

Born Where, Stuck Where? Spatial Inequality of Opportunity and Intergenerational Income Persistence in Multan, Pakistan

Fareed Shareef¹, Muhammad Ramzan Sheikh², Sadia Bibi³, Sana Sultan⁴

¹Professor of Economics, Director Public Instructions (DPI) Colleges, South Punjab, Pakistan

Email: fareedsharif76@gmail.com

²Professor and Director, School of Economics, Bahauddin Zakariya University, Multan, Pakistan

Email: ramzansheikh@bzu.edu.pk

³Assistant Professor, School of Economics, Bahauddin Zakariya University, Multan, Pakistan

Email: sadia.bibi@bzu.edu.pk

⁴PhD Scholar, COMSATS University Islamabad, Vehari Campus, Pakistan

Email: Sanasultan093@gmail.com

Abstract

This paper examines whether inequality of opportunity (IOp) and intergenerational income persistence differ between urban and rural areas using original household survey data from Multan District, Pakistan. We combine parametric and non-parametric Ferreira-Gignoux decompositions of the mean log deviation (MLD) with intergenerational elasticity (IGE) models that interact parental socioeconomic status with rural residence. The findings (which we term the Multan Spatial Paradox) are as follows. First, the IGE is statistically indistinguishable across the urban-rural boundary and the interaction term is insignificant in every specification. Second, observable circumstances (gender, parental education and birth order) explain a substantially larger share of income inequality in urban areas than in rural areas and this gap holds across all MLD-based estimators. Third, rural Multan exhibits considerably higher total income inequality almost all of which arises within circumstance types. Subgroup regressions show that parental status, gender, education and experience significantly determine urban earnings whereas own education is the only significant predictor of rural earnings. We attribute the paradox to the informal agrarian economy in which income variation is driven by land, irrigation, livestock and seasonal labour demand, none of which enter the standard circumstance set. The urban advantage appears as a modest, near-parallel level premium rather than as stronger transmission of parental advantage. The results call for an expanded circumstance set in rural IOp studies and for policies that widen rural access to formal employment, secondary education and productive assets.

Keywords: inequality of opportunity, intergenerational mobility, urban-rural inequality, Ferreira-Gignoux decomposition, informal economy, Pakistan

JEL Classification: D63, I32, J62, O15, R10

Introduction

Whether the circumstances into which a person is born shape their economic prospects in adulthood and whether that influence differs from one place to another is a central question for development economics and for public policy in low and middle income countries (Corak, 2013; Narayan et al., 2018; World Bank, 2006). Two related bodies of research address this question.

Received 04 March 2026; Revised 03 April 2026; Accepted 17 April 2026; Published (online) 25 April 2026



Attribution 4.0 International ([CC BY 4.0](https://creativecommons.org/licenses/by/4.0/))

Corresponding Author Email: ramzansheikh@bzu.edu.pk

DOI: <https://doi.org/10.69671/socialprism.3.8.2026.262>

The first is rooted in the luck-egalitarian philosophy of Rawls (1971), Dworkin (1981), Arneson (1989), and Cohen (1989) and was formalised by Roemer (1998). It differentiates inequality that is caused by factors out of individual control (gender, parental background, birthplace) from inequality that results from individual effort and choice. Empirical studies following Bourguignon et al. (2007), Checchi and Peragine (2010), and Ferreira and Gignoux (2011) confirm that circumstances play an important role in determining income and consumption inequality in developing countries. Dependence is estimated to range from 15 to 60 percent depending on the outcome, the set of circumstances and the estimator (Brunori et al., 2013; Hassine, 2012; Roemer & Trannoy, 2016; Singh, 2012). A second line of research examines intergenerational persistence directly as the elasticity of child income with respect to parental income (IGE) a theoretical model developed by Becker and Tomes (1979, 1986) and an empirical tradition started by Solon (1992, 1999). There is a “Great Gatsby curve” across countries where more unequal societies tend to have lower mobility and developing economies tend to have more persistent mobility than high-income economies (Corak, 2013; Durlauf et al., 2022), and there is a “Great Stagnation curve” across countries with the developing economies showing greater mobility persistence than high income economies (Narayan et al., 2018; van der Weide et al., 2024).

The concept of place has now emerged as a key element of both literatures. Chetty et al. (2014) found that variation between commuting zones in the United States is large and that much of it can be explained by the causal effect of having grown up in a better neighbourhood. Similar regional differences are reported in Canada (Connolly et al., 2019), Sweden (Heidrich, 2017), Australia (Deutscher & Mazumder, 2020), Italy (Acciari et al., 2022), China (Fan et al., 2021), India (Asher et al., 2024) and in Africa in general (Alesina et al., 2021). The most obvious spatial divide in developing countries is between urban and rural areas. The wage gap between urban and rural workers is substantial as is the wage gap between rural workers with similar observable traits (Gollin et al., 2014; Young, 2013). The part of the wage gap is due to the fact that cities attract more skilled workers (Combes et al., 2008; Hicks et al., 2021; Lagakos, 2020). Children in rural areas may also have less access to good schools, health care and a lack of employment opportunities especially that may limit them from breaking out of their parents’ economic cycle (Emran & Shilpi, 2015; Lipton, 1977; World Bank, 2009).

These questions are of great significance in the context of Pakistan. According to the regional evidence, Pakistan is one of the least mobile countries in South Asia. According to Khan and Patra (2024), chances that the status of a Pakistani child is independent of his or her parents’ status is as low as 20% while Bussolo et al. (2026) conclude that circumstances explain around 46% of consumption inequality and 60% of wage inequality among Pakistanis. National studies point out strong persistence in educational attainment (Muhammad & Jamil, 2020; Muhammad et al., 2022) the fact that the children of informally employed fathers remain confined to low level of education (Kishwar & Alam, 2021) and the lack of a “social elevator” at the top of the occupational distribution (Andlib et al., 2025). Rural Punjab also has a historical baggage of landed hierarchy which continues to influence the process of schooling transition between the propertied and non-propertied group (Cheema & Naseer, 2013; Jacoby & Mansuri, 2015). However, there are two gaps in evidence. First, most studies of inequality of opportunity (IOp) in the region are conducted at the national level and assume that the process that creates IOp is the same across space treating urban or rural place of birth as one more circumstance (Bussolo et al.,

2026; Rama et al., 2015). Second, as in most of the world, Pakistan has a limited number of studies on intergenerational income persistence due to the lack of matched parent-child income data and the few datasets available are subject to truncation bias (Emran et al., 2018). But little is known about how economic benefit is transmitted from parents to children and perhaps at the same rate in a Pakistani city and its surrounding countryside.

In this paper these gaps are addressed by conducting a household survey with 613 adult respondents in Multan District, southern Punjab. The survey seeks the respondents' self-reported income and parental income from a previous retrospective time period and the situation factors for IOp analysis. Multan is an ideal place to answer the question. The urban population of its core area (2023 census, Pakistan Bureau of Statistics 2.2 million) is a regional centre for commerce, public administration and higher education while the rural population is dependent on crop farming, livestock and seasonal wage employment. In Pakistan, agricultural land is highly skewed with 97% of the farmers having less than 12.5 acres while a small percentage of agricultural holdings having more than 100 acres are controlling a disproportionate share of agricultural land (PBS 2025). The district thus sets up a formal and credentialed urban labour market and an informal and asset-based agrarian economy in the same administration while controlling for provincial policy, culture and macroeconomic conditions.

We combine two complementary approaches. We apply the parametric Ferreira-Gignoux decomposition and a non-parametric between-type decomposition of the mean log deviation (MLD) to measure IOp separately in urban and rural Multan and we estimate fully interacted IGE models to test whether the transmission of parental advantage differs across the urban-rural boundary. The results reveal what we call the Multan Spatial Paradox. First, the IGE is statistically the same in urban (0.281) and rural (0.260) Multan. Second, observable circumstances explain three to six times more income inequality in urban areas (7.7%-24.7%) than in rural areas (2.5%-4.2%). Third, rural Multan nevertheless has 64% higher total income inequality (MLD of 0.691 against 0.422). We argue that this combination arises because rural incomes depend on land, irrigation, livestock and weather. None of which appear in the standard circumstance set. Rural IOp is therefore understated rather than absent.

The paper makes three contributions. First, to our knowledge it is the first study to estimate urban-rural differences in both IOp and the IGE within a single Pakistani district using matched parent-child income data. Second, by placing the IOp decomposition beside interaction-based tests of the IGE, it shows that similar intergenerational elasticities can conceal very different transmission mechanisms, a point with wider relevance for mobility research in agrarian economies (Emran & Shilpi, 2011; Mogstad & Torsvik, 2023). Third, it identifies specific omitted circumstances especially inherited land and productive assets that future IOp studies in South Asia should measure (Agarwal, 1994; Quisumbing et al., 2004).

Literature Review

Theory and Measurement of Inequality of Opportunity

The philosophical foundations of IOp measurement lie in the luck-egalitarian tradition. Rawls (1971), Dworkin (1981), Arneson (1989) and Cohen (1989) each argued in different ways that inequalities arising from factors beyond a person's control are morally objectionable whereas

inequalities arising from responsible choice may be acceptable. Roemer (1998) turned this idea into an operational framework by partitioning the determinants of an outcome into circumstances such as family background, gender and place of birth and effort. Individuals who share the same circumstances form a type and equality of opportunity requires that the distribution of outcomes should not differ across types. Subsequent work distinguished between ex ante approaches which compare the value of opportunity sets across types and ex post approaches which compare outcomes among people exerting the same effort (Fleurbaey & Peragine, 2013; Ramos & Van de gaer, 2016; Roemer & Trannoy, 2016).

