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ISSN 2279-6916 Working papers
(Dipartimento di Economia Università degli studi Roma Tre) (online)

Working Paper n° 222, 2017

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Copie della presente pubblicazione possono essere richieste alla Redazione.

esemplare fuori commercio
ai sensi della legge 14 aprile 2004 n.106

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Land inequality and growth: meta-analysis and relevance for contemporary development in Africa

Nadia Cuffaro, Giovanna D'Agostino***[1]

Abstract

In this paper we review the literature on inequality and growth, with a focus on land inequality, and apply meta-analysis to the subset of studies that have focused on the impact of land inequality on long term growth. Next we discuss the relevance of the issue, focusing on Africa. The literature on inequality and growth has firmly established a strong role of land inequality as a determinant of income inequality, and the negative impact of land inequality on long term growth, and also that inequality in assets ownership, once established, is very difficult to reverse. Land inequality negatively affects growth essentially in the long run and in the developing areas. Next, the article argues the contemporary relevance of the topic, through the example of Africa, where complex land markets and strong commercial pressure on land, including large scale land acquisitions by foreign investors, may result in land concentration.

Keywords: Economic Growth, Land Inequality, Meta-Analysis, Meta Regression, Large Scale Land Acquisitions.

JEL Classification: Q15, O47

Acknowledgements: The authors wish to thank Caterina Conigliani and Maria Pina Cipollina for their helpful comments and suggestions. The usual disclaimer applies.

Introduction

The role of inequality in growth has a permanent importance in the research agenda of economists and international institutions and has also been investigated through meta-analysis (de Dominicis *et al.*, 2008; Neves *et al.*, 2016). The role of land inequality however has been less investigated, but we believe that it deserves renewed attention for several reasons.

First a large literature on inequality and growth has firmly established (i) The negative impact of asset (land) inequality on long term growth; (ii) A strong role of land inequality as a determinant of

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income inequality; and (iii) The fact that high levels of inequality in asset ownership, once established, are very difficult to reverse. Second, increasing commercial pressure on land in many developing countries, and especially recent trends in FDI in land in the context of insecure rights, may lead to increasing and “excessive” land concentration and shape the development pattern in the direction of inequality for a long time.

In this paper we review the literature on inequality and growth, with a focus on land inequality, and apply meta-analysis to the subset of studies that have focused on the impact of land inequality (Gini Index) on long term growth. Next we discuss the relevance of the issue, focusing on Africa, where increasing commercial pressure on agriculture and increasing flows of foreign direct investments are shaping the pattern of agrarian structures from traditional property rights towards more “modern” forms and where evidence from the large scale land acquisitions (or “land grabbing”) debate points out to significant restructuring in the direction of land inequality.

1. Land inequality and growth. The debate

Research on land distribution and growth is strictly interconnected to the broader research agenda on inequality and growth. For a very simple taxonomy of this literature and in order to establish a framework for the subset of studies included in the meta-analysis (i.e. studies that include the Gini land coefficient in the estimation of the average annual growth rate of GDP) one could distinguish three types of contributions: (i) Mainly empirically oriented, econometric analysis; (ii) Political economy models; (iii) Mainly historical approaches, that apply econometric analysis to the study of colonialism.

1.1 Empirically oriented, econometric analysis

Many early empirically oriented contributions have analysed the relationship between inequality, especially asset/land inequality and growth in relation to World Bank research and policies on poverty reduction[2] (Birdsall and Londoño, 1997b; Deininger and Squire, 1998; World Bank, 2006). In particular Deininger and Squire (1996) developed two data sets, one on income inequality and one on land inequality (the latter based on FAO World Census of Agriculture)[3]. Their results show that initial income inequality is not a robust determinant of future growth, whilst initial inequality of assets, as

[2] The many complementarities between equity – defined as equal opportunities for individuals – and prosperity were at the core of the 2006 World Development Report, which extensively argues that the complementarities arise from many market failures in developing countries, notably in the markets for credit, insurance, land, and human capital.

[3] Some previous studies (e.g. Alesina and Rodrik, 1994) had use the Taylor and Hudson (1972) database.

proxied by the distribution of land, has a significant effect on subsequent growth. According to the authors, the negative relationship between asset inequality and growth emerges if investments in human or physical capital have to be financed through credit, information is costly and imperfect, agents obtain credit only if they own assets that can be used as collateral. A more unequal distribution of assets would then imply that, for any given level of per capita income, a greater number of people are credit-constrained.

The Deininger and Squire database is also used by Birdsall and Londoño (1997a) for econometric analysis of growth as a function of: capital accumulation, initial conditions in terms of income level, education level, inequality in income, land and education. They find that the rate of capital accumulation has a strong impact, and that income inequality is negatively associated with long term growth. However, once the variables measuring initial asset inequality (land and human capital) are entered, income inequality itself is no longer statistically significant, suggesting that the effect of income inequality on growth reflects differences in access of different groups to productive assets. Moreover, the authors estimate that these negative effects are much larger on income growth of the poorest, leading to the conclusion that a better distribution of assets would reduce poverty both directly and indirectly through the general growth rate effect.

Similarly in Deininger and Olinto (1999) initial asset inequality, as measured by the land distribution, has a significant growth-reducing impact. The authors also point out that policies of deregulation and privatization of state assets may, if not implemented carefully, lead to large increases in the inequality of asset distribution and long term negative consequences. For example, fire-sales of assets without an adequate regulatory framework, such as those experienced in many Eastern European countries after socialism, lead to huge jumps in inequality and such high levels of inequality are very difficult and costly to reverse.

This consideration is of indirect but strong relevance to the contemporary land issues in Africa discussed in the next sections, given the institutional conditions in which the land markets operate, with uncertain individual rights and the State generally playing a crucial role as ultimate holder of the right to alienate land.

Note also that an implication of this literature is that countries that reduced the inequality in land ownership through a land reform in the aftermath of World War II should have had higher growth. This is actually often mentioned in the literature on economic development as a determinant of the better growth performance of Asian countries, such as Japan, South Korea, or Taiwan, versus Latin American countries.

1.2 Political economy models

A part of the literature on inequality and growth focuses on how an economy's initial configuration of resources shapes the political struggle for income and wealth distribution which, in turn, affects long-run growth. This generally works through a political economy mechanism with a pivotal voter who decides on the value of some redistributive policy instrument, which determines the rate of growth of the economy (e.g. Alesina and Rodrik, 1994; Persson and Tabellini, 1994). Land inequality has a role in some of these political economy models because inequality in land ownership is likely to be highly correlated with inequality in the distribution of accumulating assets, hence the Gini coefficient of land ownership has been used as a proxy for wealth distribution (Alesina and Rodrik 1994).

