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Spatial Disadvantages or Spatial Poverty Traps: Household Evidence from Rural Kenya

by

W.J. Burke and T.S. Jayne

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EXECUTIVE SUMMARY

The goals of this study are: 1) to determine the relative importance of spatial factors in explaining household wealth; 2) to identify the spatial characteristics of the chronically poorest, the consistently well off, and households escaping from poverty as well as descending into poverty; 3) to determine effects of compound disadvantages on the likelihood of chronic poverty; and 4) to assess the evidence of spatial poverty traps (SPTs).

Quantitative analysis is conducted using panel data collected from 1275 households, each surveyed four times with a structured questionnaire over an 11 year period from 1997 to 2007. We identified four distinct groups. The chronically poor are defined as households remaining consistently in the bottom third (tercile) of households ranked by wealth in each of the four survey years. Roughly 12.9% of the nationwide sample was found to be chronically poor. The consistently non-poor are defined as households consistently in the upper tercile of households ranked by wealth, and this group formed 16.2% of the total sample. The third and fourth groups were those households found to have risen from poverty (starting in the bottom tercile and ending in the top tercile, the ascending) and those who were in the top asset tercile in 1997 and fell to the bottom tercile by 2007 (the declining). Relatively few households in the sample were in either the upwardly mobile category (3.8%) or the downwardly mobile category (3.6%).

Findings show that spatial factors, indeed, are a substantial determinant of wealth, explaining a relatively similar share of the total variation in wealth as household-specific factors. The chronically poor and the consistently non-poor households tended to cluster into areas with particular spatial characteristics. Bivariate analysis show a pattern of correlation between spatial characteristics and chronic poverty. By contrast, there were very few spatial features that were associated with the location of households rising from and falling into poverty.

With respect to general isolation and remoteness, we find that the chronically poor are disproportionately likely to be far from a motorable road, and more likely to live in areas with relatively little access to education. This is particularly true in terms of higher education. The overwhelming majority (70%) of the chronically poorest households reside in divisions where fewer than 1 in 4 household heads have more than eight years of education. This is true of only 21% of the consistently wealthy. Households rising from and descending into poverty are equally likely to come from well connected or isolated areas.

There is strong evidence that areas with land constraints and with relatively low agricultural potential are more likely to contain chronically impoverished households. Nearly 4 in 5 households consistently in the bottom wealth tercile are found in an agriculture zone considered to be of mid-low to lowest potential. Perhaps the most striking determining factor is the prevalence of poverty in areas of land constraints. Nearly 75% of the chronically poor households are found in divisions where median farm size is smaller than two acres. By contrast, fewer than 7% of the chronically poor are in divisions where median farm size is greater than four acres. Statistical correlations indicate that land availability decreases with population density. The strong correlation between poverty and rising land constraints has been fuelling both poverty and conflict throughout Africa for decades, and there is no reason to expect Kenya to be immune.

Much literature on SPTs suggests that the likelihood of poverty increases when spatial disadvantages overlap. Results of Probit estimation confirm this, and highlight some specific relationships. For example, low average rainfall, market isolation, and land constraints increase the probability of chronic poverty above and beyond their individual effects. We refer to this as compounded effects – certain features in combination increase the likelihood of a household being poor more so than the sum of their individual effects.

Although there is strong correlation between spatial factors and static welfare, there are four other important conclusions from the study. First, not all households in areas characterized by spatial poverty traps are chronically poor. Although there is some clustering of poor households, they are often surrounded by others who manage to remain above the bottom tercile, or even rise out of poverty in some cases, indicating that spatial factors are not wholly determinant of poverty.

Secondly, not all chronically poor are in spatial poverty traps. We see a number of households that are consistently in the bottom third of the sample in terms of wealth, who do not reside in areas of low or variable rainfall, market isolation, severe land constraints, or other spatial features found in this analysis to be correlated with poverty.

Thirdly, there is little or no evidence of spatial factors playing a defining role in the ability to rise from poverty. In fact, the proportion of households that have climbed out of poverty is not greatly different between areas of low and high mean wealth.

Fourth, household-specific factors are also shown to be of considerable importance in explaining the variation in household wealth across this nationwide sample. The degree of variation in wealth within communities is as large as the degree of variation across communities. In fact, results show that the relative explanatory power of spatial factors, though substantial, is slightly less than that of household-specific factors.

Together, these points call into question the appropriateness of defining areas as poverty traps. While evidence suggests that spatial disadvantages have an increasing and compounding effect on the *likelihood* of chronic poverty, one's poverty status and especially one's ability to escape from poverty are not clearly defined by location. These conclusions, if they are found to hold elsewhere in rural Africa, may warrant a reassessment of whether spatial traps or perhaps spatial disadvantage may be a more accurate way of describing the spatial dimensions of poverty in this region. Just as there are many composite facets to an area being spatially disadvantaged, there are also many factors driving chronic poverty and poverty dynamics. This includes spatial factors, but also household-specific factors. The considerable heterogeneity of smallholder households typically found even within a given community underscores the limits of conceptualizing poverty primarily in spatial terms and highlights the need for policy to also address the important household-level factors leading to high levels of variation in wealth with communities.

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LIST OF ACRONYMS

AE	Adult Equivalents
AEZ	Agro-ecological Zone
ANOVA	Analysis of Variance
CPI	Consumer Price Index
CPRC	Chronic Poverty Research Centre
FEWS	Famine Early Warning System
GDP	Gross Domestic Product
GPS	Geographic Positioning System
Ksh	Kenyan Schilling
OLS	Ordinary Least Squares
REP	Relative Explanatory Power
SPT	Spatial Poverty Trap

1. INTRODUCTION

For at least four decades, African governments and donors have experimented with a series of alternative approaches for addressing rural poverty, each giving way to a new paradigm as the persistence of poverty created disillusionment with prevailing approaches.[1] In 2005, more than 40% of Sub-Saharan Africa's population was estimated to be below the poverty line, and this situation appears to have only marginally improved over the past decade (World Bank 2007). Despite successive years of 5% growth in real gross domestic product (GDP) in Sub-Saharan Africa 2004, 2005, and 2006, rural poverty appears to be declining minimally or in some cases even increasing (World Economic Situation and Prospects 2006).

Despite the ubiquity of the problem, the very nature of chronic poverty remains poorly understood. Whereas a certain share of the world's poor hover around a poverty line, occasionally falling below it as a result of exogenous shocks and subsequently recovering, the chronically poor show little sign of improving (CPRC 2005).

There is a recent and growing interest among researchers and policy makers in the spatial factors influencing chronic poverty, specifically the concept of spatial poverty traps (SPTs). This interest is highlighted by, among other studies, the World Bank's focus on the subject in its forthcoming 2009 World Development Report's *Seeing the World in 3D* (Jalan and Ravallion 1997; Bird et al. 2002; Bird and Higgins forthcoming, and references therein).

A spatial poverty trap, as defined by Jalan and Ravallion (1997), exists when a "household living in [a] better endowed area sees its standard of living rising over time, while [an otherwise similar household's] does not."[2] Factors associated with such traps range from physical and economic isolation to low agricultural potential and political neglect, and are more likely to adversely affect wealth in areas where multiple factors are present (CPRC 2005). Moreover, there may be important compounding effects, i.e., the presence of two or more spatial factors associated with poverty may interact in ways that entrench households in chronic poverty more so than the sum of their separate effects.

For better or worse, the majority of studies on SPTs tend to be conducted at regional or international levels, and thus lack a finer resolution or household perspective (Bird, McKay, and Shinyekwa 2007). Variations in mean household wealth or poverty rates across regions may mask considerable inter-household variations in wealth within a given region. Moreover, it is possible that the percentage of rural households ascending out of poverty is just as high in relatively poor regions as in relatively non-poor regions. If this were found to be true, the meaning of spatial poverty traps would need to be reconsidered as it might imply that the factors trapping households in poverty are more likely to be household-specific than area-specific. Unfortunately, there is very limited empirical evidence on these issues owing to the dearth of panel household-level data necessary to conduct such analysis.

The objectives of this research are to: 1) determine the relative importance of spatial vs. household-level factors in explaining variations in wealth and poverty, both across regions and communities and among households within communities; 2) identify the spatial characteristics of the chronically poorest, consistently wealthiest, and transient households;

[1] These broad strategies included growth and trickle down in the 1960's; integrated rural development and basic human needs in the 1970's; structural adjustment and economic liberalization in the 1980's and 1990's; and most recently, participatory poverty reduction strategies and a focus on pro-poor growth.

[2] Parenthetic statements added for clarification.

3) determine the importance of compounding effects on the likelihood of chronic poverty; and 4) ultimately assess the evidence of spatial poverty traps.

This study will contribute to filling the gap in fine resolution analysis of SPTs using longitudinal data from 1,275 rural farm households in Kenya extensively interviewed four times over an 11 year period from 1997 to 2007, and employing a poverty mobility matrix framed in the context of each observation's spatial poverty determinants.

We find there is indeed strong evidence that spatial factors play a substantial role in explaining wealth and poverty, particularly those related to an areas agricultural potential, such as availability of land. Moreover, we see that compounded spatial effects are statistically significant, meaning that areas with two or more spatial factors associated with poverty contain a greater proportion of chronically poor households than would be found by the sum of their individual spatial effects. However, we also find a non-trivial number of households who are not consistently poor, some even rising from poverty, despite being located in spatially disadvantaged areas. Also, there are a number of chronically poor households in areas that are *not* spatially disadvantaged. In fact, household-specific factors explain a roughly equal proportion of the variation in household wealth as spatial factors. Moreover, there is little evidence that households rising from or falling into poverty over the 11 year period were located in areas with particular spatial features. This leads us to conclude that while spatial disadvantages are clearly an important consideration for policy makers, the identification of spatial poverty traps may be misleading, since the primary factors associated with chronic poverty are complex and include spatial features but clearly extend beyond them.

2. CONCEPTUAL FRAMEWORK

Spatial poverty traps are generally regarded as places where households are (and remain) poor when they would not be if given different geographic circumstances (Jalan and Ravallion 1997; Ravallion and Wodon 1997; CPRC 2005). Specifically, the characteristics of a SPT have been categorized into four primary categories: 1) remoteness and isolation, 2) having poor agro-ecological potential, 3) weak economic integration, and 4) being politically less favored (CPRC 2005; Bird, McKay, and Shinyekwa 2007).

Remoteness and isolation encompasses a wide range of specific characteristics which may lead to persistent poverty within a region. These include a village's distance to infrastructure such as roads, or health services, and the availability of an education.

Low agricultural potential similarly includes several possible factors. Among these are the availability and quality of land, as well as the level and variability of rainfall (especially where rain-fed agriculture predominates, as in Kenya).

Weak integration refers to an area's connectedness with markets both physically and practically. Physical connection, for instance, includes distance to the nearest farm input (i.e., fertilizer) markets. Practical connectedness includes the fiscal and opportunity (time) costs of accessing markets.