Ferreira and Gignoux (2011) proposed the most widely used ex ante estimator. Log income is regressed on a vector of observed circumstances and the inequality of the resulting predicted or “smoothed,” distribution is expressed as a share of total inequality. Because the MLD is additively decomposable and path independent (Bourguignon, 1979; Shorrocks, 1980), it is the preferred index for this purpose. The estimate below represents a lower limit of the true IOp because no survey covers all situations. A non-parametric alternative consists of assigning each individual the average income of his or her type and calculating between-type inequality directly (Checchi & Peragine, 2010). The two estimators are known to have their own limitations: the parametric one assumes a functional form while the non-parametric one is prone to overfitting in cases of many types and small cells and tends to overestimate IOp (Brunori et al., 2019). New machine-learning methods focus on the regression tree approach and forests which try to reconcile these two forms of bias (Brunori et al., 2023; Hufe et al., 2022).

They have been used extensively. In Latin America, Bourguignon et al. (2007) and Ferreira and Gignoux (2011) have demonstrated that circumstances account for a significant part of earnings and income inequality and Brunori et al. (2013) have demonstrated that IOp is significantly correlated with overall inequality and with intergenerational persistence across countries. There is similar evidence for urban India (Das & Biswas, 2022) and for Indian men (Singh, 2012) where approximately one-fourth of the earnings inequality is due to conditions. IOp also plays a role in aggregate consequences: a number of studies have linked higher IOp with lower growth in future, but cross-country estimates are sensitive to measurement choice (Ferreira et al., 2018; Marrero & Rodríguez, 2013). In South Asia, Rama et al. (2015) found that circumstances account for 28% to 60% of inequality in access to education, health and jobs and Bussolo et al. (2026) estimate that circumstances explain 35% to 69% of the inequality in wages and consumption across the region.

Spatial Inequality of Opportunity

The geography of opportunity has been increasingly important since Chetty et al. (2014) demonstrated that the geographical location of children’s birth affects their adult outcomes in the United States even amongst children from similarly low-income families. Chetty and Hendren (2018) showed that these disparities are partially reducible and each extra year of childhood spent in a higher quality area significantly increases adult earnings. Since then similar spatial variation of mobility has been reported in Canada (Connolly et al., 2019) Sweden (Heidrich, 2017) Australia (Deutscher & Mazumder, 2020) and Italy (Acciari et al., 2022). Mogstad and Torsvik (2023) examine this evidence and underscore the importance of neighbourhoods, schools and local labour markets for mediation between family background and adult outcomes.

The urban-rural dimension of inequality is the predominant one in developing countries (Kanbur & Venables, 2005; World Bank, 2009). Gómez-Lobo and Oviedo (2025) show that the rural-urban income gap in Latin America is much larger, both absolutely and relative to overall inequality than in developed countries. The United Nations (2020) and OECD (2018) also raise the alarm about the significantly lower opportunities for rural children in education, health and connectivity. There are two explanations in the literature to the urban wage premium. The first focuses on the real productivity differences stemming from agglomeration effects, learning and better job matching that occur in cities (De la Roca & Puga, 2017; Duranton & Puga, 2004; Glaeser & Maré, 2001) and the second on the low productivity of traditional agriculture (Gollin et al., 2014; Lewis, 1954). The second focuses on sorting whereby the more qualified or better networked individuals choose to move to cities leading to the canceling out of much of the raw gap once worker characteristics are controlled for (Combes et al., 2008; Hicks et al., 2021; Lagakos, 2020; Young, 2013). The Kuznets (1955) hypothesis also makes another prediction: inequality should be greater in the urban sector in the case of a structural transformation where there are more different occupations and income levels as can be seen in Kanbur and Zhuang (2013).

These projections are complicated by rural South Asia's unique characteristics. In Pakistan, land ownership is skewed, bias against it is mainly due to inheritance and being landless is strongly linked to rural poverty (Anwar et al., 2004). Based on the latest agricultural census, average size of farms in Pakistan has further decreased and a large majority of farmers are engaged in very small scale farming operations whereas a small minority of large farms are holding a disproportionately high share of the farmland (PBS, 2025). Agricultural incomes are also very volatile. It is influenced by farm size, soil quality, irrigation, relative prices of inputs, and weather and families mitigate these shocks by relying on informal insurance, selling assets and diversifying into non-farm activities (Dercon, 2002; Kurosaki, 2006; Morduch, 1995; Townsend, 1994). Research on decomposition of rural Pakistan indicates that the source of income, especially agricultural and non-farm income has significant impact on measured inequality (Adams, 1994; Adams & He, 1995). In the neighbouring Indian Punjab, Gini coefficient of farm household income is about 0.48 (Saini & Kaur, 2022).

Intergenerational Mobility in Pakistan and South Asia

Education and occupation have been the two main aspects of intergenerational mobility studied in South Asia so far with a lack of data on incomes for two generations. Hnatkovska et al. (2013) documented convergence in educational and occupational status for the Indians' historically disadvantaged groups while Azam and Bhatt (2015) noted that educational mobility has increased but remains relatively low in India and that it is even lower in rural areas. Asher et al. (2024) demonstrated that upward educational mobility is indeed generally lower among historically disadvantaged groups and in rural areas. Emran and Shilpi (2015) pointed out that the gender and geographical determinants of educational mobility in post-reform India. Globally, the results of this study by van der Weide et al. (2024) indicate that there is less educational mobility in developing economy countries than in high income countries, on average.

Muhammad and Jamil (2020) revealed that there is a higher level of mobility in educational attainment at the primary and secondary level in Pakistan while the extremes in the distribution showed very low levels of mobility. Muhammad et al. (2022) also observed a high level of

education persistence and significant differences across provinces in Pakistan. Cheema and Naseer (2013) traced how historical landed hierarchies in rural Punjab continue to depress schooling among non-propertied groups while Jacoby and Mansuri (2015) showed that social hierarchy impedes the economic mobility of low-status groups in rural Pakistan. Kishwar and Alam (2021) found that educational persistence is concentrated at low levels of education among the children of informally employed fathers and Andlib et al. (2025) concluded that Pakistan's social elevator is effectively "broken," with parental education, household wealth, and region of residence all shaping children's prospects. For Multan specifically, earlier analyses of the household survey documented significant transmission of education (Sharif et al., 2016), occupation (Shareef et al., 2021) and social capital (Azid et al., 2021) across generations.

Income-based estimates of the IGE for Pakistan remain scarce and measuring the IGE in developing countries raises well-known difficulties. Single-year or retrospective measures of parental income contain transitory noise and therefore attenuate the IGE towards zero (Haider & Solon, 2006; Mazumder, 2005; Solon, 1992). Co-resident samples exclude children who have formed separate households typically the more mobile and thereby bias estimates (Emran et al., 2018). Surveying adult children directly and asking them to report their parents' income during their adolescence avoids co-residence truncation and follows the approach reviewed by Narayan et al. (2018) although it cannot eliminate recall error. To our knowledge, no prior study has estimated urban-rural differences in the IGE within a Pakistani district using interaction models or applied the Ferreira-Gignoux framework separately to urban and rural subsamples in Pakistan.

The Rural Informal Economy and the Limits of the Standard Framework

A less discussed limitation of the Ferreira-Gignoux framework is that its usual circumstance set was designed with formal labour markets in mind. Gender, parental education and birth order predict earnings well where jobs are allocated through credentials, bureaucratic pay scales and professional networks (Ioannides & Loury, 2004; Magruder, 2010). They are less good predictors in the informal sector of the agrarian economy where income relies on land and livestock inheritance, access to irrigation water, seasonal fluctuations in labour demand and weather shocks. However in those contexts, a large portion of the intergenerational transfer of advantage occurs via physical assets (Emran & Shilpi, 2011; Quisumbing et al., 2004). In addition, land inheritance is also significantly gendered in South Asia, further disconnecting the passing on of wealth from the passing on of schooling (Agarwal, 1994; Estudillo et al., 2001).

However, Brunori et al. (2013; 2019) point out that important circumstances are not observed and that IOp estimates for agrarian economies might underestimate actual IOp while Mogstad and Torsvik (2023) emphasize that an important pathway of intergenerational transmission is wealth, including land which is often not captured in income-based measures. Land distribution is also unequal at the broader level of development because it limits credit availability, investment and human capital development of the poor (Binswanger et al., 1995; Deininger & Squire, 1998). The standard framework will report low IOp in rural areas even if rural opportunity is highly unequal if these asset-based pathways are dominant on the incomes of rural people.

Research Hypotheses

The literature reviewed above suggests three conventional expectations which we test against the Multan data. First, because rural children face thinner labour markets, weaker schools and entrenched social hierarchies, intergenerational persistence should be higher in rural areas (Asher et al., 2024; Cheema & Naseer, 2013; Emran & Shilpi, 2015). Second, for the same reasons, circumstances should explain a larger share of rural than urban inequality (Bussolo et al., 2026; Rama et al., 2015). Third, following the Kuznets (1955) logic, total income inequality should be higher in the more diversified urban sector (Kanbur & Zhuang, 2013). Formally:

H1: The IGE is higher in rural than in urban Multan.