In Alesina and Rodrik (1994) spending on public services is financed through a tax on capital income[4] whilst the unskilled labour force is not subject to taxation. Growth is driven by the expansion of the capital stock, in turn determined by individual saving decisions. The tax on capital induces a lower rate of capital accumulation. An individual whose income derives entirely from capital prefers the tax rate that maximizes the economy's growth rate; anyone else would prefer a higher tax, with a correspondingly lower growth rate. The lower an individual's share of capital income (relative to his labour income), the higher is his ideal tax. Under majority voting, the political equilibrium yields a tax rate that is the ideal tax rate of the median voter, the latter identified by his relative factor endowment. In this setting the more equitable is distribution in the economy; the better endowed is the median voter with capital. Hence the greater is the inequality of wealth and income, the higher the rate of taxation, and the lower growth[5].

Galor and Zeira (1993) develop a model where individuals are assumed to be identical with regard to their potential skills and preferences and differ only with respect to their inherited wealth. With credit market imperfections (there are enforcement and supervision costs on individual borrowers, hence the borrowing interest rate is higher than the lending rate) the inheritance of each individual determines whether she invests in human capital or not. The long run dynamics of the economy depend also on initial wealth: there are rich dynasties and poor dynasties, the initial distribution of wealth determines how big these two groups of dynasties are, and therefore what is the long-run equilibrium in the economy.

[4] Physical capital, human capital, and all proprietary technology, i.e. the tax is on all resources that are accumulated.

[5] This is not a consensual conclusion in this strand of literature. Other authors have argued that redistribution through the tax system may yield opposite results if progressive redistribution helps beneficiaries to overcome the effects of some capital market imperfection or liquidity constraint which prevented them from investing in profitable projects or in human capital (Borguignon and Verdier, 2000; Galor and Zeira, 1993; Perotti, 1993; Banerjee and Newmann, 1991; Benabou, 1996; Piketty, 1997).

Finally, Borguignon and Verdier (2000) derive strong implications of inequality not only for growth but also for politics in a political economy model based on the assumption that political participation is solely determined by the educational level, or more generally by the socio-economic status of citizens and also that human capital accumulation is the sole engine of growth. Fixed costs of education and liquidity constraints deny poor persons both education (in the absence of transfers from the upper income) and political action. Implications include that initial income inequality negatively affects both the likelihood for a country to be a democracy and its average rate of growth and reduces the speed of full democratization for countries which are experiencing a democratic transition.

1.3 Mainly historical approaches

A strand of literature on developing countries focuses on the relationship between colonial institutions and patterns of growth, by applying econometric analysis to colonialism. For example Acemoglu *et al.* (2001) estimate that differences in economic institutions account for a large share of the differences in income per-capita in the world and hold that colonialism mattered for development because it shaped the institutions of different societies, by either setting “extractive states” or trying to “replicate” European institutions[6]. Acemoglu and Robinson (2012) argue that the extractive institutions, which strip the vast mass of the population of incentives or opportunities, are associated with poverty.

This strand of literature is not part of our subset for meta-analysis but it gives crucial insights on the strong role of land inequality as a determinant of income inequality. For example Frankema (2008) concentrates on the cross-country variation in land inequality at the end of the colonial age and on the impact of initial land inequality on current income inequality in a study focused on Latin America, where the heavy colonial heritage of land inequality is a major pillar of persistent high levels of income inequality. Land inequality is explained as a function of the following variables: the feasibility of cash or food crops, population density, a dummy for Iberian colony and one for other European colonization, settler conditions (mortality rates) and the presence of Catholic Church[7]. Current income

[6] In Acemoglu *et al.* (2001) economic performance is a function of institutions and institutions in turn are a function of the mortality rates expected by the first European settlers in the colonies (mortality rates are an instrumental variable influencing institutions). Different colonization strategies were influenced by the feasibility of colonial settlements: at one extreme, European powers set up "extractives states”, at the other many Europeans migrated and settled in a number of colonies, and tried to replicate European institutions, with strong emphasis on private property and checks against government power, as in the case of the United States, Australia, and New Zealand. Where the colonial powers set up authoritarian and absolutists states with the purpose of solidifying their control and facilitating the extraction of resources, extractive institutions mostly persisted.

[7] A natural environment suitable to cash-crop production is associated with high levels of income inequality in the long run since cash crops such as sugar, tobacco, coffee, cocoa, rubber, and bananas can be efficiently produced on large estates exploiting coerced indigenous or slave labor, whilst a specialization in scale-neutral food crops has a moderating effect on land inequality (Engerman and Sokoloff, 1997; Easterly, 2002). High

inequality is explained as a function of land inequality, the level of economic development, and measures of the quality of institutions. Results show that land inequality at independence generally had a strong impact on subsequent income inequality directly (because of the share of rural inequality in total inequality) and indirectly because of path dependent effects of land inequality on the distribution of non-land assets. The nature of the political system and the quality of institutions also have a strong role.

In the case of the colonial history of Sub-Saharan Africa unfavourable conditions for colonial settlers resulted in less land appropriation and land concentration than in other regions and high income inequality was more the result of the colonialists rent seeking activities in tax collection trade and exploitation of natural resources.

1.4 Meta-analysis

For the purpose of meta-analysis as discussed in the next section, we restricted our sample to studies that make use of the Gini index as a measure of inequality in the distribution of land and that utilize a linear model to link land inequality to growth (Table 1 and Appendix 1).

The Alesina and Rodrik (1994) model is included because the authors use the Gini index land coefficient in a cross country analysis and -controlling for initial levels of income, human capital and land distribution- find a statistically significant negative relationship between inequality in land distribution and economic growth. Most of the subsequent studies included in our meta-analysis that do use cross-country regressions find that reductions in countries' growth are caused by an unequal distribution of asset, such as land distribution, and not by income inequality (Balisacan and Fuwa, 2003; Caselli, 2005, Deininger and Squire, 1998; Keefer and Knack., 2002; Li, Squire and Zou, 1998; Li, Xu and Zou, 2000; Weede, 1997).

The cross-country estimates have received several critiques, due to the omitted variables in the regression model, such as technology, climate, institutions and any other variable specific to each country. To address this methodological concerns, Deininger and Olinto (2000), Fort and Ruben (2006), Li, Squire, and Zou (1998) and Mo (2003) use panel data econometric methods, fixed-effect estimators in order to account for country specific characteristic. The results of these studies offer a more mixed picture as will be discussed in the next section.

The conclusions of two previous meta-analytical assessments of the inequality growth nexus confirm the relevance of our topic: de Dominicis *et al.* (2008) support the critique that income

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settler mortality rates reduce rates of colonial settlement and are negatively related to land inequality.

inequality is a poor proxy of wealth inequality, Neves *et al.* (2016) state that land and human inequality are more pernicious to subsequent growth than income inequality is.

Our review differs from these other assessments essentially because we focus only on land inequality. De Dominicis *et al.* (2008) refer to the Gini index of income inequality; Neves *et al.* (2016) include all studies that examine the impact on growth of inequality in income, land, and human capital distribution, but indeed most of their estimates (42 out of 49) are selected from studies that use income distribution to measure inequality and only seven on wealth, in the form of land or human capital.

As for the choice of sample of the studies, we opted to consider all studies published or unpublished, and all estimates as de Dominicis *et al.* (2008), whilst Neves *et al.* (2016) include only published studies, from each study the estimate preferred by the authors and exclude single country studies.

