# Rural poverty dynamics and refugee communities in South Africa: A spatial-temporal model

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ABSTRACT

The assimilation of refugees into their host community economic structures is often problematic. The paper investigates the ability of refugees in rural South Africa to accumulate assets over time relative to their host community. Bayesian spatial temporal modeling was employed to analyze a longitudinal database that indicated the asset accumulation rate of former refugee households was similar to their host community, however, they were unable to close the wealth gap. A series of geo-statistical wealth maps illustrate that there is a spatial element to the higher levels of absolute poverty in the former refugee villages. The primary reason for this is their physical location in drier conditions that are established further away from facilities and infrastructure. Neighboring South African villages in close proximity, however, display lower levels of absolute poverty suggesting that the spatial location of the refugees only partially explains their disadvantaged situation. In this regard, the results indicate that the wealth of former refugee households continues to be more compromised by comparatively by higher mortality levels, poorer education and less access to high return employment opportunities. The long term impact of low initial asset status appears to be perpetuated in this instance by difficulties in obtaining legal status in order to access state pensions, facilities and opportunities. The usefulness of the results is that they can be used to sharpen the targeting of differentiated policy in a given geographical area for refugee communities in rural Africa.

**Keywords -** refugee, rural poverty, socio economic position, South African, Mozambican

## INTRODUCTION

The assimilation of refugees into their host community economic structures is often problematic from a number of perspectives. Firstly, the traumatic nature of their transition is exacerbated because these communities arrive with few assets and experience difficulties with respect to their initial assimilation into the economic and social structures of the host country (O'Brien *et al.,* 2008; Chambers, 1986). Secondly, the difficulties of the transition are aggravated by high levels of poverty in rural Africa that have increased in recent decades as a result of globalization, disease, climate change and urban migration (Bryceson, 2004; Mertz *et al.,* 2005; Rodgers, 2008; Sherbinin *et al.,* 2008). Finally, the disadvantaged economic situation of refugee communities is perpetuated because of an inability to access institutions and invest in new opportunities (Binswanger 2004; Kydd *et al.,* 2004; Sherbinin *et al.* 2008).

Former Mozambican refugees in rural South Africa arrived with very few assets as a result of fleeing from a civil war (1975-1992). In addition, their situation was compromised by high levels of poverty in rural South Africa due to historical legacies that have fundamentally skewed the wealth and population demographics of the country (Bryceson, 2002a: 2002b ; Machethe, 2004; Kariuki, 2004). In this regard, South Africa's highly skewed bi-modal economy has exacerbated the plight of the rural poor as a result of a focus on urban industrial development at the expense of the rural economy (Bryceson 2002a, 2002b). Furthermore, despite consistent GDP growth from 1994, income inequality in rural South Africa has deepened (Armstrong *et al.,* 2008). As a result of these circumstances, former Mozambican refugees experience higher levels of poverty and mortality nearly twenty years after their arrival (Rodgers, 2008; Collinson, 2010).

This paper investigates the ability of refugees in a rural South African community to improve their asset wealth (Socio-economic position-SEP) relative to their host community. In particular, the paper investigates the dynamics of asset accumulation in a refugee community in order to target, as well as make policy suggestions for their assimilation. The first research question tests whether the asset accumulation rates of former refugees and local households are different, as well as whether there is a persistent wealth gap (SEP) between the two sets of households. The second research question tests whether there is a spatial element that influences the household wealth of refugees. The third research question investigates what variables influence the asset wealth (SEP) of households in a rural community, as well as whether these variables show significant differences between former refugee and local households.

The importance of the study is underlined by the World Bank's increasing concern about rural poverty in Africa that has contributed to rapid urbanization, overcrowding and a fierce competition for scarce resources. This problem is particularly problematic in South Africa (Machethe, 2004; Bryceson, 2004; Mertz *et al.* 2005). In particular, the study makes a contribution by extending the rural poverty debate to include a refugee context (Schatz, 2009; Onyut *et al.,* 2009). The paper also makes a methodological contribution as a result of the application of a Bayesian multivariate model to track socio economic phenomena like poverty dynamics. In particular, this method ensures that the significance of predictor variables is not overstated due to spatial correlation (Elliot *et al.,* 2000). Finally, the use of simulation based Bayesian kriging maps makes a contribution by their ability to predict wealth (poverty) at village level in order to sharpen the focus of geographical targeting for policy makers (Gelfand *et al.,* 1999).

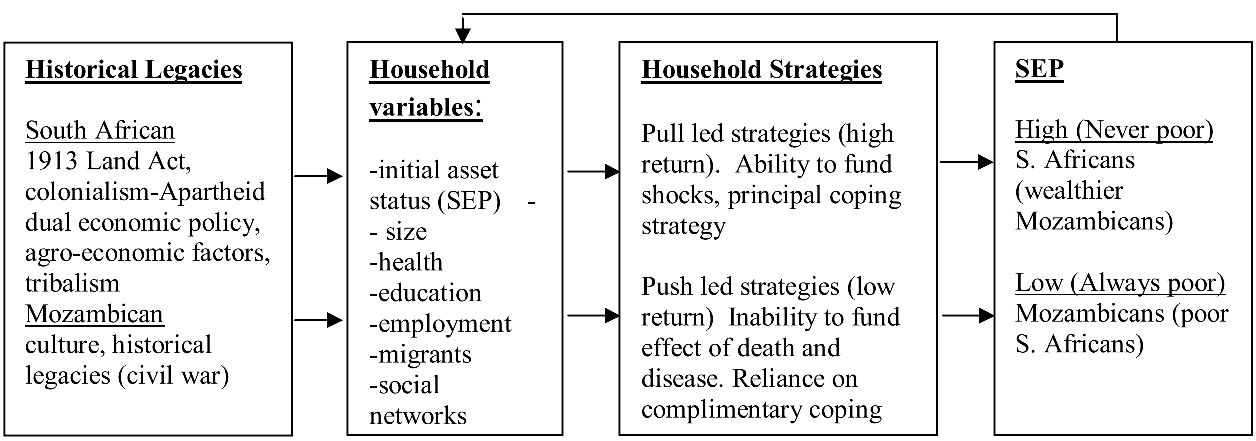
The remainder of the paper is structured as follows: Section 2 outlines a conceptual framework that explains the dynamics of asset accumulation rates and their impact on socio economic position (SEP). Section 3, describes the data and method employed. Sections 4 and 5 present and discuss the results respectively. Finally, Section 6 concludes the study and makes some policy recommendations.

## A CONCEPTUAL FRAMEWORK

This section develops a conceptual framework, illustrated in Figure 1, to explain the dynamics and direction of asset accumulation in a rural community. In this regard, the historical legacies of communities influence the initial asset status of households, as well as their characteristics. These factors, in turn, influence their choice of household strategies that largely determine income earning opportunities, asset accumulation rates and their outcome, namely, asset wealth or socio economic position (SEP).

### *Household asset wealth ( SEP)*

**Figure 1: The dynamics of socio economic position (SEP)**




*source (Kuhlman, 1990; Collinson 2010)

Rural households are likely to experience different levels of asset wealth over time as the family producer/consumer ratio changes (Chayanov, 1986; Krishna, 2006). Household wealth or SEP incorporates some measures of physical and social resources, as well as household status in a local social hierarchy (Howe *et al.,* 2008). In Figure 1, initial SEP status is explained as a long term effect of inter-generational transfers that include natural, social, human, physical and financial assets (Wu and Pretty 2004; Barrett, 2005). SEP is often measured by using a bundle of household assets (Booysen *et al.,* 2008) and can be disaggregated into four possible categories of rural wealth status. Two of these categories include "always poor" (poor then poor now) and "descending into poverty" (not poor then, poor now). The other two groups are "never poor" and "ascending out of poverty" (poor then, not poor now). Changes in SEP can be calculated by estimating the aggregated difference between the number of households that ascend out of poverty from those that descend into poverty during a given time period (Sen, 2003; Krishna, 2006).

***Historical legacies and household characteristics***

Historical legacies have fundamentally influenced many African countries that have been subjected to decades of colonial rule, inept governments, corruption, succession wars and agro-climatic change (Bryceson, 2004; Mertz *et al.,* 2005; Rodgers, 2008; Sherbinin *et al.,* 2008). In South Africa, for instance, the 1913 Land Act largely determined where Black citizens could live for the next nine decades. Furthermore, historical economic policies have influenced the development of a dual economy that is largely urban based. These legacies, illustrated in Figure 1, have had a pervasive long term effect on the initial SEP of households, institutions and infrastructure (Williamson, 2000; Barrett, 2005). In this regard, initial asset status (SEP) is a critical factor that perpetuates a household's options (Barrett, 2005), as well as impacts on the household SEP growth rate and strategy choices, household size, education, social status and employment opportunities (Schwarze and Zeller, 2005; Anriquez and Valdes, 2006; Vermeulen *et al.,* 2008; Xing *et al.,* 2008).