H2: Observable circumstances explain a larger share of income inequality in rural than in urban Multan.

H3: Total income inequality is higher in urban than in rural Multan.

Data and Descriptive Statistics

Study Area and Sample

This analysis is based on a primary survey conducted among 613 households in Multan District of Punjab, Pakistan. Out of these 455 (74%) live in the city of Multan and peri-urban areas while 158 respondents (26%) reside in neighbouring villages and agricultural settlements. Multan is a large urban centre approximately 2.2 million people and an agrarian hinterland typical of southern Punjab which renders it an appropriate site for a comparison of urban and rural transmission in the same institutional environment.

Variables

Child income refers to the income of the respondent from all sources in Pakistani rupees (PKR) per month. Parental income is measured backwards: it is the highest estimate of parental income made by the respondent at the time they were 10-15 years old. This is a common method used in contexts where administrative data is not available (Narayan et al., 2018). All incomes are log-transformed for estimation of IGE. The circumstance variables in the Ferreira-Gignoux decomposition are: respondent's gender, father's education (high/dad had secondary education, low/dad did not have secondary education), mother's education (high/mother had secondary education, low/mother did not have secondary education) and birth order (an indicator of the eldest child). Other than that, the regression models utilize a composite of parent socioeconomic status (ParentSES), the respondent's number of years in school and the number of years of working experience.

Descriptive Statistics

Table 1 reports summary statistics for the full sample and for the urban and rural subsamples. The comparison reveals clear differences in income levels, income dispersion and family background between the two areas.

Table 1

Descriptive Statistics by Area

Variable	Full sample (N = 613)	Urban (N = 455)	Rural (N = 158)
Mean child income (PKR)	18,240	19,580	15,890
SD of child income (PKR)	14,620	13,980	16,310
MLD (child income)	0.492	0.422	0.691
Gini (child income)	0.521	0.482	0.617
Mean parental income (PKR)	12,680	13,840	9,420
Male (%)	71.4	72.3	68.4
Father's education high (%)	38.7	43.5	23.4
Mother's education high (%)	24.1	27.8	13.9
Eldest child (%)	31.7	30.8	34.2
IGE (bivariate)	—	0.281***	0.260***

Note. PKR = Pakistani rupees; SD = standard deviation; MLD = mean log deviation; IGE = intergenerational elasticity of income from a bivariate OLS regression of log child income on log parental income. Income values are approximate monthly figures.

*** $p < .01$.

Table 1 shows that urban respondents are generally faring better on nearly all of the indicators. The mean income of mean child in the urban areas is 23% higher than that in the rural areas while the mean income of mean parents is 47% higher in urban areas than in rural areas. The disparity is even more pronounced in terms of parental education: 43.5% of the urban respondents have fathers with at least secondary education while 23.4% of the rural respondents have the same level of education for their fathers and 27.8% and 13.9% of the urban and rural respondents respectively have mothers with at least secondary education. The gaps are comparable with the known urban advantage in schooling and low educational level of rural women in Pakistan (Aslam, 2009; Cheema & Naseer, 2013; Muhammad et al., 2022). The male respondents (71.4%) were more prevalent owing to low participation rates of women in the labour force in Pakistan (Klasen, 2019).

The most striking feature of Table 1 is dispersion. Despite lower mean income, rural incomes have a higher standard deviation (PKR 16,310 against PKR 13,980), a higher Gini coefficient (0.617 against 0.482) and a 64% higher MLD (0.691 against 0.422). Rural Multan is therefore both poorer and more unequal than urban Multan contrary to H3. This pattern is consistent with evidence that agricultural and non-farm income sources generate large income differences among rural households in Pakistan and the Indian Punjab (Adams, 1994; Saini & Kaur, 2022) and that rural incomes are exposed to large idiosyncratic shocks (Kurosaki, 2006). It provides the first indication of the rural paradox examined below.

Empirical Methodology

Ferreira-Gignoux Decomposition of Inequality of Opportunity

Following Ferreira and Gignoux (2011), we estimate a parametric lower bound on IOp by regressing log child income on the circumstance vector $C = [\text{gender, father's education, mother's education, eldest child}]$ using ordinary least squares (OLS):

$$\ln Y_i = \alpha + C_i' \beta + \varepsilon_i \quad (1)$$

The fitted values $\hat{\mu}_i = \exp(\hat{\alpha} + C_i' \hat{\beta})$ form a smoothed distribution in which all inequality is due to observed circumstances. The relative IOp measure is the ratio of inequality in this smoothed distribution to total inequality:

$$\theta = I(\hat{\mu}) / I(Y), \text{ where } MLD(Y) = (1/N) \sum_i \ln(\bar{y} / y_i) \quad (2)$$

where $I(\cdot)$ is either the MLD or the Gini coefficient and $\bar{y}$ is mean income. We report both versions for comparability with the international literature (Brunori et al., 2013; Ferreira & Gignoux, 2011).

We also compute a non-parametric between-type decomposition. Types are defined by the full cross-product of gender, father's education, mother's education and the eldest-child indicator, giving up to 16 types in each area. Because the MLD is additively decomposable (Shorrocks, 1980), total inequality can be split into between-type and within-type components:

$$MLD(Y) = MLD_B + MLD_W, \quad \theta_{NP} = MLD_B / MLD(Y) \quad (3)$$

where MLD_B is the MLD of the distribution in which each person receives their type mean, and MLD_W is the population-weighted average of within-type MLDs (Checchi & Peragine, 2010).

Interaction Models for the Urban-Rural IGE

To test directly whether intergenerational transmission differs across the urban-rural boundary, we estimate a fully interacted model:

$$Y_i = \alpha + \beta_1 \text{ParentSES}_i + \beta_2 \text{Rural}_i + \gamma(\text{ParentSES}_i \times \text{Rural}_i) + X_i' \delta + \varepsilon_i \quad (4)$$

where β_1 measures the return to parental advantage in urban areas (the reference group), β_2 measures the rural income differential and γ tests whether parental advantage translates into child income differently in rural areas. X is a vector of controls: gender, years of schooling, years of experience, eldest-child status and father's and mother's education. We estimate four specifications: (1) ParentSES without controls (2) ParentSES with controls (3) log parental income without controls which gives the conventional IGE and (4) log parental income with controls. The key test in each case is $H_0: \gamma = 0$.

Separate Subgroup Models

To identify which variables drive income within each area, we also estimate separate OLS earnings equations for the urban ($N = 455$) and rural ($N = 158$) subsamples:

$$\ln Y_i = \alpha + \beta \text{ParentSES}_i + \lambda \text{Male}_i + \rho \text{Educ}_i + \phi \text{Exper}_i + \kappa \text{Eldest}_i + u_i \quad (5)$$

This specification follows the Mincerian tradition (Mincer, 1974; Heckman et al., 2006), augmented with family background variables and allows every coefficient to differ between the two areas.

Results

Inequality of Opportunity: Urban and Rural Multan

We begin with the parametric Ferreira-Gignoux decomposition. Table 2 reports total inequality, the inequality of the smoothed distribution and the resulting relative IOp shares for the full sample and for each area.

Table 2

Ferreira-Gignoux Parametric Decomposition of Inequality of Opportunity by Area

Group	N	MLD (Y)	IOp (MLD)	Relative IOp, MLD (%)	Gini (Y)	Relative IOp, Gini (%)	R ²
Full sample	613	0.492	0.034	6.8	0.521	28.1	0.085
Urban	455	0.422	0.033	7.7	0.482	29.3	0.099
Rural	158	0.691	0.017	2.5	0.617	15.2	0.031

Note. Circumstances are gender, father's education (high), mother's education (high), and eldest-child status; area is excluded from the subgroup circumstance sets. Estimates are parametric lower bounds following Ferreira and Gignoux (2011). MLD = mean log deviation; IOp = inequality of opportunity.

Table 2 shows a clear urban-rural contrast. Observable circumstances account for 7.7% of total urban income inequality under the MLD-based measure but only 2.5% of rural inequality (a threefold difference). The Gini-based measure which is known to yield larger shares (Brunori et al., 2013) gives the same ranking: 29.3% in urban areas against 15.2% in rural areas. The R² of the circumstance regression is also three times larger in urban areas (0.099 against 0.031) showing that family background and gender predict urban incomes far better than rural incomes. The urban estimates are close to the international range for developing countries. For instance, Das and Biswas (2022) attribute about one-quarter of urban Indian earnings inequality to circumstances and Singh (2012) shows substantial circumstance-driven earnings inequality among Indian men. The very small rural share is the first sign that the standard circumstance set does not capture how rural incomes are generated.

Because the parametric approach imposes a log-linear functional form, we check the results with the non-parametric decomposition reported in Table 3.