Lacking political favor applies to areas that are either adversely associated with ruling political parties or areas where investments are considered to produce lower tangible (and thus political) returns to investments. Although this is certainly as valid in Kenya as in the rest of the world, one could argue (and some have) that in many cases this is a root cause of several of the remoteness and weak integration issues already outlined. Practically speaking, it is difficult to trace spatial variables such as road density, market access, educational attainment, and/or landholding size to past policy and public investment decisions, although their influence on these variables is undeniable. Hence, while an analysis of factors associated with poverty using household survey data is able to identify the importance of various household and spatial factors, the indirect role of public policy in shaping the observed values of these household and spatial variables cannot be ascertained. For these reasons, such an analysis is likely to underemphasize the role of policy and government investments in influencing poverty rates.

A considerably more vigorous treatment of this framework can be found in the Chronic Poverty Research Centre's *Chronic Poverty Report* (CPRC 2005; Chapter 3). This brief overview, however, provides the foundation of the analysis conducted in this study.

3. PROCEDURE

3.1. Data

This study uses panel data from four surveys implemented by the Tegemeo Institute of Egerton University in Nairobi, Kenya. In 1997, the sampling frame was designed in consultation with the Central Bureau of Statistics, and contained 1,500 households randomly chosen to represent eight different agricultural-ecological zones (AEZ), reflecting population distribution. Of the original sample, 1,428 households (95%) were re-interviewed in 2000, 1,324 (88%) were re-interviewed in 2004, and 1,275 (85%) were re-interviewed in 2007. Holding consistently at or below 7% of the original sample per survey, this attrition rate is reasonably low compared to similar surveys in developing countries (Alderman et al. 2001)

These data will be supplemented with monthly rainfall data, obtained from the National Weather Service Climate Prediction Centre as part of a Famine Early Warning System (FEWS) project dating back to 1995. The data are produced at the levels of 0.1 degrees of longitude and latitude, and interpolated using information from rain stations throughout the country as well as satellite data on cloud cover and top temperatures. Data are matched to households using longitude and latitude coordinates collected via the Geographic Positioning System (GPS) during the most recent round of surveys.

3.2. Methods

To address the research objectives, this random sample must first be segregated according to their dynamic welfare status. That is, in order to determine the spatial characteristics of the chronically poor, we must first identify them. This study does so employing a poverty mobility matrix, which computes an indicator of household welfare, then determines how relative welfare changes (or doesn't change) over time.

3.2.1. Measuring Welfare and the Poverty Mobility Matrix

Many prior studies have focused on consumption and income levels as measures of household welfare. More recently, however, there is a trend towards observing the value of a household's assets as a more appropriate measure of welfare. The main argument is that asset levels are less susceptible to random shocks than income, and hence a more stable indicator of household welfare. This is especially true in regions where rain-fed agriculture is a major source of annual income and where weather-induced fluctuations in annual income are high (examples in Carter and Barrett 2006; Barrett and Swallow 2006; Krishna 2004).

An asset-based measure of welfare is computed by multiplying the number of a household's productive assets by the local value of each, and aggregating values to the household level.[3] Then, using a Kenyan Consumer Price Index (CPI), household wealth values in each survey year are deflated to a common base year, 2007 in this case. Finally, real 2007 wealth is divided by the number of adult equivalents (AE) according to the World Bank's gender and age based scale.

[3] Productive assets include: ploughs (tractor and animal traction), cart, trailer, tractor, cars, trucks, spray pump, irrigation equipment, water tanks, stores, wheelbarrow, combine harvester, donkey, bulls, chickens, goats, sheep, calves, cows, pigs, turkeys, and ducks.

Finally, the ratio of wealth per AE is stratified into terciles (or thirds) for each year, yielding three relative poverty rankings: very poor, moderately poor, and non-poor. This procedure is conducted in each year (1997, 2000, 2004, and 2007), revealing the path of each household's relative welfare. This study focuses on the four specific poverty mobility groups who are:

1. chronically poor (those in the bottom tercile in each of the four years);
2. descending households (those in the top in 1997 and bottom in 2007);
3. ascending households (those in the bottom in 1997 and top in 2007); and
4. consistently non-poor (those in the top in each of the four years).

Of the 1275 households in the sample, 165 are identified as chronically the poorest, 46 have fallen into poverty (the descending), 49 have climbed from poverty (the ascending), and 207 are consistently among the wealthiest households.[4] Ascending households' wealth per adult equivalent is 906% higher in 2007 than it had been 1997 on average. Conversely, descending households' wealth had been 1,202% higher in 1997 than it is in 2007, on average. Changes in median are 559% and 714% respectively.[5]

3.2.2. Determining Spatial Characteristics of Poverty and Their Significance

In order to discover whether spatial factors are a substantial determinant of wealth and poverty, the first objective of this study, both regression and descriptive analysis will be employed. First, regression analysis will show the share of variation in wealth explained by spatial and households specific determinants. If the share of variation in household wealth explained by spatial factors is relatively high, then this would indicate that spatial factors are indeed important. Second, using the GPS coordinates collected during the 2007 survey, households will be plotted on an administrative map of Kenya to show whether there is noticeable clustering of poorer (and non-poor) households. Finally, a more quantitative approach to identify clusters will be taken by showing frequencies of each poverty group by their administrative division (and districts). Also, scatter plots will examine the relationship between mean wealth in an area and its share of households rising from poverty. Geographic clustering, should it exist, would clearly provide evidence of SPTs.

To identify the spatial characteristics of the chronically poorest households, the second objective, we examine the correlation between household poverty and spatial factors such as distances to roads and markets, fare to markets, and factors related to agricultural potential. Displaying poverty group frequencies by spatial factor quartiles is a useful method that circumvents the potential issue of outliers distorting results. Evidence that the chronically poor are disproportionately disadvantaged in terms of spatial factors would lend support to the theory of spatial poverty traps, although in some cases the direction of causality may be difficult to identify.

Finally, much of the literature suggests that it is where these factors overlap that "traps" are found. This will be tested using a probability (Probit) model of household poverty as a function of household characteristics and community characteristics. The set of household characteristics available from the survey data include age, education and gender of household

[4] This leaves 808 households in some other, non-coded poverty mobility group.

[5] Median and Mean asset wealth per adult equivalent for each group over time can be found in Appendix A

head, adult equivalents and number of prime-aged (15-59) deaths, livestock and non-farm shares of income, household acres farmed, land tenure, and number of crops. The set of available community variables are zone dummy variables, prevalence of uneducated household heads, mean and variance of main season rainfall (1997 to 2007), distance to motorable road, fare to nearest market, distance to fertilizer retailer, and local median farm size. See Table 1 for a description of all variables used in the models.

Some factors, such as distance to a motorable road, are expected to have a positive and significant coefficient in the model (i.e., the farther from a road, the more likely one is to be poor). Conversely, the availability of land will likely decrease this probability, so the coefficient on the local median farm size is expected to be negative in this estimation. In addition to these household and spatial variables, we include interaction terms that measure the influence of particular combinations of factors distinct from their individual effect on poverty. This approach tests for the presence of compounding spatial impacts.

Table 1. Distribution of Factors Associated with Poverty

	Percentile			
Variable	25%	50%	75%	Mean
Household Head Characteristics				
No education = 1 if yes, 0 if no	.	.	.	.20
1 to 4 years education = 1 if yes, 0 if no	.	.	.	.20
5 to 8 years education = 1 if yes, 0 if no	.	.	.	.33
9 to 12 years education = 1 if yes, 0 if no	.	.	.	.21
More than 12 years (or college) = 1 if yes, 0 if no	.	.	.	.06
Age of Household Head (Years)	43	53	63	54
female headed household = 1 if yes, 0 if no	.	.	.	.12
Household Characteristics				
Number of Prime Age (15 to 59) deaths	0	0	0	.07
Adult Equivalents (ae)	4.0	5.5	7.3	5.8
Livestock Net Income share (%)	1	10	26	17
Off-farm Net Income share (%)	6	30	58	35
Crop Net Income share (%)	25	46	72	49
Main season land farmed (acres)	1.45	2.60	4.54	4.16
Total number of crops cultivated by household	8	11	15	11.7
Major Tenure Own Land With Deed = 1 if yes	.	.	.	.48
Community Characteristics				
1997 - 2007 Mean Main Season Rainfall (mm)	405	552	731	560
1997 - 2007 Main Season Rainfall Variance (mm^2)	16765	24848	45046	43190
Village Distance to Motorable Road (km)	.10	.25	1.00	.75
Fare to nearest market center (1997 Kenyan Schilling - Ksh)	10	15	20	18
Distance to fertilizer seller (km)	1.8	3.5	9.0	8.5
Median main season land farmed by division (acres)	1.71	2.06	3.90	2.71
Share of division HH heads with no education (%)	11	18	24	20

Source: Tegemeo Household survey data 1997, 2000, 2004, 2007. Rainfall data from National Weather Service and FEWS program.

4. RESULTS

4.1. Distribution of Asset-Wealth Over Time

In dynamic poverty analysis a logical first step is to examine the distribution of wealth as time progresses. Are the poorest today as poor as they were a decade ago? Is the wedge between the wealthiest and poorest growing or shrinking? Figures 1 and 2 are bar charts examining the distribution of wealth over time. Each cluster of bars represents a percentile of the distribution (or the mean), and each bar a specific year (1997, 2000, 2004, and 2007, left to right). The vertical axis shows the asset-wealth (in thousands of 2007 Ksh) found at each point in the distribution. Figure 1 shows the distribution of wealth per adult equivalent, while Figure 2 shows the distribution of total wealth per household.

In both measures of welfare the poorest 10% of households are somewhat better off in 2007 than the poorest of 1997. In 1997 the lowest 10th percentile had real wealth of less than 800 Ksh per adult equivalent, but by 2007 that number had risen to nearly 1,200. The real wealth of the bottom 25th percentile seems fairly stagnant over the sample period. From the 50th percentile upwards, however, real wealth seems to be declining over time, which, in turn, draws mean wealth into a downward trend. In all, there seems to be a closing gap between the wealthiest and poorest households, but unfortunately this is driven by decreasing wealth of the wealthy, rather than rising wealth of the poor.

The fact that overall wealth appears to be declining may suggest a trap of sorts, but, this analysis lacks the spatial resolution to determine whether traps exist at the household level. In reality, a number of households transcend poverty levels within this distribution, and one must consider trends in their spatial features (or lack thereof) before taking for granted that traps exist.

