.125			*0.0736*			*0.009*		
Ethnicity															
Urdu							1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Punjabi							1.059	0.600	1.868	1.251	0.722	2.167	1.312	0.775	2.219
Sindhi							0.680	0.304	1.519	1.528	0.684	3.412	1.706	0.767	3.796
Pushto							1.027	0.545	1.937	1.123	0.560	2.250	1.214	0.584	2.526
Balochi							0.286	0.060	1.355	0.611	0.127	2.939	0.769	0.194	3.045
Multani							0.633	0.347	1.154	1.041	0.598	1.812	1.089	0.627	1.894
Other							0.620	0.337	1.143	0.968	0.529	1.774	0.972	0.529	1.786
							0.059			*0.556*			*0.484*		
Education															
No education										1.000	1.000	1.000	1.000	1.000	1.000
Some education										0.407	0.200	0.825	0.423	0.213	0.838
										0.013			*0.014*		
Respondent's Occupation															
Not working										1.000	1.000	1.000	1.000	1.000	1.000
Non-manual labour										0.410	0.200	0.842	0.430	0.209	0.887
Manual labour										0.477	0.325	0.700	0.596	0.408	0.869

										<0.001			*0.003*		
Province															
Punjab										1.000	1.000	1.000	1.000	1.000	1.000
Sindh										0.407	0.243	0.679	0.442	0.260	0.753
Khyber Pakhtunkhwa										1.185	0.623	2.252	1.473	0.739	2.934
Baluchistan										0.570	0.211	1.541	0.689	0.245	1.935
Gilgit Balistan										0.098	0.031	0.313	0.224	0.070	0.715
Islamabad(ICT)										1.434	0.939	2.190	1.241	0.820	1.878
										<0.001			*<0.001*		
Residence															
Rural										1.000	1.000	1.000	1.000	1.000	1.000
Urban										2.523	1.859	3.424	1.513	1.068	2.144
										<0.001			*0.020*		
Wealth Quintile															
Lowest quintile													1.000	1.000	1.000
2nd quintile													1.093	0.559	2.137
3rd quintile													2.603	1.413	4.794
4th quintile													4.862	2.461	9.607
Highest quintile													6.181	3.045	12.547
													<0.001		
Constant	1.022	0.498	2.098	0.076	0.033	0.175	0.122	0.028	0.525	0.076	0.017	0.350	0.023	0.006	0.095
	0.952			*<0.001*			*0.005*			*0.001*			*<0.001*		
Level 1 units	2971			2971			2971			2971			2971		
Level 2 units	492			492			492			492			492		
Level 3 units	121			121			121			121			121		

Table 7. Fixed effects from the multilevel model (outcome Obese) (3dp)

**OR are conditional on PSU and district level random effects.*

***Measures the effect of a one standard deviation increase in Gini index*

Discussion

This investigation sought to determine whether higher district wealth inequality is a risk factor for a country wide Double Malnutrition Burden in Pakistan amongst reproductive aged women. Results of the multilevel analysis found that wealth inequality is associated with higher odds of underweight, relative to normal weight, even after controlling for a number of social, geographical and demographic variables. On the other hand, inequality was associated with a lower odds of overweight and obesity prior to adjusting for individual wealth quintile, and this association was only limited to women with no education. Any association with overweight or obesity disappeared however, after adjusting for wealth. The same conclusions were made using the 90/10 ratios of percentiles as the key exposure, demonstrating the robustness of initial findings.

Underweight

The negative association of wealth inequality and underweight is independent of social-economic position. The relationship is likely mediated by relatively lower social cohesion in unequal areas, leading to weak social safety nets (Martin et al 2004; Subramanian et al 2007), a lack of social capital investment (Kawachi et al 1997; Martin et al (2004)), higher food insecurity (Subramanian et al 2007; Martin et al 2004; Townsend et al 2001), or water and sanitation volatility. Wealth inequality may also cause an imbalance in access to the resources needed to improve one's nutritional status (Nowatzki 2012). The conclusions demonstrate that it is not only income inequality that is associated with negative health, or in this instance negative weight outcomes.