Table 3

Non-Parametric Between-Type Decomposition of the Mean Log Deviation by Area

Group	N	Total MLD	Between-type MLD (IOp)	Relative IOp (%)	Within-type MLD
Full sample	613	0.492	0.085	17.3	0.407
Urban	455	0.422	0.104	24.7	0.318
Rural	158	0.691	0.029	4.2	0.662

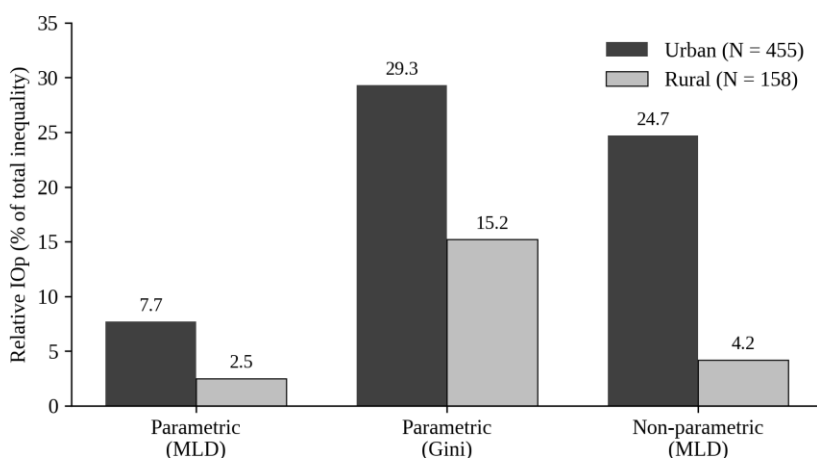
Note. Relative IOp = between-type MLD / total MLD. Types are the cross-product of gender × father's education × mother's education × eldest-child status (up to 16 types). The same circumstance set is used in both areas.

The non-parametric estimates in Table 3 are larger than the parametric ones which is expected because this estimator captures interactions among circumstances and tends to overstate IOp when cells are small (Brunori et al., 2019). The urban-rural ranking becomes even sharper. Circumstances explain 24.7% of urban inequality but only 4.2% of rural inequality a ratio of about six to one. The small-sample upward bias should inflate the rural estimate more than the urban one because rural types contain fewer observations. That the rural share remains so low despite this bias strengthens the conclusion that rural inequality is largely unrelated to the standard circumstances. H2 is therefore rejected: circumstances explain far more inequality in urban than in rural Multan.

Figure 1 brings together the three relative IOp measures from Tables 2 and 3 to show that the urban-rural ranking does not depend on the choice of estimator.

Figure 1

Relative Inequality of Opportunity by Area and Estimator



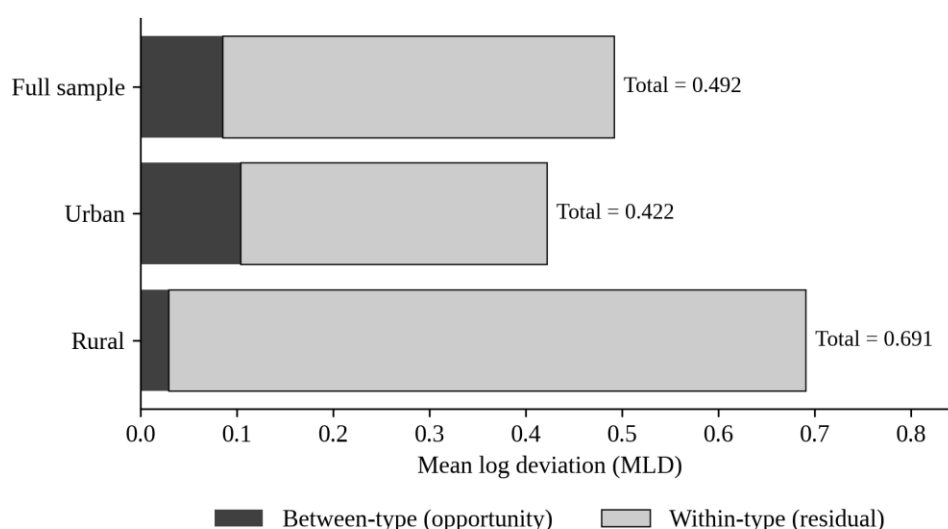
Note. Bars show the share of total inequality explained by observed circumstances. Values are taken from Tables 2 and 3.

As Figure 1 shows urban IOp exceeds rural IOp under every estimator by a factor of roughly two under the Gini-based measure three under the parametric MLD measure and six under the non-parametric MLD measure. The consistency of this ranking across methods with different biases suggests that the urban-rural gap in measured IOp is a robust feature of the data rather than a product of the estimator (Ferreira & Gignoux, 2011; Brunori et al., 2019).

Figure 2 decomposes total MLD into its between-type and within-type components to show where rural inequality comes from.

Figure 2

Between-Type and Within-Type Components of Income Inequality (MLD)



Note. Between-type inequality reflects differences across circumstance types; within-type inequality reflects differences among individuals with the same observed circumstances. Values are taken from Table 3.

Figure 2 makes the source of the rural paradox visible. Rural total MLD (0.691) is 64% higher than urban MLD (0.422) yet almost all of it (0.662 or 96%) lies within types. In other words, rural respondents with the same gender, parental education and birth order have very different incomes. By contrast, the between-type component is larger in urban areas (0.104) than in rural areas (0.029) in absolute terms as well. This pattern is consistent with studies showing that rural income inequality in South Asia is driven mainly by differences in landholding, crop income, livestock and access to non-farm work (Adams, 1994; Adams & He, 1995; Saini & Kaur, 2022) and by exposure to weather and price shocks (Dercon, 2002; Kurosaki, 2006), none of which are included in the circumstance set.

Interaction Models: Testing for Urban–Rural Differences in the IGE

The IOp results describe how much inequality is linked to circumstances but do not show whether parental advantage is transmitted at different rates in the two areas. Table 4 therefore reports the four interaction models.

Table 4

Interaction Models of Child Income on Parental Status and Rural Residence

Variable	Model 1	Model 2	Model 3	Model 4
ParentSES (β_1)	1.738*** (0.295)	1.357*** (0.294)		
ln(Parental income) (β_1)			0.281*** (0.034)	0.229*** (0.034)
Rural (β_2)	−0.131 (0.123)	n.r.	n.r.	n.r.
ParentSES × Rural (γ)	0.536 (0.636)	0.299 (0.601)		
ln(Parental income) × Rural (γ)			−0.022 (0.063)	−0.028 (0.059)
p-value of γ	.400	.620	.732	.639
Controls	No	Yes	No	Yes
N	613	613	605	605
R ²	0.092	0.229	0.147	0.277

Note. Dependent variable: log monthly child income. Standard errors in parentheses. Controls: male, years of schooling, years of experience, eldest-child status, father’s education (high), and mother’s education (high). n.r. = not reported; the rural level coefficient is statistically insignificant in all specifications (p between .29 and .99). The sample in Models 3 and 4 excludes eight respondents with missing parental income.

*** p < .01.

The coefficient on parental status is positive and highly significant in every specification in Table 4. In Model 1, a one-unit increase in the ParentSES index raises child income by 1.738 log points in urban areas (p < .001) and in Model 3 the urban IGE is 0.281 meaning that a 10% increase in parental income is associated with a 2.8% increase in child income. The positive sign is consistent with the Becker and Tomes (1979, 1986) model in which better-off parents invest more in their children’s human capital and with the transmission of abilities, preferences and social connections within families (Black & Devereux, 2011; Bowles & Gintis, 2002; Solon, 1999). Parental contacts are another channel in the Pakistani labour market where many good jobs come as a referral from parents (Kishwar & Alam, 2021; Magruder, 2010; Shareef et al., 2021). When controls are added, the ParentSES coefficient falls by 22% (from 1.738 to 1.357) and the IGE falls by 19% (from 0.281 to 0.229). This drop suggests that some of the parental effect is mediated by the child’s own schooling and experience while the rest goes through direct avenues like networks, wealth transfers and inherited attitudes as Blanden et al. (2007) show.

The rural level coefficient (β_2) is negative in Model 1 (-0.131) suggesting that the rural respondents earn approximately 12% less than the urban respondents with the same parental status. The negative relationship is predicted by the fact that agriculture is less productive and there are few formal jobs and less pay in rural labour markets (Gollin et al. 2014; Lewis 1954; Young 2013). However, it is in fact not statistically significant in Model 1 ($p = .286$) and in all other specifications. This finding implies that large portions of the compositional difference between the urban and rural earnings groups are attributable to educational and income imbalances between urban and rural parents so that controlling for these differences leaves little room for a further income difference based on residence. This interpretation is consistent with evidence showing that sorting of workers accounts for much of the spatial variation in wages (Combes et al., 2008; Hicks et al., 2021; Lagakos, 2020).

The key result concerns the interaction term γ which is statistically insignificant in all four models (p between .400 and .732). The sign of γ is positive in the ParentSES models (0.536 and 0.299) and negative in the log parental income models (-0.022 and -0.028). A positive sign would be consistent with the idea that rural status is more closely tied to land and other physical assets which pass directly from parents to children through inheritance (Cheema & Naseer, 2013; Emran & Shilpi, 2011; Quisumbing et al., 2004). A negative sign would be consistent with rural parental income being more volatile and seasonal so that retrospective reports contain more transitory noise and the IGE is attenuated (Kurosaki, 2006; Mazumder, 2005; Solon, 1992) and with rural child incomes being exposed to shocks unrelated to family background (Dercon, 2002; Townsend, 1994). Because the signs differ across measures and none is statistically significant, we conclude that parental advantage is transmitted at statistically indistinguishable rates in urban and rural Multan. H1 is therefore rejected.

5.3 Subgroup Models: Drivers of Income Within Each Area

The pooled interaction models constrain the effects of the control variables to be equal across areas. To examine what drives income within each area, Table 5 reports separate OLS earnings equations for the urban and rural subsamples.