*Household Characteristics, Strategy and SEP*

The dynamics of asset accumulation rates are primarily influenced by existing household assets and characteristics that are mediated by the presence of institutions, shocks and opportunities . A household's size, health, education levels and social networks, illustrated in Figure 1, largely determine its income generating strategies. These strategies, in turn, influence asset accumulation rates that translate into the SEP of the household. SEP, however, also has a reverse (cyclical) influence (see direction) on household characteristics in that wealth created is often re-directed at improving social status, education or health (Sen, 2003; Krishna, 2006).

A wide range of household strategies influence SEP in rural Africa and the opportunity led strategies of wealthier rural households are very different from the survival led strategies of the poor (Barrett, 2005). Wealthier households (Never Poor), for example, are better able to adopt high return strategies (pull led) because they have the necessary assets, ability and social networks to access opportunities. Wealthier households (high SEP), moreover, are able to fund investment opportunities like new technology or diversification that further accelerates asset accumulation and raises SEP. Improved SEP, moreover, allows a household to invest in healthcare needs and education, to elevate social status, and facilitates the future adoption of high return strategies (Barrett *et al.,* 2001; Barrett, 2005; Ardington *et al.*, 2009). Conversely, poorer households (Always Poor) are more likely to have higher numbers of dependents, a poor education and limited social status and networks. These households are, in effect, forced into adopting complimentary type low risk, low return strategies in order to survive because they lack both the assets and ability to fund high return options. They also have limited funds to invest in healthcare and education and they are less able to fund shocks. These households, in effect, remain locked into low income opportunities because they are unable to fund investments that would improve their strategic options (Elmquist and Olsson, 2006; IIYama *et al.,* 2008; Krishna, 2006; Mendola, 2008; Lay *et al.,* 2008; Sen, 2003; Wouterse and Pieterse, 2008). Because of a combination of a lower initial asset status (SEP) and less lucrative strategy options, poorer rural households are unable to close the wealth gap (SEP) with richer households (Barrett, 2005). Poorer households, moreover are also more vulnerable to natural disasters, illness and death than richer households (Schatz and Ogunmefun, 2007; Goudge *et al*., 2009a, 2009b; Schatz *et al.,* 2011), as well as less able to sustain economically inactive dependents (Urassa *et al.,* 2001; Lay *et al..,* 2008; Wouterse and Taylor, 2008; IIYama *et al.,* 2008).

## DATA AND METHOD

This section briefly describes the location and type of data used to test the research questions before outlining how the data were analyzed.

### *The Data*

The Agincourt Health and Socio-Demographic Surveillance Site (HDSS) constitutes a rural sub-district of the Bushbuckridge municipal area that is located in Mpumalanga Province in the northeast of South Africa. A national park, forming the border with Mozambique, is situated on the eastern boundary of the site. Furthermore, the site occupies 400 square kilometres that includes 21 villages with a combined population of 70 000 inhabitants living in 12 167 households. A third of this population are of Mozambican origin, many of them arriving as refugees in the early to mid-1980s during the civil war (Schatz, 2009). Although we have differentiated South African households from their former refugee (Mozambican) counterparts, all Shangaan speaking people in South Africa can be traced back to the colonial or local succession wars in Mozambique dating back to the period 1830-1890. This initial influx of refugees assimilated themselves into predominantly Sotho speaking South African communities. In 1970 the Shangaan leadership assumed formal control of the area when a separate Bantustan called Gazankulu was created. It is, therefore, somewhat ironic that households in the area are now classified as South African or former Mozambican (Polzer, 2004). In fact, the latter category relates to more recent former refugees that fled from Mozambique as a result of a civil war (1975-1992). For the purposes of this paper we use the term former (Mozambican) refugee for those inhabitants who arrived in the mid-1980s as a result of the civil war in Mozambique. The original inhabitants of this area are referred to as South African.

A household level (unit of analysis) panel data structure was used for the years 2001, 2003, 2005 and 2007. The data recorded the establishment of new households established after 2001, as well as recorded dissolutions between 2001 and 2007. In order to track households identified as former Mozambican refugees, this status was established on the registration of a new household for each household member. Furthermore, the description of former refugee was retained for the full period of the study, regardless of changes in their legal status which could include the acquisition of a permanent residence document or South African citizenship (Landau, 2005). To ensure that we did not overestimate significance due to households that dissolved and reformed within the site under another identifier, we checked for households with common individual identifiers, established linkages if individuals were shared and clustered upon this in the analysis. The data used were largely categorical and were gathered as a result of censuses that included a detailed survey of the demographics of the households. In this regard, a GIS system exists for all households within the site that is updated each year. An asset survey was also conducted every two years between 2001 and 2007. The assets recorded in the surveys included a range of appliances, telecommunications facilities, transport and toilet facilities. Further assets included water supply type, the main source of cooking power and lighting and the size and structure of the family swelling. Finally, we also included the number of livestock in response to the recommendations of other researchers (Jabbar *et al.,* 2002; Berzborn, 2007). The predictor variables influencing SEP were selected on the basis of the theoretical relationships described in the conceptual framework (Figure 1). These included household head demographics (age, gender, nationality, mortality due to HIV/TB or other causes), household mortality, duration of household existence at first asset observation, dependency ration (<18:>=18 years old), migration patterns of household occupants, labour types, education, ownership or access to farming land. It should be noted that some of these predictors are not tracked annually at each census update and hence could not be included in the final multivariate model due to missing observations in certain of the panel years.

***The Methods***

The paper incorporates a combination of static and dynamic analysis. These methods include descriptive analysis, a combination of classical and Bayesian univariate and multivariate models and simulation based Bayesian kriging.

***The First Research Question***

The first research question, namely, whether the asset accumulation rate of former refugee and local households are different, as well as whether there is a persistent wealth gap between the two sets of households, was tested as follows. Firstly, a table of assets was constructed for both former refugee and South African households for the four census years (2001, 2003, 2005, 2007). The rate of asset accumulation was then tested by developing line plots based on regression models for both South African and Mozambican households using the year as a predictor. In order to test if there was a significant difference in the mean wealth (assets) of the two categories of household, a series of two sample t-tests was run for each year.

***The Second Research Question***

The second research question tests whether there is a spatial element with respect to household wealth. In order to track the location, extent and persistence of household poverty in the Agincourt HDSS site, we produced a series of spatial maps for the period 2001 to 2007. A multiple correspondence analysis index was developed as a proxy for SEP (Howe et al., 2008) and simulation based Bayesian kriging (Gelfand *et al.,* 1999) was used to produce maps for each of the four panel years of the study period. The smoothed maps predicted the MCA asset score at numerous prediction points (regular grid) within the site for each of the panel years (WinBUGS software). This approach allowed us to predict the asset count at un-sampled locations throughout the site and thus generate the smoothed maps. A baseline linear model (see Appendix 2) was used that included no covariates except a constant and spatial (village level) random effect modeled as a parametric function of distance between pairs of village centroids (Diggle *et al.,* 1998). Village centroids were superimposed on each map. Lighter areas represent higher levels of poverty (or lower SEP) while, conversely, the darker areas represent higher levels of SEP. In order to analyze areas of persistent poverty, as well as better interpret the smoothed maps, the percentage of households below the absolute poverty was calculated using a set of baseline assets (Booysen *et al.,* 2008). These assets included ownership of a radio and bicycle, a cement floor in the house, as well as access to public water and a pit latrine. This information was then used to compare poverty over the full period in South African versus former Mozambican refugee households, as well at each of the 21 villages in the site.

***The Third Research Question***

The third research question investigates what variables are associated with wealth (SEP), as well as whether these variables show significant differences between former refugee and local households. This question was tested by a range of univariate and multivariate classical and Bayesian ordinal regression models. A classical model (with no random effects) was run for comparative purposes.

We chose a Bayesian methodology to predict SEP in order to address a number of spatial and temporal problems. In this regard, objects in close proximity are often more alike. Thus common exposures (measured or unmeasured) may influence SEP similarly in households of the same geographical area, introducing spatial correlation in the outcome. Repeated data are also expected to be correlated in time. Standard statistical methods, however, assume independence of outcome measures thus ignoring correlation bias for two reasons. Firstly, the standard error of the covariates is underestimated, thereby overestimating the significance of the risk factors. Secondly, estimates of SEP outcomes would be incorrect at locations where data are lacking. Geostatistical Bayesian models relax the assumption of independence and assume that spatial correlation is a function of distance between locations. They are highly parameterized models and their full estimation has only become possible in the last decade by formulating them within a Bayesian framework (Hedeker and Gibbons, 1994) and estimating the parameters via Markov chain Monte Carlo (MCMC) simulation.

