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RESEARCH PAPER

Exploration of Dietary Diversity Heterogeneity across Rural-Urban Areas in Pakistan: Based on HIES 2018-19

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ABSTRACT

This study investigates the gap in dietary diversity and thereby quantifies this gap into its main drivers between rural and urban households. The statistical analysis based on data from the Household Integrated Expenditures Survey 2018-19 for Pakistan shows that there is a significant mean difference in household dietary diversity across rural-urban regions. To quantify the dietary diversity gap across regions, the multivariate nonlinear Oaxaca-Blinder mean decomposition method is used and we have decomposed Oaxaca-Blinder mean decomposition into the explained effect and the unexplained effect. The result of the nonlinear Oaxaca-Blinder mean decomposition method explains that the dietary diversity gap across regions is specifically due to households' characteristics like household expenditures, household head educational attainment and age etc. The mean difference ranges from 89.66% to 75.32% for dietary diversity scores and food variety scores, respectively. The household expenditures and income quintiles are major drivers of the dietary diversity gap besides other socio-demographic characteristics such as household size, marital status, educational attainment, and food security status of households across rural-urban regions. The unexplained coefficient effect (unexplained effect) is due to unobservable factors such as the role of region-specific institutions and found significant only in the case of food variety scores.

KEYWORDS Dietary Diversity Score, Dietary Diversity, Food Variety Score, Malnutrition, Oaxaca-Blinder Mean Decomposition

Introduction

During the 1980s, the established agreement was that consuming sufficient dietary energy per capita per day was necessary for food security. This argument was based on food quantity rather than food quality for food security. But the dilemma of the food quantity approach was that it ignores the importance of food quality. It is an empirically established fact that food quality ensures adequate intake of dietary energy, micronutrients, macronutrients, and protein. These are necessary elements for an active and healthy life. On the other hand, an unbalanced diet leads to malnutrition and considered a major concern at the international level, especially in developing countries (Rashid et al., 2011). The issue of malnutrition is more comprehensive than the consumption of sufficient dietary energy for food security. Malnutrition covers the issues of obesity (over-nutrition), stunting (under nutrition), and deficiency of micro-nutrients (also called hidden hunger). The deficiency of micronutrients, obesity, and stunting cause impaired cognitive growth in children, resultantly reducing productivity and attracting non-communicable diseases. In this connection, Weinberger (2004) examined the impact of iron deficiency on the productivity of Indian households who were engaged in the agricultural sector. The results showed that productivity would, on average, be 5% to 17.3 % higher if households' iron intake is based on recommended level. Similarly, Haddad and Bouis (1991) also confirmed a positive association between nutritional status and labour productivity.

The recent literature (for example, Torheim et al., 2004; Steyn et al., 2006; Moursi et al., 2008) on food insecurity uses dietary diversity as a proxy for food quality and nutrient adequacy for children, adults, and households. Ruel (2003) argued that dietary diversity is a simple count of food groups. While a food variety score counts food items consumed by adults, children, or households during the reference period. Similarly, while studying rural Mali, Torheim et al. (2004) analysed the relationship between nutrient adequacy and dietary diversity. He found that both the food variety score and dietary diversity score had a positive correlation with the mean adequacy ratio of nutrients. Likewise, Hoddinott and Yohannes (2002) analysed dietary diversity as a food security indicator for ten poor and middle-income countries. The sample of the study was based on both rural and urban sectors. They found a positive and significant correlation between dietary diversity, household food expenditures, and the availability of calories.

Further, Rah et al. (2010) found that low dietary diversity was associated with stunting in rural Bangladesh. These arguments were the outcome of cross-sectional survey data from 165,111 children under five years of age who participated in the National Surveillance project from 2003-05. Similarly, Hatloy et al. (2000) used both the food variety score and dietary diversity score as a dietary diversity indicator for assessing child nutritional status at the household level. They found a significant dietary diversity gap across rural-urban regions and found that the risk of stunted or underweight was twice in urban areas due to lower dietary diversity in children. They also confirmed a positive association between dietary diversity score and socio-economic status in both rural and urban regions in Mali. Based on the field survey data of the rural area of district Toba Tek Singh in Pakistan, Hussain et al. (2014) found the changing food patterns across the winter and summer seasons. Their study confirmed seasonal variations of dietary diversity score, food variety score, and calorie intake at the household level and found that dietary diversity was more diverse in the winter season than in the summer season and thereby households were able to manage extreme weather conditions.