Table 5

OLS Earnings Models for Urban and Rural Subsamples

Variable	Urban coefficient	p	Rural coefficient	p
Constant	1.203***	< .001	1.428***	< .001
ParentSES	1.465***	< .001	0.972	.249
Male (= 1)	0.402***	< .001	0.161	.583
Education (years)	0.069***	< .001	0.080***	< .001
Experience (years)	0.028***	< .001	0.013	.190
Eldest child (= 1)	0.087	.244	0.064	.688
N	455		158	
R²	0.242		0.185	

Note. Dependent variable: log monthly income. Coefficients are OLS estimates.

*** $p < .01$.

The income determinants are quite different in the two areas as indicated in Table 5. In urban Multan, all the variables are positive and significant at 1% level except for parental status which is positive but not significant at 1%. In rural Multan, only own education is significant. We discuss each coefficient in turn.

Parental status

The coefficient for ParentSES is positive in both areas and only significant in urban Multan (1.465, $p < .001$). The positive effects are from the intergenerational channels already mentioned: parental investment in schooling, bequests of skills and attitudes and family networks for accessing jobs (Becker & Tomes, 1986; Bowles & Gintis, 2002; Ioannides & Loury, 2004). The channels are particularly robust in a city where labor market opportunities in public-sector and professional occupations are partly based on credentials or connections (Shareef et al., 2021; Magruder, 2010). The smaller and insignificant rural coefficient (0.972, $p = .249$) confirms that rural advantage is getting passed through largely via land and livestock which is only partly through the composite ParentSES index (Emran & Shilpi, 2011; Quisumbing et al., 2004). The smaller rural sample also results in less power.

Gender

The log points for male residents in urban Multan are 0.402 log points higher than for women with comparable characteristics ($p < .001$). The positive coefficient of a male is well documented in Pakistan and developing economies generally as it reflects the occupational segregation, limited mobility for women, discriminatory hiring and pay practices and the higher share of women in lower-paid and part-time work (Aslam, 2009; Blau & Kahn, 2017; Jayachandran, 2015; Nasir, 2002). The male coefficient is also positive in rural Multan but it is smaller (0.161) and its significance is not significant ($p = .583$). In agricultural contexts, women's labour is often largely unpaid on their families' farms and in livestock raising and household income may be shared among family members, reducing the association between women's gender and reported income (Agarwal, 1994; Goldin, 1995; Klasen, 2019). Some of this is also due to low precision.

Education

In urban areas, every extra year of education contributes 6.9% to earnings and in rural areas it contributes 8.0% to earnings (both $p < .001$). The positive sign represents the conventional human capital finding (Mincer, 1974; Psacharopoulos & Patrinos, 2018) with both estimates in line with previous findings for Pakistan (Aslam, 2009; Nasir, 2002). There are two possible reasons for the slightly higher rural return. Second, education can boost farmers' capacity to embrace new technologies and make efficient input use as demonstrated by previous research on education and farm productivity (Foster & Rosenzweig, 1996; Schultz, 1975; Welch, 1970), and in rural Pakistan, education increases productivity and farm income (Fafchamps & Quisumbing, 1999; Kurosaki & Khan, 2006). Second, education is the primary pathway to better-paid rural non-farm jobs (Adams, 1994, Haggblade et al., 2010, Lanjouw & Lanjouw, 2001). The premiums on years of education are comparatively high in rural areas since laborers are less available in rural regions.

Experience

Experience has a positive and significant effect in urban areas (2.8% per year, $p < .001$) but a smaller and insignificant effect in rural areas (1.3% per year, $p = .190$). The positive sign reflects on-the-job learning and the accumulation of firm-specific and general skills (Heckman et al., 2006; Mincer, 1974). Cities offer more opportunities for such learning (De la Roca & Puga, 2017; Glaeser & Maré, 2001) whereas in agriculture and casual labour, earnings depend more on physical effort and seasonal demand than on accumulated skill. This result matches cross-country evidence that age-earnings profiles are much flatter in poorer and less formal labour markets (Lagakos et al., 2018).

Birth order

Being the eldest child has a small positive but insignificant effect in both areas (0.087 in urban and 0.064 in rural). Two opposing forces explain the positive but weak coefficient. On the one hand, first-born children often receive more parental time and resources and in South Asia son preference strengthens this advantage for eldest sons (Black et al., 2005; Booth & Kee, 2009; Jayachandran & Pande, 2017). On the other hand, in poorer households the eldest child is more likely to leave school early to work or care for siblings while later-born children may benefit from rising household income (Behrman & Taubman, 1986; Ejrnæs & Pörtner, 2004; Emerson & Souza, 2008). These offsetting effects leave birth order with little net influence on adult earnings in Multan.

Overall, the urban model explains 24.2% of the variation in log income, compared with 18.5% for the rural model. Together with the IOp results, this confirms that family background and gender are central to urban income determination whereas rural income depends mainly on own education and on factors that the model does not observe.

Intergenerational Elasticity and Total Inequality by Area

Table 6 brings together the IGE estimates from separate urban and rural regressions and the total inequality measures so that persistence and inequality can be compared directly.

Table 6

Intergenerational Elasticity and Total Inequality by Area

Group	N	IGE (bivariate)	IGE (with controls)	Total MLD	Total Gini
Urban	448	0.281***	0.239***	0.422	0.482
Rural	157	0.260***	0.171**	0.691	0.617
Difference (urban-rural)	—	0.021 (n.s.)	0.068 (n.s.)	-0.269	-0.135

Note. IGE estimates come from separate urban and rural regressions of log child income on log parental income; controls are as in Table 4. Differences in the IGE are tested using the interaction terms in Table 4 (Model 3: $p = .732$; Model 4: $p = .639$). n.s. = not significant.

*** $p < .01$. ** $p < .05$.

The results in Table 6 show that intergenerational persistence and total inequality move in opposite directions across the two areas. The bivariate IGE is almost identical in urban (0.281) and rural (0.260) Multan and even with controls the difference (0.239 against 0.171) is not significant. These values are moderate by international standards. Corak (2013) reports IGEs ranging from below 0.20 in the Nordic countries to about 0.50 in the United States and the United Kingdom and developing countries typically show higher persistence (Narayan et al., 2018). The Multan estimates are probably lower bounds because retrospective reports of parental income contain transitory and recall error that attenuates the IGE (Haider & Solon, 2006; Mazumder, 2005; Solon, 1992).

Total inequality by contrast is much higher in rural areas with an MLD 0.269 points higher and a Gini coefficient 0.135 points higher than in urban areas. This finding runs against the Kuznets (1955) expectation that inequality should be greater in the more diversified urban sector (Kanbur & Zhuang, 2013) and it confirms the rejection of H3. Taken together, Table 6 shows that rural Multan is more unequal than urban Multan without being less mobile which is the core of the Multan Spatial Paradox.

Predicted Income Profiles: A Uniform Urban Premium

To illustrate what the interaction results imply in monetary terms, Table 7 reports predicted child income at different points of the parental income distribution for urban and rural respondents, using Model 4 with controls held at their sample means.

Table 7

Predicted Child Income by Parental Income Level in Urban and Rural Areas

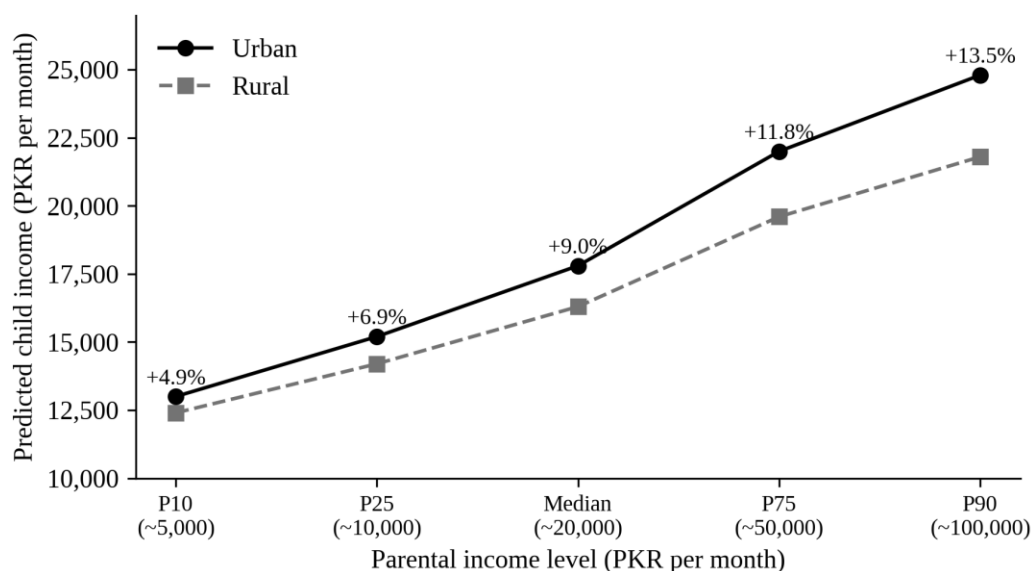
Parental income level	Parental income (PKR)	Urban predicted (PKR)	Rural predicted (PKR)	Urban premium (%)	Absolute gap (PKR)
10th percentile	5,000	13,000	12,400	4.9	600
25th percentile	10,000	15,200	14,200	6.9	1,000
Median	20,000	17,800	16,300	9.0	1,500
75th percentile	50,000	22,000	19,600	11.8	2,300
90th percentile	100,000	24,800	21,800	13.5	2,900

Note. Predicted values are from Model 4 in Table 4, with control variables held at their sample means. Urban premium = (urban – rural) / rural × 100.