*Construction of the dependent variable (SEP indices)*

A set of assets, employed by the World Bank, was used to develop a wealth (SEP) index for each household (Gwatkin *et al.,* 2000; Howe *et al.,* 2008). These assets included a balance of purchased household assets, housing quality, water and sanitation. Livestock ownership was also included in our set of assets because of their importance in rural African communities. The use of household assets (wealth indices) to determine socio economic position has been adopted by a number of other studies (Gwatkin, *et al,.* 2000; Sahn and Stifel, 2003). In this regard, household asset status is a reliable proxy for long term consumption expenditure (Booysen *et al.,* 2008). Furthermore, measures of income and consumption expenditure are difficult and costly to obtain in a rural setting and measures of income can vary widely from season to season (Howe *et al.,* 2008). SEP indices were constructed using an Absolute Asset Count, Principal Components Analysis (PCA) and Multiple Correspondence Analysis (MCA). The weights used for both the PCA and MCA indices were those from the first dimension. We chose to use an MCA based index (see Appendix 1) after a detailed evaluation of the properties of the three measures, as well as because it is better suited to categorical data (Howe *et al.*, 2008).

*Explanatory variables*

The explanatory variables used in the univariate and multivariate analysis were based on well tested issues in the literature (Sen, 2003; Malberg and Tegenu, 2007; Sherbinin *et al.,* 2008; Collinson, 2010). These variables included year, household head demographics (age at panel year, gender, nationality, death), household factors (duration or years existed at asset observation, number of individuals in household 18+ or <18, hospital admissions in a given panel year, the migrant proportion and the number of working individuals in the preceding year). Household head status was classified as former refugee or South African and a variable was developed to track the proportion of the household that were former refugees. Other predictors included the death of household heads and other household members in both the preceding and current year, education years of household occupants and household child grants received, ownership or access to and usage of farming land and selected employment opportunities in the professional and government sectors. The definition of migration discriminates between permanent and temporary to reflect a high dependency on temporary labour migration in this population (Collinson *et al.,* 2007). We also use temporary migration in the household migrant ratio because this has been shown to have significant positive linkages with SEP (Collinson et al., 2006).

*Univariate and multivariate analysis*

A preliminary analysis of the univariate relationships was carried out using Stata. In this regard, ordinal regression techniques (clustered on household level) were used to assess the relationship between the relevant ordinal wealth category and each covariate. Significant covariates (10% level) emerging from the univariate analysis were then selected as inputs for the multivariate models. These models included two non-spatial models. The first was a classical non spatial model (Stata). The parallel regression assumption was tested using the Brant Test. The second was a non spatial (WinBUGS) using a Bayesian modeling approach with the third model being a spatial (or geostatistical) model also incorporating an unstructured household level random effect. This multilevel random effects ordinal model (Hedeker and Gibbons, 1994) incorporated a Bayesian geostatistical approach in order to account for spatial correlation in the panel data set while the unstructured household level random effect was included to adjust for repeated measurements on a given household. Spatial correlation was measured at village level and a household level random effect for repeated longitudinal measurements on households. Further details of the Bayesian statistical model can be seen in Appendix 2.

## RESULTS

The results investigate the three principal research questions. These included whether the asset accumulation rare (SEP) of refugee households was different from local households, investigating the variables that are associated with SEP and determining whether differential levels of asset accumulation (poverty) can be mapped over time and space in a rural community.

### *Is the asset accumulation rate of former refugee and South African households different and is there a persistent wealth gap?*

The results indicate that the average number of assets owned, illustrated in Table 1, increased for both South African, as well as former refugee households over the period 2001 to 2007. The increase in overall asset status is supported by a considerable increase in high cost items like fridges, stoves, TV sets, video machines, cellular phones and cars. Conversely, the number of radios, fixed line telephones, bicycles, carts and livestock has declined. The results also indicate an increased access to electricity for lighting and cooking, pit toilets and a marked increase in the number of plans to extend the main dwelling. Contrary to the general increase in assets, regular water supply appears to have decreased in place of irregular water supply. The general increase in assets is supported by other studies in the province (DSP, 2006) and the positive influence of an electrification program is also commonly linked to an increase in assets (Kanagawa and Nakata, 2008).