Subramanian et al (2007), who investigate the effect of *income* inequality on the DBM in India among women aged 15-49 finds that a standard deviation increase in the state Gini coefficient is associated with a 19 per cent increase in the odds of underweight, after controlling for a number of social, demographic and behavioural factors. Similar findings were found in the context of Pakistan using the wealth index, albeit with a smaller magnitude of effect. This could be due to relative differences in the relevance of pathways through which inequality affects malnutrition, arguably due to the difference in social, political, environmental or political settings. It could also be attributable to the fact that inequality is measured at the state level (a higher geographical unit of aggregation than the one used in this study). The latter could affect results, as different levels of aggregation are associated with different pathways through which this mechanism can operate. For instance, state level income inequality may "affect political participation and patterns of government spending on welfare, public education" (Subrmanian and Kawachi 2002 p297; Kawachi and Kennedy 1999), or health services. Regardless, we expected to find more pronounced findings in this study, as wealth inequality is more heavily associated with the concentration of political power. Inequality in wealth is generally related to inequality in resource access to improve nutritional status, for instance, sanitation access or even limited social interactions in networks where improved nutritional habits can diffuse.

Conclusions regarding underweight in this study population contrast however with the conclusion made in Chang and Christakis (2005), who find no "health-impairing effect on weight status" (Chang and Christakis 2005 p92) of economic inequality in their study of women in US Metropolitan areas. They attribute their findings, to the fact that in their study inequality is measured at a more local level than others, and that their model was able to control for individual level confounding effects. However, their message that inequality is not associated with adverse weight outcomes is conditional on the assumption that inequality is not associated with higher odds of underweight, a hypothesis they did not investigate further. This paper finds that even when measuring the exposure at more local levels, and controlling for individual level factors, associations between inequality and malnourishment is observed in the context of Pakistan.

<u>Obesity/overweight</u>

Districts with higher inequality had a large number of poorer households compared to districts with relatively lower Gini scores. After this was controlled for, no association between higher inequality and higher odds of over-nutrition was found for both women with no education and some education; a result which contradicts literature and hypotheses. It should be noted however that the 'gllamm' command does not allow stratification to be accounted for. As a result, standard errors may be overestimated, creating potential for Type 2 error.

Instead, household wealth was found to be the economic factor most highly associated with higher odds of overweight and obesity in the data. This finding contradicts similar studies that also use multilevel regression analysis to control for an individual's socioeconomic status and still find a positive association between economic inequality and overweight/obesity. For example, Subramanian et al (2007) find that a one standard deviation in state income inequality in India is associated with 1.19 (95%CI 1.04 - 1.37) times the odds of overweight and 1.21 (1.12-1.29) times the odds of obesity among reproductive aged women. Diez-Roux et al (2000) also find positive associations between income inequality and higher BMI using the Robin Hood Index of inequality, after adjustment for individual income. The lack of an association found in the study suggests that the hypothesised pathways thorough which inequality could affect odds of obesity are not relevant in the context of Pakistan.

Socioeconomic position is a factor hailed globally as one of the primary risk factors for over-nutrition (McLaren 2007; Sobal and Stunkard 1989), particularly in developing countries where the positive gradient between higher socioeconomic status and weight is found to be stronger (McLaren 2007), and particularly among females (Wells et al 2012). This finding is typical of a developing country still progressing through the epidemiological and nutritional transition (Alaba and Chola 2014).

Janjua et al (2015) also find, using the same data, women in the richest wealth quintile have 6.8 (95%CI 3.3-14.2) times higher odds of obesity compared to the lowest wealth quintile, adjusted for a number of geographical, social and demographic factors.

A number of factors have been cited in the literature as key to this relationship in developing countries. The consumption of energy dense foods is strongly related to higher socioeconomic status, with stronger relationships usually found in developing countries that are in earlier stages of the nutritional transition and tend to associate larger weight with affluence and higher social status (Monteiro et al 2004; McLaren 2007). Moreover, women from more wealthy families will have the means to pay for help with household chores, thus limiting the amount of physical exertion in the home (Janjua et al 2015 p11; Song 2006). Additionally, wealth, rather than income, may be associated with higher obesity rates if they are exposed to over-nutrition in early life (Dorling et al 2007; Wells et al 2012 p487). Finally, in general, wealth is associated with an increasingly sedentary lifestyle, including jobs involving longer periods of sitting (Garg et al 2010); however, this association was accounted for through the inclusion of parameters relating to the respondent’s occupation.