Table 7 shows that urban respondents earn more than rural respondents at every level of parental income but the premium is modest rising from 4.9% (PKR 600) at the 10th percentile to 13.5% (PKR 2,900) at the 90th percentile. Figure 3 plots the two predicted profiles.

Figure 3

Predicted Child Income Across the Parental Income Distribution, Urban and Rural



Note. Predicted values from Model 4 in Table 4, with controls held at sample means. Percentages show the urban premium over rural predicted income. Values are taken from Table 7.

Figure 3 shows two nearly parallel profiles. The gap widens only gradually as parental income rises which is consistent with the small and insignificant interaction term in Model 4. If parental advantage were transmitted more strongly in urban areas, the urban line would be much steeper than the rural line. Instead, the urban advantage takes the form of a level premium that is broadly similar for children from poor and rich families. Such a premium is consistent with the higher productivity and wages of urban labour markets (Glaeser & Maré, 2001; Gollin et al., 2014) and its modest size is consistent with evidence that much of the raw urban-rural gap reflects worker composition rather than location itself (Combes et al., 2008; Hicks et al., 2021). This pattern differs sharply from that for gender where the male-female gap widens markedly with parental income from about 6% to about 75% across the parental income distribution.

Discussion and Policy Implications

Explaining the Multan Spatial Paradox

The combination of high total rural inequality, low circumstance-explained rural inequality and identical urban and rural IGEs is what we term the Multan Spatial Paradox. Its explanation lies in the structural differences between urban formal and rural informal labour markets.

In urban Multan, labour markets are more formal. Credentials, social networks and employer contacts matter and the child of an educated, high-income family has better access to public-sector jobs, professional training and referral networks that convert parental background into

income (Ioannides & Loury, 2004; Magruder, 2010). Observed circumstances are therefore strong predictors of urban income because the urban economy rewards the attributes that family background provides.

In rural Multan, income comes mainly from crop farming, livestock, day labour and seasonal work. These sources depend more on land size and quality, irrigation and weather than on family credentials (Adams, 1994; Kurosaki, 2006). Two rural respondents of the same gender, parental education and birth order may therefore have very different incomes because one inherited irrigated land and the other did not. This generates the very large within-type variance observed in the data (within-type MLD = 0.662; between-type MLD = 0.029).

The identical IGEs fit this interpretation. The IGE measures how strongly parental income predicts child income. If rural income depends mainly on inherited land which is itself correlated with parental income then the rural IGE will be positive and similar in size to the urban IGE even though the transmission mechanism is different. It operates through the transfer of assets rather than the transfer of credentials (Emran & Shilpi, 2011; Mogstad & Torsvik, 2023; Quisumbing et al., 2004). Similar IGE values can therefore conceal very different mechanisms, one of which (credential-based transmission in urban areas) is captured by the standard circumstance set and one of which (asset-based transmission in rural areas) is not. This limitation is important for interpreting IGE estimates in agrarian economies.

Why the Rural Gender Effect Disappears

The insignificant rural gender coefficient (0.161, $p = .583$) is consistent with the informal-economy interpretation. Income from agriculture and livestock does not carry the same formal-sector gender premium found in urban labour markets because it depends mainly on plot size and productivity rather than on the worker's gender and because women's farm work is often unpaid and absorbed into household income (Agarwal, 1994; Goldin, 1995). Statistical power is also a concern. With only 158 rural respondents, the standard error of the rural gender coefficient (0.292) is about four times that of the urban estimate. The point estimate which implies a premium of about 17%, is not negligible and a larger rural sample might reveal a significant gap.

Policy Implications

The findings have several implications for inequality and poverty reduction in Multan District and in comparable urban-rural settings across Pakistan and South Asia.

Expanding access to formal employment

The insignificant interaction terms imply that the urban-rural income gap is a level effect driven by access to better-paid formal jobs rather than by differences in the transmission of family advantage. The policy priority should therefore be to expand formal and non-farm employment in rural areas through rural industrial zones, support for rural non-farm enterprises, and investment in transport and digital infrastructure (Haggblade et al., 2010; Lanjouw & Lanjouw, 2001).

Extending the circumstance set in rural IOp measurement

The low rural IOp estimates (2.5%–4.2%) should not be read as evidence that rural children enjoy equal opportunity. They reflect the inadequacy of the standard circumstance set for informal agrarian economies. Future IOp studies in rural Pakistan and South Asia should include inherited land, irrigation access, livestock holdings, caste or *biradari* affiliation and distance to markets as circumstances (Brunori et al., 2019; Jacoby & Mansuri, 2015). These factors are as morally arbitrary as gender or parental education.

Addressing land inequality

Because land is a central determinant of rural income and is unequally distributed (Anwar et al., 2004; PBS, 2025) measures that improve land access for smallholders and landless households such as secure tenancy rights, land record digitization, and access to agricultural credit would address the circumstance that our framework cannot observe but that the evidence suggests is most important (Binswanger et al., 1995; Deininger & Squire, 1998).

Education as the rural equalizer

Own education is the only significant predictor of rural income in our subgroup models. Expanding access to good-quality secondary and vocational education in rural Multan could therefore reduce rural inequality through a channel that works largely independently of family background in line with evidence on the returns to schooling in rural Pakistan (Fafchamps & Quisumbing, 1999; Kurosaki & Khan, 2006) and with the case for universal secondary education in agrarian settings (Psacharopoulos & Patrinos, 2018).

Limitations and Directions for Future Research

Several limitations should be noted. First, parental income is reported retrospectively so it is subject to recall error that likely attenuates the IGE (Haider & Solon, 2006; Solon, 1992). Second, the rural sample ($N = 158$) is modest which limits statistical power for detecting urban-rural differences and makes the non-parametric estimates sensitive to small cell sizes (Brunori et al., 2019). Third, the data come from a single district so the results should be generalized with care. Fourth, the survey does not record land inheritance, livestock or irrigation access which prevents a direct test of the asset-based explanation proposed here. Future research should collect these variables, use larger rural samples and apply tree-based IOp estimators that are less sensitive to the choice of functional form (Brunori et al., 2023; Hufe et al., 2022).

Conclusion

This paper has documented the Multan Spatial Paradox, an urban-rural contrast in the structure of income inequality that contradicts the common expectation that more rigid rural social structures produce greater circumstance-driven inequality. Using survey data from 613 households in Multan District, the Ferreira-Gignoux decomposition and interaction-based IGE models, we establish three findings.

First, intergenerational income persistence is statistically identical in urban and rural Multan (bivariate IGE of about 0.28 and 0.26) which rules out the hypothesis that the rural sector transmits economic advantage more strongly across generations. Second, observable circumstances explain three to six times more urban than rural income inequality with urban IOP between 7.7% and 24.7% and rural IOP between 2.5% and 4.2% on MLD-based measures. Third, rural total inequality is 64% higher than urban inequality (MLD of 0.691 against 0.422) and almost all of it arises within circumstance types which points to informal-economy factors such as land quality, agricultural productivity and seasonal labour demand that lie outside the standard circumstance set.

These findings have methodological implications for IOP research in developing countries. The Ferreira-Gignoux lower bound depends on the observed circumstance set and in rural informal economies where the most important circumstances (land, assets and informal inheritance) are unobserved, it may lie far below true IOP. Future work should develop expanded circumstance sets for agrarian contexts and test whether landholding explains the within-type variance left unexplained here.

For policy, the main implication is that the urban-rural income gap in Multan is a level effect associated with the urban wage premium not a difference in intergenerational transmission. Closing it requires expanding access to formal and non-farm employment in rural areas, not equalising transmission rates that are already similar. Within rural areas, education which is the only significant predictor of rural income in our models offers the most accessible route to reducing inequality and widening economic opportunity for rural children regardless of family background.

References

1. Acciari, P., Polo, A., & Violante, G. L. (2022). And yet it moves: Intergenerational mobility in Italy. *American Economic Journal: Applied Economics*, 14(3), 118–163.
2. Adams, R. H., Jr. (1994). Non-farm income and inequality in rural Pakistan: A decomposition analysis. *Journal of Development Studies*, 31(1), 110–133.
3. Adams, R. H., Jr., & He, J. J. (1995). *Sources of income inequality and poverty in rural Pakistan* (Research Report No. 102). International Food Policy Research Institute.
4. Agarwal, B. (1994). *A field of one's own: Gender and land rights in South Asia*. Cambridge University Press.
5. Alesina, A., Hohmann, S., Michalopoulos, S., & Papaioannou, E. (2021). Intergenerational mobility in Africa. *Econometrica*, 89(1), 1–35. <https://doi.org/10.3982/ECTA17018>
6. Andlib, Z., Sadiq, M., & Scicchitano, S. (2025). Intergenerational (im)mobility in Pakistan: Is the social elevator broken? *Eurasian Economic Review*, 15(4), 985–1019.
7. Anwar, T., Qureshi, S. K., & Ali, H. (2004). Landlessness and rural poverty in Pakistan. *The Pakistan Development Review*, 43(4), 855–874.
8. Arneson, R. J. (1989). Equality and equal opportunity for welfare. *Philosophical Studies*, 56(1), 77–93.