2 Meta-analysis. Econometric approach

Meta-analysis is a quantitative literature review method which has been broadly used as an alternative approach to the narrative one. It is a statistical method to analyse a collection of studies regarding the same subject. Glass (1976) coined the term meta-analysis as "the analysis of the analyses", and since then meta-analysis has been performed in the medical and social sciences. However, in the last two decades, the technique has been used in other fields of research, including economics (Stanley, 1998, 2004; Görg and Strobl, 2001; Rose and Stanley, 2005). In comparison with traditional qualitative literature reviews, meta-analysis has the advantage of summarizing studies' findings in a systematic way, with the purpose of avoiding wrong interpretations or wrong review conclusions (Shadish, 1982). Moreover, a quantitative methodology is more useful than qualitative reviews in stressing heterogeneity in the wide fields of the literature (Light *et al.*, 1984). The aim of meta-analysis is synthesizing results from separate but similar studies, and at the same time highlighting the possible sources of heterogeneity. In this section we use it to investigate the relationship between land inequality and economic growth.

Land inequality can be quantified in different ways. We have chosen to use the Gini Index as a measure of the degree of inequality of land distribution among households. An index of zero represents perfect equality, while a value of 1 (or 100, depending on scale) implies perfect inequality. We have preferred use this index in order to have the highest degree of comparability between different estimates of the impact of inequality in land asset on growth.

The standard procedure in the empirical literature is to assume a simple linear relationship between land inequality and growth. The growth rate of per capita income is regressed on a series of covariates potentially explaining difference in growth rates of countries, including a measure of land inequality.

2.1 The data

In the first phase of the meta-analysis we conducted a systematic search of the literature on the impact of land inequality on growth, via electronic sources. We searched Google and Economic Literature Index for any references on "*inequality land and growth*" and "*distribution land and growth*" in the title or in the abstract of articles published and unpublished. We obtained a number of papers, but, in order to have comparability of the population under investigation, we restricted our sample to studies that use the Gini Land Index as a measure of the inequality of land distribution and utilize a linear model linking land inequality to growth. The majority of the scholars do assume a linear relationship between land inequality and growth, while a non-linear may be more appropriate. To date there are, however, not enough studies to implement a statistical analysis of a non-linear relationship between the two variables.

The search lefts us with 13 studies and 111 observations, since, for example, we excluded studies that use simultaneous equation and studies that did not publish all the statistical information relevant to keep comparability. We then defined the variable to meta-analyse as the estimate of the average annual growth rate with respect to the Gini Land coefficient. This is our measure of the *effect size*, as it quantifies the orientation and the size of the correlation between land inequality and growth. Most quantitative conventional studies estimate a regression of the following form:

$$g = \beta_0 + \Sigma_{m=1...M}\, \beta_m X_m + \alpha LandInequality + e; \tag{1}$$

with m = 1,….M, where: g is the average annual growth rate (usually measured as a logarithm of per-capita GDP); Land Inequality is the measure of land inequality (Gini Index), X_m is a vector of other variables that influence the growth; *e* is the usual disturbance term; parameter α is the effect size.

A frequent problem in conducting a meta-analysis occurs when more than one estimate of the effect size is given in a single study. Stanley (2005) and Rose and Stanley (2005) propose different solutions, for example to use the average estimate, the median estimate, or the estimate preferred by the author. We opted to pick up all estimates by each study. This criteria left us a total of 111 estimates of the α coefficient associated with the Gini Index (Table 1). The Gini coefficient is measured on a 0–1 scale, for the studies that do not use these measurement units, the appropriate conversions of the collected values were made. The effect size is interpreted as the increase in average annual growth rate induced by an increase in the Gini coefficient of one percentage point. For example, the effect of -0.0184 by

Alesina and Rodrik, 1994 (see Appendix 1) means that an increase in the Gini coefficient of one percentage point leads to a reduction in the average annual growth rate of 0.0184 percentage points.

Table 1 List and characteristics of the studies included in the meta sample and estimates of the effect size reported in the primary studies

Study	*Type of Publication*	*Structure of Data*	*Estimation Technique*	*Nr. of Estimates*	*Ranges*		*Average Effect Size*
					Min	*Max*	
Alesina and Rodrik (1994)	Journal	Cross-Country	OLS	8	-0.081	-0.052	-0.061
Balisacan and Fuwa (2003)	Journal	Cross-Country	OLS	2	0.001	0.001	0.001
Caselli (2005)	Working Paper	Cross-Country	OLS	12	-0.082	0.008	-0.042
Deininger and Olinto (2000)	Working Paper	Panel Data	System GMM	12	-0.011	0.010	-0.003
Deininger and Squire (1998)	Journal	Cross-Country	OLS	20	-0.062	0.011	-0.035
Fort and Ruben (2006)	Contributed Paper	Panel Data	System GMM	7	-0.121	0.103	-0.057
Keefer and Knack (2002)	Journal	Cross-Country	OLS	2	-0.039	-0.026	-0.033
Li and Zou (1998)	Journal	Cross-Country	OLS	4	-0.034	-0.030	-0.031
Li, Squire and Zou (1998)	Journal	Panel Data	OLS/AR/IV	6	-0.080	0.002	-0.028
Li, Xu and Zou (2000)	Journal	Panel Data	OLS/2SLS	14	-0.034	0.032	-0.003
Mo (2003)	Journal	Panel Data	OLS	10	-0.054	-0.002	-0.034
Nunn (2007)	MPRA Paper	Cross-Country	OLS	4	-0.460	0.450	-0.013
Weede (1997)	Journal	Cross-Country	OLS	10	-0.046	-0.028	-0.038
Total[8]				111			-0.030

[8] This is the sum for the fourth column and the average value for the last column. The average is calculated over the entire sample of 111 observations.

Table 1 illustrates the composition of our meta sample and reports in brackets the year of publication, whether the paper has been published or not, the number of observations and range, and the average value of the estimates.

It is easily observable from the above list that the average estimated effect size is slightly smaller than zero. Approximately 91% of the estimates are negative (90 out of a total of 111), and approximately 19% (21) are positive.

2.2 Meta-analysis of the effects of land inequality on growth

We use meta-analytical techniques to characterize our sample and investigate in detail the results of the effects of land inequality on growth. First, we start by pooling all effects reported by the primary studies collected in our meta sample, and then we test for the presence of heterogeneity in the effect sizes and for possible publication bias.

2.2.1 Pooled Fixed and Random effects estimates of the effect size.

One possibility of a meta-analysis is to estimate the combined effect. If all studies in the sample were equally precise we could simply compute the mean of the effect sizes. However, if some studies were more precise than others, we want to assign more weight to the studies that carry more information. Hence, rather than compute a simple mean of the effect sizes we compute a weighted mean. Therefore, the first question is what combined estimate of all studies adequately represents the true underlying effect between land inequality and growth? To answer this question, we choose two widely used estimators in meta-analysis: the *pooled fixed effect estimator* and the *pooled random effect estimator*. Both of them are weighted averages of the effect size estimates reported by the studies, but they differ in their underlying assumptions.