In contrast to findings for many developing countries, overweight and obesity is commonly associated with poverty and low socioeconomic status in developed countries (Mendez and Popkin 2004; Traill 2006). Consequently, this association is not expected to hold throughout Pakistan’s economic development as evidence demonstrates that as countries develop, this association begins to reverse. Reasons for this weakened association include improved knowledge regarding adverse health implications of excessive overweight and people of higher social standings not only aspiring to lower BMI, but also have the knowledge about how to achieve it (Traill 2006).

Limitations and Generalisability

Findings from this study should be considered with awareness of its limitations.

The first limitation concerns the use of the wealth index as the measure from which to generate measures of inequality and its inclusion in the model as a covariate. A commonly cited advantage of the asset index is the fact that social desirability bias and recall bias associated with collection of income data or consumption information is limited through direct observation by interviewers (Howe et al 2008 p2; Sahn and Stifel 2003). However, contradictory conclusions were found by Onwujekwe et al (2006) who claims sub-standard reliability of the collection of wealth index components, based on differences between interviewers or between tests (Onwujekwe et al 2006; Howe et al 2008 p2). If this is the case for the DHS Pakistan 2012-13, the use of the wealth index to create district level indicators or as a risk factor for health outcomes will be limited due to its lack of comparability between subjects.

Howe et al (2008) also claim that the wealth index may not accurately represent one's wealth due to the fact that the Principal Component Analysis used to create the index should be used exclusively with continuous data that follows a normal distribution. Rather, binary data is used which may be linearly dependent on one another and lead to multi-collinearity and inaccurate wealth score estimates.

Moreover, although the ownership of assets used to form the wealth index are commonly thought to represent one's ability to afford them, there are a range of reasons as to why one may or may not have certain possessions, which may not relate to wealth. Such reasons include credit accessibility, whether such goods are available in certain areas or different preferences for certain products (Johnston and Abreu 2013). This could result in the misclassification of wealth scores, and therefore misleading results. If all households in are equally as likely to be misclassified with respect to the wealth score, results of the analysis may be underestimated. Further study could look into supplementing the data with other measures of individual or household income or wealth to check for the robustness of the findings. Overall, due to the problems associated with the collection and use of the wealth index, it is probable that the confounding effects may not have been able to be fully controlled for.

This study aimed to causally model the association between inequality and nutritional status. Although the data used was from a cross-sectional survey, the established association satisfies some of the Bradford Hill causality criteria (Hill 1965), for instance plausibility or a gradient of the association. Even if the sole necessary criteria, temporality, cannot be truly satisfied without use of time series or panel data, it seems improbable that much reverse causality is involved in the association as wealth, and consequently wealth inequality, is such an entrenched social and area level characteristic, which is not as susceptible to fluctuations as income. Further study should aim to use longitudinal waves to verify this assumption and understand the temporality of association.

The explanatory nature of the findings is likely affected by the inability to control for certain confounders, or include mediating variables, that were not available in the data. For instance, Subramanian et al (2007) adjust their findings for state level development, whereas Chang et al (2005) adjust their findings for median level of income in the metropolitan area their measure of inequality was measured at. Moreover, the large number of ecological studies testing similar hypotheses also control for aggregate levels of income or development. At the district level in Pakistan, higher levels of inequality are associated with lower levels of district level development. This suggests that some of the relationship between inequality and under nutrition could be due to the overall lower level of development of the district. I aimed to account for an aggregate level measure of wealth by using the median wealth score in each district, however, the indicator was omitted in order to avoid introducing spurious results associated with mutli-collinearity. Other measures of district level development that do not pose a threat to the explanatory nature of the model is advised for future studies, including district GDP, or district level measures of HDI if available.

It would have also been preferable to have potential mediators in the data set in order to gain a more comprehensive understanding of the pathway through which inequality is associated with higher odds of underweight. Such variables include those relating to district level food security or social cohesion. The use of more detailed data or even the supplementation of DHS data with other data sources providing information on mediators is advised for further study. One could potentially use hypothesised mediators by including them in the multilevel model and observing whether the measure of effect of inequality on under nutrition approaches one. If evidence of mediating is found, structural equation modelling could be used to formalise the causal pathways, and evidence could be provided through significance tests and goodness of fit estimations.