Figure 1. Distribution of Assets per Adult Equivalent Over Time

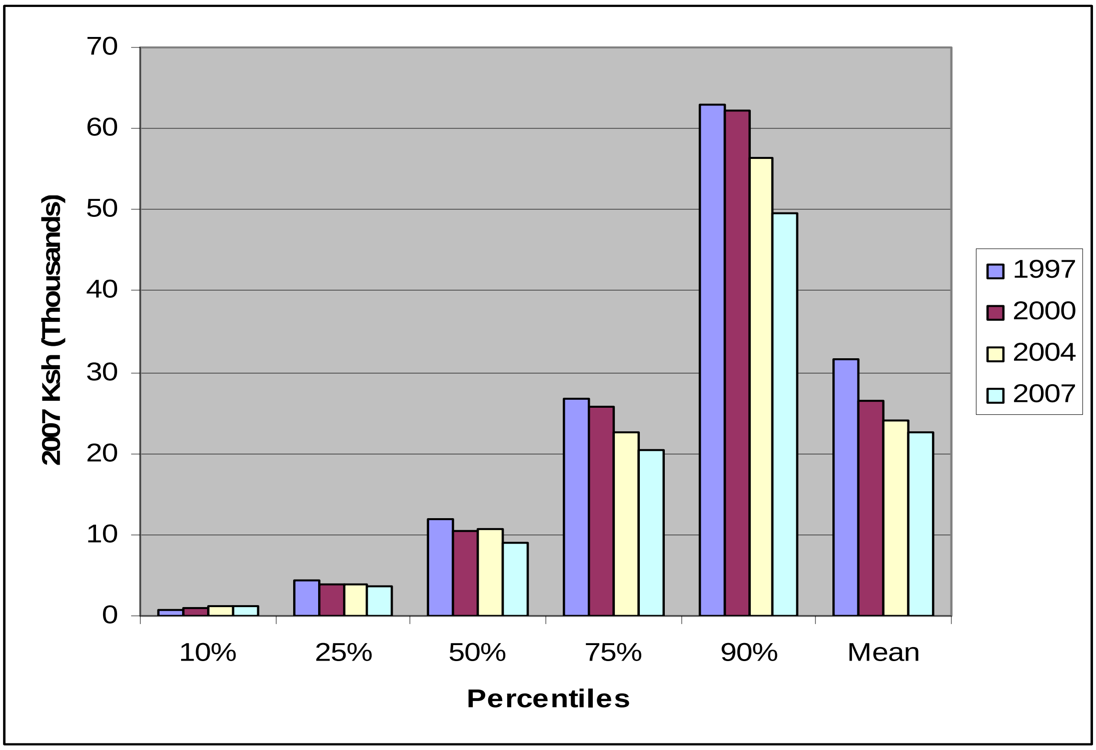
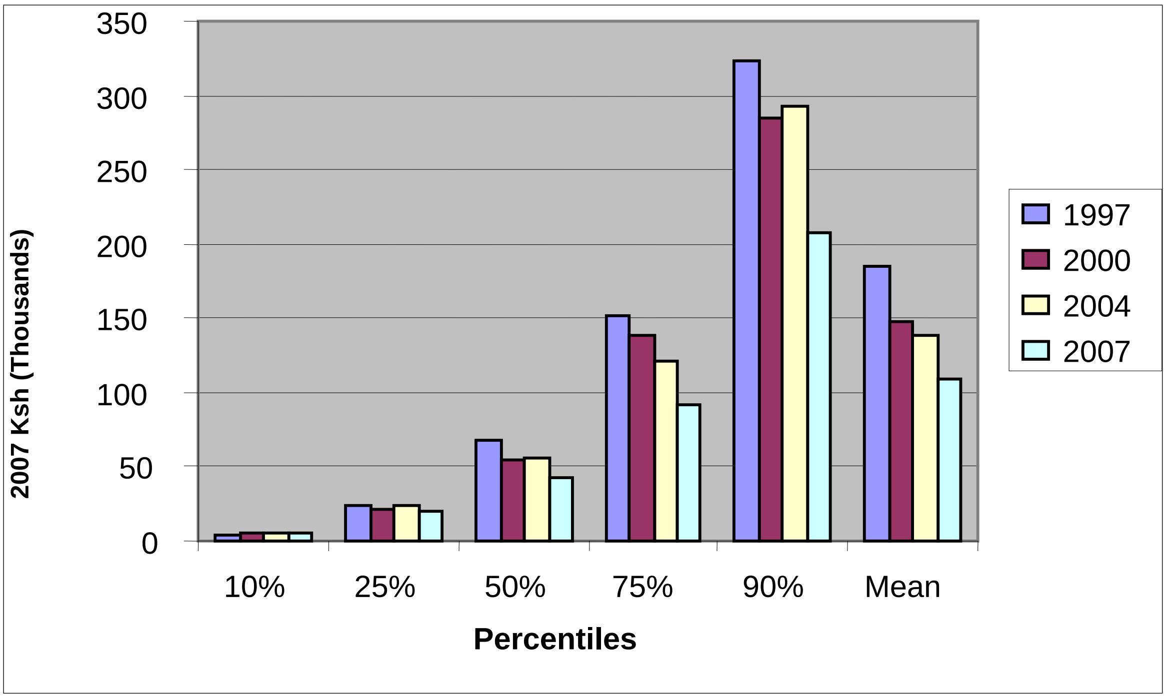


Figure 2. Distribution of Total Household Assets Over Time



4.2. Spatial Correlation and Welfare

We begin by examining poverty dynamics within Kenya by identifying the relative importance of household characteristics, spatial factors, and time in explaining the variations in household wealth in the four survey years. Recalling that each household was surveyed four times – in 1997, 2000, 2004, and 2007 – we have three observations on household wealth for each of the 1,275 households in the sample, and three observations of various lagged explanatory variables[6]. Table 2 shows the adjusted R-squared of ordinary least squares (OLS) regressions of household wealth on various sub-sets of determining factors. The R-squared results are analogous to ANOVA (analysis of variance) results. The first thing to note is that an increasing share of the variation in wealth is explained as the focus of the spatial factors narrows from agro-ecological zones (explaining 3.9% of the variation in household wealth, row a), to districts (5.6%, row b), to divisions (10.3%, row c), to villages (14.8%, row d). This highlights the importance, as indicated by others, of finer resolution analysis when considering spatial poverty traps.

The next piece of evidence taken from Table 2 is how the explanatory power of spatial factors (row g) compares to that of household characteristics (row f) and the full set of all variables (row h). The largest share of variance we are able to explain is 26% using all household, spatial, and time variables, while the spatial factors alone explain 16.5%. This is comparable to the share explained by household characteristics, 17.5%.

[6] Note, although there are four years of panel data, the lagging of explanatory variables (to capture dynamic effects) results in three periods of observations within the models. For consistency, this was imposed on regressions with only time-constant determinants as well.

Table 2. Spatial, Time, and Household Characteristics Explaining Variation in Wealth

Asset Value $_{it}$ =	Share of Variation Explained [a]	Relative Explanatory Power
a. f_1(Constant, Agricultural Zone Dummies)	.039	.153
b. f_2(Constant, District Dummies)	.056	.220
c. f_3(Constant, Division Dummies)	.103	.404
d. f_4(Constant, Village Dummies)	.148	.580
e. f_5(Constant, Time Dummies)	.001	.004
f. f_6(Constant, Household Characteristics[b])	.175	.686
g. f_7(Constant, Spatial Factors[c])	.165	.647
h. f_8(Constant, Time Dummies, Household and Spatial Characteristics)	.255	1

Source: Tegemeo Household Survey Data 1997, 2000, 2004, 2007

Notes: (a) Statistically, this is the R-squared from each regression via OLS, adjusted to account for differing numbers of explanatory variables. (b) Household Characteristics are age, education, and gender of household head, the number of adult equivalents and prime aged adult (15-59) deaths, shares of income from livestock and off-farm, main season acres farmed, whether land is primarily owned, and the number of crops cultivated (c) Spatial factors include village dummies, 11 year average rainfall (including quadratic), 11 year variance of rainfall, whether the household farms a short season, distances to motroable roads, tarmac roads, fertilizer retailers, fare to nearest market, share of uneducated household heads by division, and land availability

Another way to frame these results compares the power of each set of factors relative to that of all given information. Call this the relative explanatory power (REP), or the ratio of explained variation to total explained variation. These figures tell us the relative importance of a set of factors in the total explained variation. We find a REP of 0.69 for household characteristics, and 0.65 for spatial factors, indicating that both are fairly important determinants of wealth.

In short, the analysis of variance provides strong evidence that spatial factors are a substantial determinant of a household's welfare (poverty) status.

This is further examined in Figures 3 through 5, where observations are plotted on an administrative map of Kenya using coordinates collected via GPS during the 2007 survey. In Figure 3 the entire sample is shown. Here we can see that there is evidence of clustering not only among the chronically poor, but also among the consistently non-poor. In one highlighted area we discover 22 of the 78 households are chronically poor, while only one is consistently in the top wealth tercile. This seems to indicate a spatial component to the wealth of the observations in this area, but also note this leaves 53 households in the same area which were not chronically in the poorest tercile despite an evident spatial disadvantage.

Another striking region highlighted in Figure 3 shows 43 of 51 households consistently in the top wealth tercile, and only one is chronically in the bottom. Although not indicated on this map, these households are very near Nakuru, one of Kenya's major market centers, indicating the benefits of not being a remote household.

Figure 4 includes only the households identified as chronically poor, or in the bottom wealth tercile in each year. When juxtaposed with the national sample, Figure 4 demonstrates that much of the chronic poverty is located in the western portion of Kenya, while there seems to be very few chronically poor in the middle of the country, nearest to Nairobi. Within regions and villages there is also considerable evidence of spatial clustering of the chronically poor. Figure 4 highlights a few areas in particular where, within three divisions, we find 43% of the chronically poorest households.

Figure 5 shows the location of only those identified as consistently non-poor. Again, this group shows some clustering, with 39% of those households found in the three highlighted areas. This geographic clustering of chronically poor and non-poor households clearly illustrates a spatial dimension to poverty, but so far we have provided no evidence of the relative difficulty of climbing out of poverty as a function of location, i.e., spatial poverty traps.

For a more quantified analysis, Table 3 shows the frequencies of each poverty group by administrative districts and divisions. Here again we find evidence of the importance of spatial factors in determining chronic poverty. Again, 43% of the chronically poor (highlighted in Figure 4) are located in Kalolenii, Marani, and Mumias divisions. Conversely, less than 2% of the consistently non-poor (3 households) are in these divisions. We see the 39% of consistently non-poor households highlighted in Figure 5 are in three divisions (West Abothogucii, Njoro, and Moiben). Table 3 further shows that within these three divisions there is only a single observation that is chronically poor.

Although these results provide evidence of geographic correlation in wealth, it is important to note that there are a number of areas where wealthy and impoverished households coexist. Consider, for example, Kilome, which contains 72 sample households. Among them, 6 are chronically poor, but another 6 are consistently in the wealthiest tercile. Two of these are descending households over the 11-year period, yet 3 others are ascending in the same period. Throughout the sample there are numerous chronically poor and consistently wealthy households geographically side-by-side. Even within the divisions mentioned above there are a considerable number of observations which do not fit into a specified poverty mobility group.