Literature Review

In the recent past, understanding the main drivers of the dietary diversity gap across regions or within a country has emerged as an important research question due to the issue of malnutrition in the world and especially in developing countries like Pakistan. In this respect, Liu et al. (2014) found that urban households had relatively greater access to a diversified diet than rural households. While studying Ethiopia, Hirvonen (2016) also found a dietary diversity gap among children in rural-urban areas of the country. In the case of Pakistan, the latest available Household Integrated Expenditures Survey (HIES) 2018-19 shows that urban households have significantly greater dietary diversity (for both dietary diversity score and food variety score) than rural households (see Table1 for further details). The rural-urban gap in dietary diversity arises the research question: what are the main drivers which explain the observed difference of dietary diversity across rural-urban regions in Pakistan? To unearth this question, this study uses the most recent nonlinear multivariate Oaxaca-Blinder mean decomposition method following the work of Yun (2004), Sinning et al. (2008), and Park and Lohr (2010). The nonlinear multivariate Oaxaca-Blinder mean decomposition is an extension of the seminal work of Oaxaca (1973) and Blinder (1973), the linear mean decomposition method. The Oaxaca-Blinder decomposition method initially used to explain wage differentials found due to race or gender in the United States labour market. Afterwards, this approach gained popularity and attracted the attention of researchers in health and nutrition economics to explain health and nutrition inequalities between regions, ethnicities, genders, and over time (Mehta et al., 2013; Wu et al., 2014; Ciaian et al., 2018; Singleton et al., 2020; Thi et al., 2018).

Hirvonen (2016) utilized the Poisson decomposition method to decompose children's mean difference in dietary diversity scores across rural-urban areas in Ethiopia. The evidence confirmed the importance of wealth and parental education to generate the dietary diversity gap across regions. Whereas Worku et al. (2017) used linear Oaxaca-Blinder decomposition methods to decompose the mean difference in calorie intake across rural and urban regions. The diet transformation in Ethiopia between 1996 and 2011 was due to improvements in household income. Using Vietnam Household Living Standard Survey data, Thi et al. (2018) used decomposition methods to analyse the transformation of calorie intake and macronutrient consumption between 2004-2014. The result of the study confirmed that food expenditures and household size were the main drivers of dietary diversity transformation over time.

Solow (1957) was the pioneer who used the decomposition method to quantify the contributions of labour, capital, and other unexplained factors to economic growth. While Oaxaca (1973) and Blinder (1973) used the mean decomposition method to explain the contributions of factors to male-female wage differentials. The mean decomposition technique developed by Oaxaca (1973) and Blinder (1973) earlier used extensively in labour economics (Kunze, 2008; Singh & Ningthoujam, 2022), but the use of the mean decomposition technique in the analysis of dietary diversity across regions found scant in the emerging literature on food insecurity.

The above-cited research literature confirms that the mean decomposition method used extensively overtime at the household level for the investigation of children's gap in dietary diversity scores across regions, and calorie intake gap across regions. But to the best of our knowledge, no study has decomposed the dietary diversity gap (in terms of both food variety score and dietary diversity score) at the household level across regions, especially in the case of Pakistan, which is the gap in the empirical literature. Therefore, to fill this gap, the main objective of this study is to find out whether there is a dietary diversity gap between rural and urban areas in Pakistan. If there exists a significant mean difference in dietary diversity across rural-urban areas, then we quantify the observed mean difference of dietary diversity gap into its main drivers by using the multivariate nonlinear Oaxaca-Blinder decomposition method. This study will also help to answer whether the differences in dietary diversity across regions are due to differences in observed characteristics (explained effect) of households or due to differences in coefficients (unexplained effect).