9. Asher, S., Novosad, P., & Rafkin, C. (2024). Intergenerational mobility in India: New measures and estimates across time and social groups. *American Economic Journal: Applied Economics*, 16(2), 66–98.
10. Aslam, M. (2009). Education gender gaps in Pakistan: Is the labor market to blame? *Economic Development and Cultural Change*, 57(4), 747–784. <https://doi.org/10.1086/598767>
11. Azam, M., & Bhatt, V. (2015). Like father, like son? Intergenerational educational mobility in India. *Demography*, 52(6), 1929–1959.
12. Azid, T., Shareef, F., & Kayani, Z. (2021). Intergenerational transmission of family and communication social capital in Pakistan: An empirical analysis. *International Journal of Education Economics and Development*, 12(4), 412–429.
13. Becker, G. S., & Tomes, N. (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy*, 87(6), 1153–1189.
14. Becker, G. S., & Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of Labor Economics*, 4(3, Part 2), S1–S39.
15. Behrman, J. R., & Taubman, P. (1986). Birth order, schooling, and earnings. *Journal of Labor Economics*, 4(3, Part 2), S121–S145.
16. Binswanger, H. P., Deininger, K., & Feder, G. (1995). Power, distortions, revolt and reform in agricultural land relations. In J. Behrman & T. N. Srinivasan (Eds.), *Handbook of development economics* (Vol. 3B, pp. 2659–2772). Elsevier.
17. Black, S. E., & Devereux, P. J. (2011). Recent developments in intergenerational mobility. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 4B, pp. 1487–1541). Elsevier.
18. Black, S. E., Devereux, P. J., & Salvanes, K. G. (2005). The more the merrier? The effect of family size and birth order on children's education. *The Quarterly Journal of Economics*, 120(2), 669–700.
19. Blanden, J., Gregg, P., & Macmillan, L. (2007). Accounting for intergenerational income persistence: Noncognitive skills, ability and education. *The Economic Journal*, 117(519), C43–C60.
20. Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3), 789–865.
21. Booth, A. L., & Kee, H. J. (2009). Birth order matters: The effect of family size and birth order on educational attainment. *Journal of Population Economics*, 22(2), 367–397.
22. Bourguignon, F. (1979). Decomposable income inequality measures. *Econometrica*, 47(4), 901–920. <https://doi.org/10.2307/1914138>
23. Bourguignon, F., Ferreira, F. H. G., & Menéndez, M. (2007). Inequality of opportunity in Brazil. *Review of Income and Wealth*, 53(4), 585–618.
24. Bowles, S., & Gintis, H. (2002). The inheritance of inequality. *Journal of Economic Perspectives*, 16(3), 3–30.
25. Brunori, P., Ferreira, F. H. G., & Peragine, V. (2013). Inequality of opportunity, income inequality, and economic mobility: Some international comparisons. In E. Paus (Ed.), *Getting development right: Structural transformation, inclusion, and sustainability in the post-crisis era* (pp. 85–115). Palgrave Macmillan.
26. Brunori, P., Hufe, P., & Mahler, D. G. (2023). The roots of inequality: Estimating inequality of opportunity from regression trees and forests. *The Scandinavian Journal of Economics*, 125(4), 900–932. <https://doi.org/10.1111/sjoe.12530>

27. Brunori, P., Peragine, V., & Serlenga, L. (2019). Upward and downward bias when measuring inequality of opportunity. *Social Choice and Welfare*, 52(4), 635–661.
28. Bussolo, M., Peragine, V., & Reutzels, F. (2026). *Inequality of opportunity in South Asia: The puzzle of educational gains without consumption gains* (Policy Research Working Paper No. 11395). World Bank.
29. Checchi, D., & Peragine, V. (2010). Inequality of opportunity in Italy. *The Journal of Economic Inequality*, 8(4), 429–450.
30. Cheema, A., & Naseer, M. F. (2013). Historical inequality and intergenerational educational mobility: The dynamics of change in rural Punjab. *The Lahore Journal of Economics*, 18(Special Edition), 211–231.
31. Chetty, R., & Hendren, N. (2018). The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects. *The Quarterly Journal of Economics*, 133(3), 1107–1162. <https://doi.org/10.1093/qje/qjy007>
32. Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics*, 129(4), 1553–1623. <https://doi.org/10.1093/qje/qju022>
33. Cohen, G. A. (1989). On the currency of egalitarian justice. *Ethics*, 99(4), 906–944.
34. Combes, P.-P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters! *Journal of Urban Economics*, 63(2), 723–742.
35. Connolly, M., Corak, M., & Haack, C. (2019). Intergenerational mobility between and within Canada and the United States. *Journal of Labor Economics*, 37(S2), S595–S641.
36. Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives*, 27(3), 79–102. <https://doi.org/10.1257/jep.27.3.79>
37. Das, P., & Biswas, S. (2022). Social identity, gender and unequal opportunity of earning in urban India: 2017–2018 to 2019–2020. *The Indian Journal of Labour Economics*, 65(1), 39–57. <https://doi.org/10.1007/s41027-022-00360-2>
38. De la Roca, J., & Puga, D. (2017). Learning by working in big cities. *The Review of Economic Studies*, 84(1), 106–142.
39. Deininger, K., & Squire, L. (1998). New ways of looking at old issues: Inequality and growth. *Journal of Development Economics*, 57(2), 259–287.
40. Dercon, S. (2002). Income risk, coping strategies, and safety nets. *The World Bank Research Observer*, 17(2), 141–166.
41. Deutscher, N., & Mazumder, B. (2020). Intergenerational mobility across Australia and the stability of regional estimates. *Labour Economics*, 66, Article 101861.
42. Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (Vol. 4, pp. 2063–2117). Elsevier.
43. Durlauf, S. N., Kourtellos, A., & Tan, C. M. (2022). The Great Gatsby curve. *Annual Review of Economics*, 14, 571–605.
44. Dworkin, R. (1981). What is equality? Part 2: Equality of resources. *Philosophy & Public Affairs*, 10(4), 283–345.
45. Ejrnæs, M., & Pörtner, C. C. (2004). Birth order and the intrahousehold allocation of time and education. *The Review of Economics and Statistics*, 86(4), 1008–1019.
46. Emerson, P. M., & Souza, A. P. (2008). Birth order, child labor, and school attendance in Brazil. *World Development*, 36(9), 1647–1664.

47. Emran, M. S., Greene, W., & Shilpi, F. (2018). When measure matters: Coresidency, truncation bias, and intergenerational mobility in developing countries. *Journal of Human Resources*, 53(3), 589–607. <https://doi.org/10.3368/jhr.53.3.0216-7737R1>
48. Emran, M. S., & Shilpi, F. (2011). Intergenerational occupational mobility in rural economy: Evidence from Nepal and Vietnam. *Journal of Human Resources*, 46(2), 427–458.
49. Emran, M. S., & Shilpi, F. (2015). Gender, geography, and generations: Intergenerational educational mobility in post-reform India. *World Development*, 72, 362–380.
50. Estudillo, J. P., Quisumbing, A. R., & Otsuka, K. (2001). Gender differences in land inheritance, schooling and lifetime income: Evidence from the rural Philippines. *Journal of Development Studies*, 37(4), 23–48.
51. Fafchamps, M., & Quisumbing, A. R. (1999). Human capital, productivity, and labor allocation in rural Pakistan. *Journal of Human Resources*, 34(2), 369–406.
52. Fan, Y., Yi, J., & Zhang, J. (2021). Rising intergenerational income persistence in China. *American Economic Journal: Economic Policy*, 13(1), 202–230.
53. Ferreira, F. H. G., & Gignoux, J. (2011). The measurement of inequality of opportunity: Theory and an application to Latin America. *Review of Income and Wealth*, 57(4), 622–657.
54. Ferreira, F. H. G., Lakner, C., Lugo, M. A., & Özler, B. (2018). Inequality of opportunity and economic growth: How much can cross-country regressions really tell us? *Review of Income and Wealth*, 64(4), 800–827. <https://doi.org/10.1111/roiw.12311>
55. Fleurbaey, M., & Peragine, V. (2013). Ex ante versus ex post equality of opportunity. *Economica*, 80(317), 118–130.
56. Foster, A. D., & Rosenzweig, M. R. (1996). Technical change and human-capital returns and investments: Evidence from the green revolution. *The American Economic Review*, 86(4), 931–953.
57. Glaeser, E. L., & Maré, D. C. (2001). Cities and skills. *Journal of Labor Economics*, 19(2), 316–342.
58. Goldin, C. (1995). The U-shaped female labor force function in economic development and economic history. In T. P. Schultz (Ed.), *Investment in women's human capital* (pp. 61–90). University of Chicago Press.
59. Gollin, D., Lagakos, D., & Waugh, M. E. (2014). The agricultural productivity gap. *The Quarterly Journal of Economics*, 129(2), 939–993. <https://doi.org/10.1093/qje/qjt056>
60. Gómez-Lobo, A., & Oviedo, D. (2025). Spatial inequality and income disparities in Latin America: A multiscale analysis. *Oxford Open Economics*, 4(Supplement 1), i307–i333. <https://doi.org/10.1093/ooec/odae039>
61. Haggblade, S., Hazell, P., & Reardon, T. (2010). The rural non-farm economy: Prospects for growth and poverty reduction. *World Development*, 38(10), 1429–1441.
62. Haider, S., & Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *The American Economic Review*, 96(4), 1308–1320.
63. Hassine, N. B. (2012). Inequality of opportunity in Egypt. *The World Bank Economic Review*, 26(2), 265–295.
64. Heckman, J. J., Lochner, L. J., & Todd, P. E. (2006). Earnings functions, rates of return and treatment effects: The Mincer equation and beyond. In E. A. Hanushek & F. Welch (Eds.), *Handbook of the economics of education* (Vol. 1, pp. 307–458). Elsevier.