Figure 3. Geographic Location of Sample Households

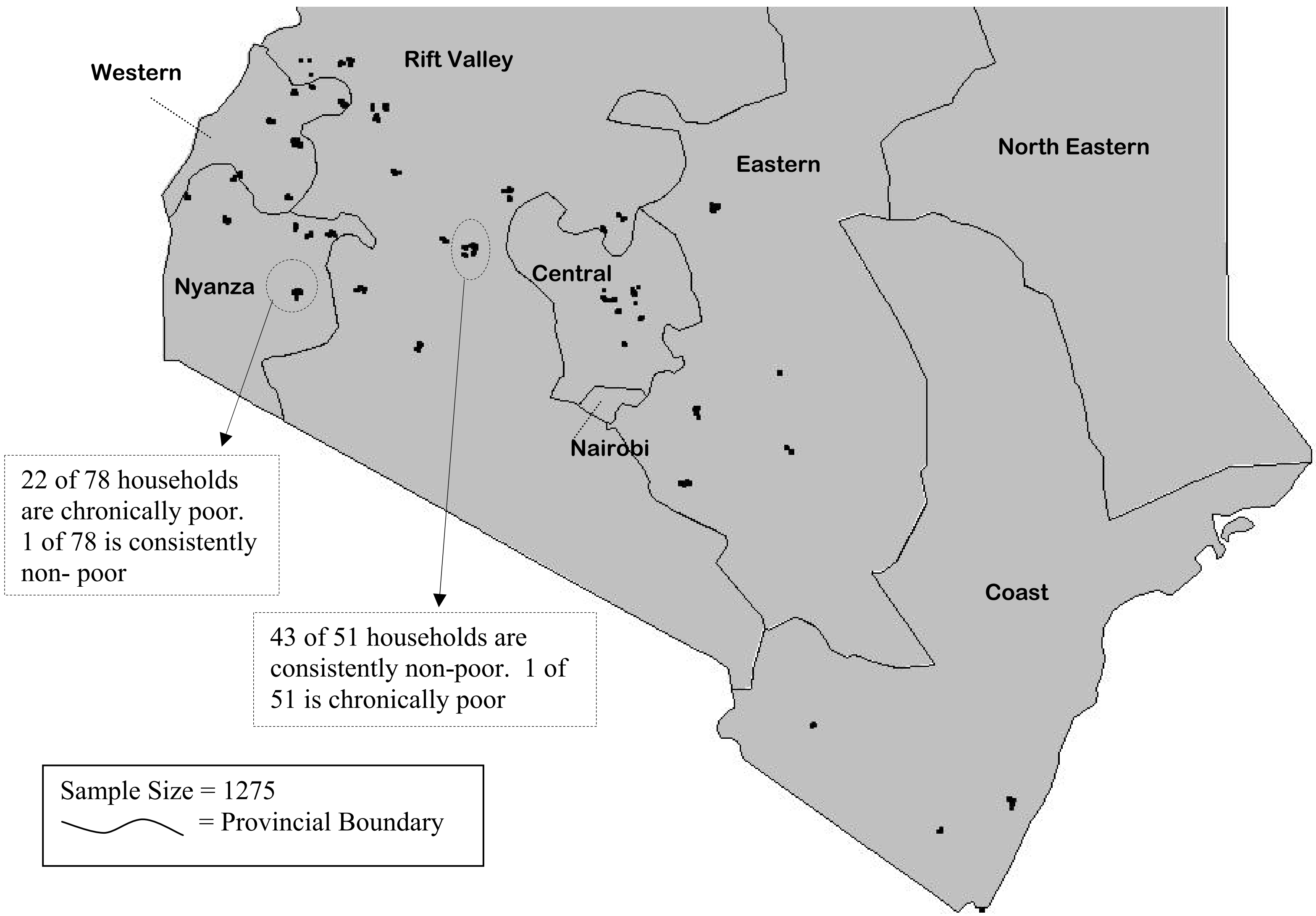


Figure 4. Geographic Location of the Chronically Poor

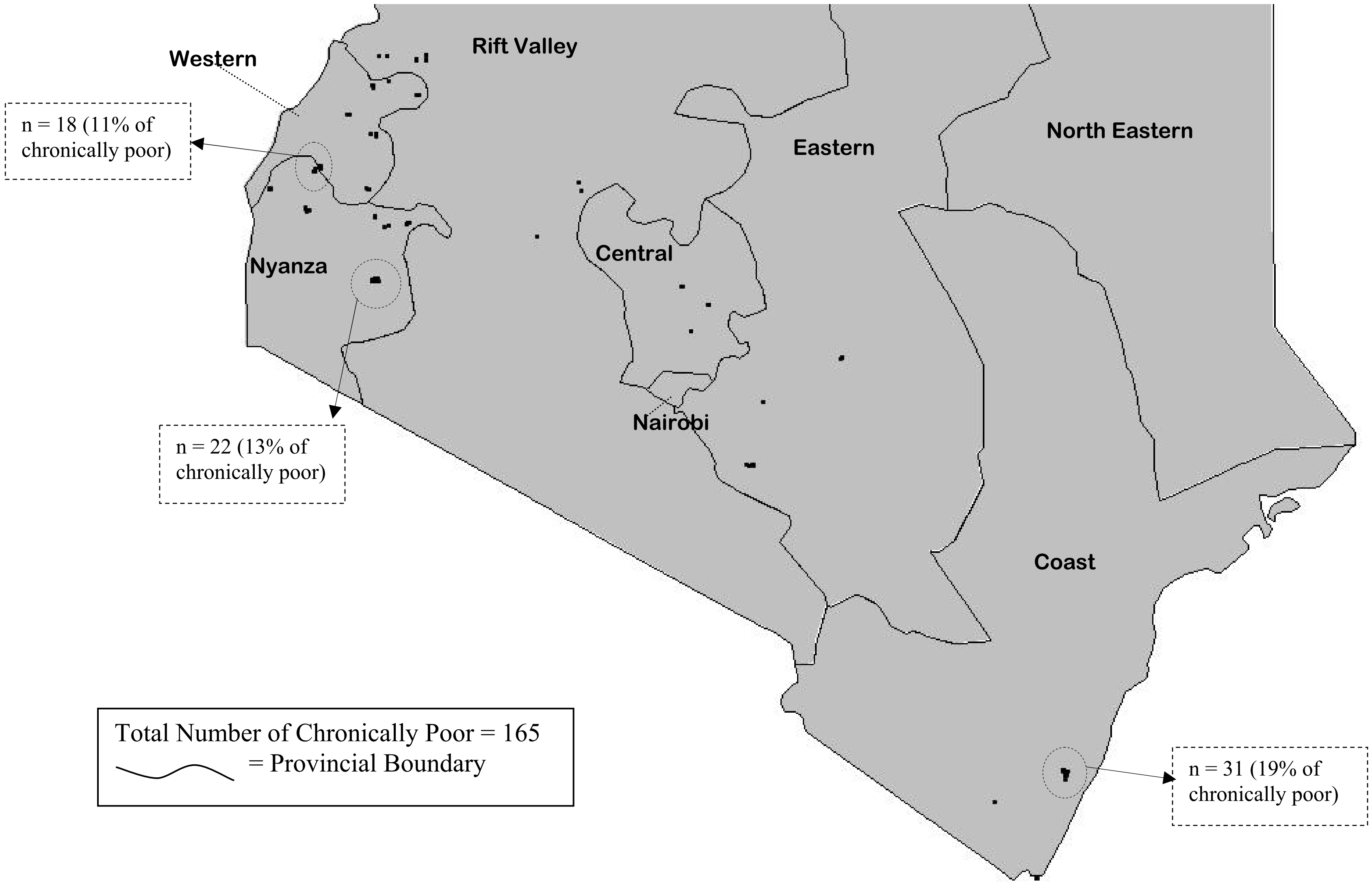


Figure 5. Geographic Location of Consistently Non-poor

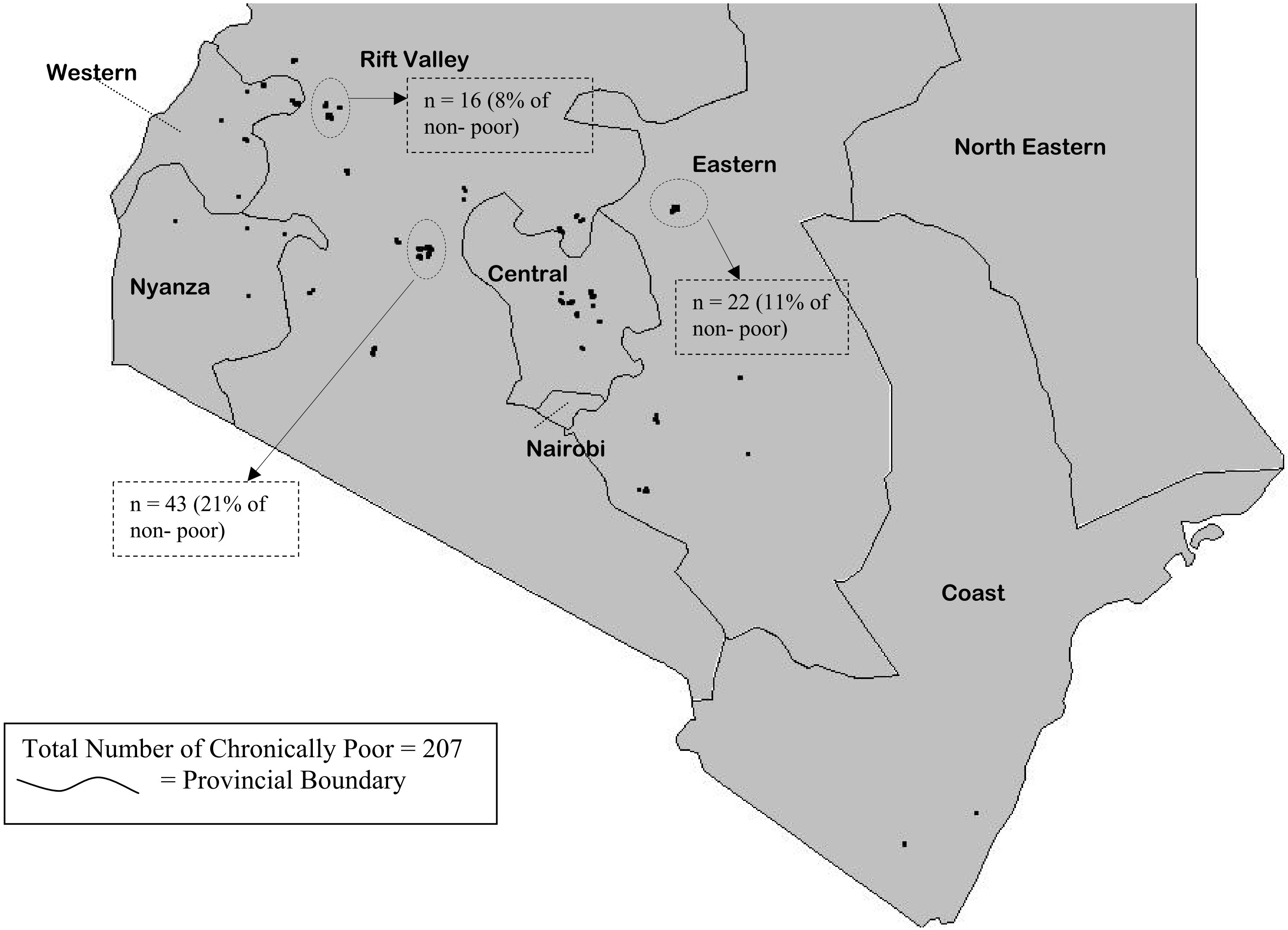


Table 3. Poverty Mobility Groups by Division

		Poverty Mobility Group[a]					
District	Division	Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)	Total
Kilifi	Kalolenii	31	2	2	2	14	51
Kwale	Kinango	1	0	0	3	2	6
	Msambweni	6	2	2	0	8	18
Taita Taveta	Mwatate	0	2	1	0	6	9
Kitui	Chuluni	0	1	0	2	12	15
Machakos	Mwala	1	1	2	4	12	20
Makueni	Kilome	6	2	3	6	55	72
Meru	W. Abothogucii	0	2	1	22	55	80
Mwingi	Migwani	4	2	0	2	21	29
Kisii	Marani	22	1	2	1	52	78
Kisumu	Kadibo	3	2	1	0	18	24
	Nyando	7	3	4	1	28	43
	Winam	3	2	1	1	14	21
Siaya	Bondo	9	3	1	1	26	40
	Uranga	6	2	2	0	15	25
Bungoma	Kanduyi	2	2	2	1	36	43
	Kimilili	4	0	0	1	15	20
	Tongaren	1	1	0	4	7	13
Kakamega	Kabras	4	1	3	3	48	59
	Mumias	18	0	3	0	25	46
	Lugari	2	0	1	8	11	22
Vihiga	Sabatia	7	1	0	1	42	51
Muranga	Kandara	5	0	1	2	21	29
	Kangema	0	1	2	3	12	18
	Kiharu	4	0	2	2	11	19
Nyeri	Mukurweini	0	3	3	11	22	39
	Othaya	2	2	2	14	37	57
Bomet	Kimulot	0	2	3	6	23	34
Nakuru	Mbogoine	2	0	0	3	19	24
	Molo	0	1	1	5	14	21
	Njoro	1	0	0	43	7	51
Narok	Ololunga	0	1	0	12	8	21
Trans Nzoia	Cherangani	9	0	1	5	22	37
	Saboti	5	0	0	0	9	14
Uasin Gishu	Ainabkoi	0	0	1	9	29	39
	Moiben	0	2	0	16	32	50
Laikipia	Lamuria	0	2	2	13	20	37
	Total	165	46	49	207	808	1275

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007.
Notes (a) Chronically poorest are in the bottom wealth tercile in each survey year, falling into poverty are in the top third in 1997 and bottom third in 2007, rising from poverty are in the bottom in 1997 and top in 2007, and consistently non-poor are in the top wealth tercile in each survey period.

Figure 6. Divisional Wealth by Share of Initially Poor Households Rising from Poverty

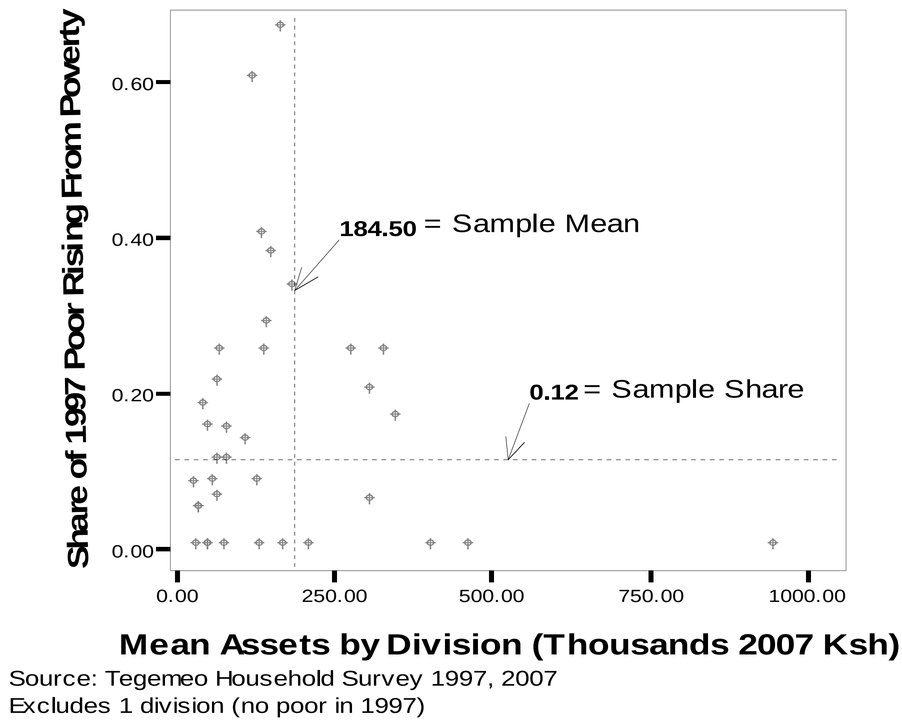


Figure 6 investigates the potential existence of spatial poverty traps using a scatter plot. Each point represents an administrative division. The horizontal axis shows average total wealth among households in the division during 1997. On the vertical axis is the share of initially poor households in the division which are ascending over the 11 year period, as defined by the poverty mobility matrix.[7] There is also a vertical reference line which represents the average household wealth for the entire sample. Divisions falling to the left of this line are those whose mean wealth is less than that of the total sample, and those to the right have above average wealth. A horizontal reference line indicates the share of initially poor in the total sample that are ascending over time. Divisions falling above (below) this line have seen a disproportionately large (small) share of its poor households rising from poverty.

Quadrants created by these reference lines illustrate some interesting possible relationships between geography and wealth. First, below and to the left of the reference lines we find divisions with lower than average wealth among their households in 1997 and a disproportionately small number of poor households rising from poverty. In other words, divisions in this area may, in fact, point to potential poverty traps, especially the observations in this quadrant falling on the horizontal axis (i.e., those with no households rising from poverty over time).

Divisions to the left and above the reference lines, on the other hand, are those with lower than average wealth per household, yet who see a disproportionately large share of the poor rising from poverty. In other words, in these divisions we find households who were surrounded by deeper than normal poverty, yet managed to escape their own during the 11

[7] It should be noted that the results discussed in reference to Figure 6 are fairly robust to various criteria for rising from poverty other than that described by this particular poverty mobility matrix. Further results are available from the corresponding author upon request.

year period. Divisions found in this area of the plot provide countervailing evidence which suggests that, while some households may be spatially disadvantaged, it would not be accurate to describe them as trapped in poverty.

In Figure 6 we see both such divisions. Notice, for example, that there are five divisions with lower than usual mean wealth, and within which none of the initially poor are ascending households. On the other hand, there are four other divisions where, despite lower than normal mean wealth in 1997, nearly 40% or more of the initially poor households have risen from poverty. This highlights an important distinction between the spatially disadvantaged and those trapped in poverty.