The rest of the paper proceeds as follows: section 2 delineates the data source and variables description. Section 3 discusses the econometric methodology of multivariate nonlinear Oaxaca-Blinder mean decomposition for count data. In section 4, results and discussion of descriptive statistics and multivariate nonlinear Oaxaca-Blinder mean decomposition presented and discussed. In section 5, the conclusion, policy implications, and limitations of the study discussed.

Material and Methods

The analysis of the said study is based on the nationally representative eleventh round of cross-sectional data of the Household Integrated Economic Survey (HIES) 2018-19. This survey was conducted by the Pakistan Bureau of Statistics from August 2018 to June 2019. The current round of HIES at the provincial level survey covered 24,809 households and provided detailed outcome indicators on education, health, population welfare, housing, water sanitation and hygiene, Information Communication and Technology (ICT), Food Insecurity Experience Scale (FIES) by Food and Agricultural organizations (FAO) to monitor Sustainable Development Goals reference indicator 2.1.2 (Prevalence of moderate or severe food insecurity in the population), and income and expenditures. After cleaning data, we used a final sample of 23,978 households out of which 15,460 were from rural areas while the remaining 8,518 were from urban areas.

Variables Description

The selection of explanatory variables was based on previous empirical studies on diet quality and dietary diversity (see for example, Rashid et al., 2011; Ciaian et al., 2018; Singleton et al., 2020; Ekasari et al., 2021; Hendraini & Soedarto, 2021).

For the dependent variable, we used household dietary diversity calculated by counting food groups (dietary diversity score) and food items (food variety score) consumed over the reference period of the last fortnight and (or) a month by the household. There are eleven food groups showing that the dietary diversity score ranges between 1 to 11 while for the food variety score, the counting of food items consumed from food groups ranges from 1 to 69.

Following the literature (for example, Ogundari & Abdulai, 2013) on developing countries, real monthly household expenditures per adult equivalent in Pakistani Rupee (PKR) used as a proxy variable for permanent income. Manig and Moneta (2014) and Thi et al. (2018) observed certain advantages of taking total expenditures as a proxy for permanent income. For example, they argued that total expenditures are less volatile than income; households normally under-report income than expenditures; hence they concluded that expenditures may be a better indicator of living standards than income. To investigate dietary diversity for different income groups across regions, we have used income quintiles based on expenditures in this study. Further, we have also used another proxy for socio-economic status of household, namely owned agricultural land as a dummy variable showing 1 when households owned agricultural land and 0 otherwise.

To capture socio-demographic and household-related variables, we have included household size adjusted to adult equivalent (AE), age (in years), sex (male or female), marital status (never married, married and widow or divorced) of household head, the dependency ratio (No. of kids and elderly/household size), educational attainment (no education, primary, middle, secondary/higher secondary school certificate, and university). Further, using the United Nations Food and Agricultural Organization's Food Insecurity Experience Scale (FAO's FIES) module (see Appendix A for further details), we have used the households' food security status. For the geographic location, we have used the rural-urban region and distinguished these regions into four provinces that are, Punjab, Sindh, Khyber Pakhtunkhwa (KP), and Baluchistan.

Econometric Model

As earlier discussed, the seminal work of Oaxaca (1973) and Blinder (1973) developed the linear decomposition method to quantify wage differentials. The Oaxaca-Blinder decomposition method decomposes the observed gap in an outcome variable (in our case dietary diversity between rural-urban households) into two parts. The first part is due to differences in the household's observed socio-economic and demographic characteristics (endowments) such as expenditures, age, educational attainment of household head and household size (also called explained effect). Whereas the second part is due to differences in unobserved characteristics of households, the role of region-specific institutions, and cultural norms across rural-urban regions (also called unexplained effect or covariate effect).