Under the *fixed effect* model we can assume that there is one true effect size which is shared by all the included studies. It follows that the combined effect is the estimate of the common effect size. The fixed effect estimator assumes that there is no heterogeneity among studies' results and that different magnitude of the estimates is due to sampling variation. Statistically, this is equivalent to the hypothesis that all effect sizes are equal, for example $\alpha_1 = \alpha_2 = \alpha_3 = \ldots = \alpha_n = \alpha$, where α_j represents the effect of size of the j^{th} observation (in our case, j = 1,2,3...111) and α is the true effect size, or population effect size (Hedges *et al.*, 1985). The observed effects will be distributed around α (the common effect), and will have a variance σ^2 that depends primarily on the sample size for each study.

Hence, T_i is the effect size and is determined by the common effect α plus the within-study error ε_i (the different magnitude of the estimates is due to sampling variation). More generally, for any observed effect T_i,

$$T_i = \alpha + \varepsilon_i \tag{2}$$

In the fixed effect model there is only one level of sampling, since all studies are sampled from a population with effect size α. Therefore, there is only one source of sampling error, ε, within - study error, thus the weighted mean or the pooled effect estimate is, then, computed as follows:

$$\overline{T}_{\bullet} = \frac{\sum_{i=1}^{k} w_i T_i}{\sum_{i=1}^{k} w_i} \tag{3}$$

where i= 1, …., k are independent observations of the effect size T_i and w_i is a weight assigned to the i^{th} study.

The weights are $w_j = 1/v_j$, where v_j is the estimated variance of the effect size. The method is known as the 'inverse variance' (de Dominicis *et al.,* 2008) i.e. the statistic is a weighted average of all effect sizes in the sample, with weights inversely proportional to the precision of the estimates (Hedges and Olkin, 1985; de Dominicis *et al.,* 2008).

On the opposite the *random effect* estimator assumes heterogeneity among studies results. There is not a single true effect across studies; each study has its own "true" effect size, randomly picked from a larger population with a fixed mean and variance. Rather than assume that there is one true effect, we allow that there is a distribution of true effect sizes. The combined effect α, therefore, can not represent the one common effect, but instead represents the mean of the population of true effects. Hence, the variance associated with each effect size has two components, one regarding the sample level, as in the fixed effect model (within – variance) and the other one regarding the random effect variance (between – variance). The matter will be to take into account both sources of imprecision. T_i, hence, is determined by the true effect θ_i plus the within-study error ε_i. More generally, for any observed effect T_i,

$$T_i = \theta_i + \varepsilon_i = \alpha + \zeta_i + \varepsilon_i \tag{4}$$

where θ_i, is determined by the mean of all true effects, α and the between-study error ζ_i. In the random effect estimator both sources of variation are assumed to be normally distributed, with mean zero but variance v_i and t^2. As the fixed effect estimator, the random effect estimator is also an inverse – variance weighted estimator of **T.**, although the weights are now equal to $w_i = 1/ v_i + t^2$, where v_i

represents the estimate of the within study variance and t^2 the estimates of the between study variance. For further calculation's details we refer to Borenstein *et al.* (2007).

We have calculated the pooled estimates of the effect size in our sample. The fixed effect shows a value of *-0.0022* instead the random effect shows a value of *-0.0129* and both are statistically significant a 1% level. Hence, a preliminary finding of our meta-analysis is that land inequality seems to influence growth negatively; there is a trade – off between land inequality and economic growth.

2.2.2 Testing for heterogeneity of effect size.

Now we want to test the hypothesis of heterogeneity by performing the so-called *Q*-test. A *Q*–test on the pooled estimates is performed to check for the presence of heterogeneity among estimates. It is formally a test of the null hypothesis of homogeneity ($H_0 : \alpha_1 = \alpha_2 = \alpha_3 ... = \alpha_N$) versus the alternative that at least one of the effect sizes differs from the rest. If all N studies have the same population effect size, namely H_0 is true, the *Q*-test has an asymptotic chi-squared distribution with k -1 degrees of freedom (Hedges, 1982). On the opposite, if the value of Q exceeds the upper critical value of the chi – square distribution, the null hypothesis of homogeneity of the underlying population effect size is rejected. The Q-statistic has the following form:

$$Q = \sum_{i=1}^{k} w_i T_i^2 - \frac{\left(\sum_{i=1}^{k} w_i T_i\right)^2}{\sum_{i=1}^{k} w_i} \qquad (5)$$

with all notations as before, and as before for further calculation details, we refer to Borenstein *et al.* (2007). In our meta sample, the *Q*-test is 1030, which is larger than 135.4802, namely the 95% critical value of the chi-squared distribution with 110 degree of freedom. Thus, the hypothesis of heterogeneity is accepted and the null hypothesis of homogeneity is rejected with a p-value < 0.001.

The amount of heterogeneity can be computed using I^2 index developed by Higgins and Thompson (2002). This index tells us the proportion of total variation across studies due to heterogeneity and is equal to:

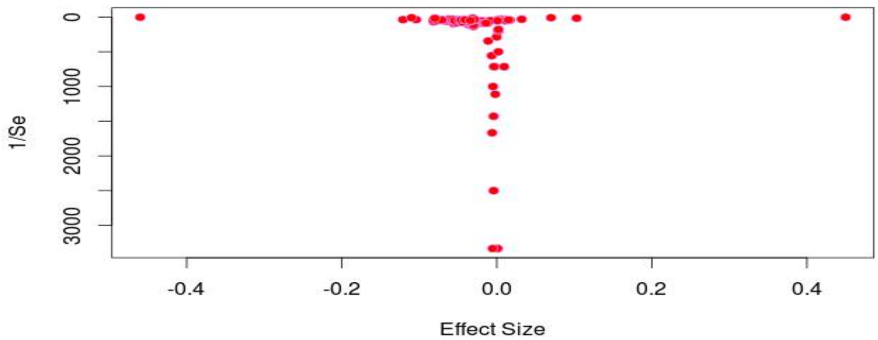
$$I^2 = \frac{Q - (N - 1)}{Q} \times 100\%. \qquad (6)$$

In our meta sample I^2 is equal to 89,32%, which reveals a high degree of heterogeneity. Hence, the results provided by the *Q*-test and the I^2 index, have two implications. Firstly, the random effects estimator is preferable to the fixed effects estimator, as the latter relies on an assumption that does not hold. Secondly, there is excess variation in the reported estimates of the effect size that we are going to explain in the last section by a meta-regression analysis.