A further limitation regards the issue of non-collapsibility of odds ratios, which may change the measure of effect of the Gini index where considerable confounding is not present (Pang, Kaufman and Platt 2012). The model used in this study may have been susceptible to this due to the modelling of binary outcomes and interpretation of corresponding odds ratios. Those wishing to remedy this limitation may wish to use a linear anthropometric measure as the primary outcome, although relevant associations and policy implications may be more difficult to identify.

Finally, the inherent problem with controlling for confounding effects of an individual level factor when measuring the effect of a contextual exposure is that some over-adjustment could have occurred, where variables with some influence on the causal pathway could have been controlled for. As a result the true adjusted association could lie between the crude association and this study's potentially over-adjusted one.

As DHS data sets are specifically designed to be nationally representative, the results of this study are generalisable to the areas in Pakistan where data collection took place. The findings may not be generalisable however to other countries. Even in settings traditionally thought of as culturally similar to Pakistan, such as India, factors such as the religious diversity or the caste system may play interfering roles in the associations established in this study.

Caution is also urged in over interpretation of our findings, as the analysis was only carried out using a restricted sample (only women in every third household had a recorded BMI), therefore introducing potentially higher random error.

Further studies may also wish to examine how the association between inequality and underweight varies by income level. Diez-Roux (2000) find that income inequality is associated with higher BMI exclusively in the low income category, as one would expect them to be more adversely affected by the negative effects of social cohesion or unequal access to services than those in higher income stratum. We urge that attention be paid to relative sample sizes in each income category to avoid spurious results, and detrimental policy implications.

Conclusion and Recommendations

This paper has found that established associations between income inequality and adverse weight outcomes may not be easily extrapolated to wealth inequality. Whereas women living in less egalitarian areas may face significant challenges relating to undernourishment, it was found that after controlling for wealth, women in less egalitarian areas did not differ to counterparts in more equal districts with respect to the risk of over-nutrition.

Barriers to tackling under-nutrition in Pakistan, including food price inflation, lack of food security, shortages of safe and clean water (Zaidi and Mohmand 2013), in addition to the unequal power concentration among the wealthy are all likely to be closely tied to higher wealth inequality.

Findings of this investigation suggest that policies aimed at wealth redistribution and provision of social safety nets are necessary to reduce the risk of under-nutrition among reproductive aged women. Social security policies should place emphasis on the reduction of consumption uncertainty and provide sufficient insulation to economic shocks, including food price inflation and food security (Nowatzki 2012; Starfield and Birn 2007). Programmes are urged to target the impoverished, as the poor in the more unequal areas are the ones least likely to make use of public provision of water, sanitation, healthcare and shelter (Subramanian et al 2007).

Considerable attention should be paid to the provinces of Baluchistan and Sindh, where a meagre 36.5 per cent and 28.2 per cent of households are food secure, relative to the Pakistan average of 42.0 per cent. Moreover water and sanitation volatility is also a significant problem in Baluchistan where, for example, only 31.0 per cent of households have a flush toilet, compared to the Pakistan average of 66.0 per cent (Zaidi and Mohmand 2013).

As women with some education had lower odds of overweight and obesity, emphasis on community level dietary education is recommended to reduce the overconsumption of energy dense and fatty foods, and generally promote a more active lifestyle. Janjua et al (2015) also suggest that emphasis on education could have spill over benefits on underweight women through emulation of nutritional practices.

Appendix

UNDERWEIGHT	Model A			Model B		
	OR / *p-value*	**95% CI**		**OR / *p-value***	**95% CI**	
Ratio of Percentiles (90/10)	1.033	1.012	1.054	1.028	1.003	1.055
	0.012			*0.031*		
Age	0.985	0.972	0.998	0.987	0.972	1.003
	0.022			*0.111*		
Marital Status						
Married	1.000	1.000	1.000	1.000	1.000	1.000
Widowed	1.457	0.764	2.779	1.436	0.695	2.966
Divorced	10.557	2.007	55.541	10.659	2.034	55.866
Separated	1.869	0.671	5.208	1.888	0.690	5.165
	0.012			*0.020*		
Ethnicity						
Urdu	1.000	1.000	1.000	1.000	1.000	1.000
Punjabi	0.831	0.490	1.409	0.744	0.433	1.278
Sindhi	1.442	0.828	2.514	1.226	0.672	2.235
Pushto	0.335	0.142	0.790	0.300	0.134	0.669
Balochi	1.459	0.790	2.693	1.195	0.620	2.306
Saraiki	0.787	0.456	1.359	0.689	0.384	1.235
Other	0.962	0.468	1.979	0.848	0.440	1.635
	<0.001			*0.001*		
Education						
No education	1.000	1.000	1.000	1.000	1.000	1.000
Some education	0.874	0.634	1.203	1.029	0.732	1.446
	0.408			*0.871*		
Respondent's Occupation						
Not working	1.000	1.000	1.000	1.000	1.000	1.000
Non-manual labour	0.645	0.271	1.538	0.682	0.273	1.705
Manual labour	1.363	1.024	1.815	1.294	0.975	1.717
	0.040			*0.127*		
Province						