65. Heidrich, S. (2017). Intergenerational mobility in Sweden: A regional perspective. *Journal of Population Economics*, 30(4), 1241–1280.
66. Hicks, J. H., Kleemans, M., Li, N. Y., & Miguel, E. (2021). Reevaluating agricultural productivity gaps with longitudinal microdata. *Journal of the European Economic Association*, 19(3), 1522–1555.
67. Hnatkovska, V., Lahiri, A., & Paul, S. (2013). Breaking the caste barrier: Intergenerational mobility in India. *Journal of Human Resources*, 48(2), 435–473.
68. Hufe, P., Kanbur, R., & Peichl, A. (2022). Measuring unfair inequality: Reconciling equality of opportunity and freedom from poverty. *The Review of Economic Studies*, 89(6), 3345–3380.
69. Ioannides, Y. M., & Loury, L. D. (2004). Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature*, 42(4), 1056–1093.
70. Jacoby, H. G., & Mansuri, G. (2015). Crossing boundaries: How social hierarchy impedes economic mobility. *Journal of Economic Behavior & Organization*, 117, 135–154.
71. Jayachandran, S. (2015). The roots of gender inequality in developing countries. *Annual Review of Economics*, 7, 63–88.
72. Jayachandran, S., & Pande, R. (2017). Why are Indian children so short? The role of birth order and son preference. *The American Economic Review*, 107(9), 2600–2629.
73. Kanbur, R., & Venables, A. J. (Eds.). (2005). *Spatial inequality and development*. Oxford University Press.
74. Kanbur, R., & Zhuang, J. (2013). Urbanization and inequality in Asia. *Asian Development Review*, 30(1), 131–147.
75. Khan, Z. A., & Patra, B. (2024). Intergenerational mobility in South Asia. *South Asia Economic Journal*, 25(1), 7–25. <https://doi.org/10.1177/13915614241226538>
76. Kishwar, S., & Alam, K. (2021). Educational mobility across generations of formally and informally employed: Evidence from Pakistan. *International Journal of Educational Development*, 87, Article 102505. <https://doi.org/10.1016/j.ijedudev.2021.102505>
77. Klasen, S. (2019). What explains uneven female labor force participation levels and trends in developing countries? *The World Bank Research Observer*, 34(2), 161–197.
78. Kurosaki, T. (2006). Consumption vulnerability to risk in rural Pakistan. *Journal of Development Studies*, 42(1), 70–89.
79. Kurosaki, T., & Khan, H. (2006). Human capital, productivity, and stratification in rural Pakistan. *Review of Development Economics*, 10(1), 116–134.
80. Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review*, 45(1), 1–28.
81. Lagakos, D. (2020). Urban-rural gaps in the developing world: Does internal migration offer opportunities? *Journal of Economic Perspectives*, 34(3), 174–192.
82. Lagakos, D., Moll, B., Porzio, T., Qian, N., & Schoellman, T. (2018). Life cycle wage growth across countries. *Journal of Political Economy*, 126(2), 797–849.
83. Lanjouw, J. O., & Lanjouw, P. (2001). The rural non-farm sector: Issues and evidence from developing countries. *Agricultural Economics*, 26(1), 1–23.
84. Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *The Manchester School*, 22(2), 139–191.
85. Lipton, M. (1977). *Why poor people stay poor: Urban bias in world development*. Harvard University Press.

86. Magruder, J. R. (2010). Intergenerational networks, unemployment, and persistent inequality in South Africa. *American Economic Journal: Applied Economics*, 2(1), 62–85.
87. Marrero, G. A., & Rodríguez, J. G. (2013). Inequality of opportunity and growth. *Journal of Development Economics*, 104, 107–122.
88. Mazumder, B. (2005). Fortunate sons: New estimates of intergenerational mobility in the United States using Social Security earnings data. *The Review of Economics and Statistics*, 87(2), 235–255.
89. Mincer, J. (1974). *Schooling, experience, and earnings*. National Bureau of Economic Research.
90. Mogstad, M., & Torsvik, G. (2023). Family background, neighborhoods, and intergenerational mobility. In S. Lundberg & A. Voena (Eds.), *Handbook of the economics of the family* (Vol. 1, pp. 327–387). North-Holland. <https://doi.org/10.1016/bs.hefam.2023.01.005>
91. Morduch, J. (1995). Income smoothing and consumption smoothing. *Journal of Economic Perspectives*, 9(3), 103–114.
92. Muhammad, M., & Jamil, M. (2020). Intergenerational mobility in educational attainments. *The Pakistan Development Review*, 59(2), 179–198.
93. Muhammad, M., Shirazi, N. S., & Khan, Z. (2022). Intergenerational mobility in educational attainments: A comparative analysis at provincial level of Pakistan. *International Journal of Education Economics and Development*, 13(1), 38–57.
94. Narayan, A., Van der Weide, R., Cojocar, A., Lakner, C., Redaelli, S., Mahler, D. G., Ramasubbaiah, R. G. N., & Thewissen, S. (2018). *Fair progress? Economic mobility across generations around the world*. World Bank.
95. Nasir, Z. M. (2002). Returns to human capital in Pakistan: A gender disaggregated analysis. *The Pakistan Development Review*, 41(1), 1–28.
96. OECD. (2018). *A broken social elevator? How to promote social mobility*. OECD Publishing.
97. Pakistan Bureau of Statistics. (2023). *7th population and housing census 2023: The digital census*. Government of Pakistan.
98. Pakistan Bureau of Statistics. (2025). *7th agricultural census 2024*. Government of Pakistan.
99. Psacharopoulos, G., & Patrinos, H. A. (2018). Returns to investment in education: A decennial review of the global literature. *Education Economics*, 26(5), 445–458.
100. Quisumbing, A. R., Estudillo, J. P., & Otsuka, K. (2004). *Land and schooling: Transferring wealth across generations*. Johns Hopkins University Press.
101. Rama, M., Béteille, T., Li, Y., Mitra, P. K., & Newman, J. L. (2015). *Addressing inequality in South Asia*. World Bank.
102. Ramos, X., & Van de gaer, D. (2016). Approaches to inequality of opportunity: Principles, measures and evidence. *Journal of Economic Surveys*, 30(5), 855–883.
103. Rawls, J. (1971). *A theory of justice*. Harvard University Press.
104. Roemer, J. E. (1998). *Equality of opportunity*. Harvard University Press.
105. Roemer, J. E., & Trannoy, A. (2016). Equality of opportunity: Theory and measurement. *Journal of Economic Literature*, 54(4), 1288–1332.

106. Saini, R., & Kaur, M. (2022). Income inequality and its decomposition among farm households in Punjab. *Cogent Food & Agriculture*, 8(1), Article 2069314. <https://doi.org/10.1080/23311932.2022.2069314>
107. Schultz, T. W. (1975). The value of the ability to deal with disequilibria. *Journal of Economic Literature*, 13(3), 827–846.
108. Shareef, F., Azid, T., & Shirazi, N. S. (2021). Intergenerational mobility of education and occupation in Pakistan: A multinomial logistic analysis. *International Journal of Education Economics and Development*, 12(4), 360–380.
109. Sharif, F., Khawaja, M. J., & Azid, T. (2016). Does education transmit across generations? An evidence from Multan district (Pakistan). *International Journal of Social Economics*, 43(7), 760–778. <https://doi.org/10.1108/IJSE-11-2014-0222>
110. Shorrocks, A. F. (1980). The class of additively decomposable inequality measures. *Econometrica*, 48(3), 613–625.
111. Singh, A. (2012). Inequality of opportunity in earnings and consumption expenditure: The case of Indian men. *Review of Income and Wealth*, 58(1), 79–106.
112. Solon, G. (1992). Intergenerational income mobility in the United States. *The American Economic Review*, 82(3), 393–408.
113. Solon, G. (1999). Intergenerational mobility in the labor market. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 3A, pp. 1761–1800). Elsevier.
114. Townsend, R. M. (1994). Risk and insurance in village India. *Econometrica*, 62(3), 539–591.
115. United Nations. (2020). *World social report 2020: Inequality in a rapidly changing world*. Department of Economic and Social Affairs.
116. van der Weide, R., Lakner, C., Mahler, D. G., Narayan, A., & Gupta, R. (2024). Intergenerational mobility around the world: A new database. *Journal of Development Economics*, 166, Article 103167. <https://doi.org/10.1016/j.jdeveco.2023.103167>
117. Welch, F. (1970). Education in production. *Journal of Political Economy*, 78(1), 35–59.
118. World Bank. (2006). *World development report 2006: Equity and development*. World Bank.
119. World Bank. (2009). *World development report 2009: Reshaping economic geography*. World Bank.
120. Young, A. (2013). Inequality, the urban-rural gap, and migration. *The Quarterly Journal of Economics*, 128(4), 1727–1785. <https://doi.org/10.1093/qje/qjt025>