2.2.3 Testing and correcting publication bias.

In this section we shall take in consideration only one possible kind of bias, namely in the publication of the results. Publication bias refers to a distortion in the process of reporting results (Sutton *et al.*, 2000). There are several forms of publication bias, first authors and journal editors may be interested in publishing results in a certain direction, second, there may be a tendency to publish only statistically significant findings, leaving aside non-significant findings or studies. These are the most common forms of publication bias, which have been widely recognized. A popular plot for detecting the presence of publication bias is the *funnel plot* (Egger *et al.*, 1997). It is a scatter diagram that compares the estimates of the effect size (in our analysis the estimated coefficient of the impact of land inequality on growth) from each study in the horizontal axis against its precision in the vertical axis, measured by the inverse of the estimate of the standard error. This plot should show a funnel shape centred around the true overall mean because in the absence of publication bias, estimates will vary randomly and symmetrically around the true effect size, and estimates provided by studies with larger samples and hence lower standard deviations will be closer to the true effect size, while those provided by small sample studies will be spread out the true effect size. Publication bias may lead to asymmetrical funnel plots.

Figure 1. Funnel Plot



The funnel graph in Figure 1 plots on the horizontal axis the estimated coefficients in our sample of studies, and on the vertical axis the associated inverse of the standard errors. The result seems to be clear: the funnel is asymmetrical with a tendency to values on left side (negative values). However, visual inspection are subjective and somehow ambiguous (Stanley *et al.*, 2008). In fact, Egger *et al.* (1997) proposed a test for detecting asymmetry of the funnel plot, the so called Funnel Asymmetry Test (FAT). It involves a regression between a study's reported effect size and its estimated standard error, namely the test determines if the intercept deviates significantly from zero. Since the dependent variable, the effect size, is an estimated regression coefficient drawn from each study, the equation has a problem of heteroskedasticity. In order to deal with this problem, we divide the variables of the regression by each standard-error (for further calculation's details we refer to Neves *et al.*, 2016). Next, we estimate our regression using an OLS, and Newey-West[9] procedure (Newey *et al.*, 1987). This procedure, consistently, estimates standard-errors in the presence of heteroskedasticity and autocorrelation between disturbance errors. In our sample, this procedure is necessary given the presumable existence of correlation between observations drawn from the same study.

Table 2. Results of the test detecting for the presence of asymmetry of the results

Moderator Variable	***Estimate***	***Std. Error***	***t value***	***Pr(>|t|)***
Constant	*-1.8209677*	*0.3001640*	*-6.0666*	*1.926e-08 ****
1/Standard-Error	*-0.0011815*	*0.0016364*	*-0.7220*	*0.4718*

Notes:

Coefficients are estimated by OLS. Standard errors are calculated using Newey-West Procedure[10](1987) heteroskedastic-consistent variance-covariance matrix.

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Residual standard error: 2.556 on 109 degrees of freedom

Multiple R-squared: 0.07723, Adjusted R-squared: 0.06876

F-statistic: 9.123 on 1 and 109 DF, p-value: 0.003145

In our meta sample the estimated intercept is negative, with an associated statistical significance at 1%. Hence, there is asymmetry, confirming the previous interpretation of the funnel graph, revealing signs of publication bias in favour of a given direction, in our case negative direction.

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[9] See Newey and West (1987) for a discussion on the calculations of a covariance matrix in case of autocorrelation and heteroskedasticity.

[10] Newey – West produces standard errors for coefficients estimated by OLS regression. The error structure is assumed to be heteroskedastic and possibly autocorrelated up to some lag. We have choose lag = NULL, thus the function automatically estimates the number of lags to use.

2.3 Meta-Regression

In this section we try to explain the heterogeneity of the reported effect sizes using meta-regression analysis. Met- regression is a tool to investigate heterogeneity in the findings of a body of studies, namely the extent to which excess heterogeneity among studies' results can be linked to studies' characteristics. Usually it is a regression of the following form:

$$Y_j = \beta_0 + \sum_{k=1}^{K} \beta_k X_{kj} + e_j, \quad j = 1, 2, \ldots, N, \tag{7}$$

where the dependent variable, Y_j, is a summary statistic, usually a regression parameter, picked out from each primary study in our meta sample; while X_{kj} are the independent variables (or "moderator variables"), which should include characteristics of the method, design and data of the empirical studies, in order to explain variation in study to study; β_k are the meta-regression coefficients reflecting the effect of each characteristic on Y_j ; and e_j is the meta-regression disturbance term. The independent variables should include dummy variables, which reflect if independent variables were omitted or included in the primary study, variables that account for types of regression and sources and so forth (Stanley and Jarrell, 1989). We choose as moderator variables those reflecting characteristics of the primary studies that are supposed to influence the estimates of the land inequality effect on growth. We select seven characteristics: (i) the structure of the data; (ii) the estimation techniques; (iii) the inclusion of regional dummies in the primary studies; (iv) the development level of the countries included in the sample; (v) the database used for land inequality. (vi) the inclusion of another variable measuring inequality beyond land inequality; (vii) whether land inequality is measured at the beginning of the period of investigation.

We follow the econometric suggestions of Neves *et al.* (2016), hence we correct for the heteroskedasticity dividing all the variables by the standard-errors, and the autocorrelation using the Newey – West procedure[11] (Newey *et al.*, 1987). Table 3 presents the estimation results.

[11] See Newey and West (1987) for a discussion on the calculations of a covariance matrix in case of autocorrelation.

Table 3. Results of the meta-regression.

The dependent variable is the effect size drawn from primary study and weighted by a measure of precision (in our case the standard error).

Moderator Variable	*Estimate*	*Std. Error*	*t value*	*Pr(>|t|)*
All moderator variables enter the regression equation as dummy variables and are divided by Se (Standard Error). Number of observations: 111				
Constant	-1.1719e+00	2.0090e-01	-5.8333	6.579e-08 ***
Another measure of inequality included beyond land inequality	6.1181e-06	2.4528e-04	0.0249	0.980150
Dynamic of the land inequality measure	4.3497e-03	4.7274e-03	0.9201	0.359715
FAO Dataset	-9.1818e-03	4.1102e-03	-2.2339	0.027694 *
Other Dataset of land inequality	1.9430e-02	6.1552e-03	3.1567	0.002103 **
Cross Country (Structure of the Data)	-2.2445e-02	4.6166e-03	-4.8618	4.279e-06 ***
Estimation Method-	-1.7450e-02	7.3103e-03	-2.3871	0.018843 *
Sample of Countries - OECD	1.2711e-01	2.6656e-02	4.7685	6.255e-06 ***
Regional Dummy	1.6824e-02	1.4649e-03	11.4846	< 2.2e-16 ***
Sample of Countries – LDCs and OECD	-1.8516e-02	1.6406e-03	-11.2862	< 2.2e-16 ***

Notes:

Coefficients are estimated by OLS. Standard errors are calculated using Newey-West Procedure (1987) heteroskedastic-consistent variance-covariance matrix.

*Signif. Codes: '***','**', '*', referring respectively to the 1% (high significance), 5% (medium significance), 10% (low significance) level.*

Residual standard error: 1.695 on 101 degrees of freedom

Multiple R-squared: 0.623, Adjusted R-squared: 0.5894

F-statistic: 18.55 on 9 and 101 DF, p-value: < 2.2e-1

In the following we compare results to Neves *et al.* (2016)'s findings, but not to de Dominicis *et al.* (2008)'s, because only the former study includes a measure of wealth inequality in the form of land or human capital.