The linear Oaxaca-Blinder decomposition method only restricts to linear regression models and its application to nonlinear and binary dependent variable models was limited. Yun (2004) and Fairlie (2005) extended the linear Oaxaca-Blinder technique to logit and probit models for binary dependent variables to fill the gap in literature. Further, an extension of the Oaxaca-Blinder decomposition for nonlinear models and count data models was developed by Bauer and Sinning (2008) and Powers et al. (2011). The nonlinear Oaxaca-Blinder decomposition method developed by Sinning et al. (2008) is used to decompose mean outcome differential for both linear and nonlinear regression models. This method cannot separate the contribution of single variables to explain the mean differential (i.e., mean difference). However, Powers et al. (2011) extended the Oaxaca-Blinder decomposition method to captures detailed decomposition output for all explanatory variables. Therefore, we applied Powers et al. (2011) model for detailed decomposition.

The mean difference in dietary diversity across the rural-urban area is expressed in Equation (1).

$$\overline{DD}_R - \overline{DD}_U = \left[f\left(\bar{X}_R\hat{\beta}_R\right) - f\left(\bar{X}_U\hat{\beta}_R\right)\right] + \left[f\left(\bar{X}_U\hat{\beta}_R\right) - f\left(\bar{X}_U\hat{\beta}_U\right)\right] \quad (1)$$

In Equation (1), $\overline{DD}$ represents mean of dietary diversity score or food variety score while subscript R and U respectively stand for rural and urban regions, $\bar{X}$ refers to a vector of covariates at mean values and $\hat{\beta}$ refers to the regression coefficient estimated for rural and urban regions. In the first part of Equation (1), that is $\left[f\left(\bar{X}_R\hat{\beta}_R\right) - f\left(\bar{X}_U\hat{\beta}_R\right)\right]$ is the explained component. This part explains mean differences due to households' characteristics or endowments differences across the regions. While, the second part of Equation (1), that is $\left[f\left(\bar{X}_U\hat{\beta}_R\right) - f\left(\bar{X}_U\hat{\beta}_U\right)\right]$ called unexplained component, which is due to the differences in estimated coefficients.

In Equation (1), f used for the functional form which depends on the underlying data generating process (linear or nonlinear). The dependent variable is dietary diversity, which takes only non-negative integer values. We have used Poisson decomposition analysis for the count data, which is the appropriate technique for mean decomposition. The Poisson regression model given in Equation (2) used to estimate $\hat{\beta}$ for rural and urban regions separately.

$$DD = \exp(\acute{X}\beta + \varepsilon) \quad (2)$$

In Equation (2), $\acute{X}$ is a vector of explanatory variables, which represent socio-economic and demographic characteristics of households while ε represents the error term.

In a detailed decomposition analysis, the contribution of each covariate variable also examined for dietary diversity across regions. In line with the work of Yun (2004) and to control the sensitivity of the order of variables in the decomposition equation, we have used the weights, which are proportional to the overall contribution of the characteristics or coefficients to the mean difference. The detailed decomposition for dietary diversity by using weights given in Equation (3).

$$\overline{DD}_R - \overline{DD}_U = \sum_{i=1}^{K} w_{\Delta X}^{i} \left[f\left(\bar{X}_R\hat{\beta}_R\right) - f\left(\bar{X}_U\hat{\beta}_R\right)\right] + \sum_{i=1}^{K} w_{\Delta\beta}^{i} \left[f\left(\bar{X}_U\hat{\beta}_R\right) - f\left(\bar{X}_U\hat{\beta}_U\right)\right] \quad (3)$$

In Equation (3), the weights for covariate *i* are

$$W_{\Delta X}^{i} = \frac{(\bar{X}_R^i - \bar{X}_U^i)\beta_R^i}{(\bar{X}_U - \bar{X}_U)\beta_R}$$

and

$$W_{\Delta\beta}^{i} = \frac{\bar{X}_U^i(\beta_R^i - \beta_U^i)}{\bar{X}_U(\beta_R - \beta_U)} \quad (4)$$

In Equation (4), the sum of weights from each category that is weight for characteristics, $W_{\Delta X}^{i}$ and weight for coefficients, $W_{\Delta\beta}^{i}$ should be equal to one.

For multivariate nonlinear Oaxaca-Blinder decomposition, we have used Powers et al. (2011) written "mvdcmp" program in Stata 15.