## Table 1: Asset Status-Number (percent) of households in possession of item

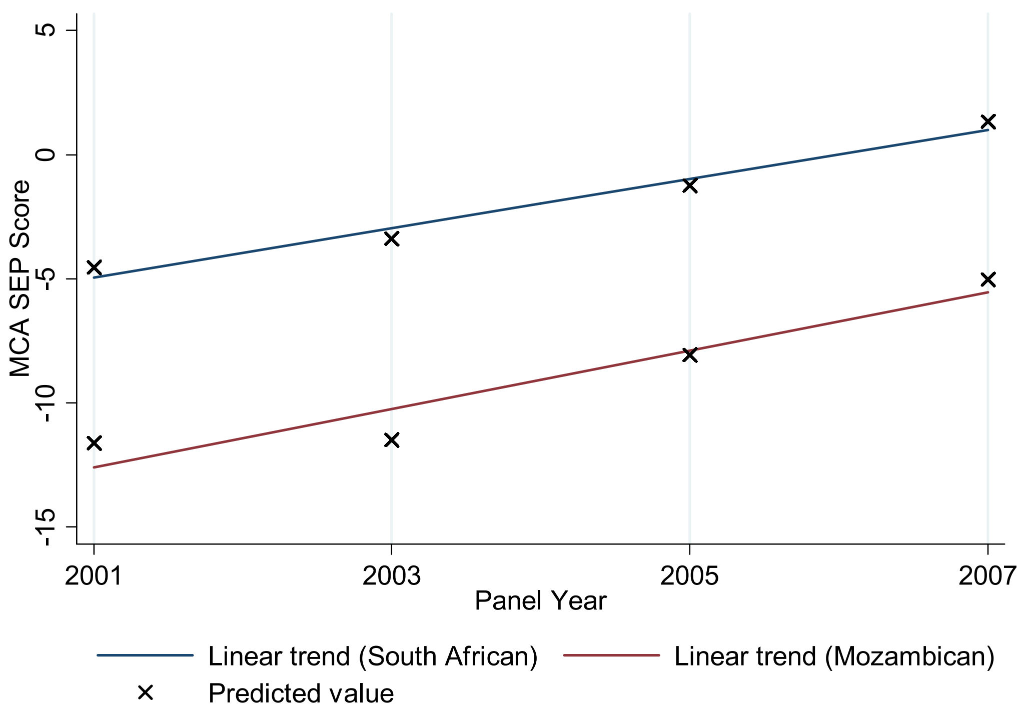
| | South African | | | | | Mozambican | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Factor | 2001 | 2003 | 2005 | 2007 | Overall | 2001 | 2003 | 2005 | 2007 | Overall |
| **Number of households** | 7,243 | 7,762 | 7,786 | 7,655 | 30,446 | 2,917 | 3,208 | 3,151 | 3,241 | 12,517 |
| Ave number of assets (std. dev.)[iii] | 7.73 (2.83) | 7.71 (2.72) | 8.35 (2.50) | 9.10 (2.45) | 8.23 (2.69) | 5.83 (2.41) | 5.71 (2.42) | 6.47 (2.44) | 7.27 (2.66) | 6.33 (2.57) |
| Asset totals (%) | | | | | | | | | | |
| Fridge | 3526(48.7) | 4272(55) | 5157(66.2) | 5746(75.1) | 18759(61.6) | 710(24.3) | 786(24.5) | 1241(39.4) | 1707(52.7) | 4458(35.6) |
| Stove | 3577(49.4) | 3991(51.4) | 4878(62.7) | 5750(75.1) | 18196(59.8) | 503(17.2) | 509(15.9) | 894(28.4) | 1463(45.1) | 3369(26.9) |
| TV | 4236(58.5) | 4778(61.6) | 5083(65.3) | 5388(70.4) | 19485(64) | 1305(44.7) | 1313(40.9) | 1526(48.4) | 1652(51) | 5796(46.3) |
| Video machine | 544(7.5) | 718(9.3) | 1149(14.8) | 3269(42.7) | 5680(18.7) | 69(2.4) | 89(2.8) | 170(5.4) | 1010(31.2) | 1338(10.7) |
| Satellite dish | 23(0.3) | 26(0.3) | 48(0.6) | 157(2.1) | 254(0.8) | 3(0.1) | 3(0.1) | 10(0.3) | 22(0.7) | 38(0.3) |
| Radio | 3048(42.1) | 1878(24.2) | 1878(24.1) | 1885(24.6) | 8689(28.5) | 1148(39.4) | 921(28.7) | 795(25.2) | 639(19.7) | 3503(28) |
| Fixed phone | 325(4.5) | 216(2.8) | 166(2.1) | 212(2.8) | 919(3) | 19(0.7) | 12(0.4) | 18(0.6) | 41(1.3) | 90(0.7) |
| Cellular phone | 2839(39.2) | 4348(56) | 6082(78.1) | 6646(86.8) | 19915(65.4) | 944(32.4) | 1376(42.9) | 2209(70.1) | 2627(81.1) | 7156(57.2) |
| Car | 1177(16.3) | 1184(15.3) | 1316(16.9) | 1356(17.7) | 5033(16.5) | 298(10.2) | 306(9.5) | 327(10.4) | 344(10.6) | 1275(10.2) |
| Motorbike | 57(0.8) | 29(0.4) | 27(0.3) | 58(0.8) | 171(0.6) | 9(0.3) | 6(0.2) | 14(0.4) | 14(0.4) | 43(0.3) |
| Bicycle | 942(13) | 789(10.2) | 803(10.3) | 692(9) | 3226(10.6) | 430(14.7) | 363(11.3) | 328(10.4) | 237(7.3) | 1358(10.8) |
| Cart | 329(4.5) | 257(3.3) | 187(2.4) | 193(2.5) | 966(3.2) | 15(0.5) | 15(0.5) | 27(0.9) | 20(0.6) | 77(0.6) |
| Ave number of rooms (std. dev.) | 2.85 (1.58) | 2.72 (1.29) | 2.83 (1.33) | 2.86 (1.35) | 2.81 (1.39) | 2.52 (1.48) | 2.48 (1.38) | 2.59 (1.47) | 2.5 (1.42) | 2.54 (1.44) |
| Power for lighting (%) | | | | | | | | | | |
| Electricity | 5835(80.6) | 6849(88.2) | 7437(95.5) | 7357(96.1) | 27478(90.3) | 1347(46.2) | 1485(46.3) | 2326(73.8) | 2485(76.7) | 7643(61.1) |
| Battery/Generator | 4(0.1) | 10(0.1) | 10(0.1) | 8(0.1) | 32(0.1) | 4(0.1) | 1(0) | 6(0.2) | 3(0.1) | 14(0.1) |
| Solar Power | 5(0.1) | 5(0.1) | 1(0) | 58(0.8) | 69(0.2) | 2(0.1) | 4(0.1) | 2(0.1) | 50(1.5) | 58(0.5) |
| Paraffin | 387(5.3) | 203(2.6) | 69(0.9) | 47(0.6) | 706(2.3) | 632(21.7) | 535(16.7) | 211(6.7) | 138(4.3) | 1516(12.1) |
| Candles | 1011(14) | 689(8.9) | 266(3.4) | 185(2.4) | 2151(7.1) | 928(31.8) | 1179(36.8) | 602(19.1) | 562(17.3) | 3271(26.1) |
| Other | 1(0) | 6(0.1) | 3(0) | 0(0) | 10(0) | 4(0.1) | 4(0.1) | 4(0.1) | 3(0.1) | 15(0.1) |
| Power for cooking (%) | | | | | | | | | | |
| Electricity | 1383(19.1) | 1899(24.5) | 2045(26.3) | 3039(39.7) | 8366(27.5) | 111(3.8) | 130(4.1) | 195(6.2) | 476(14.7) | 912(7.3) |
| Gas Bottle | 225(3.1) | 181(2.3) | 215(2.8) | 141(1.8) | 762(2.5) | 21(0.7) | 22(0.7) | 26(0.8) | 22(0.7) | 91(0.7) |
| Paraffin | 508(7) | 446(5.7) | 350(4.5) | 137(1.8) | 1441(4.7) | 79(2.7) | 82(2.6) | 108(3.4) | 40(1.2) | 309(2.5) |
| Wood | 5088(70.2) | 5219(67.2) | 5170(66.4) | 4329(56.6) | 19806(65.1) | 2692(92.3) | 2968(92.5) | 2817(89.4) | 2697(83.2) | 11174(89.3) |
| Other | 39(0.5) | 17(0.2) | 6(0.1) | 9(0.1) | 71(0.2) | 14(0.5) | 6(0.2) | 5(0.2) | 6(0.2) | 31(0.2) |
| Toilet facility type (%) | | | | | | | | | | |
| Modern | 21(0.3) | 17(0.2) | 27(0.3) | 26(0.3) | 91(0.3) | 1(0) | 0(0) | 1(0) | 2(0.1) | 4(0) |
| VIP | 76(1) | 39(0.5) | 193(2.5) | 284(3.7) | 592(1.9) | 14(0.5) | 15(0.5) | 55(1.7) | 100(3.1) | 184(1.5) |
| Pit Toilet | 5044(69.6) | 5404(69.6) | 5689(73.1) | 5862(76.6) | 21999(72.3) | 1128(38.7) | 1298(40.5) | 1502(47.7) | 1777(54.8) | 5705(45.6) |
| None | 2095(28.9) | 2300(29.6) | 1874(24.1) | 1470(19.2) | 7739(25.4) | 1773(60.8) | 1894(59) | 1593(50.6) | 1354(41.8) | 6614(52.8) |
| Unknown | 7(0.1) | 2(0) | 3(0) | 13(0.2) | 25(0.1) | 1(0) | 1(0) | 0(0) | 8(0.2) | 10(0.1) |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Water availability (%) | | | | | | | | | | |
| Always | 796(11) | 978(12.6) | 873(11.2) | 747(9.8) | 3394(11.1) | 237(8.1) | 204(6.4) | 674(21.4) | 436(13.5) | 1551(12.4) |
| Most of the time | 2833(39.1) | 1854(23.9) | 2160(27.7) | 2493(32.6) | 9340(30.7) | 1550(53.1) | 535(16.7) | 1247(39.6) | 985(30.4) | 4317(34.5) |
| Few hours a day | 347(4.8) | 295(3.8) | 587(7.5) | 561(7.3) | 1790(5.9) | 95(3.3) | 69(2.2) | 197(6.3) | 268(8.3) | 629(5) |
| Irregular | 3258(45) | 4634(59.7) | 4165(53.5) | 3847(50.3) | 15904(52.2) | 1035(35.5) | 2400(74.8) | 1030(32.7) | 1551(47.9) | 6016(48.1) |
| Unknown | 9(0.1) | 1(0) | 1(0) | 7(0.1) | 18(0.1) | 0(0) | 0(0) | 3(0.1) | 1(0) | 4(0) |
| Water supply (%) | | | | | | | | | | |
| Tap in house | 72(1) | 48(0.6) | 60(0.8) | 41(0.5) | 221(0.7) | 10(0.3) | 10(0.3) | 7(0.2) | 16(0.5) | 43(0.3) |
| Tap in yard | 1574(21.7) | 866(11.2) | 1512(19.4) | 2093(27.3) | 6045(19.9) | 181(6.2) | 110(3.4) | 181(5.7) | 254(7.8) | 726(5.8) |
| Tap in street | 4661(64.4) | 5524(71.2) | 5982(76.8) | 5379(70.3) | 21546(70.8) | 2402(82.3) | 2898(90.3) | 2888(91.7) | 2955(91.2) | 11143(89) |
| Other | 936(12.9) | 1324(17.1) | 232(3) | 142(1.9) | 2634(8.7) | 324(11.1) | 190(5.9) | 75(2.4) | 16(0.5) | 605(4.8) |
| Livestock (%) | | | | | | | | | | |
| Cattle | 1503(20.8) | 1331(17.1) | 1307(16.8) | 1254(16.4) | 5395(17.7) | 80(2.7) | 89(2.8) | 87(2.8) | 81(2.5) | 337(2.7) |
| Poultry | 4552(62.8) | 4307(55.5) | 3268(42) | 3035(39.6) | 15162(49.8) | 1965(67.4) | 1826(56.9) | 1203(38.2) | 1314(40.5) | 6308(50.4) |
| Pigs | 409(5.6) | 284(3.7) | 270(3.5) | 240(3.1) | 1203(4) | 30(1) | 14(0.4) | 20(0.6) | 12(0.4) | 76(0.6) |
| Goats | 973(13.4) | 789(10.2) | 770(9.9) | 710(9.3) | 3242(10.6) | 346(11.9) | 347(10.8) | 340(10.8) | 334(10.3) | 1367(10.9) |
| Main dwelling still under construction (%) | 1253(17.3) | 1519(19.6) | 1613(20.7) | 1419(18.5) | 5804(19.1) | 332(11.4) | 427(13.3) | 685(21.7) | 546(16.8) | 1990(15.9) |
| Plans to extend main dwelling (%) | 217(3) | 135(1.7) | 113(1.5) | 395(5.2) | 860(2.8) | 84(2.9) | 27(0.8) | 40(1.3) | 287(8.9) | 438(3.5) |

iii Significant increasing trend (assets) for both South African, as well as former refugee households ($\beta = 0.03$, $p<0.001$) between 2001-2007

The results in Table 1 indicate that the average number of assets owned increased by 17.7 per cent for South African households and by 24.7 per cent for former refugee households. In order to assess the asset accumulation rates of the two groups, simple bivariate regression models for South African and former refugee households were developed using time as a predictor (census year). SEP or asset wealth, moreover, was calculated using a multiple correspondence analysis (MCA) index (Booysen *et al.,* 2008) in order to develop a more superior measure of wealth than the number of assets illustrated in Table 1. A temporal line curve, illustrated in Figure 2, indicates a highly significant increasing relationship betwen time and SEP for both (pooled) South African and Mozambican households ($p<0.001$). The two models, moreover, had almost identical coefficients ($\exp(\beta)=1.20$) for the predictor (time) indicating a similar asset accumulation rate for both sets of households from 2001 to 2007. A consistent asset gap is, therefore, maintained for the full period.