(i) As first stage we have investigated the structure of the data. We have defined a dummy labelled *Cross Country (Structure of data)* which has a value equal to one when the primary study estimate is based on the use of -cross country data, and zero otherwise. The coefficient is -negative and statistically significant at 1% level. The negative estimate of the coefficient of Cross Country confirms the idea that cross-section studies typically report a negative relationship between land inequality and growth, whereas panel studies present more diverse results. This finding is in line with Neves *et al.* (2016). Panel data contain observations of multiple phenomena obtained over multiple time periods for the same countries or individuals. Studies that use this type of data actually show mixed results as for the direction of the impact of inequality on growth with some positive coefficients. This is possibly because the average annual growth rates of the panel studies are short-medium-run: most of them assess the impact of inequality on growth over five-year periods. Indeed, Deininger and Olinto (2000) use a sample of 5-year for 60 countries, Mo (2003) uses a panel data set covering 1960–85, divided into 5-year sub-periods. However, as also highlighted in the previous section, the transmission channels between inequality and growth are likely to operate differently in different time horizons (Knowles, 2005). By and large, the positive effects of inequality on growth, for example associated to the increase of savings or to large-scale investments, are likely to operate in the short-run. On the contrary, the negative effects, associated for example to credit constraints or excessive taxation that limits capital accumulation, are more likely to operate in the long-run. Hence, we should expect stronger confirmation of a negative impact of inequality on growth in cross-section studies.

(ii) As second stage we have investigated the estimation techniques. The dummy labelled *Estimation Method* has value equal to one if the primary study is not based on OLS method. The variable is statistically significant at 10% level, thus has low significance. Almost all cross-section studies estimate the inequality–growth linkage using OLS, whilst panel studies use several estimators. The panel estimation techniques are fixed and random models, or Instrumental Variables (IV) estimator, or still, OLS to “within groups” and so on. However, as noted by several authors (e.g., Deininger and Olindo, 2000), neither of these techniques are completely adequate to estimate the inequality–growth linkage. For example, the fixed estimator can lead to biased results, because, as in the case of inequality, variables are persistent over time or their variation is mostly cross-section. Instead the random effects estimator is inconsistent, as the usual explanatory variables used to investigate the impacts of inequality on growth are typically correlated with the country-specific effects. Hence, many panel studies have used more appropriate estimation techniques, the most common being the system GMM estimators, developed by Arellano and Bovver (1995). However, our dummy *Estimation Method variable* has a low significance. Hence, there is no evidence to suggest that the heterogeneity of the effects sizes is explained by differences on estimation techniques. Also this finding is in line with Neves *et al.* (2016).

(iii) We introduce a variable *Regional dummy,* equal to one if regional variables are included in the primary studies and it is positive and significant at 1% level. Also this finding is in line with Neves *et al.* (2016). Indeed the impact of inequality on growth may differ substantially across countries and regions; hence the inclusion of regional dummies as explanatory variables especially in the growth regression of cross-section primary studies weakens the negative effect of inequality on growth

(iv) We continue our investigation analysing the development level of the countries included in the meta sample through the introduction of three dummies in our regression. *Sample of Countries – OECD* assumes value equal to one when the primary study includes only *OECD* countries. The coefficient is positive and statistically significant at 1%, supporting the idea that inequality affects less OECD countries compared other countries. Eventually, we include the dummy *Sample of Countries – LDCs and OECD,* which is equal to one when in the primary study both OECD and LDCs countries are included; the results show that this variable is negative and highly significant. This means that most of the heterogeneity can be explained by which sample of countries is considered; furthermore this finding supports the hypothesis that land inequality is especially relevant, with a negative impact on growth, for developing countries.

(v) Our fourth dummy is *database used for land inequality*. We have controlled for the use of different database for land inequality in the primary study. The main used datasets are FAO World Census of Agriculture and Taylor Hudson dataset. FAO census was initiated in 1924 by the International Institute of Agriculture (IIA) in Rome, the predecessor of the FAO. Instead, Taylor and Hudson (1972) present a dataset consisting of Gini coefficients of land distribution for 54 different countries in some year close to 1960. The dummy *FAO dataset* is equal to one if the dataset used is from FAO dataset. In this case the coefficient is negative and it is significant at 10% level. While *Other Dataset of land inequality* is equal to one if the dataset used is neither FAO nor Taylor and Hudson, and it is positive and significant at 5% level. Hence, heterogeneity is also explained by which dataset is used. In fact the primary studies, in our meta sample that find a positive relationship between land inequality and growth are, for example, Balisacan and Fuwa (2003) and Li, Squire, and Zou (1998) whose land inequality dataset is based on agricultural census and World Bank national accounts.

(vi) Eventually, we checked if the relationship between land inequality and growth can be affected if land inequality is measured at the beginning of the period under investigation or another measure of inequality is included in the primary study. Dummy *Dynamic of land inequality measure* is equal to one if land inequality is measured at the beginning of the period under investigation, and dummy *Another measure of inequality included beyond land inequality* is equal to one if in the primary study another measure of inequality is included as for example income inequality. Both variables are not statistically significant.

2.4 Conclusions of meta-analysis

In our assessment we first use two weighted averages of the effect size estimates reported by the studies (the *pooled fixed effect estimator* and the *pooled random effect estimator* respectively) based on the assumption that there is or there is not only one “true” effect. Both indicators are statistically significant, indicating that land inequality seems to influence growth negatively. Next we test the hypothesis of heterogeneity of results by performing the so-called *Q*-tes, t which reveals a great degree of heterogeneity and also find that the random effects estimator is preferable to the fixed effects estimator, and that there is excess variation in the reported estimates of the effect size (a finding that we try to explain by a meta-regression analysis).

We do test for publication bias i.e. a bias to publish results pointing in a certain direction and find a bias in favour of the negative direction of results.

Our meta-regression includes seven characteristics that may influence the heterogeneity of results: (i) The structure of the data (cross section or panel); (ii) The estimation techniques; (iii) The inclusion of regional dummies (iv) The development level of the countries included in the sample; (v) The database used for land inequality. (vi) the inclusion of another variable measuring inequality beyond land inequality; (vii) Whether land inequality is measured at the beginning of the period of investigation.

Major findings are (i) Cross-section studies typically report a negative relationship between land inequality and growth, whereas panel studies present more diverse results; (ii) The coefficient associated with Regional dummy is positive and is statistically different from zero, i.e. country and regional specificities play a crucial role in explaining the heterogeneity found in the reported effect sizes; (iii) The estimates of the land inequality–growth relationship are significantly affected by the development level of the countries included in the sample of the primary studies and the negative impact emerges only when countries at lower level of development are included.

3. Relevance of the topic: commercial pressure on land in Africa and the risk of land concentration

In this last section we argue the relevance of our topic for the contemporary debate on development by focusing on Africa, because the region is experiencing increasing commercial pressure on land, including foreign investments in large scale land acquisitions, and this trend takes place in the context of complex structures of property rights and complex land markets.