Results and Discussion

Summary statistics in Table 1 show the differences between dietary diversity and other socio-economic and demographic variables across rural-urban areas. To check the significant mean difference of variables across regions, we have used the student's two-tailed *t*-test.

Table 1
Summary Statistics

Variable	Rural	Urban	Total	Mean difference
Food variety score	28.35	32.97	29.99	-4.62***
	(6.432)	(8.089)	(7.404)	
Dietary diversity score	9.140	9.489	9.264	-0.35***
	(1.000)	(1.030)	(1.024)	
Expenditures (In PKR.)	8.446	8.803	8.573	-0.36***
	(0.445)	(0.545)	(0.512)	
Age of household head (years)	3.771	3.795	3.779	-0.02***
	(0.317)	(0.293)	(0.309)	
Household size (AE)	5.903	5.741	5.845	0.16***
	(2.859)	(2.844)	(2.854)	
Dependency ratio	0.423	0.362	0.402	0.06***
	(0.236)	(0.238)	(0.239)	
Sex of household head				
Male	0.898	0.919	0.905	-0.02***
	(0.303)	(0.273)	(0.293)	
Female	0.102	0.0811	0.0945	0.02***
	(0.303)	(0.273)	(0.293)	
Marital status				
Never married	0.0182	0.0272	0.0214	-0.01***
	(0.134)	(0.163)	(0.145)	
Married	0.914	0.898	0.908	0.02***
	(0.280)	(0.303)	(0.288)	
Widow/divorced	0.0674	0.0751	0.0701	-0.01**
	(0.251)	(0.264)	(0.255)	
Owned agri. Land (0/1)				
Yes	0.0973	0.0391	0.0766	0.06***
	(0.296)	(0.194)	(0.266)	
No	0.903	0.961	0.923	-0.06***
	(0.296)	(0.194)	(0.266)	
Food security status				
Food secure	0.580	0.733	0.635	-0.15***
	(0.494)	(0.442)	(0.482)	
Mild insecurity	0.189	0.148	0.175	0.04***
	(0.392)	(0.355)	(0.380)	
Moderate insecurity	0.142	0.0795	0.120	0.06***
	(0.349)	(0.271)	(0.324)	
Severe insecurity	0.0891	0.0391	0.0713	0.05***
	(0.285)	(0.194)	(0.257)	
Educational attainment				
No schooling	0.503	0.301	0.431	0.20***
	(0.500)	(0.459)	(0.495)	

Primary	0.164	0.141	0.156	0.02***
	(0.371)	(0.348)	(0.363)	
Middle	0.116	0.137	0.124	-0.02***
	(0.321)	(0.344)	(0.329)	
SSC/HSSC	0.173	0.285	0.212	-0.11***
	(0.378)	(0.451)	(0.409)	
University	0.0436	0.135	0.0761	-0.09***
	(0.204)	(0.342)	(0.265)	
Province/region				
Punjab	0.499	0.455	0.483	0.04***
	(0.500)	(0.498)	(0.500)	
Sindh	0.214	0.295	0.243	-0.08***
	(0.410)	(0.456)	(0.429)	
KP	0.192	0.166	0.183	0.03***
	(0.394)	(0.372)	(0.386)	
Baluchistan	0.0950	0.0834	0.0908	0.01***
	(0.293)	(0.276)	(0.287)	
Income quintiles				
Lowest	0.229	0.0763	0.175	0.15***
	(0.420)	(0.266)	(0.380)	
Lower	0.220	0.120	0.185	0.10***
	(0.414)	(0.326)	(0.388)	
Middle	0.213	0.169	0.197	0.04***
	(0.409)	(0.375)	(0.398)	
Higher	0.190	0.248	0.211	-0.06***
	(0.392)	(0.432)	(0.408)	
Highest	0.148	0.386	0.233	-0.24***
	(0.355)	(0.487)	(0.423)	

Note: *** and ** are respectively shows statistical significance based on two-tailed t-test and denoted respectively at $p < 0.01$ and $p < 0.05$. Standard deviation (SD) given in (). Expenditures and age of household head are in natural log and 0/1 are dummy variables. Similarly, KP stands for Khyber Pakhtunkhwa, SSC stands for secondary school certificate and HSSC stands for higher secondary school certificate.

