The Effect of Initial Land Distribution on Income Growth and Distribution in Kenya

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DECLARATION

I declare that the thesis which I hereby submit for the degree of Master of Science in Agricultural Economics at the University of Pretoria is my own work and has not been previously submitted by me for a degree at another university. Where secondary material is used, this has been fully acknowledged and referenced in accordance with university requirements. I am aware of university policy and implications regarding plagiarism.

Signature: ....

Name: Paul Chimuka Samboko

Date: April, 2015

DEDICATION

To my dear parents, Paul and Rosemary Samboko

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ABSTRACT

Poverty is a major challenge worldwide and poverty reduction remains a critical aspect of developmental efforts. The rate and extent of poverty reduction associated with agricultural growth in primarily agrarian societies has commonly been assumed to depend importantly on the distribution of productive assets in general and land assets in particular. However, recent evidence by Jayne, et al., (2003) and Jayne et al., (2014) has shown that landholdings are becoming more concentrated and operated land is declining in some African countries like Ghana, Zambia, and Kenya. This trend means that efforts by governments and donor agencies to reduce chronic poverty will partly depend on understanding the joint effect of the distribution of productive assets on growth and income distribution. Without this understanding, agricultural productivity growth may contribute less to rural poverty reduction than usually assumed. Understanding the potential adverse effects of the rising land concentration on agricultural growth's poverty reduction potential, also offers an opportunity to limit the wastage of government and donor resources, as interventions aimed at poverty reduction can be targeted at other growth enhancing investments that yield higher returns than investments aimed at improving agricultural productivity. Against this background, this study explains the relationships between initial land distribution at the village level, growth of household income and the distribution of income at the village level in Kenya.

Although a number of studies have looked at the relationship between inequality and growth, the difficulties associated with such a process remain central to the debates in the growth literature. Finding high quality panel data that allows for cross-country estimation using panel econometric techniques remains problematic. Even with high quality data, questions remain on the comparability of institutional structures across countries. The problem of endogeneity and how to address it also remains at the centre of growth empirics and past studies have revealed several weaknesses. In combination, these challenges have been cited as a major internal threat to validity of past growth empirical works.

To overcome the econometric challenges in the majority past studies, this study uses the system generalized method of moments to deal with the dynamic nature of the growth model and the unobserved individual- and time-specific effects. It also uses the first differences estimator for the econometric analysis of the effect of land distribution on income distribution since its construction is not dynamic. To address the endogeneity problem in both models, I use the "Jackknife" procedure and/or lagged values o of all endogenous variables. For instance, the endogeneity arising from the fact that growth and distribution affect each other, the village land gini coefficient corresponding to a household is computed using observations of operated land for other households in a village while excluding its own. This study also uses a 13 year panel micro-level dataset for Kenyan rural farming households to overcome the data-related challenges. By using a nationally representative panel dataset, the study also takes care of the unobserved heterogeneity that gets lumped up in the error term in the discredited single cross-sectional analyses. By adopting a joint determination of the effects of various covariates on growth and inequality, the study recognizes the fact that the two outcomes are generated by the same underlying processes and thus should not be analyzed in isolation. This is advantageous as it yields complete messages for the policy maker whose interest is in promoting growth while reducing inequality.

While it seems impossible to fully solve for the endogeneity problem and thus establish causal effects, the study identifies the effects of several variables on growth and inequality while arguing that it is possible under certain qualifications, which are explained in the literature review section. The results reveal that operational landholdings at the village level are becoming fairly concentrated over time in Kenya and that rising land concentration has impeded growth. The distribution of both income and operational landholdings spatially is such that the two reduce as the distance from the district/headquarters rises.

What is clear from this study is that the inequalities in the operational landholdings at the village level significantly impede the beneficial impact of agricultural growth on income growth. The inequality of landholdings at the village-level impedes growth of a household's net income per adult equivalent by 0.512, else equal. In addition, results show that inequalities in landholdings at the village-level also perpetuate village income inequalities, with the *ceteris paribus* effect being almost one to one. Results also show that growth is positively affected by the operational landholdings corresponding to a household and the average level of education in a household. However, the rise in the population density has had an adverse effect on growth, given its negative impact on operated land. This shows that households have been unable to compensate for their losses in land by higher output and profits per hectare.

The negative effect of inequalities in the distribution of operational landholdings at the village level on agricultural growth should be considered in Kenya's rural development agenda. It means that in programs to achieve higher agricultural growth, the poorer households are less able to benefit than those better off, and the programs will have a lower impact on income growth than under conditions of relative landholding equality. What happens to the distribution of landholdings is therefore very important to the potential poverty impact of any growth enhancing innovation or program. Government needs to be very vigilant that their policies and programs do not facilitate aggregation of landholdings in fewer hands. For these reasons, land policies may have profound effects on the effectiveness of national agricultural and poverty reduction strategies. The results also have major implications on how other African governments experiencing a rising land concentration need to allocate the unallocated arable land in the medium to long term (e.g. Zambia). Instead of allocating the remaining arable land by means of large farm-blocks that ultimately increase inequalities in the distribution of landholdings; the best alternative could involve allocating land by means of small-medium parcels ranging from 5-20 hectares. This way the land is divided among more people and the effect of inequality on growth could be less than if the alternative policy is adopted. But this needs an understanding of the influence of the farm size-productivity relationship in these countries.

While this study identifies the effect of village land distribution on growth and income distributions, as well as how inequality is distributed across time and space in rural Kenya. It does not identify the reasons behind the spatial distribution of land and income. In addition, it does not identify the mechanisms by which inequality reduces growth and this warrants further research.

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ACRONYMS

DGMM	Differences Generalized Method of Moments
GLS	Generalized Least Squares
GMM	Generalized Method of Moments
KR-3SLS	Keane-Runkle Three-stage Least Squares
LHBI	Lewbel Heteroskedasticity-based Identification Procedure
LS	Lundberg and Squire
MLE	Maximum Likelihood Estimator
MSU	Michigan State University
OLS	Ordinary Least Squares
SEA	Standard Enumeration Area
SGMM	System Generalized Method of Moments
SSA	Sub-Saharan Africa
QMLE	Quasi-maximum Likelihood Estimation

CHAPTER ONE

INTRODUCTION

Poverty continues to affect many people in Africa. Chen and Ravallion, (2006) highlight that the share of the world's poor people living in Africa has risen considerably. Sub-Saharan Africa (SSA) in particular has become the region with the highest incidence and depth of extreme poverty. A major characteristic of the world's poor is a heavy dependence on rain-fed agriculture for their livelihood. Thus, to break the cycle of rural poverty, agricultural productivity growth is important given its positive impacts on farm incomes and in stimulating the rural non-farm sector (Timmer, 2008). In light of this, several countries have devised strategies to address the problem through various development strategies outlined in their poverty reduction strategy papers. However, despite decades of efforts to reduce poverty, the high levels of chronic poverty in SSA's rural areas remain problematic. Whereas some poor countries in the world have recorded relatively higher chronic rural poverty reduction rates, others have had their poor experiencing transitions into and out of poverty (see World Bank, 2000). One explanation to this phenomenon is that while growth is an essential condition for poverty reduction, it is insufficient (Timmer 2008). Many factors while working through other economic processes interact to determine the rate and extent of poverty reduction. These factors include, but are not confined to, the extent of inequality in the distribution of income and productive assets (for examples see Deininger & Olinto, 1999; Huang, Lin & Yeh 2009; Lundberg & Squire, 2003; & Bigsten et al., 2003).

The unequal distribution of productive assets has been demonstrated to be one of the fundamental deterrents to poverty reduction via growth. It impacts negatively on the poor's participation in economic growth (Bigsten et al., 2003; Timmer, 2008; World Bank, 2000). One can identify several channels through which this works. These channels include the redistributive political economy[1], capital market imperfections[2], individual saving rates[3],

[1]See Alesina and Rodrik, (1994) and Borck, (2007).
[2] See Piketty, (1997), Aghion and Bolton, (1997), and Galor and Zeira, (1993).
[3] See Barro, (2000).

endogenous fertility[4], and sociopolitical unrest[5]. A detailed discussion on these channels and how they bring about the relationship between inequality and growth is provided for in section 2.2. Through these channels, and while working in different ways, inequality negatively impacts growth by preventing the poor from undertaking profitable indivisible investments. The negative effect on the poor's human and physical capital formation is of particular relevance in this respect. Furthermore, inequality negatively impacts on the poor's ability to effectively respond to exogenous shocks in a coordinated manner. It also impedes growth via a reduction in economic efficiency since the poor are more likely to engage in less productive activities such as social unrest in more unequal societies. But where social unrest due to high inequalities is absent, the poor tend to be remarkably efficient in their use of capital despite having very little of it (see Rosenzweig & Binswanger, 1992 who provide panel evidence from rural India on investments, wealth and rainfall).

It is widely accepted and acknowledged that *ceteris paribus*, agrarian societies with a more egalitarian distribution of land assets will have higher growth-induced poverty reduction than those where it is inegalitarian (World Bank 2000). This is because, land is a major productive asset in primarily agrarian societies, and it has been shown that in more equal societies, the benefits from an equitable land distribution are more widely shared than in societies with an inegalitarian land distribution pattern. Consequently, growth-induced poverty reduction is higher in societies where the initial land distribution is more equitable than in those where it is inegalitarian (Ravallion & Datt, 2002; World Bank, 2000). The importance of the distribution of landholdings in agrarian societies is further emphasized by Fort, (2007) who argues that in studying the growth-inequality relationship, our focus should lean more on the unequal distribution of productive assets than that of income since the theoretical relationship between inequality and growth is better explained by the former than the latter. Based on the above, I hypothesized that in Kenya the rate of poverty reduction associated with agricultural growth is reduced by the initial inequality of operational landholdings at the village level.

[4] See Galor and Zang, (1997) and De La Croix and Doepke, (2003).
[5] See Alesina and Perotti, (1996).

1.1 PROBLEM STATEMENT AND RATIONALE

Recent trends in much of Sub-Saharan Africa (SSA) point towards sharply declining farm-sizes due to rapid population increases in rural areas in particular. In addition, landholdings are becoming more concentrated (Jayne, et al., 2003, and Jayne et al., 2014). At the same time, evidence suggests that the rising rural population density has had a significant and adverse effect on rural household incomes, even though the effect on rural off-farm income has been shown to be weak (Muyanga & Jayne , 2014). These trends call for rapid agricultural intensification and technical change if agriculture is to contribute to poverty reduction in much of Sub-Saharan Africa. Otherwise they will to some extent undoubtedly contribute to the persistent poverty problem in the region where agricultural growth is seen as the main pathway towards rural poverty reduction. Similar to the situation in many developing countries in SSA such as Zambia which has rural chronic poverty rates of up to 80 % (Tembo and Sitko, 2013), Kenya is no exception to the persistent poverty problem. Rural chronic poverty in Kenya remains high, with trends showing that while urban poverty reduced from 34.4% in 2005/06 to 33.5% in 2009, rural poverty increased from 49.7% to 50.5% for the same period (Republic of Kenya 2014). The high rural poverty levels and how this might be linked to the rising concentration of landholdings are of particular interest in this study.

What is evident is that while the rising concentration of landholdings is documented, the potential adverse effect of initial land distribution on income growth and distribution as well as that of growth of income on subsequent land distribution remains to be studied. Hence, the potential effect of the underlying initial land distribution on agricultural productivity and its magnitude remain questions of high relevance in the development agenda of poor countries to effectively prevent social stratification and ensure that the rural poor escape chronic poverty. Thus, there is need for further analysis to understand the joint determinants of income growth and distribution if we are to advance growth-induced poverty reduction while creating an equitable society.

Furthermore, a critical review of the global literature on growth-inequality linkages shows that rigorous and policy-relevant analyses concerning the effect of the productive asset (land) distribution on income growth and distribution have not been conducted up until recent works by Lundberg and Squire (2003) (LS) . The focus of the majority of the empirical works on growth and inequality has been on the distribution of income as a wealth measure with very few studies including productive assets (e.g., Balisacan & Fuwa, 2004 ; and Fort, 2007). This in itself is problematic in light of the theoretical importance of productive assets in the growth and inequality literature. In addition, even the various studies that have looked at income inequality and its effect on growth reveal inadequacies in either the econometric methods or quality of data used or both.

To bring this argument into perspective, LS highlight important methodological shortcomings in the adopted econometric estimation techniques in previous studies irrespective of the quality of data used. They indicate that the estimators used in the majority of these studies may not have fully addressed the problems of endogeneity, unobserved heterogeneity, and autocorrelation that are usually encountered. The LS study starts with the argument that it seems plausible that growth and inequality are interdependent and thus shouldn't be analyzed in isolation, this is further emphasized and shown by Huang, Lin and Yeh, (2009). Central to the econometric challenges is the issue of fully addressing the endogeneity problem in the models. Doing so using instrumental variables is an empirically daunting task as previous studies show. It is impossible to find instruments that influence either growth or inequality but not the other, and others which influence the other endogenous variable(s) but not growth and the rest of the explanatory variables in the models.

To overcome the econometric challenges, the common approach involves estimation by instrumental variable procedures while using lagged values of the endogenous covariates as instruments. But given the dynamic nature of the models, there is need to rid the models of serial correlation first using the dynamic estimators[6] to yield consistent results (section 2.3.3 discusses serial correlation in detail). As such LS used Keane and Runkle's three-stage least squares procedure to first eliminate serial correlation before final estimation using two-stage least squares. The Keane-Runkle three-stage least squares (KR-3SLS) estimation procedure has been argued to yield truly consistent and unbiased estimates for the parameters of interest in panel analyses where serial correlation is inherent and instruments are predetermined but not strictly exogenous (see Keane and Runkle, 1992). Its

[6] Examples include the two-stage estimator of Kripfganz and Schwarz, (2014), the system generalized method of moments (SGMM)and the differences generalized method of moments (DGMM)

superiority among panel data instrumental variable estimators using predetermined instruments is further emphasized by Ziliak, (1997). Apart from using instruments, other possible ways of adddressing the edogeneity problem when modelling growth include computing localized inequality measures corresponding to individual *i* using only observations other than its own *i* (i.e. “Jackknifing” inequality indices or any other explanatory variables such as income and education)[7]. This however, is only possible when conducting the analysis at the micro-level (i.e. using country-specific data for households). When modelling the drivers of localized inequality, all covariates can be computed in a similar manner and the endogeneity problem is no longer there (estimation would then proceed at the localized level using the first differences estimator). Section 2.4 discusses this procedure in detail using an example from Benjamin, Brandt and Giles, (2011) who used household level data from rural China. Other authors such as Huang, Lin and Yeh, (2009) have opted for identification using heteroskedasticity in light of the challenges associated with finding valid instruments for the endogenous covariates. This procedure can be used in combination with the weakly exogenous instruments and its merits and potential shortcomings are further discussed in the literature review section.

While the endogeneity issue is critical in the debates, another important issue was raised by Lundberg and Squire, (2003) (LS). Specifically, LS argue that analysing growth and inequality in isolation yields incomplete policy messages, hence a simultaneous examination of the two processes is imperative if the results are to provide complete messages for the policy maker whose interest is to promote growth while reducing inequality. The key finding in this study is that while land inequality significantly reduces growth, it has no significant effect on income inequality. However, they found that the marginal impact of land distribution on growth for the developing countries is almost zero. In addition, while higher education is seen to reduce income inequality, it was found to have no significant effect on growth.

However, in as much as LS make an important methodological contribution to the growth empirics, the quality of the data set used in their study has been called into question in various studies preceding and following it (e.g., Knowles, 2005 ; and Deininger & Olinto, 1999). More specifically, the comparability of the income and expenditure data still

[7] Details about the procedure and the intuition behind it are discussed in section 2.4.

remains a contentious issue despite transformations. This issue is further discussed in the literature review section using Knowles, (2005) who showed that results of the growth empirics are dependent on the quality of data used among other factors[8]. This has necessitated the call for careful interpretations of the findings from various studies that have used the Deininger and Squire data set. And thus highlights the need to further show why their approach is the most acceptable in modelling growth-inequality linkages using better quality data perhaps more at the micro level.

Since the late 1990's, there has been a shift towards using micro-level datasets which are of better quality. The use of regional or household-level data that is specific to a country has many advantages when compared to the cross-country data that is plagued with various data quality concerns relating to comparability between income and expenditure data. With country-specific data, the initial factor endowments, and histories are the same while the political and institutional characteristics are likely to be similar across localities. Because of this, the effect of unobserved heterogeneity as one of the mechanisms through which inequality and growth are related is reduced. As such, with country-specific data, one is able to isolate a "true" impact of inequality on growth and vice-versa. The use of household-level data also allows one to minimize the measurement error problem usually encountered in the cross-country studies. One can also control for flexible functional forms of initial income that may be confounded with initial inequality while also allowing for an exploration of the location-specific heterogeneity of the impact of inequality (Benjamin, Brandt & Giles 2011).