In summary, various results from the above analyses show considerable evidence suggesting the importance of spatial factors as a determinant of wealth. However, there are three other important observations: 1) not all households in the evidently disadvantaged areas are chronically poor; 2) some households in areas of low mean wealth do climb out of poverty, and the percentage of households doing so is no lower in these poor areas as it is in the relatively wealthier areas; and 3) not all of the chronically poor are in areas that seem to be spatially disadvantaged. Altogether, this suggests that a household's geographic characteristics are one set of important factors determining their wealth (or poverty), but a non-trivial amount of poverty is explainable by other factors. These findings also suggest that the word trap may not be completely applicable in combination with spatial poverty. Certainly there are spatial factors correlated with poverty, and relatively few households in the sample have clearly climbed out of poverty (i.e., started in the bottom 33% of households ranked by wealth in the initial 1997 survey and ended up in the top 33% by 2007), suggesting that there are indeed factors that keep household trapped in poverty. Yet households who have escaped poverty in this sample are no less likely to reside in relatively poor communities than in wealthier ones.

4.3. Spatial Characteristics of Poverty Mobility Groups

We now turn to the study's second objective, identification of the spatial characteristics of the chronically poor. This is done using the results of the poverty mobility matrix, framed in the context of geographic factors thought to influence welfare.

4.3.1. Remoteness and Isolation

One of the categorical characteristics of spatial poverty traps outlined in the literature is remoteness and isolation. This includes an area's distance from public goods such as infrastructure and access to health care or education. One would expect to find that farther distances and less availability are associated with persistent poverty.

When considering isolation related factors it is important to keep in mind that despite these being the initial conditions of an eleven year panel, it is not prudent to assume causality. That is, it is quite possible that it is an area's wealth that brings about the construction of roads, rather than the construction of a road that brings wealth. Causality aside, however, numerous correlations prove interesting.

In Table 4 poverty groups are presented in the context of their initial distance to a tarmac road. The SPT framework would expect the chronically poor to be disproportionately in the farthest quartiles from a tarmac road and vice versa for the consistently well-off.

Table 4. Poverty Mobility Groups by Initial Distance to Tarmac Road

Tarmac road distance quartile	Poverty Mobility Group Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
Nearest (<1.5 km)	27.9%	21.7%	20.4%	31.4%	23.1%
Mid-Near (1.5 to 5.5 km)	23.6%	30.4%	32.7%	19.8%	25.5%
Mid-Far (5.5 to 11.5 km)	21.2%	15.3%	16.3%	30.9%	27.4%
Farthest (>11.5 km)	27.3%	32.6%	30.6%	17.9%	24.0%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007.

Table 5 segregates each poverty group according to proximity quartiles of another infrastructure indicator, distance to motorable roads (i.e., unpaved roads suitable for a motor vehicle). Results in Table 4 are mixed, but the story in Table 5 is more consistent with the SPT theory. Nearly two thirds of the non-poor households are less than a quarter of a kilometer from such a road, the median distance for the sample. Conversely, 68% of the chronically poorest households are farther than .25 km. It is also interesting to note in Table 5 that 63% of descending households are farther than the median distance from a motorable road. However, almost half of the ascending households are located in the bottom two quartiles of distance to a motorable road. There appears to be little bivariate correlation between households either rising from or falling into poverty and their distance to roads. In fact, over the entire sample period, households both rising from and falling into poverty have a positive correlation with this distance (0.014 and 0.011 respectively), and neither coefficient is statistically significant.