**Figure 2: Comparative model of predicted asset score (MCA weighted) by household head nationality and panel year**

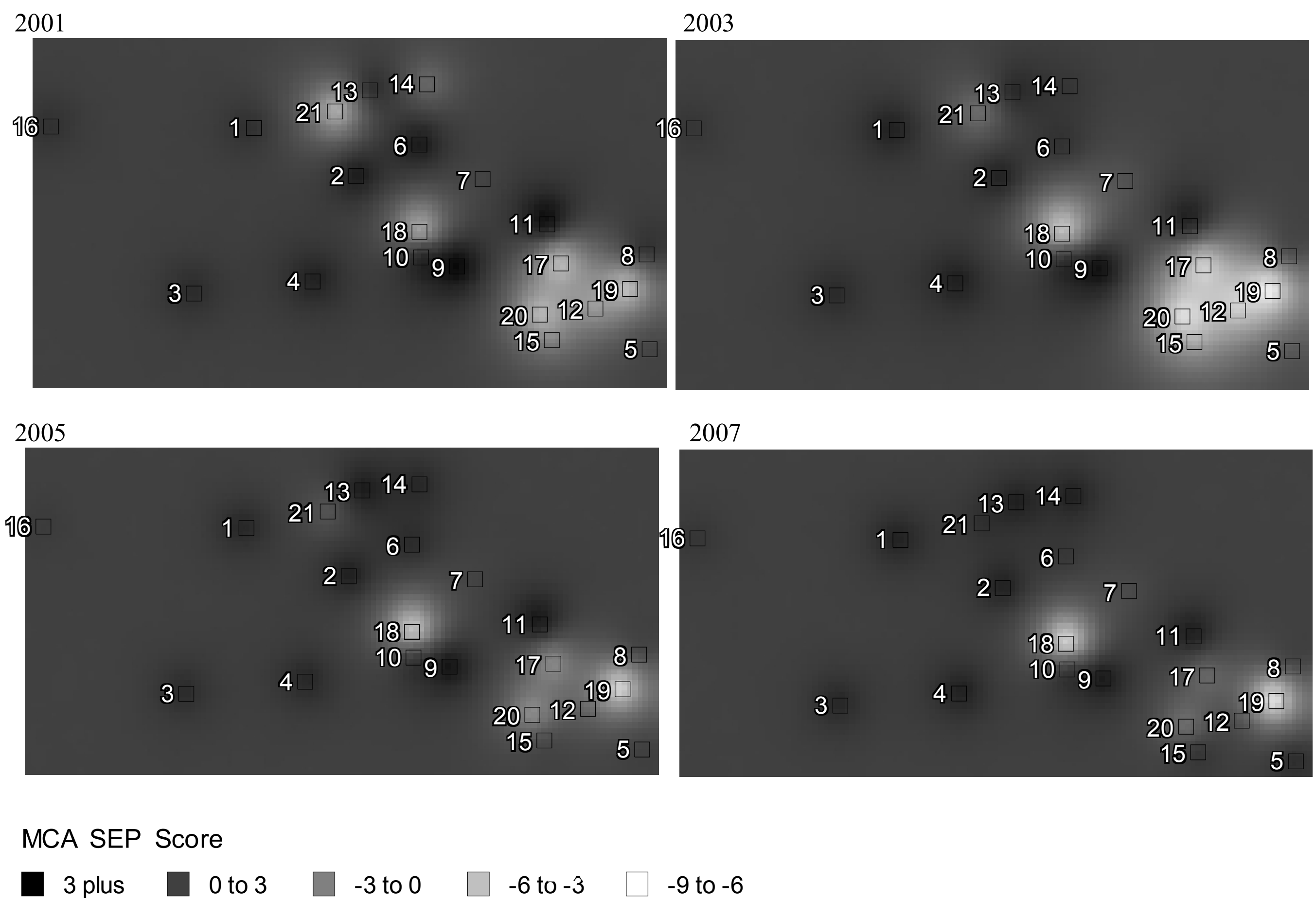



A series of two sample t-tests for each of the four census years confirms a highly significant ($p<0.001$) difference between the wealth (SEP) levels of the two sets of households with mean difference in absolute asset count of approximately 1.8. Finally, the asset gap (asset count-not MCA) between South African and former refugee households appears to widen in 2003 (Table 1), but restabilizes in 2005 through to 2007 and we conclude a persistent constant gap (Figure 2) based on the weighted asset index (MCA).

*Is there a spatial element with respect to household wealth?*

The four spatial temporal maps, illustrated in Figure 3, show the spatial proximity of 21 villages, as well as indicate the level of assets owned (MCA index) for each of the four census years. The maps indicate a general increase in asset ownership (maps darken) for the period except for 2003 that indicates a decrease in asset wealth in some of the villages in the south east. In particular, the maps indicate a cluster of five poorer former Mozambican villages (12, 17-20) in 2001 that reduce to two in 2007 (18, 19) that have markedly lower levels of SEP than the other 19 villages. These villages all had a high percentage (> 75 percent) of former Mozambican refugee households and are mostly (except for Village 18) clustered in the south east sector of the site. Villages 17 and 19, moreover, are situated in close proximity to the border of a national park that runs approximately south east through the site. Conversely, the South African villages in the south east sector of the site (5, 8, 11,15) had lower absolute poverty levels than the neighboring refugee villages.

**Figure 3: The mean predicted or kriged MCA SEP score (darker color implies increasing wealth): 2001-2007**



In order to demonstrate the differential wealth of former refugees, Table 2 shows that former refugee households retained twice the level of absolute poverty compared to South African households.

**Table 2: Households (HH) below the absolute poverty line by nationality and village**

| Factor | Category | 2001 | 2003 | 2005 | 2007 |
|---|---|---|---|---|---|
| Mozambican | poor HH | 1,481 | 1,704 | 1,343 | 1,260 |
| | total HH | 3,041 | 3,240 | 3,208 | 3,520 |
| | % HHs | 48.70% | 52.59% | 41.86% | 35.80% |
| | 95% CI | 46.92 – 50.48% | 50.87 – 54.31% | 40.16 - 43.57% | 34.21 - 37.38% |
| South African | poor HH | 2,470 | 2,201 | 1,807 | 1,404 |
| | total HH | 7,694 | 7,851 | 7,928 | 8,153 |
| | % HHs | 32.10% | 28.03% | 22.79% | 17.22% |
| | 95% CI | 31.06 – 33.15% | 27.04 - 29.03% | 21.87 - 23.72% | 16.40 - 18.04% |

Further analysis of absolute poverty levels, illustrated in Table 3 show that the poorer villages indicated as former Mozambican in 2001 (Villages 12, 17-20) all had in excess of 75 per cent Mozambican households. These villages all had absolute poverty level percentages (columns 2001 to 2007) of more than 50 percent in 2001.

**Table 3: Households below the absolute poverty line by village**

| Village | Number of Households [i] | Mozambican (%) [i] | 2001 (%) | 2003 (%) | 2005 (%) | 2007 (%) |
|---|---|---|---|---|---|---|
| 1 | 1347 | 16.3% | 33.9 | 32.7 | 25.1 | 17.6 |
| 2 | 605 | 20.0% | 35.8 | 29.2 | 21.1 | 21.7 |
| 3 | 1172 | 15.9% | 40.4 | 28.8 | 27.3 | 17.7 |
| 4 | 684 | 8.9% | 38.3 | 25.7 | 26.4 | 17.8 |
| 5 | 622 | 28.0% | 31.5 | 37.2 | 31.2 | 21.3 |
| 6 | 723 | 25.3% | 30.7 | 32.4 | 22.9 | 23.6 |
| 7 | 438 | 40.2% | 42.5 | 39.8 | 32.0 | 28.0 |
| 8 | 1138 | 47.7% | 28.8 | 31.0 | 31.6 | 25.3 |
| 9 | 933 | 12.0% | 28.4 | 23.7 | 21.2 | 17.6 |
| 10 | 896 | 48.5% | 30.5 | 27.8 | 27.2 | 17.9 |
| 11 | 1253 | 31.5% | 21.7 | 25.9 | 15.5 | 15.0 |
| 12 | 463 | 77.1% | 57.2 | 60.7 | 32.0 | 25.1 |
| 13 | 658 | 10.9% | 33.8 | 30.3 | 23.0 | 19.4 |
| 14 | 404 | 4.0% | 42.9 | 35.5 | 27.2 | 21.4 |
| 15 | 608 | 38.8% | 39.3 | 52.1 | 33.4 | 21.7 |
| 16 | 857 | 5.5% | 38.4 | 35.7 | 30.2 | 25.7 |
| 17 | 468 | 97.6% | 65.0 | 68.7 | 41.8 | 37.7 |
| 18 | 242 | 95.0% | 88.6 | 80.0 | 82.9 | 81.4 |
| 19 | 262 | 96.6% | 55.2 | 66.0 | 74.1 | 76.4 |
| 20 | 218 | 81.7% | 56.0 | 63.3 | 50.4 | 35.7 |
| 21 | 703 | 7.3% | 74.6 | 52.1 | 39.4 | 28.9 |

i: based on estimates for 2001-2007

Villages 18 and 19 retained absolute poverty level percentages of 81 and 76 percent, respectively, in 2007. Interestingly, many of the poorer South African villages (Villages 5-8) were also situated in close proximity to the border of the national park running south east through the site. Village 21 (South African), however, has higher levels of absolute poverty because it was established as a low cost housing site for disadvantaged South African citizens. In general, more infrastructure and facilities are located in the western sector of the site. It is interesting to note the villages with a very high Mozambican content (>50%) also indicated a lag factor that was maintained throughout the period 2001 to 2007. The results, therefore, demonstrate that there is a spatial element with respect to the distribution of SEP across the site and that, despite an overall improvement in SEP, households in former refugee villages are more likely to fall under the absolute poverty line than those in South African villages.