China is of particular interest in the growth empirics in as far as panel micro-level data is concerned. Studies that have looked at inequality and growth at the micro-level in rural China include Ravallion, (1998) who used panel household data in four provinces of southern China, Wan, Lu and Chen, (2006) on the other hand conducted their analysis at a meso-level, with their study utilizing regional data from 29 Chinese provinces. While Benjamin, Brandt and Giles, (2011) used panel household level data for rural China.

[8] de Dominicis et al., (2006) also show this but because they used over 78% of the discredited cross-sectional studies for their meta-analysis, their findings are not discussed here.

While Ravallion's focus was on whether aggregation to the village level hides the harmful effects of asset inequalities on consumption growth, Benjamin, Brandt and Giles, (2011) focused on the effects of income inequality on growth, and Wan, Lu and Chen, (2006) focused on how the effect of inequality on growth varies across time (i.e. in the short, medium and long-run). All three studies confirm that growth is reduced by existing local inequalities regardless of whether asset or income inequality was used. As discussed in section 2.4 of the literature review, using the findings by Benjamin, Brandt and Giles, (2011), arguably and depending on the scenario, one key lesson from the growth literature is that interpreting the estimates as causal effects may be wrong because it is impossible to isolate the effect of other mechanisms that might have generated initial inequalities, and predicting initial inequalities using instruments is impossible. However, if one is willing to assume that they have a long enough time-span and thus adequate covariation between inequality and growth the effect of unobserved heterogeneity can be removed via differencing and as such they can interpret the results as depicting causal effects rather than correlations (see section 2.5.2 for a detailed review).

A further survey of studies on Africa as a region experiencing relatively high poverty levels reveal that studies on growth-inequality linkages in the region are uncommon. This is partly because panel household-level data sets on African countries are hard to find. One study that has attempted to bridge this gap is the one by Odedokun and Round, (2004). However, the authors conducted a regional cross-sectional analysis using cross-country data. This in itself is not very useful given the well documented problems of bias associated with cross-sectional analyses and the problems of comparability of data when analyzing across countries.

With the availability of panel data sets in some countries such as Kenya and Zambia, more reliable within-country analyses are likely to be conducted. What is even more encouraging is that in time, more such panel datasets will be available in the World Bank's living standards measurement surveys (LSMS) database for selected countries such as Malawi, Tanzania and Uganda given the fact that the econometric analysis of growth and inequality needs panels covering at least three time periods.

This study will therefore bridge these knowledge gaps by describing the effect of initial land distribution at the village level on growth and income distribution among smallholders in rural Kenya while connecting this to the process of poverty reduction. To overcome the concerns in the past literature, the study will use high quality household-level panel data collected over a 13 year period, while fully addressing the econometric challenges usually encountered in estimation.

Identifying and quantifying the possible impact of the initial land distribution pattern on rural income growth and distribution is an essential step towards understanding whether it is better to focus on distribution of assets rather than income for chronic poverty alleviation and creation of an equitable society. Without such an understanding, agricultural growth may contribute less to rural poverty reduction than usually assumed. Furthermore, understanding these relationships (if at all they exist) may limit the possibility of wastage of government and donor resources targeted at rural development. It is expected that the results of this study will provide policy-relevant answers relating to the land and poverty questions while contributing to the empirical literature. The simultaneous examination of both outcomes is essential for a complete set of policy recommendations aimed at promoting growth while creating an equitable society. This study's main contribution to the body of knowledge is thus a panel analysis of the joint determinants of income growth and inequality using rigorous panel estimation techniques and country-specific data.

1.2 STUDY OBJECTIVES

The overall objective of this study is to describe the relationship between initial land distribution, income distribution and growth among smallholders in rural Kenya.

The study specifically seeks to:

i. Describe the land inequality dynamics across time and space.
ii. Describe the income inequality dynamics across time and space.
iii. Determine the effect of initial land distribution at the village level on rural income growth.
iv. Determine the effect of initial land distribution on income distribution at the village level.

1.3 RESEARCH HYPOTHESES

i. Land inequality does not detrimentally affect the contribution of agricultural productivity to income growth.

ii. Land inequality does not detrimentally affect the contribution of agricultural productivity growth on income distribution.

1.4 THESIS OUTLINE

The thesis is organized into six chapters. Chapter one provides the introduction and outlines the problem statement and rationale. It also presents the study objectives and research hypotheses. Chapter two presents a review of the literature relevant to the study, focusing on the challenges encountered when estimating growth equations and solutions to these problems, as well as an evaluation of past studies on inequality-growth linkages. The chapter ends with a summary of conclusions based on the literature review. Chapter three outlines the research methods and procedures, looking specifically at the data and data sources as well as the analytical procedures to be used. It also presents the empirical models to be estimated. In chapter four, a descriptive analysis of the key variables including trends in land and non-land assets is presented. I also test for the presence of multiple equilibria while analyzing the distribution of inequality by distance from the nearest district/headquarters. In chapter five, the core of the thesis is discussed using the econometric estimates. Finally, chapter six presents a summary, conclusion and recommendations of the study as well as implications for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, a motivation of the study and its methods and procedures is presented through a critical review and evaluation of past studies looking at inequality-growth linkages. In the various studies on inequality and growth, the earliest studies were conducted using cross-sections of countries and these have been discredited and will no longer be considered in this review. The core of the literature relies on the panel surveys which have been conducted at the cross-country level and much of the literature will cover these. Country-specific studies with household panel or cross-sectional data, as done in this thesis only became available since the late 1990's (e.g. Ravallion, 1998, and Benjamin, Brandt and Giles, 2011). Typically, the panels are constructed at a localized level (e.g. village, enumeration area, city, etc.) while other studies have looked at household level growth and how this relates to localized inequality. Of these studies, the country-specific cross-sectional studies just as with the cross-country cross sections are of no value due to the bias in the parameter estimates resulting from omitted variables and the failure to fully account for endogenous variables.

Given the shortcomings in the cross-sectional studies, there has been an increase in the use of panel estimation techniques which offer more precise estimates than the out of favour cross-sectional analyses. The panel estimation techniques are used to address the problems of autocorrelation, endogeneity, and unobserved fixed effects usually encountered in the econometric analyses. From previous studies, a critical look at the various panel estimation techniques used to overcome the econometric issues usually encountered in growth studies is presented, the ways in which the issues were addressed, and finally a highlight on any shortcomings that might have rendered the results of past studies invalid for statistical inference is presented. I also discuss the possibility of circumventing the endogeneity problem and thus analysing growth and inequality using the first differences and fixed effects at a micro- as opposed to the cross-country level. In addition, the literature review also indicates that the majority of the early studies looking at causal explanations of growth and inequality looked at the two relationships in isolation; this has been discredited in a recent study by Lundberg and Squire, (2003) (LS) who showed that as opposed to the simultaneous examination of growth and inequality, independent examinations yield potentially misleading or at best incomplete results for policy makers. LS in particular argue that because growth and inequality are the outcome of similar processes, they should not be analysed in isolation. With a simultaneous examination, policy makers can gain better understanding on how to advance growth while reducing inequality.

2.2 REVIEW OF THE LITERATURE ON THE PATHWAYS THROUGH WHICH THE DISTRIBUTION OF PRODUCTIVE ASSETS AFFECTS INCOME GROWTH

The literature on the theoretical linkages between wealth inequality and growth indicates several classes of models explaining why inequality would affect growth. Perotti, (1996), Ehrahrt, (2002), Deininger and Olinto, (1999), and de Dominicis et al., (2008) present summaries of broad categories of channels through which these outcomes are linked. The authors refer to these channels as the redistributive political economy, capital market imperfections, endogenous fertility and socio-political channels. Barro, (2000) extends this classification by adding individual saving rates as another channel relating growth to inequality.

The relationship between endogenous fertility, wealth distribution and growth has been demonstrated in a number of empirical works (e.g., Galor & Zang, 1997; De La Croix & Doepke, 2003 ; and Perotti, 1996). The authors indicate that endogenous fertility affects growth through its impact on human capital investments. According to De La Croix and Doepke, (2003), for one to be able to answer how the distribution of wealth affects growth, the fertility differential between the rich and the poor should be taken into account, since parents face a trade-off between quality and quantity of their children depending on their income. The basic argument is that poor parents will opt for quantity as opposed to the quality of their children, consequently, they invest less in their children's education. If there is a large fertility differential between the poor and the rich, one would expect that average education will fall in time, or grow more slowly. Perotti, (1996) summarizes the relationship by indicating that: (1) growth increases as investment in human capital increases and fertility decreases (2) fertility decreases as investment in human capital increases as equality increases[9] and (3) growth increases as equality increases. Thus, as inequality in a society increases, fertility is likely to rise and this will reduce the growth in human capital investment. Ultimately, the reduction in human capital investments negatively affects growth.

In redistributive political economy models, such as those presented in Alesina and Rodrik, (1994) and Borck, (2007), distribution will only affect growth through the median voter. The median voter hypothesis as presented in Meltzer and Richard, (1981) asserts that with majority rule, the voter with median income among the citizens with the right to vote is influential. Therefore, in very unequal societies (assuming perfect capital markets), to the extent that the mean income exceeds the median income, the (myopic) median voter will prefer wealth redistribution. More redistribution may create disincentives for investment in human and physical capital. Consequently, more inegalitarian societies will grow at slower rates *ceteris paribus*. As Deininger and Olinto, (1999) indicate, this arises because the voters perceive that they will derive short-term economic gains from wealth redistribution, and hence usher in governments that advance policies encompassing any such gains. This is unlikely to happen in more egalitarian societies since the median voter is more endowed with capital, otherwise, they would hurt themselves if they advocated for redistribution through voting, hence capital accumulation and growth will be higher in such societies (Alesina & Rodrik, 1994 ; Deininger & Olinto, 1999). Whereas the model places emphasis on democratic arrangements, even dictatorial governments respond to social demands and thus the argument holds even for non-democratic governments (Alesina & Rodrik 1994).

However, there are caveats to this simple relationship. As Borck, (2007) highlights, it is not always that redistribution of wealth runs from the rich to the poor, in some cases, it runs in the opposite direction if political power rises with income. The politically powerful rich may use the political machinery more than the poor, as indicated in the political-loser hypothesis of Acemoglu and Robinson, (2000). Political power among economic agents is critical for any changes to occur in the socio-economic environment. As a result, the effect of inequality on growth via the median-voter hypothesis may only hold for such

[9]The statement is true only for the average fertility, provided there is no time trend to education. In the case where a time trend exists, it is the rate of change in fertility that decreases.

government expenses as social cash transfers but not for other spending categories such as education. As Deininger and Olinto, (1999) highlight, if the proceeds from the taxes that are meant as a redistribution tool are used in public good investments, the relationship can be reversed and sometimes not hold since voting behaviours resulting from inequality become difficult to predict. Moreover, individuals may not be as short sighted as implicitly assumed, and thus, their voting decisions might not reflect an advancement of short-term self-interest through redistributive policies of governments aspiring for election into power. Furthermore, under certain conditions, redistribution may eliminate poverty through growth if every poor society receives a share of the redistribution and the total redistribution for that particular society does not converge to zero (Cooper 1998).

In addition, the prospect of upward mobility (POUM) hypothesis presented in Benabou and Ok, (2001) further argues that there exists a range of incomes below the mean where individuals in societies will oppose redistributions if their expected future income is an increasing function of today's income and taxes are preset for longer periods. Furthermore, Deininger and Olinto, (1999) point out that to the degree that income inequality reflects the outcome of an economic process that includes income redistribution through taxation, the reason for the relationship's existance is blurred. More empirical evidence by Deininger and Squire, (1998) suggests that democracy through voting provides little support for this channel as a mechanism through which inequality affects growth. More specifically, they found that initial inequality affected future growth in undemocratic societies but not in democratic ones.

Another channel identified as linking growth to inequality relates to imperfections in the credit markets. Several models have shown how imperfect credit markets negatively impact growth (e.g., Piketty, 1997; Aghion & Bolton, 1997; Galor & Zeira, 1993; and Mookherjee & Ray, 2003). Imperfections in the credit market mean that the interest rates for individual borrowers are higher than those of the lenders (Galor & Zeira, 1993). This results from the fact that lenders have to deal with the moral hazard and adverse selection problems in their decisions to lend. Moral hazard results from the fact that lenders do not observe individual ability whilst adverse selection results because labour input is unobservable. Both of these are an added cost which has to be accounted for in the lending process. For lenders to ensure that borrowers have enough incentives to pay back, they demand collateral. Hence, in models with capital market imperfections, individuals are assumed as capable of undertaking profitable indivisible[10]investments, and with limited access to credit, these investments are an increasing function of initial productive asset endowments. Any credit contraints arising from the failure to produce collateral when borrowing will negatively impact on the poor's ability to undertake any such investments. Hence, the poor forego human-capital and other investments that would otherwise offer relatively higher rates of return. Consequently, societies with a more egalitarian wealth distribution grow faster at least during the transition to a steady-state. This is because an equitable productive asset distribution helps in overcoming asset thresholds for more individuals in society resulting in higher aggregate investment and formation of human and physical capital. Important to note in as far as this channel is concerned is the fact that the key mechanism in this respect is not imperfect capital markets per se but rather the fact that the rate of return on capital exceeds the rate of growth (Piketty, 1997) .

Following Alesina and Perotti, (1996), the socio-political channel is another mechanism providing evidence for an inverse relationship between inequality and growth. The authors indicate that inequality fuels social discontent, which increases socio-political instability. This creates uncertainty about the policy environment and property rights in the politico-economic environment and hence a reduction in investments. With a reduction in investments, growth is impeded. Furthermore, Barro, (2000) points out that in societies with more inegalitarian wealth distributions, in addition to rent-seeking by the rich, the poor are motivated to engage in disruptive activities that are outside the normal markets. As Alesina and Perotti, (1996) highlight, there is an increase in the probability of revolutions, crime ,and violent protests. While working through economic efficiency and social stability, these activities affect transaction costs in markets, investment incentives , productivity, levels of mass violence, and the ability of socieies to effectively respond to exogenous shocks in a coordinated manner. Socio-political instability discourages investment by disrupting market activities and labor relations, it also creates uncertainty regarding the political and legal environment (Perotti 1996). Instead of channeling their energies towards productive activities, the poor are more likely to devote their precious resources on disruptive activities. This implies that productivity reduces and ultimately growth declines atleast in the transition to the steady-state. In similar respects, Keefer and

[10]Indivisibility means each project entails a minimal size or that there is a technological non-convexity (Galor and Zeira, 1993)

Knack, (2002) argue that the inequality of land-holdings reduces security of property and contract rights, the result of which is a reduction in growth. Thus, through the sociopolitical channel, more inegalitarian wealth distributions impede growth.

Finally, Barro, (2000) presents individual saving rates as a complementary mechanism to the imperfect credit markets model as the source of the link between inequality and growth. He indicates that if it is true that individual saving rates rise with the level of income, then redistribution of resources from the rich to the poor will lower aggregate savings in an economy. Since, with credit rationing investment is to a certain degree dependent on savings, it is expected that an increase in inequality will raise the investment levels. Ultimately, inequality will enhance growth at least in the transition to the steady-state.

From the various theoretical linkages presented above, pathways that are likely to apply for Kenya include the redistributive political economy, and social-political unrest. The political economy model could relate growth to inequality in this instance if the political activity relating to the assignment of land rights at the village level leads to concentration of landholdings. This could happen if the relatively more powerful and rich households with the power to influence political decisions may act in such a way that they grab land from the poor driving them into landlessnes. Such power distortions and the resulting land grab means that farm sizes for the rich increase and those of the poor reduce, and if this is the case, the negative farmsize-productivity relationship kicks in and growth is less than it is expected to be. Thus villages where this is the case are likely to grow slowly than comparable villages where inequalities resulting from power distortions are less of a problem.

The socio-political unrest model could also apply in that, where social unrest is likely to result due to grievances relating to land concentration caused by any such land grabs by the politically powerful. The socio-political unrest model by discouraging investments and creating uncertainty in property rights can only apply if there is a high proportion of land under private tenure as opposed to customary tenure. It is unlikely to apply in countries such as Zambia since most of the land there is under customary tenure and such tenure status' have been shown to be highly secure. Thus investment decisions on land are unlikely to be affected by the acquisition of a private tenure status as shown by Hichaambwa, Sitko and Chamberlain, (2014) for Zambia.