Punjab	1.000	1.000	1.000	1.000	1.000	1.000
Sindh	0.838	0.617	1.138	0.831	0.591	1.169
Khyber Pakhtunkhwa	0.920	0.486	1.741	0.891	0.493	1.612
Baluchistan	0.470	0.228	0.968	0.463	0.258	0.831
Gilgit Balistan	0.242	0.112	0.523	0.208	0.087	0.496
Islamabad(ICT)	1.011	0.739	1.383	1.249	0.696	2.242
	<0.001			*0.001*		
Residence						
Rural	1.000	1.000	1.000	1.000	1.000	1.000
Urban	0.758	0.552	1.040	0.953	0.663	1.370
	0.086			*0.794*		
Wealth Quintile						
Lowest quintile				1.000	1.000	1.000
2nd quintile				0.854	0.566	1.288
3rd quintile				0.845	0.540	1.321
4th quintile				0.678	0.382	1.203
Highest quintile				0.393	0.206	0.750
				0.052		
Constant	0.394	0.190	0.817	0.494	0.213	1.148
	0.012			*0.101*		
Level 1 units	2804			2804		
Level 2 units	480			480		
Level 3 units	121			121		

Table 8. Fixed effects from the multilevel model (outcome Underweight, exposure 90/10 ratio of percentiles) (3dp)

**OR are conditional on PSU and district level random effects*

OVERWEIGHT	Model A			Model B		
	OR* / *p-value*	95% CI		OR* / *p-value*	95% CI	
Ratio of percentiles (90/10)						
ROP * Education Interaction						
No education	0.986	0.956	1.016	0.998	0.968	1.029
	0.355			*0.895*		
Some education	1.000	1.001	1.001	1.000	1.001	1.002
	0.244			*0.290*		
Age	1.052	1.039	1.065	1.047	1.034	1.060
	<0.001			*<0.001*		
Marital Status						
Married	1.000	1.000	1.000	1.000	1.000	1.000
Widowed	1.341	0.784	2.293	1.448	0.837	2.506
Divorced	6.371	2.429	16.706	6.608	1.761	24.795
Separated	0.714	0.242	2.103	0.672	0.170	2.650
	<0.001			*0.005*		
Ethnicity						
Urdu	1.000	1.000	1.000	1.000	1.000	1.000
Punjabi	0.873	0.601	1.266	0.906	0.581	1.410
Sindhi	0.611	0.372	1.005	0.747	0.437	1.277
Pushto	0.707	0.397	1.258	0.723	0.419	1.247
Balochi	0.119	0.043	0.327	0.147	0.061	0.355
Saraiki	0.462	0.308	0.692	0.513	0.317	0.829
Other	0.662	0.401	1.095	0.684	0.434	1.077
	<0.001			*<0.001*		
Education						
No education	1.000	1.000	1.000	1.000	1.000	1.000
Some education	1.126	0.814	1.557	0.809	0.548	1.196
	0.474			*0.288*		
Respondent's Occupation						
Not working	1.000	1.000	1.000	1.000	1.000	1.000
Non-manual labour	0.995	0.582	1.699	0.988	0.623	1.566