***What variables influence asset wealth (SEP)*** *?*

The bivariate results, illustrated in Table 4, indicated a number of highly significant relationships (<0.001) between SEP and a range of predictor variables. In this regard, SEP was significantly positively influenced by older male household heads, as well as older households. Furthermore, SEP was positively associated with the number of working individuals, by the proportion of temporary migrants and especially by access to farming land. Households with higher levels of secondary and tertiary education, moreover, had a 4.8 fold higher chance of being wealthier. The biggest influence on wealth creation, however, was a situation when more than one household member was employed in the government, professional or skilled private sector that positively increased the odds of increased SEP by 10.38 fold.

Household SEP was negatively influenced if it was headed by a former refugee and, the larger the percentage of former refugee household members, the lower the SEP. Household deaths also had a major negative effect on SEP, especially if the household head died due to HIV/AIDS infection. SEP also appeared to be negatively influenced by the number of child grants received.

**Table 4: Bivariate ordinal regression analysis of variables influencing household SEP (asset wealth) using a household level yearly panel data structure**

| Factor | N | Odds ratio | 95% CI | P value |
|---|---|---|---|---|
| Household head age (continuous) | 45,346 | 1.008 | 1.006-1.010 | <0.001 |
| Household head 40 or more years of age | 31,085/45,346 | 1.63 | 1.51-1.77 | <0.001 |
| Male household head | 28,037/45,344 | 1.47 | 1.38-1.55 | <0.001 |
| Mozambican head | 12,654/45,313 | 0.28 | 0.26-0.30 | <0.001 |
| South African head | 32,659 | 1.00 | | |
| Mozambican head (In migrated post 1993) | 62 | 0.72 | 0.34-1.51 | 0.382 |
| Mozambican head (In migrated pre 1993) | 12,592 | 0.30 | 0.28-0.32 | <0.001 |
| % Mozambican content of household | 45,401 | 0.27 | 0.25-0.29 | <0.001 |
| Duration of existence of household at first asset status | 45,411 | 1.14 | 1.13-1.15 | <0.001 |
| Household existed for 2 or more years before first asset observation | 44,271/45,411 | 2.50 | 2.14-2.90 | <0.001 |
| Number of individuals in household 18+ | 45,411 | 1.28 | 1.25-1.29 | <0.001 |
| Number of individuals in household <18 | 45,411 | 1.09 | 1.08-1.11 | <0.001 |
| Number of working individuals in preceding year | 22,589 | 1.47 | 1.43-1.51 | <0.001 |
| Proportion of household that are migrants | 45,128 | 1.52 | 1.34-1.72 | <0.001 |
| Average 4+ migrant months per household individual per year | 11,334/45,128 | 1.23 | 1.17-1.29 | <0.001 |
| Household head death | 227/45,411 | 0.58 | 0.48-0.71 | <0.001 |
| Household head death in given year (pre September) [i] | 113/45,411 | 0.89 | 0.63-1.25 | 0.493 |
| Household head status | | | | |
| Alive | 45,184 | 1.00 | | |
| Died (non HIV/AIDS) | 267 | 0.65 | 0.57-0.73 | <0.001 |
| Died (HIV/AIDS) | 95 | 0.30 | 0.20-0.44 | <0.001 |
| Household deaths in given year [i] | 45,411 | 1.10 | 0.96-1.27 | 0.163 |
| Cumulative household deaths to given year [i] | 45,411 | 1.01 | 0.98-1.05 | 0.475 |
| Number of household hospital admissions | 11,620 | 1.00 | 0.89-1.13 | 0.968 |
| Number of education years in household | 8948 | 1.01 | 1.00-1.01 | 0.022 |
| Average secondary plus education level years per household individual | 520/8948 | 4.81 | 4.51-5.14 | <0.001 |
| Ownership or access to and usage of farming land [ii] | 9,209/11,596 | 2.29 | 2.10-2.49 | <0.001 |
| Number of child grants received [ii] | 3,901 | 0.84 | 0.76-0.92 | <0.001 |
| Number of child grants received in previous year [ii] | 3,901 | 0.90 | 0.83-0.98 | 0.017 |
| Labour type | 43,821 | | | |
| None involved in government, professional or private sector skilled work | 23,878 | 1.00 | | |
| At least one individual involved in only one of the above | 17,504 | 2.44 | 2.29-2.59 | <0.001 |
| Individuals involved in two or more of the above | 2,439 | 10.38 | 9.26-11.62 | <0.001 |

i: similarly non-significant when comparing these numbers in preceding year to current year SEP
ii: large percentage of missing data (due to nature of certain specialized modules) hence not included in final multivariate models

The multivariate results, illustrated in Table 5, incorporate three different models. All three models are reasonably consistent with respect to their prediction of the odds ratios for a majority of the predictors. The difference in the odds ratios between Model 1 and Models 2-3 is explained by the fact that the latter two models incorporate an unstructured household level random effect. The models confirmed a consistent significant positive relationship between SEP and time that supports the contention of an overall increase in asset wealth (SEP) between 2001 and 2007. In this regard, SEP growth in 2003 was only marginal for South African households and negative for former refugee households.

**Table 5: Multivariate multilevel ordinal (MCA SEP tertiale as outcome) regression analysis using a household level yearly panel data structure comparing different modelling approaches: classical, Bayesian unstructured household level random effects, and parametric distance spatial random effect**

| | Model 1: Non-spatial model [i] (Stata – classical fixed effects model) | | Model 2: Non-spatial random effect model (WinBUGS) | | Model 3: Spatial random effect model [iii] (WinBUGS) | |
|---|---|---|---|---|---|---|
| Factor | OR | 95%CI | OR | 95%CI | OR | 95%CI |
| Year | 1.13 | 1.12,1.15 | 1.22 | 1.2,1.25 | 1.23 | 1.20,1.25 |
| Relative SEP loss (or gain) of Mozambican headed households versus South African headed by panel year relative to 2001 baseline | | | | | | |
| 2001 | 1 | | --- | | --- | |
| 2003 | 0.78 | 0.72,0.83 | --- | --- | --- | --- |
| 2005 | 1.01 | 0.93,1.09 | --- | --- | --- | --- |
| 2007 | 1.03 | 0.94,1.12 | --- | --- | --- | --- |
| Household size of 3 or more | 2.84 | 2.6,3.09 | 3.96 | 3.52,4.43 | 4.08 | 3.64,4.55 |
| Household existed for at least 2 or more years before first asset observation | 1.59 | 1.35,1.86 | 2.02 | 1.56,2.58 | 1.72 | 1.31,2.20 |
| Household head age of 40 or more years | 1.29 | 1.21,1.37 | 1.5 | 1.38,1.64 | 1.47 | 1.35,1.60 |
| Male household head | 1.57 | 1.48,1.67 | 2.12 | 1.91,2.34 | 2.13 | 1.93,2.35 |
| Mozambican household head | 0.36 | 0.33,0.38 | 0.17 | 0.15,0.2 | 0.20 | 0.17,0.23) |
| Household head alive | 1 | | 1 | | | |
| Died (non HIV/AIDS) | 0.81 | 0.71,0.92 | 0.67 | 0.54,0.82 | 0.65 | 0.53,0.79 |
| Died (HIV/AIDS) | 0.50 | 0.33,0.76 | 0.32 | 0.13,0.63 | 0.31 | 0.13,0.63 |
| Average 4+ migrant months per household individual per year | 1.01 | 0.96,1.07 | 1.07 | 1.00,1.15 [ii] | 1.08 | 1.00,1.15 |
| Average of secondary or higher education level years per household individual | 2.57 | 2.39,2.76 | 5.31 | 4.72,5.99 | 4.54 | 4.05,5.09 |
| None involved in government, professional or private sector skilled work | 1 | | 1 | | | |
| At least one individual involved in only one of the above | 1.83 | 1.72,1.95 | 3.02 | 2.71,3.36 | 2.88 | 2.59,3.18 |
| Individuals involved in two or more of the above | 5.13 | 4.55,5.77 | 18.70 | 15.26,23 | 16.20 | 13.36,19.00 |
| Constant | --- | --- | -3.1 | -3.37,-2.82 | -3.30 | -4.06,-2.00 |
| $\sigma_u 2$ (household) | --- | --- | 5.12 | 4.87,5.39 | 4.71 | 4.48,4.96 |
| $\sigma_w 2$ (spatial) | --- | --- | --- | --- | 1.22 | 0.62,2.34 |
| Range (meters) | --- | --- | --- | --- | 2378 | 17,794,269 |
| AIC(Stata)/DIC(WinBUGS) | 79282.3 | --- | 61918.9 | --- | 61670.7 | --- |

i. Brant Test of Parallel Regression Assumption: $\chi^2$: 19.6, p> $\chi^2$: 0.108 i.e. sufficient evidence to suggest that the parallel regression assumption has not been violated
ii: significant at 10% level
iii: model also includes an unstructured household level random effect (pooled)

An interactive effect or empirical estimation of relative gains (or losses) by household nationality and panel year (using 2001 as the reference) underlines the relative loss of asset wealth (SEP) of former refugee households compared to their host community in 2003 (see Model 1: OR=0.78, $p<0.001$). This confirms the previous observations with respect to the trend of assets owned (Table 1), as well as the results of the reported SEP changes in the 2003 spatial map (Figure 3). Thereafter, there was no significant gain in the years 2005 and 2007 as shown by the odds ratios that were slightly above 1 (see Model 1).