2.3 OVERCOMING THE ECONOMETRIC ISSUES

2.3.1 Unobserved variables and endogeneity

The standard growth and inequality models assume that some variables are common to both models while others are not. That is to say some variables in the growth model are independent of inequality and others in the inequality model are independent of growth. However, by dropping this orthogonality assumption, growth is allowed to enter the equality equation and vice-versa. As such, the conventional structural models used in analysing growth and income distribution covariates are as specified in equations (1) and (2) respectively:

$$Y_{it} = \alpha_1 + \beta_1 G_{it} + \beta_2 Y_{it-1} + \delta_1' Z_i + \varepsilon_{1it} \qquad (1)$$

$$D_{it} = \alpha_2 + \omega_1 G_{it} + \omega_2 Y_{it} + \delta_2' Z_i + \varepsilon_{2it} \qquad (2)$$

Where Y_{it} denotes the natural logarithm of the per-capita income growth of the *i'th* individual[11] in period *t*. D_{it} and G_{it} represent the localized (i.e. village level) distribution of income and operational land-holdings in time period *t* respectively, while Z_i represents a vector of individual- or location-specific conditioning variables, ε_{nit} is an error term containing an individual-specific effect (v_n), a persistent time-varying effect τ_{nt}, and a purely random error term e_{nit} such that $\varepsilon_{nit} = v_{in} + \tau_{nt} + e_{nit}$. While $\beta_1, \beta_2, \omega_1, \omega_2$ and α_n are scalar parameters for $G_{it}, Y_{it-1}, Y_{it}, G_{it}$ and the intercepts in each equation respectively, *n* indexes the equation number. The parameter vectors represented by δ_1' and δ_2' are associated with the vectors of conditioning variables (Z_i) in each equation. The vector of conditioning variables (Z) in equations (1) and (2) can be decomposed into a vector of endogenous variables (R) and a vector of exogenous variables (Q). Examples of exogenous variables in this respect include agro-climatic potential, remoteness or closeness of an individual to the nearest district headquarters and/or major city, while an example of an endogenous conditioning variable is the average level of education.

[11]The word "individual" may refer to various sites including countries, villages, standard enumeration areas (SEAs), and cities. For a household level analysis, this may be income corresponding to a household.

There are two problems with the structural equations, to address these problems; one can re-write the equations in first differences as shown in equations (3) and (4) below:

$$y_{it} = \tau_{1t} + \beta_1 g_{it} + \beta_2 y_{it-1} + [\delta'_{1q}, \delta'_{1r}]\begin{bmatrix} q \\ r \end{bmatrix} + e^*_{1it} \qquad (3)$$

$$d_{it} = \tau_{2t} + \omega_1 g_{it} + \omega_2 y_{it} + [\delta'_{2q}, \delta'_{2r}]\begin{bmatrix} q \\ r \end{bmatrix} + e^*_{2it} \qquad \text{(t=1,…,T)} \qquad (4)$$

Where the variables maintain their descriptions as in equations (1) and (2) above but are in first differences, which are written in lower case letters of the original variables. The parameter vectors δ'_{nq} and δ'_{nr} are associated with the exogenous (q) and endogenous variables (r) respectively. The scalar parameter τ_{nt} represents the time-varying effect in each of equations (3) and (4). Because the individual-specific time-constant error component (v_{in}) drops out, the error terms are no longer correlated with the regressors.

To overcome the endogeneity issue that growth and inequality influence each other, the two- stage least squares estimator (2SLS) is typically used. This technique requires instrumental variables so that equations (2) and (3) can be consistently estimated. 2SLS can be used if for each of the two equations, there exists at least one or more instruments (W_n) such that $E(e^*_{nit}|\, W_n) = 0$, i.e. the endogenous variables are not correlated with the error term of the estimation equation. At least one of the instrumental variables should be able to influence growth but not inequality while the other instrumental variable should be able to influence inequality but not growth. Then in the first stage the endogenous variables are predicted using all variables, including the respective instruments. As a consequence, given the distribution of the error term, the coefficients of the resulting second stage equations are unbiased.

However, finding an instrument that influences either growth or inequality but not the other, and others which influence *r* but not *y* and *d* is impossible. For example village-level characteristics are likely to influence both village growth and inequality, and this renders them unsuitable as instruments.

Nevertheless, a number of instruments have been used in the growth-inequality literature; typically instruments include lagged values of the endogenous regressors (e.g., included twice lagged income, lagged measures of the distribution of operational land-holdings, and lagged average education as instruments for the initial growth, inequality, and education respectively). A more comprehensive and detailed list of instruments used in inequality-growth studies can be found in Durlauf et al., (2005).

Without valid instruments, the endogeneity problem cannot be overcome using the 2SLS procedure. The solution to the endogeneity problem proposed by Keane and Runkle, (1992) (KR) calls for alternative estimators that consistently estimate the parameters. It is assumed that past (initial) values of the endogenous variables are at least weakly exogenous, which is motivated by the fact that they change only very slowly over time, but have a persistent influence on growth and/or inequality. Weak exogeneity of a set of variables means that past values of the endogenous variables are uncorrelated with the error term of the estimation equation, while that is not the case for future values, this implies that $E(\varepsilon_{nit}|W) = 0 \ \forall \, s \leq t,$ but $E(\varepsilon_{nit}|W) \neq 0 \ \forall \, s > t$. This assumption means that lagged values of growth, education, and inequality qualify as weakly exogenous variables. In contrast for W to be strictly exogenous the variables relate to the error term in such a way that $E(\varepsilon_{nit}|W) = 0 \ \forall \, t$.

Estimators that can be employed in panel data modelling with serial correlation under the weak exogeneity assumption include the differences- (DGMM) and the system-generalized methods of moments (SGMM) that were proposed by Arellano and Bond, (1991) and Arellano and Bover, (1995) respectively. The DGMM introduces lagged values of the endogenous covariates as instruments. However, the DGMM has been argued to lead to bad perfomances of the regression when variables are persistent over time. This arises because when variables are persistent, their lagged values will be weak instruments for the first differences, and as a result, the risk that the endogenous component of growth is incompletely eliminated is significant (Temple, 1999; Roodman, 2009). Moreover, through differencing, the DGMM tends to get rid of the much needed cross-individual variability in the data, hence significantly reducing the total variability in the data. This is because most of the inequality measures relating to income and human capital vary more across villages or countries than across time. In addition, this tends to get rid of the time-invariant regressors which might be of interest to the researcher.

As a partial solution to these problems, the relatively more robust SGMM was developed which combines regressions in levels and first differences. In this formulation, variables in levels instrument for those variables in first differences and variables in first differences are instuments for variables in levels (an additional moment condition)[12] and as such, the cross-individual variability in the data is preserved and the parameters of time-invariant regressors can be estimated. The SGMM estimator has been successfully applied in previous works by Deininger and Olinto, (1999) and Fort, (2007).

However, while the SGMM allows for estimation of the time-invariant regressors using the "hascons" option when analyzing the model using Stata's in-built "xtdpd" or "xtdpdsys" commands, Kripfganz and Schwarz, (2014) provide a two-stage[13] estimator that also allows for inclusion of the time-invariant regressors which performs better than SGMM on its own. In the first stage, ,the parameter estimates of the time-varying regressors are obtained either using quasi-maximum likelihood estimation (QMLE) or any other consistent estimator of the generalized method of moments (GMM) class of estimators. In the second stage, the residuals from the first stage are then regressed on the time-invariant regressors of interest. At the second stage, the assumption one makes with respect to the correlation between the time-invariant regressors and the unobserved effects is critical. One can either assume that the time-invariant regressors are uncorrelated or correlated with the unobserved effects. If one is willing to assume the former, then they can obtain the second stage estimates by ordinary least squares (OLS) while bootstrapping the second stage standard errors as the usual OLS or instrumental variable (IV) standard errors at the second stage are invalid because they are dependent on the first stage preliminary results. In the event that one makes the latter assumption with respect to the correlation between the unobservables and the time-invariant regressors, second stage estimation would proceed using instruments for the time-invariant regressors from the first stage. These instruments could be the time-varying regressors from the first stage with the assumption that these are uncorrelaed with the unobseved effects while ensuring they satisfy the usual IV requirements of instrument relevance and validity.

[12] The full set of moment conditions for the SGMM can be found in Kripfganz and Schwarz, (2014).
[13] The two-stage estimator of Kripfganz and Schwarz can be programmed; at this stage a Stata user-written command is not yet officially available to the public.

One advantage of the two-stage estimator is that provided that instrument proliferation is not a problem, one can perform SGMM on the time-varying regressors and later include the time-invariant regressors in the second stage. The parameters of the first stage time-variant variables remain robust to model misspecification with respect to the "ommited time-invariant regressors. In addition, the individual-specific effect is eliminated by use of the first differences or forward orthogonal deviations (Kripfganz and Schwarz, 2014). If however, instrument proliferation is a problem when using SGMM for the first-stage estimates, Kripfganz and Schwarz, (2014) show that the quasi maximum likelihood estimator (QMLE) performs best.

Even though the SGMM is appealing in this respect, it has also come under criticism in works by Roodman, (2009) along with the DGMM. He argues and shows that these estimators carry a great and underappreciated risk due to their capacity by default to generate seemingly valid but invalid results. This arises because these estimators are designed to generate a large number of instruments by default (i.e. the number of instruments generated is quadratic in T), and this tends to overfit the endogenous variables (overfitting bias) even as it weakens the specification tests (Roodman, 2009). The failure to detect and completely eliminate endogeneity implies that these results are little or no different from those obtained using estimators without instrumenting, an assertion which Roodman proves using the study by Forbes, (2000) on inequality and growth. Furthermore, the failure to detect endogeneity is only one of the problems emanating from the high instrument count. The phenomenon also leads to incorrect estimation of the optimal weighting matrix which is meant to correct for autocorrelation and/or heteroskedasticity or endogeneity in DGMM and SGMM among other related estimators. As a consequence, the estimates of the coefficient's standard errors tend to be downward biased. Nevertheless, the author proposes collapsing of the instrument set as a way of reducing the risks that come with instrument proliferation in DGMM and SGMM applications where t >3.

Keane and Runkle, (1992) proposed, instead of the SGMM method, an alternative and more efficient GMM estimator that allows for consistent estimation of such models. It is the so-called "Keane-Runkle three-stage least squares (KR-3SLS)" estimation technique.The procedure, just like the SGMM estimator also assumes that past (initial) values of the endogenous variables are at least weakly exogenous. This estimation technique has been implemented successfully in more recent empirical works by Lundberg and Squire, (2003) and another by Ziliak, (1997). A detailed description of the procedure and other associated assumptions is provided in the discussion on autocorrelation in section 2.3.3.

In addition to the KR-3SLS estimator, Lewbel, (2012) proposed a new heteroskedasticity-based identification procedure for simultaneous equation systems, triangular systems, and mismeasured regressor models. The method is applicable where other sources of identification , such as instrumental variables, repeated measurements, or validation studies are unavailable. This procedure has been successfully applied in the growth empirical works by Huang, Lin and Yeh, (2009). It is advantageous in that no instrumental variables are required in the identification of the structural parameters, moreover, the estimator takes on the form of the general generalized method of moments (GMM) . Though useful in addressing the endogeneity issue and unobserved variables in panel modelling, section 2.3.3 of this paper presents an argument against its applicability with respect to modelling growth and inequality.

Therefore, in light of the critics against the DGMM and SGMM estimators and the results of Ziliak, (1997), in which the KR-3SLS estimator performs best in terms of the bias/efficiency trade-off when compared to 2SLS, SGMM and DGMM,the KR-3SLS and Lewbel heteroskedasticity-based identification (LHBI[14]) procedures are more appealing in empirical application thus far.

2.3.2 Unobserved fixed effects

Another problem in identifying growth and distribution covariates results due to unobserved heterogeneity (omitted variable bias). With panel data, the influence of unobserved individual- and time-specific heterogeneity that is typically relegated to the error term in cross-sectional formulations can be eliminated or reduced using fixed- or random-effects estimators. Furthermore, whereas the first difference estimator can be used to easily eliminate the time-invariant effect, it does not eliminate the time-specific effect. This is typically done by decomposing the error into a component associated with the individual (v_{ni}), another that is associated with the time period (τ_{nt}) and a third one (e_{nit})

[14] Tentatively, the argument against the applicability of Lewbel's procedure in the growth empirics is ignored for a more comprehensive discussion in section 2.3.3.

which is the remaining individual and time-specific error that is assumed to be normally distributed. The decomposition is as follows: $\varepsilon_{nit} = v_{ni} + \tau_{nt} + e_{nit}$ (Wooldridge, 2004; Cameron & Trivedi, 2005; Mundlak, 1978). This formulation captures any omitted variables in the model that are important growth covariates but difficult to observe, examples of these include technology differences across individuals, quality and level of enforcement of institutions, and agro-climatic potential (e.g. soil quality and climatic conditions). The omitted variables lead to a correlation between the regressors and the error term, thus violating the independence (iid) assumption on the error term. This occurs because for instance, in determining growth covariates, omitted variables such as agro-climatic potential could influence an individual's income level and at the same time their land distribution. This implies that the error term which contains this heterogeneity is correlated with the regressors.

Typically, the unobserved heterogeneity takes the form of time-specific (τ_{nt}) and individual-specific (v_{in})[15] systematic components. The time-specific effects are usually assumed to affect individuals in the same way, they could include events such as famines in particular periods, hence to account for them, fixed- and random-effects formulations are usually employed (Mundlak 1978). Whether one treats the time-specific effect as fixed or random depends on whether there exists a set of instruments W which are uncorrelated with the error term such that $E[W'(\tau_t + e^*_{nit})] = 0$ in which case it is random. If however $E[W'e^*_{1it})] = 0$ and $E[W'\tau_t] \neq 0$, implying that the time-specific effect is correlated with the set of instruments, then it is treated as fixed. However, although the fixed effects and first difference estimators have previously been used in other studies, Lundberg and Squire, (2003) argued beforehand that inequality is likely to vary more across sites (e.g., countries, villages, and cities) than over-time hence these estimators are unattractive as they eliminate the corresponding cross-site variation. Moreover, they also eliminate time-invariant variables which might be of interest, this makes them further redundant in instances where one is interested in the parameter estimates of time-invariant covariates. It is also unlikely that the random effects assumption will hold in the growth and inequality estimation problem making it redundant.

[15] The individual specific effect is assumed fixed if it is allowed to be correlated with all regressors; on the other hand it is assumed random if it is independently distributed.

This therefore requires the use of an alternative instrumental variable (IV) estimator that accomodates predetermined but weakly exogenous instruments while allowing for the determination of the influence of unobserved heterogeneity. Fortunately, such estimators do exist, Arellano and Bond, (1991) and Arellano and Bover, (1995) proposed the differences- and system-generalized method of moments (GMM) respectively as alternative IV estimators of random effects models to allow for such an estimation. Another more recent estimator is the Lewbel heteroskedasticity-based identification procedure. In addition to these, Keane and Runkle, (1992) also proposed a new estimator of the instrumental variable class of GMM estimators that enabled consistent estimation of panel models with serial correlation when instruments are predetermined but weakly exogenous. These estimators have been successfully implemented in empirical works on growth-inequality linkages, examples of studies using these approaches include; Fort, (2007), Deininger and Olinto, (1999), Huang, Lin and Yeh, (2009) and Lundberg and Squire, (2003). Note that while the first differences and fixed effects estimators are discounted here, the possibility of using them is discussed further in section 2.4.

2.3.3 Autocorrelation and other special cases of GMM estimators

Another common problem in panel data models relates to the serial correlation in the error terms. Autocorrelation is a rule rather than an exception in time-series and panel data models and any failure to control for it renders the estimates invalid for statistical inference since the variance matrix of the coefficients is incorrectly estimated (Cameron & Trivedi 2005). The sources of autocorrelation include measurement errors, omitted variables, the persistence of inequality in growth models and functional form misspecification. For instance, in the models considered here, the effect of any omitted variable that is a covariate of either income growth or distribution will be captured in the error term. Consequently, that variable will be dependent on its past values and so will the error terms. In addition, any functional form misspecification in the vector of regressors will lead to autocorrelation. This arises because if a dependent variable’s relationship to its covariates is quadratic for example, omitting the squared values of the variables which grow over time will also cause the error term to grow in a quadratic manner.