Access to education is another key characteristic in determining the spatial advantages of an area. Unfortunately, while considerable data are available on the actual education of household members, there is less information on its availability. This would include factors like the distance to the nearest school and the fiscal and opportunity cost of attendance. Moreover, the education of the adults, particularly the household head, is the more relevant determinant of current welfare, which would require data from before the beginning of the survey period. To circumvent this problem, we consider the prevalence of education among household heads as a good proxy for the availability of education. An admitted caveat to this approach is the implicit assumption that the availability of education did not change much over time, since the household heads are of varying ages, and would have gone to school at

Table 5. Poverty Mobility Groups by Initial Distance to Motorable Road

Motorable road quartile	Poverty Mobility Group Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
Nearest (< .1 km)	12.1%	19.6%	18.4%	31.9%	19.6%
Mid-Near (.1 to .25 km)	20.0%	17.3%	32.6%	30.9%	30.3%
Mid-Far (.25 to 1.5 km)	40.6%	37.0%	24.5%	25.6%	27.8%
Farthest (>1.5 km)	27.3%	26.1%	24.5%	11.6%	22.3%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007.

different times. Nevertheless, a prevalence ratio is arguably the best available measure of the accessibility of education.

Specifically, we'll focus on the share of household heads with some formal education within each administrative division. A lower ratio is an indication of lower availability of education. In Table 6 divisions are classified into three groups: 1. divisions where more than 75% of the heads have some formal education (indicating relatively good access); 2. those where between 50 and 75% have some formal education; and 3. those where fewer than half of all household heads have any education (indicating relatively bad access). When examining these classifications in the context of poverty groups, one would expect to find the chronically poorest to be disproportionately more likely to be in a division with poor access to education.

Table 6 seems to support the theory that access to education is an important determinant of wealth. Notice 23% of the chronically poorest households are in a division where fewer than half of all heads received any formal education. This is remarkable since the criteria for having a formal education is fairly lenient, needing only a single year to qualify. Indeed, less than 7% of the entire sample is located in such an educationally disadvantaged division, and only 2% of the households consistently in the top wealth tercile. In absolute terms, of the 82 households located in a division where fewer than half of the household heads have formal education, 38 of them are chronically among the poorest households.

The plight of the chronically poorest is further evident when we consider the prevalence of a higher degree of education (more than eight years). Nearly 70% of the chronically poorest households are in a division where very few (less than 1 in 4) household heads have more than eight years of education. This is a disproportionate share, compared to only 21% of the consistently wealthy and 42% of the sample as a whole living in a division lacking such higher education. Altogether, these results suggest that access to an education, particularly a higher education, is an important factor determining wealth. However, access to education is not correlated with whether a household climbs out of or descends into poverty. These two groups have roughly the same characteristics with regard to the percentage of household heads in the division with at least one year of formal education.

Access to health care is yet another factor related to a household's isolation. According to SPT theory one would expect to find households farther from health care to be generally

Table 6. Formal Education Prevalence (Accessibility) By Poverty Group

	Share of Household Heads in Division With at Least 1 year of Formal Education			Total
	more than ¾ (Good Access)	½ to ¾	fewer than ½ (Bad Access)	
Poverty Group	-----------------share of poverty group (%)-----------------			
Chronically Poorest	59	18	23	100
Falling into Poverty	74	17	9	100
Rising From Poverty	78	14	8	100
Consistently Non-poor	68	30	2	100
Others	82	14	4	100
Total Sample	76.2	17.4	6.4	100

Source: Tegemeo household surveys 1997, 2000, 2004, 2007 poorer. There is fairly strong evidence in the data, however, that this is not the case. In 1997 only 14% of the chronically poorest were more than 5 km from the nearest health care centre, compared to 29% of the consistently wealthiest. Moreover, the average distance to the nearest health centre among the poorest decreased from 3.5 km in 1997 to 2.25 km in 2007. The wealthiest households, on the other hand, saw that average decrease modestly from 3.9 to 3.6 km over the same period. Rather than countervailing evidence, this is likely the result of policies aimed at extending health care networks into poorer areas of Kenya. In fact, in 2007 91% of the chronically poorest stated that the health care in their area had improved over the previous 3 years, as did 92% of those rising from poverty. The fact that welfare has not seemed to improve for many of these households only emphasizes the long-term nature of this problem and its solution, as well as pointing out the importance of quality health care.

In summary, there are indications that factors associated with a household's isolation and remoteness are correlated with chronic poverty. While distance to a tarmac road tells a bit of a mixed story, the poorest households are more likely to be far from an unpaved motorable road. We also find that one is more likely to find chronic poverty in areas where education is less accessible. With many factors, however, it is not prudent to assume causality. Wealthy households could be wealthy because they have better access to roads, for example, but it is also true that road density tends to be highest in relatively wealthy areas, where commercialization is greatest. Once again, however, there appears to be little evidence of discernable spatial relationships among households ascending or descending over time. Households rising form poverty are just as likely to be from a spatially disadvantaged area as those falling into it, and vice versa.

4.3.2. Weak Integration

Another aspect of the SPT framework is weak economic integration, meaning both physical and practical separation from markets. This is addressed in Table 7, which compares poverty groups to distance from the nearest fertilizer retailer (representing other input markets).

As expected, we notice a disproportionately large share of the households consistently poorest over 11 years (67%) are farther than the median distance to a fertilizer retailer (3.5 km) in 1997, while only 13% are 1.5 km or closer. The consistently non-poor, on the other hand, are fairly evenly distributed, with roughly 55% of that group closer than the median value. The descending households are disproportionately far from a fertilizer retailer, but so are those who have risen to the top wealth tercile over time. Once again, it is not appropriate to assume causality in this relationship. It may be that the poorest were farther from fertilizer retailers because they lacked the effective demand to attract retailers to their area.

Table 7. Poverty Mobility Groups by Initial Distance to Fertilizer Retailers

	Poverty Mobility Group				
Fertilizer retailer distance	Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
Nearest (< 1.5 km)	12.7%	17.4%	24.5%	27.1%	27.1%
Mid-Near (1.5 to 3.5 km)	20.6%	19.6%	16.3%	28.0%	28.4%
Mid-Far (3.5 to 8 km)	23.1%	23.9%	24.5%	22.2%	23.5%
Farthest (>8 km)	43.6%	39.1%	34.7%	22.7%	21.0%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007.

Table 8. Poverty Groups by Change in Fertilizer Retailers Distance

Change in km to fertilizer retailer (1997 to 2007) quartiles	Poverty Mobility Group Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
More than 4 km closer	44.2%	34.8%	34.8%	22.7%	19.8%
1 to 4 km closer	29.1%	26.1%	22.4%	21.3%	26.2%
0 to 1 km closer	17.0%	17.4%	22.4%	19.8%	26.9%
Farther away	9.7%	21.7%	20.4%	36.2%	27.1%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007.

Unlike many of the variables previously examined, market reforms and the proliferation of fertilizer retailers has caused this spatial factor to change considerably over time for most households. Table 8 examines poverty groups as they are distributed over quartiles of change in distance to a fertilizer retailer from 1997 to 2007.

Notice first, the consistently poorest households are extremely more likely to be in an area that has become more than 4 km closer to a fertilizer retailer over the sample period. Although this may seem perplexing, this may be related to the fact that these households were disproportionately farther from retailers initially, as shown in Table 7. Yet the results in Table 8 show, unsurprisingly, that improved access to input markets do not by themselves enable the poor to appreciably raise their living standards. Also noteworthy is the finding that the consistently non-poor are more likely to be farther away from an input supplier in 2007 than they were in 1997.

Surprisingly, Table 8 shows nearly identical correlation between changes in input market access and households falling into and rising from poverty. One may expect to find a lopsided share of those rising from poverty to be in the quartile with the biggest decrease in distance (4 km or more) to a fertilizer retailer, and indeed 35% of them are. However, an equal share of descending households saw that distance similarly decrease.

Table 9 considers another aspect of an area's economic integration, the fare in Ksh one must pay for transport to the nearest market centre. The fare faced by households in the sample in

Table 9. Poverty Mobility Groups by Fare to Nearest Market (1997 Ksh)

Fare quintile (1997 Ksh)	Poverty Mobility Group Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
Cheapest (< 10)	24.8%	21.7%	16.3%	12.1%	20.4%
Mid-Cheap (10 to 12.5)	14.5%	28.3%	26.5%	25.1%	26.4%
Middle (12.5 to 20)	12.2%	8.7%	10.3%	6.3%	4.6%
Mid-Expensive (20 to 30)	23.0%	19.6%	20.4%	36.7%	31.1%
Expensive (> 30)	25.5%	21.7%	26.5%	19.8%	17.5%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007.

1997 were not very evenly distributed as a whole, with around 40% being charged 12.5 Ksh or less, and 40% being charged 20 Ksh or more. Thus, this table categorizes the sample into five groups according to the fare they face, rather than quartiles.

Table 9 demonstrates mixed results. On one hand, 49% of the chronically poor face a fare greater than 20 Ksh, which is a disproportionately large portion of that group. Surprisingly, however, we find an even larger share of the consistently non-poor (57%) facing similar rates. Thus, it seems that while facing unusually high prices for transport to market does characterize the chronically poor, such prices alone are not necessarily indicative of poverty.

Like distance to a fertilizer retailer, fare to market is a factor that has varied considerably over time, even controlling for inflation. One may expect, then, to see that fare has reduced most for those rising from poverty. This is addressed in Table 10, which displays the distribution of mobility groups by changes in real (2007 Ksh) fare to market from 1997 to 2004[8] . Once again, quartiles are not a reasonable way to segregate this factor, so the total sample's distribution has been included for comparison.

The share of ascending households who have seen their real fare to market decrease by more than 30 Ksh is 28.6%, which is only modestly more than that of the entire sample (26%), and virtually the same as the share of descending households (28.3%). We see an overbalanced share of the descending experiencing an increase in fare, but in light of all the evidence, the correlation is not conclusive.

Altogether, it appears accurate to describe the poorest households as weakly integrated in some ways, but we cannot say that this has caused their poverty. Also, it seems that weak integration is not a characteristic exclusively of the poorest households. A number of the most disadvantaged in terms of distance to input retailers and cost of reaching a market manage to consistently be in the top wealth tercile. Moreover, there is no evidence of correlation between changes in market integration factors and either falling into or rising from poverty.