Manual labour	0.804	0.585	1.106	0.944	0.720	1.239
	0.352			*0.918*		
Province						
Punjab	1.000	1.000	1.000	1.000	1.000	1.000
Sindh	0.667	0.458	0.971	0.695	0.456	1.061
Khyber Pakhtunkhwa	1.715	1.000	2.939	2.218	1.346	3.655
Baluchistan	1.546	0.849	2.815	1.979	1.059	3.700
Gilgit Balistan	0.283	0.133	0.600	0.488	0.261	0.912
Islamabad(ICT)	1.207	0.955	1.526	1.049	0.677	1.627
	<0.001			*<0.001*		
Residence						
Rural	1.000	1.000	1.000	1.000	1.000	1.000
Urban	1.726	1.346	2.214	1.180	0.913	1.524
	<0.001			*0.207*		
Wealth Quintile						
Lowest quintile				1.000	1.000	1.000
2nd quintile				1.126	0.791	1.603
3rd quintile				1.840	1.213	2.790
4th quintile				3.228	2.081	5.008
Highest quintile				3.892	2.335	6.488
				<0.001		
Constant	0.114	0.057	0.228	0.067	0.031	0.143
	<0.001			*<0.001*		
Level 1 units	3551			3551		
Level 2 units	493			493		
Level 3 units	121			121		

Table 9. Fixed effects from the multilevel model (outcome Overweight, exposure 90/10 ratio of percentiles) (3dp)

**OR are conditional on PSU and district level random effects.*

OBESE	**Model 1**			**Model 2**		
	OR* / *p-value*	**95% CI**		**OR* / *p-value***	**95% CI**	
Ratio of percentiles (90/10)						
ROP* Education Interaction						
No education	0.949	0.897	1.005	0.973	0.928	1.020
	0.076			*0.255*		
Some education	0.996	0.998	1.001	0.998	1.000	1.002
	0.006			0.033		
Age	1.082	1.067	1.099	1.075	1.058	1.093
	<0.001			*<0.001*		
Household size						
1 to 2	1.000	1.000	1.000	1.000	1.000	1.000
3 to 4	0.488	0.196	1.213	0.474	0.182	1.235
5 to 9	0.469	0.170	1.290	0.443	0.177	1.108
10 +	0.354	0.138	0.910	0.280	0.110	0.715
	0.072			*0.009*		
Ethnicity						
Urdu	1.000	1.000	1.000	1.000	1.000	1.000
Punjabi	1.252	0.714	2.197	1.322	0.745	2.347
Sindhi	1.542	0.727	3.268	1.962	0.919	4.189
Pushto	1.094	0.533	2.244	1.166	0.548	2.480
Balochi	0.566	0.112	2.854	0.833	0.266	2.610
Saraiki	1.043	0.600	1.811	1.116	0.570	2.183
Other	0.946	0.504	1.777	0.936	0.494	1.772
	0.506			*0.409*		
Education						
No education	1.000	1.000	1.000	1.000	1.000	1.000
Some education	0.983	0.628	1.538	0.710	0.431	1.169
	0.938			*0.178*		
Respondent's Occupation						
Not working	1.000	1.000	1.000	1.000	1.000	1.000
Non-manual labour	0.401	0.193	0.834	0.424	0.179	1.005

Manual labour	0.468	0.320	0.685	0.599	0.396	0.906
	<0.001			*0.008*		
Province						
Punjab	1.000	1.000	1.000	1.000	1.000	1.000
Sindh	0.386	0.239	0.622	0.407	0.249	0.666
Khyber Pakhtunkhwa	1.214	0.628	2.345	1.615	0.838	3.110
Baluchistan	0.577	0.213	1.569	0.736	0.267	2.030
Gilgit Balistan	0.097	0.030	0.314	0.238	0.083	0.678
Islamabad(ICT)	1.376	1.060	1.787	1.101	0.692	1.751
	<0.001			*<0.001*		
Residence						
Rural	1.000	1.000	1.000	1.000	1.000	1.000
Urban	2.573	1.900	3.485	1.470	1.017	2.126
	<0.001			*0.041*		
Wealth Quintile						
Lowest quintile				1.000	1.000	1.000
2nd quintile				1.072	0.556	2.069
3rd quintile				2.547	1.393	4.656
4th quintile				4.963	2.566	9.599
Highest quintile				6.224	3.068	12.627
				<0.001		
Constant	0.043	0.012	0.154	0.022	0.006	0.088
	<0.001			*<0.001*		
Level 1 units	2971			2971		
Level 2 units	492			492		
Level 3 units	121			121		

Table 10. Fixed effects from the multilevel model (outcome Obese, exposure 90/10 ratio of percentiles) (3dp)

**OR are conditional on PSU and district level random effects*

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