Furthermore, as in Lundberg and Squire, (2003), the error terms in the distribution covariates equation are assumed to be serially correlated over time, this is because inequality tends to be persistent over time (Durlauf, 1996). On the other hand, while inequality is persistent over time hence introducing serial correlation in the corresponding model's error terms, the growth of income across time periods is assumed to be uncorrelated and thus no serial correlation exists in the errors because of this (see Easterly et al., 1993). Therefore, given this scenario, one can re-write the corresponding error terms in equations (1) and (2) as $\varepsilon_{1it} = [v_{1t} + v_{2t}] + \rho\varepsilon_{2i,t-1} + [e_{1it} + e_{2it}]$ and $\varepsilon_{2it} = \rho\varepsilon_{2i,t-1} + v_{2t} + \tau_{2t} + e_{2it}$ respectively. This implies that the serial correlation present in the distribution equation introduces serial correlation in the growth equation as the two equations become interdependent.

The exposition below is drawn from Hayashi and Sims, (1983) , Lewbel, (2012), Rigobon, (2003), Arellano and Bond, (1991), Arellano and Bover, (1995), Seung and Schmidt, (1998), as well as Keane and Runkle, (1992). To begin the discussion on the various econometric procedures used to eliminate autocorrelation in panel data models when instruments are predetermined but not strictly exogenous, it is important to note that most econometric estimators including least squares, instrumental variables (IV), and the method of maximum likelihood estimation can be thought of as special cases of a general estimation principle called the Generalized Method of Moments (GMM). For one to define a particular type of estimator within the GMM framework, specific conditions on the moments of the respective estimator are postulated. These usually involve restrictions on how the model's error term, covariates, and the parameters relate to each other. Thus, a specific estimator's classification within the broad GMM framework will depend on the defined moment conditions as well as the choice of the weighting matrix which is meant to correct for heteroskedasticity and/or autocorrelation as well as endogeneity. Consider an equation of the form presented in (5) below. Where *i* and *t* index for individuals and time respectively. Some elements of vector X are assumed endogenous while others are exogenous.

$$Y_{it} = X_{it} + u_{it} \qquad (t=1,\ldots,T) \qquad (5)$$

The method of instrumental variables (IV) estimation falls within the class of GMM estimators. The moment condition is that the residuals are uncorrelated with the instrumental variables (W) and it is estimated by standard two-stage least squares (2SLS).

When there is serial correlation and the errors may be uncorrelated with the set of instruments, 2SLS will be inefficient. But given the presence of serial correlation, within the instrumental variable class of estimators that can be cast using the unifying GMM framework, special[16]more efficient cases of linear IV estimators emerge.

The standard procedures such as IV estimation use the conditional moment restriction that the residuals are uncorrelated with the instrumental variables (W), other exogenous variables, and the identically and independently distributed errors (i.e. $E[u_t|W_t] = 0$). With autocorrelation this approach cannot be used as it yields inconsistent estimates of the coefficients and standard errors. To overcome this problem, other panel estimation procedures such as the forward-filter (FF) procedure[17] originally proposed by Hayashi and Sims (1983) or the system generalized method of moments (SGMM) proposed by Arellano and Bover (1995) become more appealing. Other special cases of the IV class of GMM estimators considered here include Arellano and Bond's differences generalized method of moments (DGMM), Keane and Runkle's version of the forward-filter estimator (hereafter the Keane-Runkle three stage least squares (KR-3SLS)) as well as Lewbel's Heteroskedasticity-based Identification procedure (LHBI).

Despite the more complex error structure assumed, the KR-3SLS, DGMM and SGMM estimators allow for the use of standard IV computation procedures such as 2SLS by first eliminating the serial correlation problem in the models (assuming homoskedasticity for convenience, otherwise any heteroskedasticity would have to be corrected for as in generalized least squares). The moment condition common to the FF, DGMM, SGMM, KR-3SLS and LHBI estimators can be cast in a manner depicted in equation (6) below. The moment condition means that the expected value of the error term in period *t* given a set of instrumental variables *W* is equal to zero for some time period *s* less than or equal to the reference time period *t*, while it is not equal to zero for any time periods greater than *t* (i.e. the error term is allowed to be correlated with future values of the set of instruments (W) but not with current and lagged values).

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[16] These special cases are more efficient than two-stage least squares (2SLS) and remain consistent given sources of serial correlation such as random effects. 2SLS in the presence of serial correlation and heteroskedasticity yields inconsistent coefficient estimates as well as standard errors.

[17] The idea forward-filtering procedure is discussed under the special cases of GMM, specifically using the Keane-Runkle three-stage least squares as an example.

$$E(u_t|W_s) = 0 \;\; \forall\, s \leq t, \text{ but } E(u_t|W_s) \neq 0 \;\; \forall\, s > t. \qquad (6)$$[18]

This is particularly helpful in IV estimation when the moment condition of strict exogeneity ($i.e.\ E[W_t(u_t)] = 0 \,\forall\, t$) is not satisfied. Instead lagged (W_s) values of endogenous variables can be used as depicted in the orthogonality or moment conditions presented in equation (6) above.

In addition to, though already implied by the moment condition in equation (6), the KR-3SLS, DGMM, SGMM, and the FF estimators also require that the serial correlation in the error term is independent of the set of predetermined instrumental variables (W). A condition which can be depicted as in equation (7) below:

$$E(u_t u_S|W_t, W_{t-1}, \ldots) = E(u_t u_S) \,\forall\, t > s. \qquad (7)$$[19]

Additionally, these special cases of the IV class of GMM estimators are designed to handle panel situations with small time periods and a large number of observations. Typically, the models have a single left-hand-side variable that (i) is dynamic, depending on its own past realizations[20], (ii) has individual fixed effects, (iii) has heteroskedasticity and autocorrelation within individuals but not across them.

The main difference between these estimators relates to how identification is achieved or the approach used to transform the data to one without serial correlation in the errors. Once identification is achieved, and the data transformation that eliminates the serial correlation in the residuals has been performed, the models can be estimated using standard procedures such as 2SLS or 3SLS. Otherwise, estimation without expunging serial correlation would yield inconsistent estimates.

In what follows, I present the specific approaches used to tackle serial correlation and the identification problem in the different estimators. The Keane-Runkle three-stage least squares (KR-3SLS), differences- (DGMM) and the system-generalized method of moments (SGMM) were motivated by the need to have consistent parameter estimates in models with

[18] This moment condition implies that these models are limited information since the complete variance-covariance matrix for the observed data need not be specified. Efficiency gains are achieved with a full specification of the matrix.

[19] Hayashi and Sims, (1983) show that this moment condition is already implied by the one presented in equation (6)

[20] Or as in vector autoregressions (See Holtz-Eakin ,Newey,and Rosen, 1988).

lagged dependent variables (y_{it-1}) and an individual-specific effect (v_i) as regressors, a situation depicted in equation (8) below.

$$y_{it} = y_{it-1} + X'_{it}\beta + v_i + u_{it} \qquad (8)$$

Prior to the development of estimators of the KR-3SLS, DGMM and SGMM form, individual-specific fixed effects (v_i) were typically eliminated by an estimator that involved taking deviations of variables from individual means, or first differences between time periods. Ultimately, estimation was based on the resulting moment condition that $E(u_{it} - \bar{u}_i|X_{it}) = 0$. Therefore estimation required that the vector of instrumental variables was strictly exogenous to the error term, a condition difficult to satisfy in practice. As such, the approach was argued to lead to inconsistencies in the estimates in models such as those with lagged dependent variables, since the lagged regressand is by construction correlated to the mean of the error term. This shortcoming called for the development of other more consistent estimators (e.g. KR-3SLS, DGMM, and SGMM) that first eliminated the inherent serial correlation in such models while allowing for the use of predetermined variables as instruments. The KR-3SLS, DGMM and SGMM estimators are based on the insights of Hayashi and Sims (1983) on forward-filtering. The main departure point of these estimators from the earlier approaches used to eliminate the fixed effect (v_i) is that, as opposed to demeaning (in the fixed effects case) or quasi-demeaning (in the random effects case) over all time periods these estimators compute the deviations from means computed only over current and future values of the variables while only including lagged values of predetermined/endogenous regressors as instruments (i.e. forward demeaning). As such, estimation was based on the weak exogeneity of the instrument set to ensure consistency of the estimates (Keane and Runkle, 1992, and Ziliak, 1997).

While the KR-3SLS is similar to the DGMM and SGMM in this respect, DGMM and SGMM come second best with respect to efficiency as they do not completely eliminate all forms of serial correlation (Keane & Runkle, 1992)[21]. Its superiority over DGMM and SGMM has been highlighted in studies by Ziliak, (1997) and Lundberg and Squire, (2003).

[21] The SGMM and KR-3SLS are likely to yield similar results if the serial correlation is the first order (i.e. AR(1)), otherwise KR-3SLS performs better with respect to efficiency when more complex forms of serial correlation are present in the data.

To ensure that all forms of serial correlation are eliminated, the Keane-Runkle three-stage least squares (KR-3SLS) procedure additionally employs a forward-filtering transformation of the data after two-stage least squares on the data in first-differences has been performed. As highlighted in Keane and Runkle (1992), estimators using the forward filtering procedure conduct the estimation in two steps. In the first step, two-stage least squares (2SLS) is performed on the untransformed variables and a consistent estimate of the error covariance matrix $\sum_{2SLS} = E(u_i u_i')$ given by $\hat{\sum}_{2SLS} = N^{-1}\sum_{i=1}^{N}(\hat{u}_{2SLS}\hat{u}_{2SLS}')$ is obtained for each individual. After which the filtering process takes place whereby the computed error covariance matrix is filtered by an upper triangular Cholesky decomposition, an inverse $(\sum_{2SLS}^{-1})$[22] of the resulting matrix is then calculated to yield a new matrix $(\hat{P}_{2SLS})$ such that $\sum_{2SLS}^{-1} = P_{2SLS}'P_{2SLS}$. This means that the inverse of the error covariance matrix $(\sum_{2SLS}^{-1})$ is split into a lower triangular matrix (P_{2SLS}') and an upper triangular matrix (P_{2SLS}). The filtered upper triangular covariance matrix $(\hat{P}_{2SLS})$ is now free of autocorrelation and it can be used to transform the original variables (excluding the predetermined instruments) in readiness for the second stage of the estimation process. In the second stage, the procedure requires that the variables be pre-multiplied by $\hat{Q}_{2SLS} = I_N \otimes \hat{P}_{2SLS}$[23]–the transformation process. After which the transformed equation can be estimated consistently by two-stage least squares (2SLS) using the untransformed (original) W as instruments for the endogenous variables. For consistency of the estimator, homoskedasticity is necessary, otherwise one would have to correct for heteroskedasticity as in the generalized least squares estimator when heteroskedasticity is present.

To better visualize the idea of forward-filtering, consider the matrix representation of the general IV class of efficient GMM estimators (EGMM) and compare this with that obtained using the KR-3SLS (a forward-filtering application). In equation (10) below, the KR-3SLS estimator is obtained by a pre-multiplication of the variables in the efficient GMM estimator by the weighting matrix $(\hat{Q}_{2SLS})$ to rid the model of serial correlation.

$$\hat{\beta}_{EGMM} = [X'W(M_N)^{-1}W'X]^{-1}X'W(M_N)^{-1}Y \qquad (9)$$

$$\hat{\beta}_{KR-3SLS} = \left[X'\hat{Q}_{2SLS}'W(W'W)^{-1}W'\hat{Q}_{2SLS}X\right]^{-1}X'\hat{Q}_{2SLS}'W(W'W)^{-1}\hat{Q}_{2SLS}Y \qquad (10)$$

[22] The inverse of the Cholesky matrix is cardinal as it is the one that removes the correlation.
[23] Where I_N is an n*n identity matrix such that the Kronecker product (⊗) of I_N and $\hat{P}_{2SLS}$ is a block matrix.

Where: $M_N = E(W_i' u_i u_i' W_i) = N^{-1} \sum_{i=1}^{N} W_i' \hat{u}_i \hat{u}_i' W_i$ (11)

A vital aspect of the KR-3SLS estimator is that it maintains the GMM format despite being less efficient than EGMM. The loss in efficiency is due to the fact that KR-3SLS, DGMM, and SGMM use less moment conditions than EGMM because the instruments are only weakly exogenous with respect to the residuals. Another important aspect of this estimator is that in the final 2SLS estimation of the transformed data, the set of predetermined instruments remains independent of the error term even after forward filtering (i.e. this is similar to the condition of no heteroskedasticity assumption (M_N) in EGMM as presented in equation (11) except that $E\left(W_i' u_i u_i' W_i\right) = E\left(W_i' W_i\right)$ in KR-3SLS)[24]. The forward-filtering in this respect ensures that the covariance matrix of the time-varying residuals tends to the simple case of the product of an identical variance and an identity matrix (i.e. $var(u) = \sigma^2 I$) as in OLS without serial correlation and heteroskedasticity.

A distinctive feature between DGMM and SGMM is that while DGMM is a within estimator that uses only deviations from means of the variables, SGMM combines equations in levels and in first differences. The advantage of this approach is that the variation across units of observation is not lost. This means that in SGMM the variables in levels act as instruments for those in first differences, and those in first differences act as instruments for variables in levels. Thus, given the additional instruments in first differences, SGMM uses an additional moment condition to the one presented in equation (6) above (i.e. $E(u_t|W) = 0 \ \forall\, s \leq t$, but $E(u_t|W) \neq 0 \ \forall\, s > t$). The additional moment condition given the extra variables in differences is as presented in equation (11) below:

$$E(u_t \Delta W_{it}) = 0 \qquad \forall \qquad [t=2\ldots T] \qquad (12)$$

Another estimator that has been recently applied in the growth empirics of Huang, Lin and Yeh, (2009) is that proposed by Lewbel, (2012). An estimation approach called the Lewbel heteroskedasticity-based identification procedure (LHBI). This estimator can accommodate heteroskedastic errors, serial correlation and endogenous variables. It uses differences in heteroskedasticity rather than instrumental variables to identify the system of equations. With respect to identification, the special cases of GMM estimators, KR-3SLS, DGMM,

[24] Note: KR-3SLS IV's are different from EGMM IV's, with the latter being strictly exogenous whilst the former are weakly exogenous with respect to the residuals, so the contents of W are not the same.

and SGMM use only predetermined instruments, while others such as the heteroskedasticity-based identification procedure uses heteroskedasticity or a combination of heteroskedasticity and the non-traditional instruments (i.e. lagged values of the endogenous variable(s)) to identify the structural parameters.

Given a system of simultaneous equations represented by equation (13) below, in addition to observing some heteroskedasticity in the residuals, one can achieve identification of the structural parameters on condition that the errors $u_{1t}\, and\, u_{2t}$ are identically and independently distributed (IID) with mean zero and that the errors are independent[25] of each other conditional on a vector of regressors (Z) which can be equal to or a subset of (X).

$$y_{1t} = X'\beta_1 + y_{2t}\tau_1 + u_{1t} \qquad\qquad y_{2t} = X'\beta_2 + y_{1t}\tau_2 + u_{2t} \qquad (13)$$

The estimator therefore, in addition to heteroskedasticity can accommodate autocorrelation and endogenous variables without requiring instruments or data transformations as is the case in the FF or KR-3SLS estimators. However, the introduction of non-traditional instruments such as lagged values of endogenous variables improves the quality of the estimates obtained using this procedure.

In many applications of simultaneous equation models, sources of identification such as instrumental variables may not be available. To tackle such problematic situations, the LHBI procedure uses heteroskedasticity rather than instrumental variables (IV's) or a combination of both heteroskedasticity and non-traditional IV's to identify structural parameters when "normal" IV's are not easy to find as is usually the case in growth and inequality modelling. The procedure has been recently implemented in empirical works by Huang, Lin and Yeh, (2009) following developmental works by Lewbel, (2012). The approach is growing in popularity given the challenges that come with finding appropriate instruments. In addition to the presence of some heteroskedasticity $\{i.e.\ Cov(\mathrm{Z}\, u_{nt}^2) \neq 0\ \forall\, n^{26}\}$ in at least one of the error terms, the moment conditions corresponding to this procedure are as shown in equation (14) below:

$$E(Xu_{1t}) = 0, \quad E(Xu_{2t}) = 0, cov(Z, u_{1t}u_{2t}) = 0 \qquad (14)$$

[25] Important to note is the fact that the errors need not be independent of each other for identification to be achieved. Even with correlation across residuals, Lewbel, (2012) and Rigobon, (2003) point to the fact that identification is still possible.
[26]Where n corresponds to the subscripts in each equation presented in equation (13).