All three models indicate that larger (more than 3 members), older households and households headed by a male, were wealthier (MCA asset score). In particular, all the models indicated that SEP was positively influenced by higher levels of secondary and tertiary education, as well as significantly positively influenced if household members were employed in the government, professional or private skilled sectors. The positive impact of these categories of employment on SEP was specifically marked (5.13 to 18.70 fold increase) if a household had more than one member employed in these high return sectors. Conversely, the death of the household head, especially due to HIV/AIDS, has a profound negative impact on household SEP in all the models.

*South Africans and former refugee comparisons*

The results indicate no significant difference in household head death proportions between South African and Mozambican headed households (OR=1.01; p=0.934). However, Mozambican headed households did appear to have a significantly higher overall household proportion of deaths which supports the findings of Collinson (2010). The results also indicated South Africans had a significantly higher number of secondary and tertiary education years ($p<0.001$), as well as a significantly higher proportion of migrants then their Mozambican counterparts ($p<0.001$) as confirmed in other studies (Collinson *et al.,* 2007; Rodgers, 2008). Presumably, because of the reduced ability of former refugees to access migrant options, Mozambican households had a significantly higher proportion of male headed households, however, they were younger (<40 years) than male headed South African households ($p<0.001$). Further analysis of household age (duration) indicates a significant difference ($p<0.001$) between South African households who had an average duration of 13.15 years compared to 11.59 years for former refugees. Finally, the results indicate South African households had a significantly higher proportion of individuals involved in government, professional or private sector skilled work when compared to Mozambican headed households ($p<0.001$).

## DISCUSSION

This section further discusses the results with respect to the persistence of the wealth gap, the spatial nature of poverty and the dynamics of asset accumulation.

*The persistent wealth gap*

Recent evidence in Southern Africa suggests refugees can be exposed to multiple stressors that impact negatively on their ability to integrate into the economic activities of their host community (O'Brien *et al.,* 2009). The results show that there was a persistent (constant) wealth (SEP) gap between former refugee and South African households despite the fact that former refugee households had a slightly higher asset accumulation rates in terms of the number of assets (Table 1). In this respect, the refugees arrived with very few assets (Dolan *et al.,* 1997; Rodgers, 2008) and were unable to close the wealth gap because their asset accumulation rate was influenced by lower return strategies levied off a lower initial asset base. The long term effect of a low initial asset status (Barrett, 2005), therefore, continues to affect their asset accumulation rate despite having arrived over twenty years ago (Schatz, 2009; Collinson, 2010). This inability to close the wealth gap, moreover, has been compounded by difficulties with respect to attaining legal status, as well as social discrimination with respect to labor opportunities (Landau, 2005). Finally, former Mozambican refugees were unable to access social grants until 2006 (Schatz, 2009) and were, thus, precluded from this important stabilizing source of income that was available to South African residents (Booysen and Van Der Berg, 2005). The question remains, however, whether there was a spatial component with respect to the wealth gap.

*The temporal spatial nature of persistent differential poverty*

The spatial location of the South African villages can be traced back to the colonial wars in Mozambique. Conversely, the more recently established refugee villages were determined twenty years ago when land was allocated to them on their arrival from Mozambique by the local authorities (see Data section). In this regard, the temporal spatial maps illustrate that the five predominantly former refugee villages (12, 17-20 in Figure 3) were poorer in 2001 and this reduced to two villages in 2007. All of these villages are (largely) situated in the south east sector of the site. Two of the villages, in particular, are located in close proximity to the border of a national park. Interestingly, some of the poorer South African villages also border the national park (6-8). Conversely, Village 11(South African) has lower levels of poverty possibly as a result of a clinic and the fact that it is relatively close to an exit road. A common denominator with respect to the all the villages in the south east is that they are located in a drier area that is more suited to livestock and shows little potential for intensive agriculture. The south eastern side of the site, moreover, also has lower levels of infrastructure and facilities although two South African villages (5, 15) are situated relatively close to a tar road (R536) to the south of the site. The difference in poverty levels, therefore, cannot be ascribed to the spatial location alone of the former refugee villages. In this regard, the former refugees demonstrated significantly higher levels of poverty and mortality (Collinson, 2010), as well as lower levels of education and access to employment than South African households. In addition, the former refugee households are more likely to lack water and sanitation (Hargreaves *et al.,* 2004; Kahn 2006; Twine *et al.,* 2007; Schatz, 2009). Conversely, a number of the less poor South African villages are mostly located further to the west and enjoy better natural resources, rainfall and access to infrastructure, facilities and services (Collinson, 2010). The higher poverty levels in former refugee villages, in general, can possibly be explained as a combination of spatial location influencing access to natural resources and infrastructure that has been compounded by a differential access to opportunities, social networks and state pensions (Hargreaves *et al.,* 2004; Hunter *et al.,* 2007; Polzer 2007; Rodgers, 2008; Schatz 2009).

*The dynamics of asset accumulation (SEP)*

Household SEP is largely influenced by the long-term effect of the inter-generational transfer of assets (Wu & Pretty 2004; Barrett 2005). SEP, moreover, influences a household's characteristics, in combination with a wide range of other variables, to determine its initial asset status at the starting point of an asset accumulation cycle. In particular, the results also show that older, larger South African households, headed by a male, have higher rates of asset accumulation. Male household heads, in particular, improve a households economic prospects in rural areas because of improved access to communal resources and social networks (Sen, 2003; Krishna, 2006; Goudge *et al.,* 2009a, 2009b). Furthermore, the income of many rural South African households has been stabilized by the receipt of state grants (Landau, 2005; Sherbinin *et al.,* 2008; Goudge *et al.,* 2009a, 2009b). A combination of factors, therefore, appears to trigger the ability to invest in higher return opportunities and relatively wealthier households are the most likely to respond (Binswanger 2004; Barrett, 2005; Dimba and K'Obonyo, 2007). Wealthier households also have the resources and social contacts to adopt pull led or high return strategies, as well invest in education, healthcare and social status thus perpetuating their competitive advantage into the future (Vermeulen *et al.,* 2008; Xing *et al.,* 2008; Kanagawa and Nakata, 2008; Goudge *et al.,* 2009a, 2009b). Finally, wealthier (South African) households are better able to fund the costs of shocks like death and disease and are not forced into survival strategies as a result of them (Sen, 2003; Krishna, 2006; Hosegood, 2009; Schatz *et al.,* 2011).

Conversely, the results indicate that poorer former refugee households have been more recently established, have lower levels of secondary and tertiary education and less working individuals. They also had a low initial asset status and they are physically located in drier, more marginal areas. These households also struggled to secure the necessary legal status to access institutions and employment (Rodgers, 2008; Shatz, 2009; Collinson, 2010) and were unable to access state grants until 2006 (Schatz, 2009). A combination of factors, therefore, forced the former refugees to adopt push led strategies that included low return options like farm wages, herding and petty trading (Sen, 2003; Elmquist and Olsson, 2006; Wouterse and Pieterse, 2008). Their relative disadvantage, moreover, was perpetuated by their inability to invest in healthcare and education, as well as the relatively bigger impact of shocks like death, medical expenses and drought (Twine et al., 2007).

**CONCLUSION AND RECOMMENDATIONS**

The paper illustrates the complex, and persistent, nature of asset accumulation in a refugee community in rural South Africa. The results of the first research question indicate that, even though the asset accumulation rate of former refugees was equal to that of its host community, they were unable to close the wealth gap. The usefulness of the results is that they empirically demonstrate the persistent long term impact of refugee status in a rural African community. The usefulness of the results, moreover, are that they develop and compare a comprehensive set of assets generated by a rural community that is host to a refugee community. In this regard, we believe that the construction of a multiple correspondence analysis (MCA) wealth index that includes livestock, contributed to the development of a more reliable proxy for SEP in an African context.