3.1 Land

The idea of a vast extensive margin for agriculture and of egalitarian farm structures especially in Sub-Saharan Africa has long been in the background of the development discourse. However the debate on the wave of large scale land acquisitions (LSLAs) after the 2007-8 commodity price boom has refocused attention on land in Africa and contributed to reshape the perspective on agrarian structures in the region (Jayne, Chamberlin, Headey, 2014; Deininger and Byerlee, 2011).

The data reported in table 4 on land balances as estimated by the Global Agro-Ecological Zones (GAEZ) project (Fischer *et al.*, 2011)[12], show that a large share of the remaining land suitable for agriculture and not already in use (net balance) is concentrated in Sub-Saharan Africa. Indeed, although the estimates of the area for cropland expansion are very sensitive to the definition of "potentially available" land, there is a consensus that arable land is relatively abundant in Africa as a whole (Chamberlin *et al.*, 2014; Deininger and Byerlee, 2011).

Table 4. Land balances: regional shares of world total

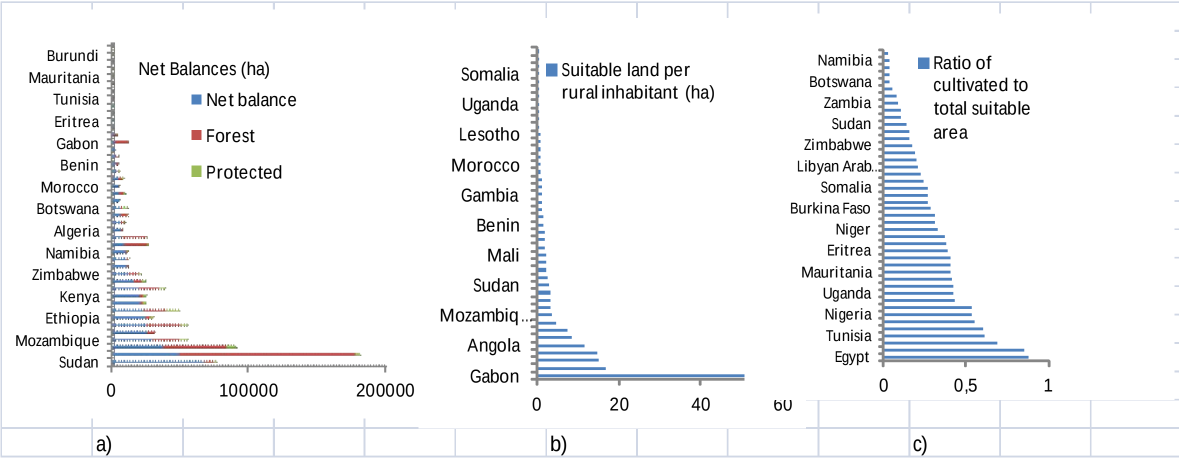
	Suitable	Cultivated	Forest	Gross balance	Net balance
Developing	64	56	67	68	68
Sub-Saharan Africa	24	15	22	27	32
Latin America	24	12	35	29	26
Near East/North Africa	2	4	0	1	3
South Asia	4	11	1	2	1
East Asia	9	14	7	7	7
Developed	35	44	33	32	32
Sources. Fischer G. *et al*., 2011; Alexandratos and Bruinsma, 2012					
Suitable land is the sum of "prime" and "good" land					
Gross balance= Suitable land-cultivated					
Net balance= Suitable land-cultivated-(forest+built+protected)					

However the data at country level (figure 2) reveal a high degree of heterogeneity among countries in terms of net land availability and population pressure on land. The net balances and the largest areas of forests are concentrated in some countries, whilst in others most land suitable for agriculture is already in use and the ratio of cultivated to suitable land ranges from 0.9 in Egypt and Rwanda to less

[12] The Gaez provides estimates of six suitability classes condensed into three: prime land, good land and marginal and not suitable land Prime land is characterized as very suitable land with attainable yields of over 80 percent of maximum constraint-free yields. Good land represents suitable and moderately suitable land with attainable yield levels of 40 to 80 percent of maximum constraint-free yields and marginal and not suitable land includes all land with estimated attainable yields that are less than 40 percent of maximum constraint-free yields.

than one per cent in seven countries. Figure 2b shows also that the amount of suitable land per rural inhabitant varies considerably and that about one third of countries have less than one hectare of land suitable for agriculture for rural inhabitant, largely as a result of demographic trends, since Sub-Saharan Africa is the only region of the world that is forecasted to have positive rates of growth of rural population to 2050 (United Nations, 2014).

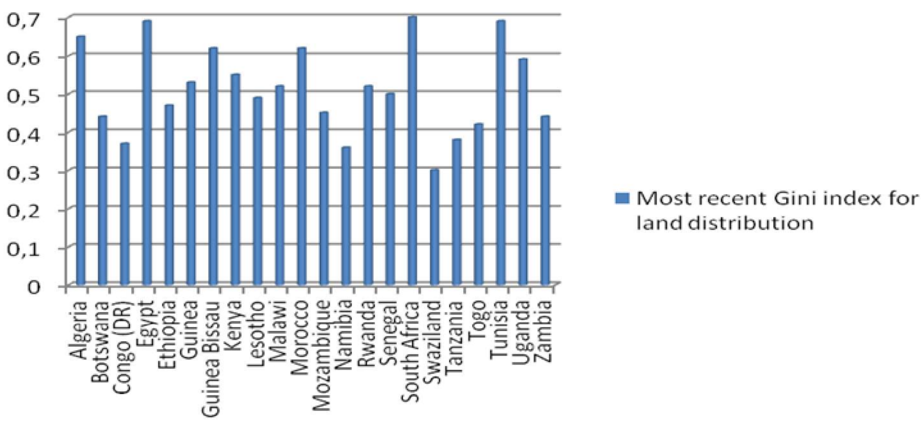
Figure 2. Land balances by country (hectares) in Africa



Source: Authors’ elaboration on GAEZ (Fisher *et al.*, 2011) data and FAO data

In summary Africa’s surplus land is concentrated within relatively few countries, whilst other countries are land constrained and, according to recent empirical evidence, experiencing declining farm sizes (Jayne, Chamberlin and Headey, 2014; HLPE, 2013; Lowder, Skoet, Raney, 2016).

Figure 3. Recent data on Gini Index for land distribution



Source: Data mostly around 2000. List of sources in GRAIN (2014)

As for land distribution, the historical record (Frankema, 2008) [13] shows that especially in West and Central Sub-Saharan Africa inequality at independence was relatively low and comparable to South and South East Asia. However, even then, there was significant heterogeneity and recent studies on land inequality in the continent have reported evidence of rising Gini coefficients over time (Headey and Jayne, 2014; Jayne, Chamberlin, Headey, 2014). Figure 3, based on data collected by GRAIN (2014) from national and international sources mostly around the year 2000, shows that more than half of the countries have Gini values above 0.5.