Drawing from Rigobon, (2003), the intuition behind using heteroskedasticity in the identification process is similar to identification using IV's. In the instrumental variable case where we have a system of demand/supply simultaneous equations, identification of the parameters in the demand equation is achieved by observing an IV that shifts the supply curve without affecting the demand curve. In the heteroskedasticity-based identification procedure, identification is achieved by assuming that one can split a given sample into two with the second sub-sample having supply shocks which are more volatile than those of the other sub-sample. Demand shocks on the other hand are assumed to be homoskedastic across both samples.

Even though one only needs a weaker assumption which requires only relative variations in the shocks to implement the procedure, but this would require clear analytical reasons for these relative differences and they would have to be tested for. The relatively higher variance in the supply shocks of one of the sub-samples implies that the cloud of possible outcomes enlarges around the demand curve. Implying that the residuals become distributed over an ellipse, and the shift in the variance implies a tilt towards the demand curve, this ellipse collapses to the demand curve as the variance of the supply shocks tends to infinity and one is able to estimate the demand curve's parameters using ordinary least squares.

However, whereas this procedure works well in other settings such as the demand/supply scenario where demand and supply are outcomes of different economic agents. It is inappropriate in modelling growth and distribution. This is because it is implausible that one would observe some heteroskedastic errors in the growth equation while observing none in the distribution equation since the two are the outcome of the same process. In which case, identification of the parameters would be problematic. Perhaps the empirical results of Huang, Lin and Yeh, (2009) who implement this procedure should be interpreted with caution in light of this.

2.4 DOES "JACKKNIFING" THE INCOME AND INEQUALITY INDICES SOLVE THE ENDOGENEITY PROBLEM WHEN USING HOUSEHOLD LEVEL DATA?

The problem of endogeneity is no doubt pronounced when conducting the growth-inequali**ty** analyses at the cross-country level. In this section, I provide answers to the question regarding whether using inequality indices or income computed for observations other than your own (i.e."Jackknifing") [27] answers all the questions relating to the endogeneity problems usually encountered. More specifically, the possibility for one to use the fixed effects and the first difference estimators is discussed when conducting the analyses at the micro- as opposed to the cross-country level. Firstly, the various empirical studies that have attempted to model the causal effects of growth on inequality and vice-versa have used mainly cross-country datasets. One of the major endogeneity problems encountered relates to the fact that they have not been able to construct the gini coefficients of either income or landholdings in a way that ensures the inexistence of the reverse causality between inequality and growth. This problem can be avoided for analyses at the micro-level, specifically when modelling growth and inequality at the household level, it is possible to compute localized (village-level) gini coefficients or inequality measures that will be exogenous to the household activities (i.e. by using the "leave one out" or "Jackknife" procedure). In the same manner, one can also control for village level conditions by computing village-level mean income for other households excluding household *i*. This is exactly the method that Benjamin, Brandt and Giles, (2011) used in their study on growth and inequality in China.

To better understand the procedure and the reasoning thereof, consider a sample[28] of N observations which can be households within enumeration areas, villages or cities. In calculating the inequality measures (e.g. gini coefficient) if one computed localized gini coefficients (e.g. at the village or enumeration area level), the exogeneity of the localized gini coefficient corresponding to an observation denoted (*i*) can be guaranteed by iteratively computing the localized gini coefficient using only observations other than that of the *i'th*

[27] The Jackknife estimates can be found by systematically leaving out the ith observation from a dataset and calculating the desired estimate using a sub-sample. Meaning that for a given sample of size N, the Jackknife estimate for the left out household (-i) is calculated using the remaining N-1 observations in the sample.
28 Note that this is essentially a sub-sample of a larger data set with multiple enumeration areas or villages.

observation (i.e. calculating the localized gini coefficient for observation *i* using only the remaining N-1 observations in a village for example). The intuition behind this is that by using observations other than *i* to compute the localized gini coefficient or any other parameter of interest, the computed gini coefficient will be independent of the corresponding error term. This is because the village distribution so computed for each household is independent of the household's activities and therefore its own error terms, so it is "truly exogenous". Karoly and Schröder, (2013) present faster ways of obtaining the Jackknifed inequality indices for the gini coefficient, mean log deviation, and the Theil index among others in Stata. Perhaps important to acknowledge in as far as this procedure is concerned is the possibility that, depending on the context, as Benjamin, Brandt and Giles, (2011) argue, some endogeneity may still exist. The authors point to the failure to find instruments that predict initial inequality as a potential source of endogeneity. Solving for it would require instruments that predict initial inequalites but are excludable from the growth equation, and any such instruments need to be uncorrelated with any institutions that may be related to subsequent growth-an impossible task. This is also highlighted by Kanbur, (2004) who argues that even if one could show an association between inequality and subsequent growth, both phenomena could be caused by a third factor affecting both, and it is hard empirically to sort out the separate effects.

To shed more light on this issue, note that whether inequality increases income or decreases it depends on the process that generates the inequality. Suppose for a given predominantly agrarian area being studied, a shoe factory starts operating nearby and employment of the poor rises, leaving larger farmer income unaffected. The growth of income goes up and inequality goes down. When the shoe factory later leaves, growth goes down and inequality up. There is a negative relationship between the increase in inequality and growth. Then consider a drop in the price of a technology or improved inputs such as fertilizer that benefits the large farmers more. The result of this is an increase in both inequality and growth . The result is a positive sign between the increase in inequality and growth. Lastly, consider the distribution of land and income in a locality, if land inequality rises because middle class income people come and settle on land previously not used, the result is a positive relationship between inequality and growth. But when they come and take it from the small farmers, these will fall into destitution, inequality and poverty increase, but growth may still go up, so the ultimate result is the classic negative relationship.

For all the three scenarios presented, the impact of growing inequality on growth depends on whether when it happens it arises because the top income quintiles rise while the bottom income quintiles remain unchanged, or whether the bottom income quintiles rise while the top income quintiles stay unchanged. In the former, an increase in inequality increases growth, while in the latter case, a decrease in inequality reduces it. As earlier indicated, it is impossible to sort out the separate empirical effects of growth on inequality and vice-versa even though a correlation can be established. The reason for this is simple, there is need to know more about the common underlying process that generates the changes in distribution and growth in order to hypothesize about the expected sign or establish a causal relationship. While keeping in mind that even with knowledge of the mechanism at play, this will work differently in the short and long run (de Dominicis et al., 2008). This is exactly the reasoning behind the interpretation of the results by Benjamin, Brandt and Giles, (2011) as depicting correlations and not causal effects. However, while this problem can be solved using fixed effects or first differencing to eliminate the effect of unobserved heterogeneity, Benjamin, Brandt and Giles, (2011) present an argument against using the two. Specifically, they state that examining growth rates over short periods is problematic because the covariation of inequality and growth may not be sufficient to identify the relationship. They also use the argument relating to measurement error as the possible driver of period to period changes in inequality and growth. But then one question immediately come to mind in as far as their argument is concerned, firstly, how does one define the so-called “long” time period required in order to have significant covariation and thus identify the relationship between the outcomes? It is such hard questions that make the growth empirics even more difficult to analyze, let alone interpret. But one would argue that if you cannot identify the relationship with fixed effects or first differences then you cannot identify it at all.

Therefore, what is clear from this is that while “Jackknifing” partly addresses one aspect of the endogeneity problem, arguments may still exist that it does not fully do so because of the difficulty in isolating the effect of the underlying process that might have generated initial inequalities and growth. But this can be done with fixed effects and first differences if one is willing to assume that there is enough covariation in the outcomes and that identification can be achieved. But one important thing to note is that while first differencing or estimation by fixed effects may work for the gini correlates model since the equation does not contain a lagged dependent variable, it will not work for the growth covariates model because of the dynamic nature of the model. Any failure to model using the dynamic estimators would yield inconsistent estimates[29]. It can only work if in modelling the equality covariates, all explanatory variables are computed using the "Jackknife" procedure for all the households in the sample. Such an analysis would then proceed with all variables corresponding to a household having being computed at the village level. Thus, what is clear is that depending on the context, the dynamic estimators are needed with twice lagged income as an instrument for past own household growth. The first differences and the fixed effects estimators will only work given the qualification above, failure to which the estimates will be inconsistent given dynamic nature of the equation.

Thus in conclusion, the procedure proposed by Keane and Runkle, (1992) seems superior in modelling growth and inequality as it handles effectively the various econometric issues that are usually encountered, however, whether it offers significantly more over the Arellano-Bover system generalized method of moments (SGMM) is a subject that depends on the nature of serial correlation in the data as well as the time periods in question. If however, the problem of serial correlation is not pronounced, it seems plausible to assume that the SGMM and KR-3SLS would yield very similar results provided one corrects for the instrument proliferation problem as suggested by Roodman, (2009). On the other hand one needs not worry about instrument proliferation when implementing SGMM with t=3. In addition, the SGMM should necessarily be implemented using the two-step procedure proposed by Kripfganz and Shwarz (2014), if one is interested in time-invariant regressors such as a region's agro-climatic potential. Finally, if the modelling is taking place at the micro-level, using "Jackknifed" covariates will undoubtedly handle the endogeneity issue for the equality model since these are exogenous and estimation can proceed using the first differences estimator under the qualifications earlier alluded to. However, first differencing will not work for the growth model because of its dynamic nature. Estimation would have to proceed using an appropriate dynamic panel estimator depending on the given scenario.

[29] See section 2.3.3 for the discussion of the consequences of having a lagged dependent variable and the use of weakly exogenous instruments.

2.5 REVIEW OF EMPIRICAL STUDIES

2.5.1 Data used in past studies

In analysing growth and inequality covariates, the various analysts in the surveyed literature have relied on aggregated cross-country datasets on net-income, gross income, or expenditure (e.g., see Forbes, 2000; Deininger & Olinto, 1999). While some studies have used panel[30]cross-country datasets, others have used cross-sectional[31] multi-nation datasets, but as discussed the cross section studies are now discredited. In addition, other studies have used country-specific data to analyze the growth-inequality relationship. The country-specific studies have been analogous to the cross-country studies, with units of analysis localized to the village, city, enumeration areas (EAs) and other levels. For instance, Dercon, (2004) conducted their analysis at the village level, while Balisacan and Fuwa, (2004) localized their analysis to the provincial level. Note that Benjamin, Brandt and Giles, (2011) also conducted a village-level analysis even though much of the focus was household level growth.

Notable from the various past studies using cross-country data is the fact that several challenges have been encountered relating to the quality of the data. The unavailability of quality data on income and asset inequality in the past has prompted fresh empirical looks of late, this has resulted from improvements in the datasets and hence "better data" for analysis (e.g.,Deininger & Squire, 1998 ; Fort, 2007; and Voitchovsky, 2005). According to Deininger and Squire, (1998) with a few exceptions, the data used in past studies have failed to satisfy the minimum criteria relevant for the results of any such studies to be valid for statistical inference. They argue that for data to produce valid results for statistical inference, the income data should be based on household surveys as opposed to national account estimates that might be sensitive to changes in estimation methods employed across time. In addition, the income data should also comprehensively cover all income sources, while being nationally representative. However, in as much as Deininger and Squire, (1998) improve its quality by transforming expenditure data to make it more comparable to income data, Knowles, (2005) argues and shows that the transformations by Deininger and Squire, (1998) do not solve the problem entirely. The results obtained by

[30]Examples of studies using panel cross-country datasets include those by Deininger & Olinto, (1999) , Lundberg & Squire, (2003) ; Fort, (2007) ; and Deininger & Squire, (1998).
[31]Examples of studies using cross-sectional multi-nation datasets include one by Quan & Koo, (1985)

Knowles, (2005) from consistently measured data actually differ from those obtained using transformed data.

The scarcity of quality country panel data on the various variables required for such analyses is even more evident in Africa as shown in a study by Odedokun and Round, (2004) who were forced into cross-sectional analysis due to panel data limitations- a practice which has long been discredited in light of the econometric shortcomings. Moreover, the nature and quality of cross-country data present has had an effect on the empirical studies' focus, in times where data on income inequality has been more available, studies have focused on income inequality as a major wealth indicator impeding growth. With collection of operational landholdings data by the food and agriculture organization's (FAO) in their agricultural census, later studies have included data on the distribution of land assets in their models. A practice which is vital in light of the fact that the theoretical basis of the detrimental effects of inequality on growth is better explained by the mal-distribution of productive assets than that of income.

2.5.2 Summary and evaluation of past studies

Since the early works on economic growth and inequality by Kuznets, (1955), a number of studies have sought to identify inequality and growth covariates. Of these studies, the (mechanistic) effect of income inequality on growth has been the major focus; very few studies have looked at the effect of land asset distributions on growth. This has been partly because of the data availability/quality challenges across countries on assets among other variables. With growing micro- and cross-country-level evidence backing the theoretical argument that it is more the distribution of land assets than that of income that impedes growth, the focus has shifted from income inequality to land assets inequality as a wealth measure determining growth (although early works by Quan & Koo, (1985) used land concentration to confirm the Kuznets' conjecture (i.e. by showing that inequality in income leads to inequality in landholdings and not vice-versa)). In the text that follows, a summary and individual evaluation of selected past studies looking at growth and inequality is presented. In light of the criticisms against the methods adopted in past studies, only studies that are adjudged to be credible are reviewed.

Lundberg and Squire, (2003) (LS) while driving home an important methodological point in the growth empirics found that the determinants of growth and inequality are not mutually exclusive. They found a significant negative relationship between education and income inequality, while education had no significant effect on growth. They also found that on average, a more egalitarian land distribution yields faster growth but land distribution has no significant effect on income inequality. However, they found that the marginal impact of land distribution on growth for the developing countries is almost Zero. This is surprising given the importance of land in the developing countries which are predominantly agrarian; one would expect this to be greater than Zero. Other variables with a positive effect on inequality included initial income, inflation, civil liberties and the Sachs-Warner index. While civil liberties perpetuated inequality, they also promoted growth. A reduction in the inequality of landholdings was found to be good for reducing income inequality. Education was also seen to have a negative effect on income inequality even though it had no significant effect on growth. The authors made an important contribution to the growth empirics as they apply to policy by simultaneously examining growth and inequality determinants. This approach provides useful and complete information for the policy maker whose interest is advancing growth and reducing inequality and argues that future studies on growth and inequality should focus on the joint determinants of both processes. While using panel cross-country data, they also consistently estimate their quasi-reduced-form regression model using the more robust KR-3SLS estimation procedure, making their findings relatively more acceptable for inference for reasons earlier alluded to.

In another study by Huang, Lin and Yeh, (2009), the focus of the analysis was the effect of inequality on growth and that of growth on inequality. In light of the endogeneity problem that is central to the growth empirics and the fact that inequality and growth are mutually dependent, the authors estimated a simultaneous equation model using data covering 83 countries for the period 1965-2003. Their preferred estimator was Lewbel's heteroskedasticity-based identification procedure (LHBI) whose advantages and potential weaknesses have been earlier alluded to. What they found was that higher inequality negatively affects growth and that faster growth tends to worsen the extent of income inequality - results which remained valid for non-OECD but not for OECD[32] countries. A

[32] OECD stands for the Organisation for Economic Co-operation and Development.

result which led them to argue that the causal relationship between inequality and growth is largely driven by developing countries.They also found that higher investment shares are associated with higher growth, while large governments were found to slow down growth. In addition, they found that lower inflation, higher secondary school enrollment, and a higher share of government expenditure in GDP tended to reduce the extent of inequalities. Similar to LS, they also confirm the theoretical rationale for a simultaneous examination of growth and inequality. However, the authors did not identify the channels through which inequality affects growth, understandably since this is likely to be different across countries. They further did not identify how the initial distribution of productive assets would impact on growth given the importance of such assets in agrarian societies for instance. It is unclear whether the relationship between inequality and growth would still hold if instead the distribution of productive assets as a wealth measure in the model. Moreover, pooled country datasets have been shown to be problematic with respect to quality as earlier argued. Furthermore, while their prefered estimator is the LHBI procedure, questions surrounding its suitability in modelling growth and inequality are subject to further debate.

While the two studies presented above are cross-country studies, more acceptable country-specific studies are almost non-existent. The only study that was adjudged to be credible is the one by Benjamin, Brandt and Giles, (2011) who looked at income inequality and growth in rural China. What the authors highlight is quite profound in the growth empirics. Essentially, their conclusion is that it is impossible to interpret the results of the estimation as indicating causal effects but rather as correlations. Effectively addressing the endogeneity problem is impossible and this is due to the failure to isolate the effect of other mechanisms that might have generated initial inequalities. Doing so would require finding an instrument that is excludable from the growth equation and this is an impossible task or alternatively by using the fixed effects or first differences estimators-methods which they argued against even though section 2.4 of this paper argues in favour of such a possibility. The authors found evidence of village level inequalities impeding growth of household income, with the effect of inequality disappearing over time due to integration of villages with the wider economy. They also found that education acts as a buffer towards the adverse effects of inequality, with more educated households being less prone to the potential negative effects of village inequality. The channel through which inequality affects growth was found to be unobserved village institutions at the start of economic reforms in rural China. However, while the authors provide evidence for income inequality and growth, the initial inequality of landholdings is likely to matter more than that of income in light of the importance of land among productive assets.