Table 10. Poverty Mobility Group by Change in Real Fare to Market

	Poverty Mobility Group				
Change in Real Fare to Market (1997 to 2004)	Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Total Sample (n=1275)
Down more than 30 Ksh	31.5%	28.3%	28.6%	23.2%	26%
Down 15 to 30 Ksh	17.0%	13.0%	18.3%	33.3%	23%
Down 0 to 15 Ksh	19.4%	21.7%	24.5%	18.4%	21%
Increased Fare	32.1%	37.0%	28.6%	25.1%	30%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007.

[8] Fare data are not available for 2007

Table 11. Poverty Mobility Groups by 11-year (1997-2007) Mean Rainfall

	Poverty Mobility Group				
11-year mean rainfall quartile	Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
220 to 405 mm	35.2%	30.4%	34.7%	18.8%	23.4%
405 to 575 mm	4.2%	21.8%	16.3%	57.5%	22.0%
575 to 735 mm	36.4%	30.4%	28.6%	15.5%	27.0%
735 to 975 mm	24.2%	17.4%	20.4%	8.2%	27.6%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007 supplemented by national weather service rainfall data.

4.3.3. Agricultural and Ecological Potential

The third category of SPT characteristics is low agro-ecological potential. This includes factors such as the presence and predictability of sufficient rainfall (especially in areas like Kenya, where agriculture is primarily rain-fed), availability and distribution of land, and soil quality. One would expect to find that households in areas with less and more variant rainfall, less land, and generally lower potential are more likely to be consistently poorer than others.

The household data set is supplemented with rainfall data collected by the National Weather Service Climate Prediction Centre as part of a Famine Early Warning System project dating back to 1995. From these data the average main season rainfall over time (including non-survey years) are calculated for each household to gain an understanding of the overall amount of rain in their area. Table 11 reports the distribution of each poverty group according to 11-year mean rainfall quartiles.

The results of this bi-variate analysis seem a bit mixed. Notice that 35% of the chronically poorest households average less than 405 mm of rainfall from 1997 to 2007, compared to only 19% of those consistently in the top wealth tercile. The disproportionate distribution of these groups in the lowest average rainfall quartile is expected. However, we also find that nearly a fourth of the poorest households average greater than 735 mm of rainfall per main season, a benefit which is only true of 8% of the consistently wealthiest. The second driest quartile is particularly puzzling, where we find a mere 4% of the poorest households an a staggering 58% of the wealthiest.

When considering Table 11, however, it is important to keep in mind that the predictability of rainfall is as or more important than how much actually falls. For example, the 11-year variance of rainfall has also been computed, and was included in regression analyses displayed in Table 3. Higher variance over time would indicate that rainfall is less predicable, which would likely hinder a households ability to accumulate wealth. Indeed, regressions show the variance of rainfall over time is highly significant, having a negative effect on wealth.

Another important factor relating to the agricultural potential is access to land. It is well known that the amount of land one farms will have a substantial impact on their welfare. In a study of spatial poverty traps, however, it is more appropriate to consider the availability of land, rather than the amount of land actually farmed. To that end, a median value of farmed

Table 12. Poverty Mobility Groups by Divisional Access to Land

	Poverty Mobility Group				
Median land access by division quartiles (1997)	Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
Very Small (< 1.75 acres)	39.4%	30.4%	28.6%	5.3%	27.1%
Small (1.75 to 2.06 acres)	32.1%	28.3%	20.4%	27.1%	22.8%
Medium (2.06 to 3.9 acres)	21.8%	23.9%	36.7%	18.8%	26.4%
Large (> 3.9 acres)	6.7%	17.4%	14.3%	48.8%	23.7%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007

land is identified for each administrative division as a proxy for land availability. In Table 12 households are ranked into quartiles according to median land access by division and distributions are compared by poverty mobility group.

These results are highly consistent with what one would expect. A remarkably disproportionate 72% of the chronically poorest are in a division where median land holdings are less than 2.06 acres per household, compared to 32% of the consistently wealthiest. Perhaps even more strikingly, 49% of the consistently non-poor households are in divisions where the median land holding is greater than 3.9 acres (the largest quartile). Conversely, fewer than 7% of the chronically poor can boast a division with a similar land endowment. Moreover, a mere 5% of the consistently wealthy households are in divisions where the median farm size is smaller than 1.75 acres (the smallest quartile). These results provide strong evidence that this aspect of an areas agricultural potential is highly important in determining wealth.

While landholding sizes vary greatly across households even within the same villages, there still is a strong spatial pattern of landholding sizes that is correlated with population density. Population density at the division level was found to be strongly inversely correlated with mean and median landholding size among households in our sample (correlation coefficients -0.33 and -0.31, respectively, both significant at the 0.01 % level).

In Table 13 we examine the correlation between areas ranked by agricultural potential and poverty mobility. Stratifying the sample of households into the nine main agro-ecological zones (AEZ) as defined by Egerton University's Tegemeo Institute, we find that areas of good agricultural potential tend to contain most of the consistently non-poor households, and areas of low agricultural potential tend to contain most of the chronically poor. Nearly four out of every five of the chronically poorest households are in an AEZ with lower agricultural potential.

However, there seems to be very little pattern between whether households rise from or fall into poverty and the agricultural potential of the area. The areas of relatively low agricultural potential contained the largest proportion of descending and ascending households. The areas of highest agricultural potential contained roughly equal proportions of households rising from and falling into poverty over the 11-year period.

Table 13. Poverty Mobility Groups by Agricultural Potential of Zones

	Poverty Mobility Group				
Agricultural Potential	Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
Highest[a]	14.5%	15.2%	14.3%	54.1%	24.2%
Mid-High[b]	6.7%	17.4%	22.4%	26.1%	19.6%
Mid-low[c]	32.1%	15.2%	24.5%	9.2%	27.6%
Lowest[d]	46.7%	52.2%	38.8%	10.6%	28.6%
Total	100%	100%	100%	100%	100%

Source: Tegemeo Survey Data 1997, 2000, 2004, 2007.
Notes: (a) High Potential Maize Zone; (b) Central Highlands; (c) Western Highlands, Western Transitional, and Marginal Rain Shadow; (d) Western Lowlands, Eastern Lowlands, and Coastal Lowlands.

In summary, there is fairly strong evidence that farm households are relatively better off in areas of high agricultural potential compared to areas of low potential. However, and perhaps surprisingly, agricultural potential has relatively little to do with whether a farm household exits out of poverty or falls into poverty.

4.4. Compound Spatial Disadvantages

In general, bi-variate analyses hint at trends in spatial poverty determinants, but the picture can be occasionally unclear. It is likely, as others have pointed out, that compounding factors are more important than any one of these determinants alone. For example, consider households facing multiple spatial disadvantages, specifically those who are in the 3rd quartile or worse of distances to motorable roads and fertilizer retailers, the 3rd or worse quintile in fare to market, and in one of the lowest potential zones.

These compound spatial disadvantages characterize 111 households (9% of the sample). Of these, 33 are chronically poor (which constitutes 20% of that group)[9]. An additional eight of these are descending households (17% of that group). Comparatively, eight of these households are consistently non-poor (4% of that group) and seven are ascending households (14% of group), despite the spatial disadvantages[10]. This example illustrates that compound spatial disadvantages at least partially contribute to chronic poverty, but, once again, we see that despite even multiple hindrances several households have gained or maintained a relatively high level of wealth.

To further investigate the importance of compounding factors, we use the Probit estimator for a model of the effects of spatial factors and their interactions on a household's likelihood of being chronically poor. According to the SPT theory, we would expect some of these factors, such as distance to a motorable road, to have a positive coefficient in estimated results. That is, we expect to find that the farther from a road, the more likely one is to be poor. Conversely, the availability of land is expected to decrease this probability, so we would expect the coefficient on the local median farm size to be negative in this estimation.

[9] Many of these are the households identified as the cluster of chronically poor in eastern Kenya highlighted in Figure 4.

[10] Note, this leaves 55 households of 111 who did not fall into one of the coded poverty groups

To identify and test compounding effects, we can interact these variables (i.e., include their product in the regression). For example, if being far from a market as well as having a high fare to get there has a compounding impact on the probability of being chronically poor, we would expect to find a negative and statistically significant coefficient on this interaction. When variables individually have countervailing expected impacts, one of the terms will be inverted in the interaction. This will give it a sensible ex-ante expectation. For example, distance to fertilizer seller is expected to have a positive coefficient, while that for local median farm size is expected to be negative. To test for a compounded effect between them, we will include the ratio of distance to fertilizer over divisional median farm size, and expect the coefficient to be positive. Table 14 summarizes the ex-ante expectations of coefficient signs for spatial factors and their interactions.

Table 14. Expected Spatial Effects and Interactions on the Probability of Being Chronically Poor

		Interactions						
Spatial Factor	Independent effect	Prevalence of uneducated	Average Rainfall [a]	Variance of Rainfall	Distance to road	Fare to Market	Distance to Fertilizer	Division med. farm size [a]
Prevalence of Uneducated Household Heads	(+)	(+/-)[b]						
Average main season rainfall [a]	(-)	(+)	(+/-)[b]					
Variance of main season rainfall	(+)	(+)	(+)	(+/-)[b]				
Distance to motorable road	(+)	(+)	(+)	(+)	(+/-)[b]			
Fare to nearest market	(+)	(+)	(+)	(+)	(+)	(+/-)[b]		
Distance to nearest fertilizer retailer	(+)	(+)	(+)	(+)	(+)	(+)	(+/-)[b]	
Median farm size by division [a]	(-)	(+)	(-)	(+)	(+)	(+)	(+)	(+/-)[b]

Notes (a) Main season rainfall and division average farm size are inverted in interactions (except with each other) so that the ex-ante expectation can be sensible. (b) Quadratic terms can represent either diminishing or exponential effects, either of which could be explained within the theory of spatial disadvantages

It should be noted that, although not the focus of this study, this model also controls for several household specific characteristics.[11] This will better ensure that the coefficients of interest truly represent spatial effects, rather than household specific effects. Finally, since interacting effects will often have uncommon units of measurement, the magnitude of coefficient estimates bears little meaning without context, and so will not be reported. Direction of effect (positive or negative), however, as well as the statistical significance are of considerable interest, and are reported in Table 15. Here, the statistically significant coefficients which conform to expectation are highlighted with a light shade, while those significant and contradicting expectation are darkly shaded. A table of full results is available from the corresponding author upon request.