The results of the second research question illustrate that the spatial location of the poorer former refugee villages does not fully explain the higher levels of absolute poverty experienced in these households. In this regard, some South African villages in close proximity also display higher absolute poverty levels but others do not. The usefulness of the results is that geo-statistical based mapping can pinpoint poverty at an acute local level where neighboring villages demonstrate significantly different levels in wealth (SEP). In a broader sense, the results illustrate how the dynamic nature of SEP can be modeled by integrating a GIS system with a combination of classical and Bayesian techniques thus expanding the methodological options for investigating social problems with spatially and temporally correlated data. In particular, the paper recommends the use of Bayesian based kriging to provide a cost effective way of geographically targeting villages that require incremental levels of policy intervention. The usefulness of the results, furthermore, is that they demonstrate that spatial location alone is unlikely to have perpetuated the wealth gap experienced by the former refugees.

The results of the third research question illustrated that a range of household characteristics significantly influenced the ability to accumulate assets. Former refugee SEP accumulation rates, for example, were more likely to be compromised by higher mortality rates, as well as poorer education levels and less access to health and high return local and migrant employment opportunities. The usefulness of these results is that they identify, quantify and differentiate the impact of certain household characteristics on the asset accumulation rates of former refugees and their host community. In this regard, household characteristics largely determine whether a household has the necessary assets to invest in a high versus low return strategy. Finally, the results of the third research question suggest that differential household characteristics probably better explains the significantly different wealth levels of the villages rather than their spatial location.

The results and discussion can be employed to suggest a number of policy interventions in a rural community that is host to a refugee community. In the short term, the results indicate that the physical location of (poorer) refugee villages (18, 19) should be targeted for differential levels of support like feeding programs, as well as the provision of basic services. In this regard, the results also indicate policy is required to ensure their access to state grants, facilities and employment. Extending the results of the paper, it becomes clear that policy interventions are needed to ensure full legal status for refugee communities in order to access facilities and employment. Furthermore, policy will need to be coordinated across a number of government departments in order to implement rural development initiatives that alleviate poverty. For example, the results indicate that mortality and education are key determinants of wealth so policy interventions, in this regard, would suggest the coordination of the health, education and finance ministries.

The reliability of our conclusions, however, is influenced by a number of limitations. Firstly, the SEP increases indicated in our results could be inflated because of exogenous factors like a government electrification program that appears to have contributed to the acquisition of a range of assets for cooking, lighting and communications in our survey. Secondly, the study coincided with a period of sustained GDP growth in South Africa that is also likely to have stimulated asset accumulation.

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**APPENDIX 1. Assessing the asset based wealth indices**

Measurements of agreement are of great importance for assessing the acceptability of a new process. The three indices were compared with each other for misclassification of households between tertiales of indices. Kappa statistics (measure of reliability based on the agreement expected on the basis of chance) were calculated to assess the agreement of classification between indices. Kappa is a preferred statistic to estimate agreement for nominal or ordinal scale data (in our case the variables are ordinal SEP indices). A Kappa statistic of one indicates perfect agreement and a value of zero indicates no agreement. In general, a Kappa statistic of less than 0.5 indicates poor agreement. Misclassification between tertiales was used as the measure of agreement (Howe et al., 2008).

The relationship between the methods, illustrated in Table 6, indicates a significantly high level of agreement between the Multiple Correspondence Analysis (MCA) and Principal Component Analysis (PCA) indexes (87%) and slightly less with the Absolute Count Analysis (ACA) index (82%). For those where there was disagreement, all were only one tertiale shift away. When comparing this disagreement for MCA versus ACA, we found that the majority of this shift was for ACA score to be one tertiale below (6152 of 8043 or 76.5%) while for MCA versus PCA this was similarly distributed above or below at 50.9% (3081 of 6054). This leads to the conclusion that the ACA generally underscores relative to MCA and PCA indices.

A decision must be made about which weights to assign to each indicator variable when constructing a wealth index. Using an equal weights approach (e.g. ACA), although simple, may be too arbitrary and simplistic, since different assets are unlikely to have equal meaning in terms of SEP. It is for this reason that a MCA tertiale index was selected for use in the final univariate and multivariate analysis, since it is it more appropriate for the analysis of the categorical data commonly collected on most assets (Howe et al, 2008) and reduces the computation time of the Bayesian model compared to a tertiale index. Moreover, a PCA index was designed for use with continuous variables while MCA makes fewer assumptions about the underlying distributions of the indicator variables and is more suitable with categorical or discrete data like those in our study (Howe et al., 2008).

**Table 6: Percentage of households (n=45 411) in the same tertiale and Kappa statistics of agreement between pairs of indices**

| Wealth Index | Absolute asset count | PCA | MCA |
|---|---|---|---|
| Absolute asset count | --- | --- | --- |
| PCA | 83%; κ=0.748* | --- | --- |
| MCA | 82%; κ=0.734* | 87%; κ=0.800* | --- |

*p < 0.001, expected agreement = 33.3%

The direction of poverty trends can also sometimes be different when using a PCA versus an MCA based asset index (Booysen et al., 2008). The most important difference, however, is that PCA requires linear constraints (i.e.

assumption that the distance between categories are the same and ordered) whereas MCA imposes fewer such constraints (Blasius and Greenacre, 2006). It should be noted that all the asset indicator variables tracked at the Agincourt field site are categorical which, as mentioned above, reinforces the use of MCA.

**APPENDIX 2: Multivariate statistical model**

The Bayesian ordinal model we used is based on that developed by Hedeker & Gibbons, 1994. It assumes that the observed socio-economic tertiale $Y_{i,t}$ of household *i* (*i* = 1,...,) at year *t* (2001,2003,2005,2007) follows a categorical distribution, $Y_{i,t} \sim \text{Categorical}(p_{i,t}, 1{:}C)$ with probability $p_{i,t}$. A continuous scale may be envisaged to underlie the SEP tertiale, with a series of thresholds $\tau_1, \tau_2, ..., \tau_{c-1}$ defining which of C categories (tertiale) a household lies in.

The likelihood model for household *i* at year *t* is then

$$\text{logit } Q_{i,t,c} = \tau_c - \mu_{i,t}$$
$$p_{i,t,1} = Q_{i,t,1}$$
$$p_{i,t,j} = Q_{i,t,j} - Q_{i,t,j-1} \text{ for } j = 2,\ldots,C\text{-}1$$
$$p_{i,t,c} = 1 - Q_{i,t,c-1}$$

with the various models as follows

1) multivariate non-spatial model $\quad \mu_{i,t} = \beta_0 + \beta X_{it} + u_i$
2) mutlivariate spatial model $\quad \mu_{i,t} = \beta_0 + \beta X_{it} + u_i + \varphi_{it}$

*The spatial kriging model was specified differently as follows:

Continuous MCA asset score for household i and year t is Normally distributed

$MCA_{i,t} \sim \text{Normal}(mu_{i,t}, \tau)$ where

$mu_{i,t} = \beta_0 + \varphi_{it}$

and $\tau$ represents the precision (1/variance) of the normal distribution and assumed ~ Gamma(1,1)

For all models: $\beta_0$ is the intercept, $X_{it}$ is the covariate vector (time constant and varying) and $\beta$ is a vector of unknown regression coefficients. The regression coefficients ($\beta$) as well as the constant ($\beta_0$) were given non-informative normal priors centered around zero, namely ~ Normal (0,0.1). To account for the spatio correlation, we introduced a village-specific random effect, $\varphi_{it}$. A household level random effect ($u_i$) for repeated longitudinal observations on a household was also introduced.

The household level random effect, $\mu_i$, was modelled as a Normal distribution, $\mu_i \sim N(\underline{0}, \sigma_u^2)$.
The village-specific random effect has a multivariate normal distribution, $\varphi_i \sim MVN(\underline{0}, \Sigma)$, with variance-covariance matrix $\Sigma$ expressed as a parametric function of distance between pairs of the 21 village centroids points. We also

assume an isotropic stationary spatial process, where $\Sigma kl = \sigma_w^2 \exp(-\phi d_{kl})$, $d_{kl}$ is the Euclidean distance between villages $k$ and $l$, $\sigma_w^2$ models the geographic variability, and $\phi$ is a smoothing parameter that controls the rate of correlation decay with increasing distance and measures the range of geographical dependency. We specified $\phi$ as a uniform distribution between $\phi_{min}$ and $\phi_{max}$ (Gelfand & Vounatsou, 2003). The range is defined as the minimum distance at which spatial correlation between locations is below 5%. This distance can be calculated as $3/u$ meters.

We choose vague Normal distributions for the $\beta$ parameters centered around zero with variance 0.1 and non-informative gamma distribution priors for all $\sigma^2$ with means and variances of 1.

MCMC simulation was applied to fit the models. We run a single chain sampler with a burn-in of 5000 iterations. Convergence was assessed by running the simulation until the Monte Carlo error for each parameter of interest was less than 5% of the sample standard deviation. The chains thereafter were sampled every single iteration until a sample size of 10 000 had been attained.