2.6 CONCLUSION

From the literature review, it is evident that analyses involving inequality-growth linkages should consider the two processes simultaneously. Furthermore, such analyses should be conducted using econometric techniques that simultaneously and adequately solve for endogeneity, autocorrelation and unobserved heterogeneity if their results are to be valid for statistical inference. The KR-3SLS procedure seems more appropriate in addressing the econometric issues usually encountered, however, for short time periods and less pronounced serial correlation, the SGMM is equally attractive, it is unlikely that the KR-3SLS results will differ significantly from the SGMM results in such a scenario. In addition, the endogeneity issue that results from growth and inequality affecting each other can be avoided if one is conducting a household-level analysis of income growth drivers, given the exogeneity of the "Jackknifed" distributions of income or land computed among households within a locality. However, while this aspect of endogeneity is dealt with, remember that the dynamic nature of the model still requires the dynamic panel estimators with twice lagged income instrumenting for past growth. On the other hand, the equality model can be estimated using the first differences or fixed effects estimators while using "Jackknifed" explanatory variables. This means that the analysis would have to proceed at the village or any other localized level. If however, the right hand side variable includes the income gini in period t-1 as opposed to land, the model reverts to a dynamic one and calls for the dynamic panel estimators too.

Whereas a number of studies on inequality-growth linkages have been conducted, a few can be deemed credible because most studies used poor quality data coupled with estimation approaches that might have been inadequate. Among the few studies that are credible, what is clear is that there is a negative relationship between income or asset inequality and the growth of income. But that it is impossible to expunge the endogeneity in growth models, some endogeneity may still exist and the best we can get are correlations as opposed to causal effects (a statement which is subject to debate). With emerging and existing panel data sets for countries in Africa and beyond, there is need to further test this relationship through more rigorous methods and high quality data while keeping in mind the limitations when it comes to interpreting the results. Furthermore, adopting a simultaneous approach to the re-examinations of the growth-inequality relationships provides for a complete set of policy messages and is the right approach for future analyses.

CHAPTER THREE

RESEARCH METHODS AND PROCEDURES

3.1 INTRODUCTION

This chapter presents a description of the analytical methods and procedures used in achieving the study objectives. It also presents the data, data sources, sampling procedures, and the variables used in the empirical model specifications.

3.2 DATA AND SAMPLING

The study used five waves of nationally representative longitudinal data collected in 1997, 2000, 2004, 2007 and 2010. The data are from Egerton University's Tegemeo Institute of Agricultural Policy Research Project (TAPRA) and were collected in collaboration with Michigan State University. The datasets cover small farming households and 8 agro-ecological zones. The surveys elicited household-level information on several variables including but not restricted to farm and off-farm income sources, ownership and operational landholdings, remittances, crop and livestock production and sales, other productive asset ownership, distances to facilities and services, and socio-demographic characteristics of household members.

The sampling was conducted in such a way that within a designated area, all villages were listed while taking into account the Agroecological zones as well as whether the selected district belonged to those districts where TAPRA had conducted much research before. In the first step, the spatial distribution of the various agro-ecological regions was identified following which the districts were divided into divisions, locations and sub-locations and then villages/wards. The list of households within a selected village was then used to randomly select households to be interviewed.

The 1997 sample consists of 1540 interviewed households. A household in this case represents one or more people that live together, eat food prepared from one kitchen and look up to one person as being their head. Out of the 1997 sample, 1,446 were re-interviewed in 2000. In 2004, from a Tegemeo Agricultural Monitoring and Policy Analysis Project (TAMPA) survey comprising 1540 households, 1397 households were re-interviewed. This number declined slightly in 2007, with a total of 1,342 households re-interviewed from the 2004 households. The 2010 sample was composed of only those households that were interviewed in 2007. It covered about 1309 randomly selected households from the original 1,342 households in 2007. So in total, from the five waves of data, there are 1309 panel households covering the 13 year period. For this analysis, 1,188 panel households are used.

3.3 ANALYTICAL METHODS

To achieve the study objectives, the analysis used all five waves of data for the descriptive analysis whilst excluding the 1997 wave in the econometric analysis because education was collected as a categorical variable in that year. The econometric analysis was conducted at two levels, the growth model was estimated at the household level whilst for the equality or gini model, the analysis proceeded at the village level. The first differences estimator was used for the equality model to eliminate the unobserved heterogeneity, while employing "Jackknifed" explanatory variables computed for each household and corresponding to a particular village from the 107 villages in the final sample. The system generalized method of moments estimator was used in estimating the growth model with twice lagged income instrumenting for the lagged dependent variable. A host of "Jackknifed" village controls are used while employing "Jackknifed" land gini coefficients to avoid the endogeneity caused by the reverse causality between growth and inequality. The rest of the endogeneity issues in the growth model are addressed using lagged values of the endogenous covariates. The unit of analysis in this study is the household, covering 1,188 households from which the panel data was collected between 1997 and 2010 in 107 villages. For the econometric analysis, one major concern as in many panel surveys is the issue of attrition bias. More specifically, one is concerned with selection bias resulting from households leaving slow-growing villages. However, for the 13 year panel surveys to be used, the attrition rate between successive years is only 5% and attrition has been observed to be largely random, and as such selection bias due to attrition is unlikely to occur (see Muyanga & Jayne , 2014 who check for possible slection bias resulting from attrition). Aside from the panel attrition problem, this is another panel limitation we have to live with. One side to the story is that analysis can be conducted on the ageing households in the sample and in this case the relationship would be that of the growth and inequality among ageing households and their peers. Ideally, one would be interested in estimating the relationship between the ageing households and all other households in the village (both new and old after controlling for attrition bias). However, it seems impossible to get any such statistically representative relationship. This is one panel limitation we have to live with. Nevertheless, the village-level differences in the ginis from the panel are likely to be highly correlated with the unobserved village-level differences in the ginis from a statistically representative survey (if it were available), so at least the coefficient on the ginis is largely picking up the effect of the "true" village-level differences in land concentration. The same logic can be extended to the other village-level variables constructed using the panel sample. So in summary, we can still say something about what is happening in the villages even by using a panel sample.

3.4 MODEL VARIABLES AND THE ESTIMATION STRATEGY

The empirical specifications for the household- and village-level models is as shown in equations (15) and (16) respectively, the selection of variables included in the empirical models for net income growth and income gini determinants was guided by the literature.

$$lny_{i,vt} = \tau_{1t} + \beta_1 lny_{i,vt-1} + \beta_1 \overline{lny_{(-\iota)vt-1}} + \beta_3 g_{-(i),vt-1} + [\delta'_{1q}\mathrm{q}] + e^*_{1it} \qquad (15)$$

$$d_{i,vt} = \tau_{2t} + \beta_1 \overline{lny_{(-\iota)vt-1}} + \beta_2 g_{-(i),vt-1} + [\delta'_{2q} q] + e^*_{2it} \qquad (\mathrm{t}=1,\ldots,\mathrm{T}) \qquad (16)$$

Where τ_{nt} is the time-specific effect, $lny_{i,vt}$ denotes the change in the natural logarithm of net income per adult equivalent for household *i* between time period t and t-1, while $lny_{i,vt-1}$ represents its lagged value. $\overline{lny_{(-\iota)vt-1}}$ denotes the change in the village mean log income for other households excluding household *i*, $d_{i,vt}$ denotes the change in the localized distribution of income for village v between period t and t-1, $g_{-(i),vt-1}$ represents the change in the "Jackknifed" initial distribution of landholdings in village v between period t and t-1. While the vector q contains the change in other village-level conditioning variables including distance to motorable road, distance to fertilizer seller, and the village population density between period t and t-1. It also contains each household's average level of education, and the average operated landholding size per adult equivalent for the growth model only, while these variables enter equation 16 correlates model in Jackknifed form (i.e. village-level; averages computed for households excluding household *i*). The variables used are defined in Table 1.

Table 1: Variables used and their definitions

Variable	Definition
Net income per adult equivalent	Includes all off-farm, crop and livestock income less expenses in natural logarithm form.[33]
Size of operational holdings per adult equivalent	Includes all land used in part or in whole for agricultural production irrespective of ownership status.
Average education	Average years of education per household or village
Mean land gini coefficient	Distribution of operational holdings per adult equivalent at the village level.
Income gini coefficient	Distribution of net-income per adult equivalent at the village level
Population density	Number of persons per square Kilometer in each village.
Distance to motorable road	Distance in Kilometers from household to a motorable road
Distance to point of fertilizer/input purchases	Kilometer distance to nearest point of input purchases

In growth regressions, income growth and the time-varying land and income distributions are likely to be endogenous. However, since the household level formulation for the growth model employed "Jackknifed" land gini coefficients computed for each of the households within a village, each households land gini coefficient is exogenous. In addition, to avoid the inconsistency in the estimates resulting from the dynamic nature of the growth model, the SGMM estimator was used, this means that income in period t-2 is used as an instrument for the change in income in period t-1. There is also reverse causality between the level of education and income growth. Thus, the lagged values of a household's average level of education was used as an instrument for the time-varying average education levels.

For the distribution equation, the change in income inequality in period t is regressed on a host of "Jackknifed" village level variables. Because the explanatory variables are in Jackknifed form, there are no problems relating to endogeneity. Moreover, the fact that these correspond to all the households in the sample, one is able to analyze the model using

[33] The village level mean income is computed as the mean of the natural logarithm of net income per adult equivalent from all sources and it is computed using the Jackknife procedure.

a larger dataset. Village-level explanatory variables used in this equation include the average level of education, distance to motorable roads, distance from a fertilizer seller, the mean land gini coefficient, and the population density.

CHAPTER FOUR

TRENDS IN SELECTED KEY VARIABLES

4.1 INTRODUCTION

As a curtain-raiser to the econometric analysis, this chapter presents an analysis of the trends in selected key variables. The relationship between land and non-land productive assets among rural farming households is explored. I also test for the presence of multiple equilibria in the dynamic path of operational landholdings to better understand growth and prospects for rural poverty reduction. The chapter also presents a descriptive analysis of the trends in land and income distribution in addition to other selected sample characteristics both at the village and household levels.

4.2 THE RELATIONSHIP BETWEEN LAND AND NON-LAND PRODUCTIVE ASSETS

In a large body of literature, it is highlighted that land assets are a major productive asset in primarily agrarian societies. It is cited as one of the three core assets required to increase the role of agriculture in poverty reduction, others are human capital and water for irrigation. The three assets determine the ability of households to participate in agricultural markets, secure livelihoods in subsistence farming, compete as entrepreneurs in the rural nonfarm sector, and find skilled employment (World Bank 2007). However, while the accumulation of land assets is important, the accumulation of other productive assets such as draft animals and equipment is also essential for the poverty reduction process. This is because a household's income earning potential will depend to some extent on their productive asset ownership. [34]Typically the value of land assets exceeds that of non-land productive assets. In particular, the ratio of land to non-land productive assets is expected to be large for the very resource poor households who mainly do not own any, or own very few non-land productive assets such as draft animals and equipment. On the other hand, for the relatively "richer" households, the ratio is expected to be relatively smaller.

[34] "..Households that can steadily accumulate assets or who enjoy steady technical change or favourable shifts in their terms of trade will grow their way out of poverty. Among very poor populations, this growth could take some time, but movement nonetheless proceeds steadily in the right direction…" (Carter & Barret 2006).

Table 2: Trends in inequality, and the relationship between productive assets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Percentiles					
VARIABLES[35]	Year of survey	mean	p10	p25	p50	p75	p90	p95
Cultivated land per adult equivalent (Ha)[36]	1997	0.411	0.131	0.198	0.320	0.536	0.831	1.038
	2000	0.327	0.0706	0.113	0.204	0.369	0.668	0.969
	2004	0.285	0.0851	0.134	0.228	0.376	0.596	0.743
	2007	0.276	0.0880	0.132	0.206	0.358	0.569	0.692
	2010	0.258	0.0837	0.122	0.195	0.331	0.525	0.674
Owned land per adult [37]equivalent (Ha)	1997	0.437	0.0438	0.111	0.23	0.469	0.998	1.47
	2004	0.555	0.0879	0.16	0.293	0.609	1.31	1.923
	2007	0.576	0.0882	0.159	0.291	0.606	1.248	1.922
	2010	0.562	0.0910	0.161	0.289	0.579	1.195	1.736
Value of non-land productive assets (constant 2010, KSh.)	1997	13,260	0	270.9	1,333	5,478	19,739	49,198
	2000	11,884	0	295	1,387	5,598	21,775	59,990
	2004	14,906	0	355.5	1,629	7,432	27,293	69,110
	2007	14,681	316.6	818.2	2,060	6,575	23,231	58,060
	2010	13,734	0	327.1	1,667	7,834	28,157	76,337
Value of owned land assets (constant 2010 KSh.)	1997	76,588	4,190	13,765	34,431	79,240	163,828	277,174
	2004	99,125	8,994	18,963	44,122	103,094	241,546	390,789
	2007	107,256	8,803	18,856	44,544	108,271	255,556	419,907
	2010	103,926	8,475	19,208	42,929	107,852	211,628	361,446
Proportion of land to non-land assets	1997	47.81	0.788	4.481	15.58	45.50	113.5	189.2
	2004	89.23	2.260	6.214	23.01	69.04	186.4	316.8
	2007	60.92	2.857	7.315	20.14	47.38	113.3	217.2
	2010	101.5	1.996	5.525	19.53	60.48	175.0	346.7
Income gini [38]coefficient (localized)	1997	0.389	0.273	0.34	0.381	0.455	0.498	0.561
	2000	0.368	0.228	0.298	0.369	0.424	0.5	0.563
	2004	0.385	0.283	0.332	0.388	0.442	0.497	0.511
	2007	0.343	0.22	0.277	0.367	0.402	0.445	0.486
	2010	0.379	0.244	0.313	0.38	0.457	0.509	0.535

Continued

[35] The statistical significances of the differences in group means are provided for in the appendices.
36 The cultivated land values are only for the main agricultural season. The short season is excluded from the analysis.
37 In 2000, data collected on owned land was incomplete, and this is excluded from the table.
38 The proportions are computed for 85% of the sample in 2000 and 2010, 81% in 1997, 89% in 2004 and the full sample in 2007.

Table 2: continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Percentiles					
VARIABLES[39]	Year of survey	mean	p10	p25	p50	p75	p90	p95
Distribution of operational landholdings at the village level (gini coefficient)	1997	0.283	0.180	0.225	0.278	0.349	0.382	0.396
	2000	0.297	0.198	0.242	0.308	0.357	0.395	0.414
	2004	0.312	0.205	0.263	0.309	0.360	0.422	0.451
	2007	0.309	0.204	0.250	0.314	0.370	0.411	0.438
	2010	0.303	0.209	0.258	0.295	0.361	0.400	0.411
Income mean log deviation (village-level)	1997	0.319	0.133	0.212	0.302	0.415	0.486	0.603
	2000	0.277	0.105	0.169	0.251	0.347	0.486	0.602
	2004	0.283	0.141	0.198	0.266	0.344	0.452	0.519
	2007	0.225	0.0990	0.136	0.233	0.290	0.364	0.416
	2010	0.284	0.105	0.176	0.260	0.373	0.506	0.579
Distribution of operational landholdings at the village level (mean log deviation	1997	0.153	0.0639	0.0998	0.136	0.203	0.260	0.290
	2000	0.169	0.0720	0.102	0.164	0.229	0.287	0.335
	2004	0.186	0.0842	0.119	0.171	0.230	0.312	0.381
	2007	0.182	0.0804	0.114	0.185	0.242	0.287	0.336
	2010	0.171	0.0850	0.122	0.149	0.222	0.276	0.295

Source: Author's calculations using the 1997, 2000, 2004 and 2007 TAPRA rural household surveys

To kick off the discussion, consider the trends in the land owned and operated in Table 2. Overall, between 1997 and 2010, the general trend points towards a decline in the average size of operated landholdings[40], with operated land having declined by about 37.2 percent between 1997 and 2010 from an initial 0.411 hectares per adult equivalent perhaps as households subdivide their land to future generations (Muyanga & Jayne 2014). This is exactly in tandem with the observation by Jayne et al., (2014) on the declining farm sizes across sub-Saharan Africa.