For mean difference analysis, the null hypothesis is that the mean difference of relevant variable is equal to zero, which assessed against the alternative hypothesis that the mean difference of relevant variable is not equal to zero across rural-urban areas. The results of the two-tailed *t*-test for the mean difference of dietary diversity, socio-economic and demographic characteristics of households across regions shown in Table 1. The mean difference of dietary diversity score and food variety score is 0.35 and 4.62, respectively, which is statistically significant between rural and urban households. The mean differences of socio-economic and demographic characteristics of households are also significantly different across rural and urban regions. The results in Table 1 accept the hypothesis that urban areas have more dietary diversity than rural areas.

The results of multivariate nonlinear Oaxaca-Blinder decomposition reported in Table 2 indicate that 0.314 (89.89%) and 3.485 (75.37%) of the observed gap in dietary diversity score and food variety score respectively explained due to differences in observable household's socio-economic and demographic variables like expenditures, age, educational attainment, and household size. The unexplained part of multivariate nonlinear decomposition for dietary diversity score is 10.11% out of total gap of dietary diversity score and statistically insignificant. But in the case of food variety score, the unexplained part is 24.63% out of total gap and it is statistically significant. It means that unobservable characteristics of households play a significant role in the choice of food items (food variety score) over food groups (dietary diversity score) across rural-urban regions.

In a detailed multivariate Oaxaca-Blinder decomposition analysis, the results for the explained differential of the dietary diversity gap across rural-urban households show that only few explanatory variables are statistically significant that explain the explained part of the dietary diversity score gap. While in the case of the food variety score gap, most of the explanatory variables are statistically significant and consistent with the earlier studies related to the decomposition of food consumption and diet quality (Ciaian et al., 2018; Singleton et al., 2020). A positive coefficient of an explanatory variable would increase the explained dietary diversity differentials (and is associated with a larger explained gap in the dietary diversity score and food variety score) of rural households (lower outcome group) relative to the reference urban households (higher outcome group). A negative coefficient of the explanatory variable was associated with a smaller explained gap in the dietary diversity of rural households compared to urban households. As expected, the explained part of the dietary diversity gap (for both dietary diversity score and food variety score) is explained by differences in household's monthly expenditures across regions, which is 41.12% and 37.46% for dietary diversity score and food variety score, respectively. Moreover, lower income quintiles (that is, lower and middle) narrow the gap of dietary diversity whereas higher income quintiles (that is, higher and highest) widen the dietary diversity gap with respect to the lowest income quintile (referenced) across rural-urban regions. These results confirm that rich households have a greater opportunity for dietary diversity as compared to poor households and the gap of dietary diversity is widening as the income of households increases across regions.

We found that households' characteristics and provincial differences have a mixed impact on the explained part of dietary diversity. Most of the households' characteristics and provincial differences have significantly explained food variety scores than dietary diversity score differentials across rural-urban regions. In the case of differential of dietary diversity scores across rural-urban regions, the coefficient of household size is negative for both dietary diversity score and food variety score, whereas the coefficient of dependency ratio is only statistically significant with a negative sign for food variety score differential.

Marital status has a mixed effect on dietary diversity differentials for both dietary diversity scores and food variety scores. The higher educational attainment of the household head significantly explains the differential in dietary diversity across rural-urban regions only for food variety scores. We further found that the higher educational attainment coefficients are greater and more positive than primary educational attainment and are associated with widening the dietary diversity gap across rural-urban regions. This is an important finding that higher educational attainment of the household head explains food variety score differentials. However, higher educational attainment of the household head is not significant in the case of dietary diversity score differentials. In the case of food insecurity status, moderate and severe food insecurity are associated with widening the mean difference in food variety scores between rural and urban households.