Table 15. Spatial Factors and Interaction Effects on Probability of Being Chronically Poor (Probit [a])

		Interactions [b]						
Spatial Factor	Independent effect	Uneducated Prevalence	Average Rainfall [c]	Variance of Rainfall	Distance to road	Fare to Market	Distance to Fertilizer	Division med. farm size [c]
Prevalence of Uneducated HH Heads	(+)[ŧ] [0.36]	(-) [0.80]						
Average main season rainfall [c]	(+) [0.45]	(-) [0.12]	(-) [0.82]					
Variance of main season rainfall	(-) [0.11]	(+)[ŧ] [0.20]	(+)[ŧ] [0.01]***	(-) [0.15]				
Distance to motorable road	(-) [.16]	(-) [0.14]	(-) [0.92]	(-) [0.87]	(+) [0.43]			
Fare to nearest market	(-) [0.85]	(-) [.84]	(+)[ŧ] [0.08]*	(-) [0.06]*	(+)[ŧ] [0.78]	(+) [0.53]		
Distance to nearest fertilizer retailer	(+)[ŧ] [0.00]***	(-) [0.38]	(-) [0.00]***	(-) [0.38]	(+)[ŧ] [0.55]	(-) [0.01]**	(+) [0.00]***	
Median farm size by division [c]	(+) [0.71]	(+)[ŧ] [0.56]	(-)[ŧ] [0.05]**	(+)[ŧ] [0.63]	(+)[ŧ] [0.00]***	(-) [0.11]	(-) [0.01]***	(+) [0.51]
Joint significance of interactions	[0.01]**	[0.08]*	[0.00]***	[0.04]**	[0.19]	[0.02]**	[0.01]***	[0.01]***

Source: Tegemeo household surveys 1997, 2000, 2004, 2007, and authors estimations.
Notes (a) Regression analysis also controls for age, education, and gender of household head, adult equivalents and number of prime-aged (15-59) deaths, livestock and non-farm shares of income, household acres farmed, land tenure, and number of crops. (b) Direction of effect (positive/negative) in parentheses, fully robust p-value in brackets. (c) Main season rainfall and division median farm size are inverted in interactions (except with each other) so that components of interactions are not expected to have countervailing effects (ŧ) Consistent with ex-ante expectations (not applicable to quadratic terms).
*Significant at 10%, ** Significant at 5%, *** Significant at 1%.

[11] These are the age, gender, and education of the household head, number of adult equivalents and number of prime-aged (15-59) deaths, livestock and non-farm shares of income, household acres farmed, land tenure, and number of crops

Results of this estimation tell a number of interesting stories. First, several of the average rainfall variable interactions are significant at a 10% level or better. For example, the ratio of variance in rainfall over mean of rainfall has an increasing effect on the probability of being chronically poor, and this relationship is significant at a 1% level. That is, in areas where rainfall is lower on average and unpredictable year to year, households are more likely to be chronically poor. On the other hand, where mean rainfall is higher and land is more available households are less likely to be chronically poor. This is evidenced in the coefficient on the product of mean rainfall and median local farm size, which is negative and significant at a 5% level. Lower average rainfall increasing the probability of chronic poverty also appears compounded in areas isolated from markets. This is shown in the coefficient on the ratio of fare to market and average rainfall, which is positive and significant at the 10% level.

The distance to the nearest fertilizer retailer and its interactions also tell an interesting story. First of all, further isolation from retailers (i.e., longer distance) appears to have an increasing and exponential effect on the probability of being chronically poor. That is, the coefficients on this distance and its quadratic term are both positive and significant at a 1% level. Somewhat surprisingly, however, this effect seems at least partially mitigated in areas with lower rainfall, less access to land, and higher fares to market. This seemingly counter intuitive result may be explained by the fact that in such areas (e.g., where rainfall and land availability are insufficient) households are likely to have diversified into non-crop activities, and thus less dependant on the inputs required to generate crop income.

As mentioned above, where land is more accessible and rainfall more abundant we see the likelihood of chronic poverty decreasing significantly. Conversely, where less land is available and areas are more isolated from road infrastructure, households are more likely to be poor. This is evidenced in the coefficient on the ratio of kilometers to a motorable road over median local farm size, which is positive and significant at a 5% level.

One interaction provides a perplexing result. The product of rainfall variance and fare to market has a negative and significant coefficient. This says as rainfall becomes less predictable and traveling to market more expensive, households are less likely to be chronically poor. This result is not consistent with the SPT theory that such households would be spatially disadvantaged.

These results have outlined some specific relationships, but one may also find it odd that many of these interaction estimates are either not statistically significant or inconsistent with the theory of SPTs. One possibility is that these factors have no compound effect on the probability of being consistently among the poorest households. However, another possible explanation is that there is a high degree of correlation between these effects. For example, if areas where distance to a road and fare to market are greater are often the same places that distance to a fertilizer seller and access to education are worse, regression analysis is less capable of distinguishing between these compound effects. This is known as a collinearity problem.

A good rule-of-thumb for determining whether this is the issue shrouding some of our results is to test the joint significance of the interactions. That is, if a group of interactions are jointly significant we can conclude that the compound effects indeed influence likelihood of poverty, despite the statistical insignificance of individual interactions within the group. These results are reported in the bottom row of Table 15, with each figure testing the joint significance of seven interactions. As we can see, 6 of the 8 sub-sets of interactions are jointly significant at the 5% level or better, and all but one is significant at the 10% level. Indeed, a test on all interactions reveals they are jointly significant at the 1% level as a whole. Although the specific nature of all interactions cannot be discerned (and one should not assume directional effect when this is so), in short, compound effects matter.

5. CONCLUSION

The goals of this study, conducted using an 11-year panel of 1275 households, were to determine the relative importance of spatial factors in explaining wealth and poverty, to identify the spatial characteristics of the chronically poorest, consistently wealthiest and transient households, to determine whether compounding effects increase the likelihood of chronic poverty, and assess the evidence of spatial poverty traps. Findings show that spatial factors, indeed, are a substantial determinant of wealth, explaining a relatively similar share of variation in wealth as other household specific factors. A considerable amount of spatial clustering among the chronically poor as well as the consistently non-poor households is evident. By contrast, households both rising from and falling into poverty were sparsely distributed across the nation-wide sampling area.

Bivariate analyses show a pattern of correlation between spatial characteristics and chronic poverty, but considerably less consistency in the spatial characteristics of households escaping from or descending into poverty. With respect to general isolation, the chronically poor are disproportionately likely to be far from a motorable road, and more likely to live in an area with decreased access to education. Households with large differences over time in their asset values, on the other hand, appear to be equally likely to come from well connected or isolated areas

Higher fares to the nearest market centre, somewhat unexpectedly, was a characteristic of chronically poor and consistently wealthy households alike. Moreover, there was no strong evidence of a causal relationship between decreased (increased) fares and rising from (falling into) poverty. On the other hand, a lopsided share of the chronically poorest households were farther from input markets in 1997, as one might expect. However, likely due to nation-wide expansion in fertilizer retailing, by 2007 this distance had decreased for most households, especially the chronically poor.

There is strong evidence that areas with land constraints and lower agricultural potential are more likely to contain chronically impoverished households The vast majority of the chronically poor reside in divisions where median farm size is smaller than two acres. By contrast, fewer than 7% live where median farm size is greater than four acres. Unsurprisingly, statistical correlations indicate that land availability decreases when population density increases. This should be an issue of the utmost concern to policy makers. The correlation between poverty and rising land constraints has been fuelling both poverty and conflict throughout Africa for decades, and there is no reason to expect Kenya to be immune.

Much literature suggests the likelihood of poverty increases when multiple spatial disadvantages overlap. Results of Probit estimation seem to confirm this, and highlight some specific relationships. For example, in areas where rainfall is lower on average and unpredictable year to year, households are more likely to be chronically poor. This is also true where land constraints are compounded by limited access to infrastructure (i.e., roads). On the other hand, where mean rainfall is higher and land is more available households are significantly less likely to be chronically poor. Jointly these factors are highly significant in determining the probability of being chronically poor, highlighting the importance of compounding effects.

Despite the strong correlation between spatial factors and static welfare, there are four other important conclusions from the study. First, not all households in apparent "spatial poverty traps" are chronically poor. Although there is some clustering of poor households, they are often surrounded by others who manage to remain above the bottom tercile, or even rise out of poverty in some cases, indicating that spatial factors are not wholly determinant of poverty.

Secondly, not all chronically poor are in spatial poverty traps. We see a number of households that are consistently in the bottom third of the sample in terms of wealth, who do not reside in areas of low or variable rainfall, market isolation, severe land constraints, or other spatial features found in this analysis to be correlated with poverty.

Thirdly, there is little or no evidence of spatial factors playing a defining role in the ability to rise from poverty. In fact, the proportion of households that have climbed out of poverty is not greatly different between areas of low and high mean wealth. Describing a household's area as a poverty trap suggests a degree of inevitability, but even in disadvantaged areas this does not seem to be the case.

Fourth, household-specific factors are also shown to be of considerable importance in explaining the variation in household wealth across this nationwide sample. The degree of variation in wealth within communities is as large as the degree of variation across communities. In fact, results show that the relative explanatory power of spatial factors, though substantial, is slightly less than that of household-specific factors.

Together, these points call into question the appropriateness of defining areas as poverty traps. While evidence suggests that spatial disadvantages have an increasing and compounding effect on the likelihood of chronic poverty, one's poverty status and especially one's ability to escape from poverty are not clearly defined by location. These conclusions, if they are found to hold elsewhere in rural Africa, may warrant a reassessment of whether spatial traps or perhaps spatial disadvantage may be a more accurate way of describing the spatial dimensions of poverty in this region. Just as there are many composite facets to an area being spatially disadvantaged, there are also many factors driving chronic poverty and poverty dynamics. This includes spatial factors, but also household-specific factors. The considerable heterogeneity of smallholder households typically found even within a given community underscores the limits of conceptualizing poverty primarily in spatial terms and highlights the need for policy to also address the important household-level factors leading to high levels of variation in wealth with communities.

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Appendix A

Table A1. Mean Household Wealth per AE[a] Over Time by Poverty Status

	Poverty Mobility Group				
	Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
Year	---Mean Asset Wealth (Thousands 2007 Ksh) per Adult Equivalent---				
1997	1.88	40.11	3.41	113.66	17.95
2000	1.97	17.96	14.48	90.17	16.44
2004	1.75	12.18	21.00	80.61	15.02
2007	1.71	3.08	34.32	78.51	12.87

Source: Tegemeo Household Surveys; 1997, 2000, 2004, 2007
Note: a) AE is Adult equivalent calculated using the World Bank's age and gender based scale

Table A2. Median Household Wealth per AE[a] Over Time by Poverty Status

	Poverty Mobility Group				
	Chronically Poorest (n=165)	Falling Into Poverty (n=46)	Rising From Poverty (n=49)	Consistently Non-Poor (n=207)	Other (n=808)
Year	--Median Asset Wealth (Thousands 2007 Ksh) per Adult Equivalent--				
1997	1.26	28.33	3.48	59.52	11.41
2000	1.53	10.42	7.42	53.58	9.91
2004	1.24	9.37	13.62	48.02	10.00
2007	1.35	3.48	22.94	46.39	8.47

Source: Tegemeo Household Surveys; 1997, 2000, 2004, 2007
Note: a) AE is Adult equivalent calculated using the World Bank's age and gender based scale