[39] The statistical significances of the differences in group means are provided for in the appendices.
[40] Operational landholdings refer to all land used wholly or in part for agricultural production irrespective of ownership status.

However, while this is true for operated land, the trends in the size of owned land point to a slight increase from an initial 0.44 hectares to 0.56 hectares per adult equivalent betweeen 1997 and 2010. Note that in the year 2000, the data collected on owned land was incomplete and this has been excluded from the table. With a decline in area operated per adult equivalent and an increase in owned area, it is likely that the increase in owned area is associated with titling, or acquisition of other forms of stronger ownership rights by households[41]. Note that Boserup-Ruthenberg would expect this solidification of land rights as a direct consequence of higher population pressure (see Boserup, 1965 or Binswanger-Mkhize & Savastano, 2014 for a summary).

With respect to the values of land[42] and non-land assets, the general trend is towards a very slight increasing value of non-land productive assets. Between 1997 and 2010, the value of non-land productive assets grew by 3.6 percent. The land assets grew in real value by about ten times that of non-land productive assets with a growth of about 36 percent. The observed sharp increase in the real value of land owned is partly a direct consequence of the rise in owned land as earlier discusseed, but more propagated by the land scarcity. At the same time, the ratio of the value of land to non-land assets increased from an initial 47.8:1 to 101.5:1 between 1997 and 2010. The general rise in the value of non-land assets did not keep up with that of land assets because of the land scarcity and its value thereof as well as of the failure to invest in response to land scarcity[43].

A look at the dynamics of inequality shows that overall inequality in the operational landholdings at the village-level increased. The land gini coefficient rose from 0.283 in 1997 to 0.303 in 2010 with the highest values having been observed in 2004 and 2007 at 0.313 and 0.309 respectively. However, the mean land gini is not entirely reflective of the extent of inequality as it averages out the various indices across villages. To do this the gini coefficients at the 10th and 90th percentiles are considered and the changes thereof. The most unequal villages had land gini coefficients as high as 0.396 for the 90th percentile in 1997 and this increased to 0.411 in 2010, the relatively more egalitarian villages had land gini coefficients of 0.180 in 1997 and this increased to 0.209 in 2010 for the 10th percentile.

[41] The nature of the secure ownership rights depends on the system of land use in place (Boserup, 1965).
42 The value of land assets is computed using the land rental rate collected in the surveys and the size of owned land.
[43] Important to keep in mind in this regard is the fact that the assets used are only those common to the five survey years.

However, the story behind the dynamics in the gini coefficient of net income per adult equivalent is different. It shows a slight decline between 1997 and 2010, with the gini coefficient having slightly reduced from an initial 0.39 to 0.38. A possible explanation is that the rural non-farm sector must have been the source of most of the income that brought about this change. The most unequal villages in 1997 with respect to income had gini coefficients averaging 0.56 for the 90^{th} percentile in 1997, this reduced slightly to 0.54 in 2010. On the other hand, the more equal villages had gini coefficients averaging about 0.39 in 1997 for the 10^{th} percentile and this value reduced slightly to 0.38 in 2010. Note that inequality measured using the mean log deviation reveals the same trends for both income and land assets.

One very important consideration in as far as analysing the dynamics of land inequality using panel household-level data is concerned is that these datasets do not adequately capture the changes in farm structure overtime and this tends to reduce the computed land gini coefficients. Note that there are also other factors that may have a downward effect on the land gini coefficient (examples include movement of labour into and out of the villages and subdivision of land). To shed more light on this, note that much of Africa has shown a rapid rise in the number of absentee landowners in the rural areas. These are mainly urban-based individuals that procure medium to large portions of land and hire their relatives or other workers to manage the farms on their behalf. They are mainly former civil servants with a good educational background and they make up about 60 percent of the medium-scale farmers in Kenya and 58 percent in Zambia. (Jayne et al. 2014). Because the rural livelihood surveys such as the World Bank’s living standards measurement surveys (LSM) or the one used in this study sample all households as opposed to farms, they will not capture any such landowners and the resulting changes in farm structure. In fact, Lowder, Skoet and Raney, (2015) find striking differences in the size of land computed using the nationally representative LSMS-type surveys and that computed using the agricultural censuses which are representative of all farms and thus include the absentee managed landholdings. Thus, in the unlikely event that rural household surveys capture the changes in farm structure overtime, this shortcoming has an effect of underestimating the changes in the village land gini coefficient and ultimately the effect that it may have on agricultural growth's poverty reduction potential[44].

In Table 3, results of an ordinary least squares regression are presented to better understand how the gini coefficients relate to the distance to the nearest town or headquarters. The data supports a linear relationship between the gini coefficients and the distance to town. As such, a linear regression is estimated. The regression results show that the distance to town is negatively related to both the land and income gini coefficients. But the marginal effects on the two are almost the same (0.0011 for the land gini and 0.0009 for the income gini). Even the intercepts show the same magnitude. This means that inequality decreases as distance to town or district headquarters increases. But to fully examine this relationship we plot both gini coefficients against the distance to town.

Table 3: The relationship between inequality and distance to nearest district

VARIABLES	(1) Income gini	(2) se	(3) Land gini	(4) se
Distance to nearest town or headquarters (Km)	-0.0009***	(0.000)	-0.0011***	(0.000)
Constant	0.3557***	(0.004)	0.3214***	(0.004)
Observations	1,188		1,188	
R-squared	0.0110		0.0157	
Adj. R-squared	0.0102		0.0149	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3 IDENTIFYING THE DYNAMIC PATH OF LAND ASSETS IN RURAL KENYA

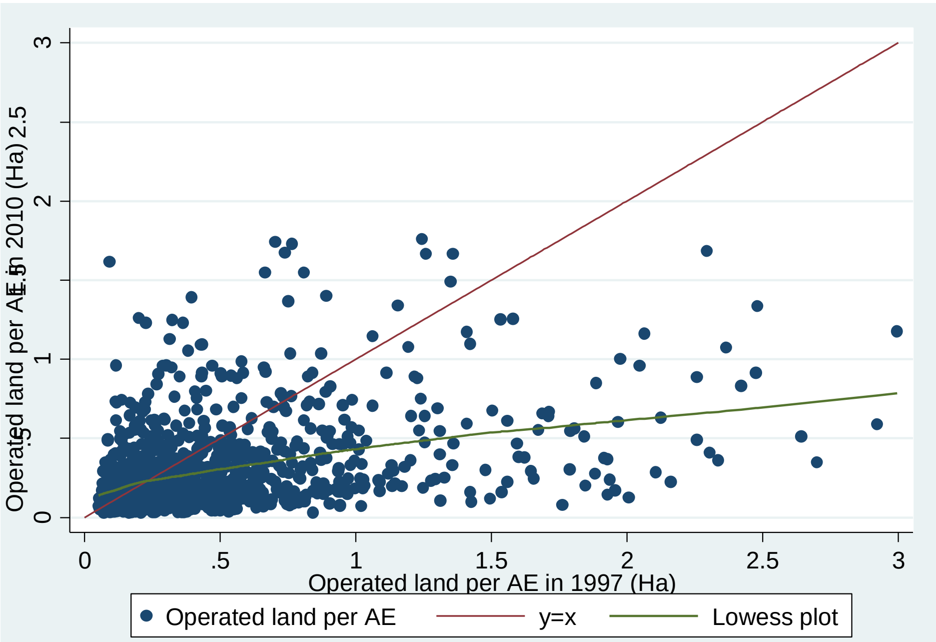
Given the importance of the accumulation of land among other productive assets, a number of studies have looked at the asset-accumulation models[45] exhibited in various countries with the aim of explaining the poverty traps observed. In Figure 1, the Lowess regression

[44] Also note that how inequality is computed matters, the localized gini coefficient will most likely differ from the gini coefficient computed over the entire sample.

[45] Carter and Barret, (2006) present a theory of asset-based poverty traps based on household asset accumulation overtime. Three models of asset accumulation are presented, one of these is the S-shaped accumulation model which shows multiple equilibria, whilst the others relax the assumption that households share a common dynamic asset path (i.e. conditional convergence models). Other examples of such studies include one by Giesbert and Schindler, (2012) in Mozambique and another by Kjuipers et al., (2013) in Uganda.

plot for operated land assets[46] is presented to identify the dynamic path of operated land assets in rural Kenya. Results show that there is no evidence of a poverty trap that is based on multiple equilibria in the dynamic asset path of operational landholdings as the Lowes plot crosses the 45 degree line at only one point. This tends to occur at around 0.23 hectares of operational landholdings per adult equivalent (AE). The 0.23 hectares per adult equivalent represents the threshold operational landholding size for Kenyan rural households if their welfare is to improve via expansion of operated land, but of course this is not the only pathway to welfare improvement. Others include the accumulation of non-land capital and employment in the non-farm sector.

Figure 1: Bivariate Lowess plot of the 2010 against the 1997 operational landholdings per adult equivalent



Source: Tegemeo Rural Household Surveys (1997 and 2010)

In light of the continued downward trend in operated land, it is unlikely that households will escape poverty in rural Kenya via expansion of operated land, that is to say, because there is no more expansion in the operated area, escape out of poverty through this mechanism is blocked. The result of the Lowess plot also shows that households drift towards a single stable equilibrium. This is in contrast to the observed dynamics relating to

[46] Note that for this analysis, normally one would use owned land. But because it is likely that the growth in owned land is likely due to a solidification of more secure ownership rights, analysis using operational landholdings is more appropriate.

non-land assets observed by Barrett et al., (2006) who found the existence of multiple equilibria in the dynamic asset paths of livestock in Northern Kenya

In Table 4, further sample characteristics are presented. Of particular interest are the years of education of household members and the net income per adult equivalent (hereafter income) as they form an integral part of the econometric analysis. What is immediately noticeable is that between 1997 and 2010, net household income per adult equivalent increased from 49,385 Kenyan shillings to 66,594 shillings. With trends in non-land assets pointing towards a very slight increase in real value, and because the operated land declined, it is likely that the observed increase in income came from the rural non-farm sector but this will have to be analyzed further.

Table 4: Selected Sample Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Percentiles					
VARIABLES	Year of survey	mean	p10	p25	p50	p75	p90	p95
Net income per adult equivalent (constant 2010 KSh.)	1997	49,385	8,020	16,750	34,588	65,364	103,150	143,006
	2000	59,996	11,799	21,795	43,651	78,701	129,216	173,866
	2004	56,865	11,407	20,186	38,617	71,439	129,654	180,536
	2007	53,441	13,749	20,710	37,921	69,143	119,832	155,989
	2010	66,594	12,318	20,616	43,125	85,002	159,032	212,264
Average years of education	1997	n/a[47]	n/a	n/a	n/a	n/a	n/a	n/a
	2000	5.64	2.83	4.10	5.48	7.22	8.67	9.57
	2004	5.75	2.60	3.75	5.25	7.29	9.50	11.17
	2007	6.19	3.00	4.48	6.00	7.78	9.71	10.67
	2010	6.65	2.86	4.67	6.46	8.33	10.50	12.29
Distance to motorable road (Km)	1997	1.08	0.00	0.05	0.50	1.50	3.00	4.00
	2000	1.24	0.01	0.10	0.50	1.50	3.00	6.00
	2004	1.05	0.02	0.10	0.50	1.50	3.00	4.00
	2007	0.51	0.05	0.10	0.20	0.50	1.00	2.00
	2010	0.44	0.00	0.05	0.20	0.50	1.00	2.00

Continued

[47] In 1997, education was collected as a categorical variable and is thus not reported here.

Table 4 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Percentiles					
VARIABLES	Year of survey	mean	p10	p25	p50	p75	p90	p95
Distance to electricity (Km)	1997	5.39	0.30	1.00	3.00	6.00	12.00	16.00
	2000	4.92	0.20	1.00	2.50	6.00	11.00	17.00
	2004	4.20	0.20	1.00	2.00	4.25	10.00	20.00
	2007	3.96	0.10	0.50	2.00	4.00	8.00	17.00
	2010	1.65	0.00	0.30	1.00	2.00	4.00	5.00
Distance to health center (Km)	1997	4.12	1.00	2.00	3.00	6.00	8.00	12.00
	2000	3.27	0.50	1.30	2.50	4.00	7.00	8.00
	2004	2.74	0.50	1.00	2.00	3.50	6.00	7.00
	2007	2.99	0.75	1.00	2.00	4.00	6.00	8.00
	2010	2.89	0.90	1.35	2.00	4.00	5.20	7.00
Distance to fertilizer seller (Km)	1997	8.27	1.00	1.50	3.50	10.00	24.50	32.00
	2000	5.60	0.50	1.00	2.50	7.00	14.00	23.70
	2004	3.88	0.50	1.00	2.00	4.00	7.00	12.50
	2007	3.23	0.50	1.00	2.00	4.00	6.00	8.00
	2010	3.68	0.50	1.50	3.00	5.00	8.00	10.00
Village population density (people per Sq. Km)	1997	324.5	135.3	221.4	308.6	423.6	547.2	577.6
	2000	486.8	169.7	310.2	456.6	627.3	886.1	964.6
	2004	496.0	233.4	330.9	467.5	599.1	773.6	1,017
	2007	530.1	222.6	366.7	511.3	682.0	775.1	947.1
	2010	575.5	270.3	279.6	401.9	537.2	706.6	928.4
Distance to nearest district/headquarters (Km)	1997-2010	12.03	3.00	5.00	8.35	17.00	26.00	30.00

Source: Author's calculations using the 1997, 2000, 2004 and 2007 TAPRA rural household surveys

The level of education among household members in the sample exhibits an upward trend. In 2000, it was 5.6 years and this rose to 5.8 and 6.2 in 2004 and 2007 respectively. It finally ended up at 6.7 years in 2010 indicating a rise in education by more than a year. Thus, there is a general upward trend in the human capital characteristics relating to education among rural Kenyan households.

The accessibility of the villages and households did improve over the 13 year period. In 1997, households were on average located within 1.1 Km from motorable roads. Since 2000, the distance declined significantly to only 0.44 Km in 2010. Opportunities to access electricity also improved with the average distance of households from a point of electricity access declining from an initial 4.1 to 2.9 Km in 2010. Thus, it appears that investment in rural infrastructure such as roads and electricity did occur between 1997 and 2010.
Even the distance to a point of fertilizer purchase declined over the 13 year survey period. In 1997, fertilizer sellers were located about 8.3Km away. This reduced to 3.7Km by 2010 indicating that input markets are coming closer to the villages than was the case in 1997. On average, the surveyed rural households are located within 12Km of the nearest district/headquarters. The remoteness ranges from 3 Km for households at the 10th percentile to about 30Km at the 90th percentile. Health centers were located closer to households in 2010 than they were in 1997 with the average distance form a health center having declined from 4.1 to 2.9Km. In 1997, the furthest households from a health center were located 12Km away while this reduced to within 5Km (10th percentile). The nearest households to a health center were located within 1Km and 0.9Km in 1997 and 2010 respectively (all values at the 10th percentile).

The average village population density has been on the rise with the number of persons for every square kilometer having risen sharply from about 325 in 1997 to 576 in 2010. In 1997, the most densely populated villages had 578 people per square Kilometer and this number rose to 928 in 2010 at the 90th percentile of the distribution. On the other hand, the least populated villages (10th percentile) had only 135 persons for every square Kilometer, this number rose to 270 people per square Kilometer in 2010 at the 90th percentile of the distribution. This trend is one of the fundamental reasons for the land pressures being observed and the adverse effect of population density on household incomes in rural Kenya as highlighted by Muyanga and Jayne, (2014).

CHAPTER FIVE

THE EFFECT OF LOCALIZED INITIAL LAND DISTRIBUTION ON INCOME GROWTH AND DISTRIBUTION

5.1 INTRODUCTION

This chapter addresses the core of the thesis; it presents a discussion on the growth and inequality covariates. It presents the empirical findings relating to the hypothesis that village-level land inequality does not detrimentally affect the contribution of agricultural productivity on income growth in rural Kenya. Secondly, it also provides evidence for the hypothesis that village-level land inequality does not detrimentally affect the contribution of agricultural productivity growth on income distribution.

5.2 RESULTS OF THE ECONOMETRIC ANALYSIS

To begin the discussion, note that this the first study that eliminates the individual-specific effect while employing the "Jackknife" procedure to fully solve for the endogeneity problem. As a result, the pure effect of inequality on growth is isolated since the effect of the underlying mechanism that generated initial inequalities does not need to be isolated anymore[48].