Table 2
Multivariate nonlinear Oaxaca-Blinder mean decomposition of dietary diversity gap between rural-urban regions

	Dietary Diversity Score				Food Variety Score			
	Explained	**(%)**	**Unexplained**	**(%)**	**Explained**	**(%)**	**Unexplained**	**(%)**
Expenditures (In PKR.)	0.144**	41.12	-2.945	-843.78	1.732***	37.46	-12.514***	-270.67
	(3.16)		(-1.69)		(22.51)		(-4.06)	
Age of household head (years)	-0.001	-0.28	0.148	42.47	0.022***	0.47	2.352*	50.87
	(-0.30)		(0.24)		(3.73)		(2.12)	
Household size (AE)	-0.013***	-3.78	0.020	5.71	-0.154***	-3.33	0.485**	10.50
	(-5.99)		(0.20)		(-41.59)		(2.79)	
Dependency ratio	-0.005	-1.33	0.010	2.96	-0.116***	-2.50	-0.044	-0.95
	(-0.50)		(0.13)		(-6.88)		(-0.30)	
Male head (0/1)	-0.001	-0.37	-0.061	-17.40	-0.003	-0.07	0.117	2.54
	(-0.43)		(-0.40)		(-0.59)		(0.42)	
Marital status								

Not married	Ref.		Ref.		Ref.		Ref.	
Married	-0.012**	-3.54	0.217	62.20	-0.072***	-1.56	1.221*	26.41
	(-3.29)		(0.80)		(-10.21)		(2.38)	
Widow/divorced	0.005*	1.29	0.015	4.34	0.026***	0.55	0.082	1.76
	(2.12)		(0.63)		(6.48)		(1.83)	
Owned Agri land (0/1)	-0.004	-1.14	-0.001	-0.32	0.011	0.23	0.004	0.08
	(-0.40)		(-0.06)		(0.62)		(0.12)	
Educational attainment								
No education	Ref.		Ref.		Ref.		Ref.	
Primary	-0.003	-0.72	0.004	1.13	-0.013**	-0.29	0.011	0.23
	(-1.01)		(0.19)		(-2.93)		(0.27)	
Middle	0.001	0.29	-0.006	-1.64	0.020***	0.44	-0.002	-0.05
	(0.43)		(-0.36)		(4.76)		(-0.08)	
SSC/HSSC	0.009	2.51	-0.006	-1.70	0.099***	2.14	-0.035	-0.77
	(0.83)		(-0.29)		(5.11)		(-0.95)	
University	0.014	3.99	-0.001	-0.21	0.160***	3.46	0.007	0.15
	(1.21)		(-0.09)		(7.88)		(0.50)	
Food security status								
Food secure	Ref.		Ref.		Ref.		Ref.	
Mild insecure	-0.003	-0.73	0.000	0.10	0.013	0.29	-0.044	-0.96
	(-0.62)		(0.01)		(1.76)		(-1.05)	
Moderate insecure	0.008	2.34	-0.005	-1.35	0.172***	3.71	-0.160***	-3.47
	(1.00)		(-0.22)		(11.06)		(-3.91)	
Sever insecurely	0.016	4.63	-0.009	-2.44	0.170***	3.68	-0.032	-0.67
	(1.72)		(-0.45)		(9.33)		(-0.88)	
Province								
Punjab	Ref.		Ref.		Ref.		Ref.	
Sindh	0.044***	12.59	-0.004	-1.16	0.280***	6.05	0.767***	16.58
	(6.77)		(-0.18)		(24.03)		(18.03)	
KP	-0.001	-0.14	0.004	1.10	0.022***	0.47	0.053	1.14
	(-0.19)		(0.16)		(4.54)		(1.23)	
Baluchistan	-0.000	-0.14	-0.001	-0.40	0.007*	0.15	-0.014	-0.31
	(-0.32)		(-0.09)		(2.52)		(-0.52)	
Income quintiles								
Lowest	Ref.		Ref.		Ref.		Ref.	
Lower	-0.020	-5.72	0.016	4.66	-0.172***	-3.71	0.126	2.71
	(-1.23)		(0.39)		(-5.56)		(1.61)	
Middle	-0.015*	-4.41	0.037	10.55	-0.127***	-2.75	0.265**	5.73
	(-2.15)		(0.84)		(-9.51)		(3.28)	
Higher	0.028**	8.10	0.057	16.37	0.234***	5.07	0.379***	8.19
	(2.77)		(1.26)		(12.55)		(4.60)	
Highest	0.123*	35.34	0.068	19.51	1.174***	25.40	0.446***	9.65
	(2.35)		(1.42)		(12.62)		(5.21)	
Constant	0.000		2.476	709.42	0.000		7.671*	165.91
	(.)		(1.44)		(.)		(2.48)	
Summary								
Explained effect	0.314***	89.89			3.485***	75.37		
	(10.23)				(64.34)			
Unexplained effect	0.035	10.11			1.139***	24.63		
	(0.70)				(12.88)			
Raw difference	0.349***	100.00			4.623***	100		
	(8.45)				(61.22)			
N	23978				23978			

Note: 0 and 1 indicate dummy variables. The never married, no education, food secure, Punjab, and lowest used as reference categories for marital status, educational attainment, Province, and income quintile respectively for categorical variables. Z-statistics is in parentheses; statistical significance level at $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Expenditures and age of household head are in the natural log. Similarly, KP stands for Khyber Pakhtunkhwa, SSC stands for secondary school certificate and HSSC stands for higher secondary school certificate.

Conclusion and Policy Recommendations

In this study, we have investigated the dietary diversity gap using the multivariate technique of nonlinear Oaxaca-Blinder mean decomposition on the rural and urban dataset of Pakistan obtained from the Household Integrated Expenditures Survey 2018-19. Overall, we found a statistically significant dietary diversity gap between rural and urban households in Pakistan. The quantification of said gap is statistically significant due to observable socio-economic, demographic, and household characteristics. The multiplicity of socio-economic and demographic characteristics of households have been used to unearth the dietary diversity gap between rural and urban households.

The differences in dietary diversity are not only due to observable household characteristics (endowments) but unobservable characteristics of households also contributed to the dietary diversity gap (or in the case of food variety score) in rural-urban regions. The role of households' observable characteristics across regions is found stronger for dietary diversity score as compared to food variety score.

In detailed decomposition, the contribution of observable characteristics of households is different for both dietary diversity indicators. In the case of dietary diversity scores, major gap across rural-urban regions is explained due to expenditures and the socio-economic status of households which is proxied by income quintiles and ownership of agricultural land. Whereas in the case of food variety score, educational attainment, food security status and provincial location of households are also contributing factors along with expenditures and socio-economic status of households across rural-urban regions.

Although we have a good representative survey of households like other cross-sectional studies, however this study is also not free from weaknesses and thus has limitations. These are: First, the recall period ranges from fortnightly and monthly for expenditures on food items, and monthly to yearly for expenditures on goods and services. Due to a long recall period, the household faced difficulty in recalling the expenditures incurred on food items, and it leads to respondent bias. To overcome the measurement errors due to the long recall period, the Food and Agricultural Organization recommended only one day recall period for dietary diversity analysis for households or individuals. Second, the focus of this study is on households, hence within households mean differences in dietary diversity could not be observed. Third, this study used households' monthly expenditures as a proxy for household income which has also its pros and cons discussed in the literature, which may limit some results interpretation.

Besides the limitations, the results are interesting with respect to the policies on dietary diversity in Pakistan. The inference of this study suggests to policymakers that nutrition and food programs can improve dietary diversity and the execution of policies should be based on a regional basis. In this connection, there is a need to improve dietary diversity across rural areas and among low-income households through income and food support programs. Through income support programs, the policymakers may ensure that income should be given directly to low-income and food insecure households, which is the most effective way to increase the dietary diversity of rural and underprivileged households. In Pakistan, the federal government has started Benazir Income Support Programme (BISP) to provide unconditional income support to underprivileged and vulnerable families for the social safety net since July 2008. We left it to future researchers who may analyse the impact of the BISP program on food quality analysis in Pakistan.

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