In Table 5, the results of the effects of various covariates on income growth are presented. Estimates are obtained using the system generalized method of moments (SGMM) which is a dynamic panel data estimator that combines equations in levels and in first differences[49]. Firstly, after controlling for the mean size of operated land among other households in the village and holding other things equal, the size of a household's own operational landholdings is seen to have a positive effect on income growth at the 99% confidence level. This result is in tandem with the finding of Lundberg and Squire, (2003) who found that the mean land size positively influences income growth. The relative magnitude of the

[48] Section 2.4 discusses these issues and how Benjamin, Brandt and Giles, (2011) argue their case against discussing their results as depicting causal effects but rather as correlations.
[49] Section 2.3 of the literature review discusses the various estimators relevant to modelling growth and inequality.

coefficient (0.567) is of particular interest and further affirms the importance of expanding operated land for income growth among rural Kenyan households. But given that land is already constrained, this is unlikely. This is particularly important given the decline in operational landholdings across the survey period, and the results relating to poverty traps based on the failure to expand operated land among the households.

In addition to this, what is evident is that after controlling for the level of education among other households in a village, a household's own education has a positive impact on growth. This relationship is significant at the 95% confidence level even though the impact of own education on growth is about 8 times less than that exhibited by that of own operational landholdings. Thus households with more educated members are expected to have faster income growth than those with less educated members, else equal.

Table 5: The Drivers of Income Growth.

VARIABLES	(1) Income growth	(2) se
Household's past income growth	-0.0125	(0.063)
Past income growth in a village ("Jackknifed")/100	-0.0003***	(0.000)
Village land gini coefficient ("Jackknifed")	-0.5117***	(0.163)
Household's average level of education	0.0721**	(0.034)
Average level of education in a village ("Jackknifed")	0.0551**	(0.026)
Household's operational landholding size per adult equivalent (hectares)	0.5670***	(0.200)
Average operational landholding size in a village ("Jackknifed") (hectares)	-0.3585*	(0.217)
Village population density persons/1000 Sq. Km	-0.3261**	(0.147)
Distance from motorable road (Km/100)	0.1415	(1.290)
Distance from a fertilizer seller (Km/10)	0.0407	(0.035)
Observations	2,376	
Number of households	1,188	
Wald Chi-square joint significance test (10 df)	86.60***	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

However, while a household's own education and the size of own operated land have positive effects on growth[50] *ceteris paribus*, the same cannot be said about the village-level population density, the past growth among other households in a village, and the initial land gini coefficient values whose coefficients are negative. What is evident is that holding other things constant and after controlling for growth among other households in the village, own past growth is not a factor in explaining a household's future income growth, even though the past growth among other households in a village is seen to exert a significant and negative effect on the growth of a household's income at the 99% confidence level perhaps while working via the labor market or final demand. However, the size of the impact is almost zero.

In addition, *ceteris paribus*, the operational land gini coefficient at the village level significantly and negatively impacts growth at the 99% confidence level. The negative effect of the land gini coefficient confirms the hypothesis that existing inequalities in the initial distribution of operational landholdings at the village level impede growth of incomes across households. This finding is supported by Benjamin, Brandt and Giles, (2011) using household-level data in China as well as Lundberg and Squire, (2003) with cross country evidence. Thus, one would expect households resident in villages with more unequal distributions of land to grow at lower rates than those where it is more egalitarian. While the *ceteris paribus* effect of the village land gini coefficient on growth is shown to be -0.512, this may be an underestimation as explained in section 4.2.

With respect to village population density and how it affects growth, results indicate that holding other things equal, population density has a negative effect on growth, with the coefficient exhibiting statistical significance at the 95% confidence level. This means that holding everything else constant; households resident in villages with higher population densities are more likely to experience reduced growth than in those where it is less dense. Because operational landholdings and other variables are held constant, one possible explanation is that rural wages which act as a source of income among the household members could be declining as the population density in these villages rises. There is no

[50] Important to note here is the fact that while these coefficients are positive in the regression output, the fact that operated land sharply declined across the 13 year period means that income growth from agriculture is also expected to have been adversely affected other things being equal, but with the rural non-farm sector also contributing to household income, the decline from agriculture is likely to have been buffered by non-farm income,

evidence that accessibility indicators as measured by the distance to fertilizer seller and to motorable roads had anything to do with income growth.

In Table 6, the results of the causal effects of various covariates on income inequality are presented. There is a positive effect of inequalities in the distribution of operational landholdings at the village level on the village-level income distribution at the 99% confidence level. This means that other things being equal, existing inequalities in the initial distribution of operational landholdings perpetuated income inequalities at the village level and this impact is almost one to one. Similar to the growth results, the magnitude of this impact may be understated as earlier alluded to. The results on the land gini coefficient are in agreement with conventional theory that income inequality is significantly and positively related to the initial inequality in the distribution of operational landholdings among other productive assets. They complement the cross country findings of Lundberg and Squire, (2003) who confirm the existence of the positive relationship for the less developed countries even though no significant relationship exists for all countries.

Table 6: The Drivers of Income Inequality

VARIABLES	(1) Income Gini	(2) se
Operational land-holding gini (Jackknifed)	0.9230***	(0.006)
Village mean income (Jackknifed)/1000	-0.0001**	(0.000)
Mean education in a village (Jackknifed)/1000	0.0002	(0.001)
Mean operational land-holding size in a village (Jackknifed)	0.0157*	(0.009)
Village population density persons/1000 Sq.	-0.0061	(0.004)
Distance from motorable road in Km/100	-0.0398	(0.040)
Distance from a fertilizer seller Km/10	0.0022	(0.001)
Observations	3,564	
Adj. R-squared	0.8924	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Furthermore, the results highlight that with other things being equal; there is a negative impact of village mean income on income inequality at the 95% level of significance.

However, the magnitude of this effect is very small. There is also a positive effect of the average operational landholding size on income gini holding other variables constant. This implies that *ceteris paribus*, a decline in operated landholdings per person is expected to reduce income inequality at the village level and vice-versa. The data does not support the existence of a relationship between population density and income inequality, as well as the distances to motorable roads and fertilizer sellers.

CHAPTER SIX

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.1 INTRODUCTION

This chapter presents a summary of the study and concludes based on the findings. It also presents recommendations relating to rural development based on the econometric results. It also highlights some implications for future growth and inequality modeling based on the experience.

6.2 SUMMARY AND CONCLUSIONS

If agricultural growth is to reduce poverty while creating an equitable society, a comprehensive understanding of the effect of initial land distribution on growth and income distribution remains an important issue for the development agenda. Against this background, this study sought to (i) describe the inequality dynamics in Kenya across time and space (ii) determine the effect of initial land distribution on rural income growth, and to (iii) determine the effect of initial land distribution on income distribution for the period 1997-2010. The main findings of the descriptive and econometric analyses are summarized in sections 6.2.1 and 6.2.2 respectively.

6.2.1 Summary of the descriptive analysis results

In rural Kenya population density is rising, farm sizes are declining fairly rapidly, inequality in land holdings is increasing slightly and in incomes it is decreasing slightly. More specifically:

Because of rapid population growth and limited rural-urban migration, rural population density has been rising rapidly.

Operational land-holdings are declining sharply in Kenya, in line with the very rapid population growth. Operated land declined by 37.2 percent between 1997 and 2010 from an initial 0.41 hectares per adult equivalent.

The operational landholdings in this particular national panel data set are becoming slightly more concentrated with the gini coefficient having increased from 0.283 to 0.303 between 1997 and 2010.

Because the study relies on household data, farms with absentee landowners are not included in the sample. As such this reduces the change in the magnitude of the land gini over time. The land gini is also affected by other factors such as movements of labour into and out of the village and subdivision of land. These are not captured by the panel sample

Income inequality exhibited a slight but statistically significant reduction from 0.39 to 0.38. The distribution of both income and operational landholdings inequality spatially is such that it is higher for villages located far from the district/headquarters. Both equality measures respond by almost the same magnitude to changes in distance to the nearest district (i.e. marginal effect=0.0001).

6.2.2 Summary of the econometric results

The population density is rising in rural Kenya, and consequently, operational landholdings are declining. This has caused a reduction in the growth of household incomes. This shows that households have been unable to compensate for their losses in land by higher output and profits per hectare.

There is a growth-enhancing effect of the average level of own household education. The result on education means that improved education is one way through which growth can be achieved.

For the period under study, inequalities in the distribution of operational land-holdings at the village level did impede growth of household incomes. The size of the *ceteris paribus* impact of the village land gini coefficient on income is estimated at -0.512, The size of a household's owned landholdings is seen to have a positive and significant effect on income growth.

Unsurprisingly, therefore, the increase in inequality in the distribution of operational landholdings increased income inequality at the village level almost one to one.

The regression results do not tell us anything about the mechanisms by which inequality reduces growth.

Analysing the causal relationship between inequality and growth is perhaps one of the most difficult tasks in the empirical economics. Using household- or farm-level panel data for analyzing growth and inequality is one way to get around the data problems that have plagued the majority of the growth empirical works and is likely to be the future of the growth empirics. But even with panel data, there are shortcomings that come with using such datasets, given that they fail to account for changes in farm structure as earlier alluded to in section 4.2. In addition, while we are able to say something about the inequality-growth relationship using panel studies we need to acknowledge that the computed gini coefficients using such data only approximate the `true' gini coefficients (those computed using a representative survey). Using the "Jackknife" procedure effectively addresses the many endogeneity related challenges and the associated difficulties in finding instruments in as far as modeling growth and inequality is concerned.

6.3 IMPLICATIONS FOR FUTURE RESEARCH

While this study identifies the effect of land inequality on growth and income distributions and vice-versa, as well as how inequality is distributed across time and space in rural Kenya. It does not look at the lagged impacts through the household and village income variables that would modify the medium- to long-run results. A simulation over 5-10 years would help understand if at all the indirect effects reinforce or mute the direct effects.

Furthermore, the study does not fully look at the "why's" of the dynamics relating to the spatial distribution of inequality. A further analysis into this issue could yield more insights into the reasons behind the observed spatial distribution of inequality.

It also does not identify the channels through which inequality relates to growth and this remains a subject for further analysis. It seems plausible that this result could be driven by the farm-size productivity relationship and this makes a case for future research. Identification of the channels through which inequality relates to growth can be done by studying what could have transpired in the Kenyan villages across the sample, perhaps by looking into power relations at the village level and how these could have led into land concentration. This can be done for selected locations in the country. A country-wide survey is unlikely as it would be a tedious and costly process. Another subject for further research is the impact of income growth on poverty in Kenya and this could also be analyzed together with the farm-size productivity relationship to better understand the trends in poverty over the 13 years.

6.4 MAIN IMPLICATIONS

Based on these findings, the study proposes the following if agricultural growth is to realistically advance income growth while reducing income inequalities.

The negative effect of inequalities in the distribution of operational landholdings at the village level on agricultural growth should be considered in Kenya's rural development agenda. It means that in programs to achieve higher agricultural growth, the poorer households are less able to benefit than those better off, and the programs will have a lower impact on poverty reduction than under conditions of relative landholding equality. What happens to the distribution of landholdings is therefore very important to the potential poverty impact of any growth enhancing innovation or program. Government needs to be very vigilant that their policies and programs do not facilitate aggregation of landholdings in fewer hands. For these reasons, land policies may have profound effects on the effectiveness of national agricultural and poverty reduction strategies.

In addition, the results relating to the impact of land inequality on income growth and distribution have implications on how African governments that still have unallocated land should allocate the remaining land (for example Zambia). Instead of allocating the remaining arable land by means of large farm-blocks that ultimately increase inequalities in the distribution of landholdings; the best alternative could involve allocating land by means of small-medium parcels ranging from 5-20 hectares. This way the land is divided among more people and the effect of inequality on growth could be less than if the alternative policy is adopted. But again one has to have an understanding of the farm-size productivity relationships to better identify the efficient farms in these countries.

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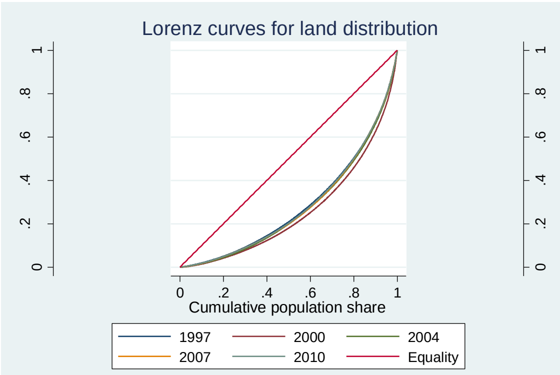
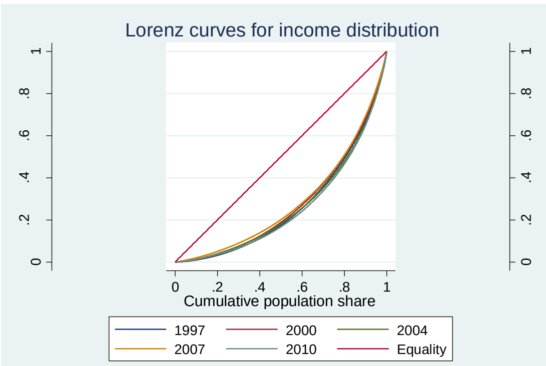
APPENDICES

Figure 2: Lorenz Curve for the distribution of operational landholdings



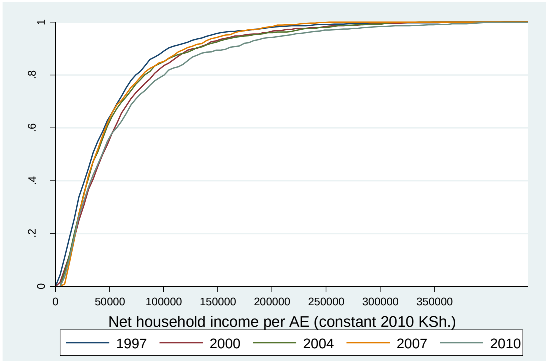
Source:Tegemeo Rural Household Surveys (1997, 2000, 2004, and 2010)

Figure 3: Lorenz Curve for the distribution of net-income per adult equivalent



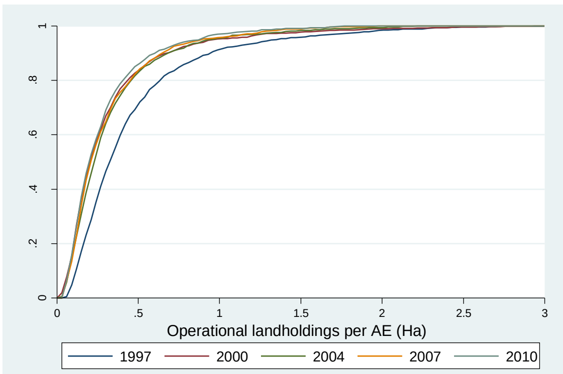
Source:Tegemeo Rural Household Surveys (1997, 2000, 2004, and 2010)

Figure 4: Cumulative Distribution of Income per Adult Equivalent



Source: Tegemeo Rural Household Surveys (1997,2000,2004,2007,2010)

Figure 5: Cumulative Distribution of Operational landholdings per Adult Equivalent



Source: Tegemeo Rural Household Surveys (1997,2000,2004,2007,2010)

Table 7: Comparison of Group Means for Variables (2000-2010)

Variable	Significance
Cultivated land per adult equivalent	***
Owned land per adult equivalent	***
Value of non-land productive assets	***
Value of owned land assets	***
Income gini coefficient	***
Land gini coefficient	***
Net income per adult equivalent	***
Average years of education	***
Distance to motorable roads	***
Distance to electricity	***
Distance to health center	***
Distance to fertilizer seller	***
Village population density	***

*** $p<0.001$

Table 8: Correlation Matrix of OLS Model Variables

	Predicted error	Income gini	Jackknifed income gini	Jackknifed land gini	Jackknifed income	Jackknifed average education	Jackknifed operated land size	Village population density	Distance to motorable roads	Distance to fertilizer seller
Predicted error	1									
Income gini	0.2807	1								
Jackknifed income gini	0.002	0.9431	1							
Jackknifed land gini	0.002	0.9431	1	1						
Jackknifed income	0.02	0.2196	0.2471	0.2471	1					
Jackknifed average education	0.0052	-0.0023	0.0043	0.0043	0.13	1				
Jackknifed operated land size	-0.0207	0.0786	0.0818	0.0818	0.1166	-0.0847	1			
Village population density	0.0474	-0.1073	-0.0954	-0.0954	-0.14	-0.0488	-0.5095	1		
Distance to motorable roads	-0.0015	-0.0075	-0.0035	-0.0035	0.0358	-0.0752	0.0832	-0.0476	1	
Distance to fertilizer seller	-0.0143	0.0891	0.0771	0.0771	0.0466	0.0658	-0.0152	-0.0533	0.0127	1