3.2 Land markets, FDI in land and inequality

The functioning of contemporary land markets in Africa may contribute to rising inequality in four ways. First, land titling, i.e. the transfer of land out of customary tenure, is increasing the supply of titled land that can be bought and sold. The distributional effects of converting land from customary to state titled land is a debated issue. From the point of view of equality/inequality of assets distribution there is in principle a clear distinction: land under customary tenure is designed to provide free ‘‘birthright access’’ to land by smallholder farmers in the community; on the opposite, land shifted from customary to titled land should then be transferred at market prices, and there is evidence of a tendency to provide ‘‘bonanza’’ discount purchases to the first buyer, domestic or foreign. However all institutions are subject to the pressure of markets and also traditional systems, insofar as they are associated to unsecure rights for users and extensive rights for governments and local authorities, do not necessarily operate for fairness (Anseeuw *et al.*, 2012b; Cotula, 2007; Cuffaro, Giovannetti, Monni, 2013; Jayne, Chamberlin, Headey, 2014; Herbst, 2000; Holden and Otsuka, 2014).

Second, there is evidence of a rise of medium-scale holdings, which is linked more to acquisitions by domestic investors belonging to the urban or rural elites than to the expansion of small-scale farmers into commercialized medium-scale stature (Jayne, Chamberlin, Headey, 2014).

Third, available data indicate that the recent wave of foreign acquisitions has targeted Africa’s land with large scale investments (Anseeuw *et al.*, 2012b; Cotula, 2009; Deininger and Byerlee, 2011). Indeed the recent debate on large scale land acquisitions has produced much evidence on increasing commercial pressure on land in the continent and on the fact that especially foreign capital has disproportionally targeted Africa with investments of very large average size.

[13] Frankema (2008) reports statistics on land Ginis in 13 world regions for a year close to independence (i.e. for the majority of Asian and African countries close to 1960). Coefficients went from 0.38 in East Asia to 0.80 in South America.

Fourth, as many contributors to the recent debate on large scale LSLAs have repeatedly stressed, the strong role of the State in the structure of property rights on land in Sub-Saharan Africa may contribute to land concentration. "State landlordism", insecurity of land tenure and the central role of the state in making land eventually available to private operators is likely to determine a pattern of acquisitions characterized by deals of very large size and commercial pressure may result in a development path that is "excessively" geared towards large farms and land concentration. This is reinforced by the fact that FDI flows are very large compared to the economic size of target countries (Alden Wily, 2011; Anseeuw *et al.*, 2012b; Cotula, 2013; Cuffaro, 2002; Cuffaro, Giovannetti, Monni, 2013; Oxfam, 2011).

The trend of LSLAs emerged mainly through media reports since the 2007-8 commodity price boom. The efforts at systematic data collection undertaken since, especially by GRAIN (2010) and International Land Coalition (Anseeuw *et al.*, 2012b) in partnership with several other centres, have improved the availability of data. In what follows, data are mostly taken from the Land Matrix dataset[14], which includes large deals made since the year 2000 for agricultural production, timber extraction, carbon trading, industry, renewable energy production, conservation, and tourism in low- and middle-income countries. These data show that the average size of contracts concluded[15] in Africa is extremely large especially in the case of international investors.

Table 5. Large-Scale Land Acquisitions by sector in Africa

	Biofuels	Food Crops	Renewable Energy	Agri unspecif.	Non-food agricultural comm	For wood and fibre	Conservation	Forest unspecif.	Livestock	Carbon sequestration/REDD	Tourism	Industry
Av size transn	172915	120558	255192	117479	155965	400934	1191822	16741	78383	840768	1899400	159917
Av size domestic	136243	56694	166005	58742	189944	216527	438152	24065	205479	243400	n.a	250
Share of sector in transn	0.147	0.171	0.043	0.077	0.044	0.291	0.07	0.01	0.016	0.06	0.071	0.008
Share of sector in domestic	0.097	0.191	0.031	0.06	0.042	0.308	0.043	0.051	0.069	0.108	0	0
Source: Land Matrix Accessed July 2016												

Source: Authors elaboration on Land Matrix Accessed July 2016

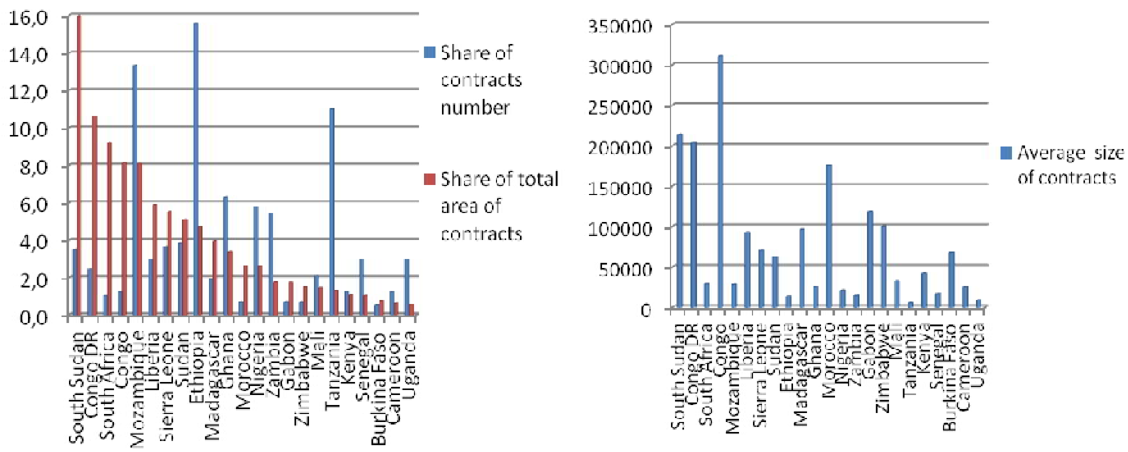
[14] International Land Coalition in partnership with several research centers (CDE, CIRAC, GIZ, GIGA) has published Land Matrix (Anseeuw *et al.*, 2012b and http://landportal.info/landmatrix). Land Matrix includes deals (purchase, lease or concession) initiated since the year 2000 and covering an area of 200 hectares or more.

[15] Land Matrix includes deals at different stages of negotiations: intended, concluded, failed.

Table 4 reports some basic data on the sectors of investment for transnational and domestic deals and the average sizes of investments in terms of area. Wood and fibre are the intended purpose of about one third of total land acquired, followed by food crops and biofuels. The latter as expected have a larger role for transnational than domestic acquisitions. The average size of reported acquisitions is very large, and the average scale of transnational acquisitions for the most important sectors exceeds that of domestic acquisitions.

The data at country level for the most targeted countries in the continent (Figures 4 a and b) confirm that the average size of contracts reported is extremely large in all countries, suggesting a trend which emerged also through a vast case studies literature (Anseeuw *et al.*, 2012a; Cotula *et al.*, 2009; Deininger and Byerlee, 2011; FAO, 2012; GTZ, 2009; Oxfam, 2011).

Figure 4 Large scale land acquisitions by target country. Shares and average size (ha)

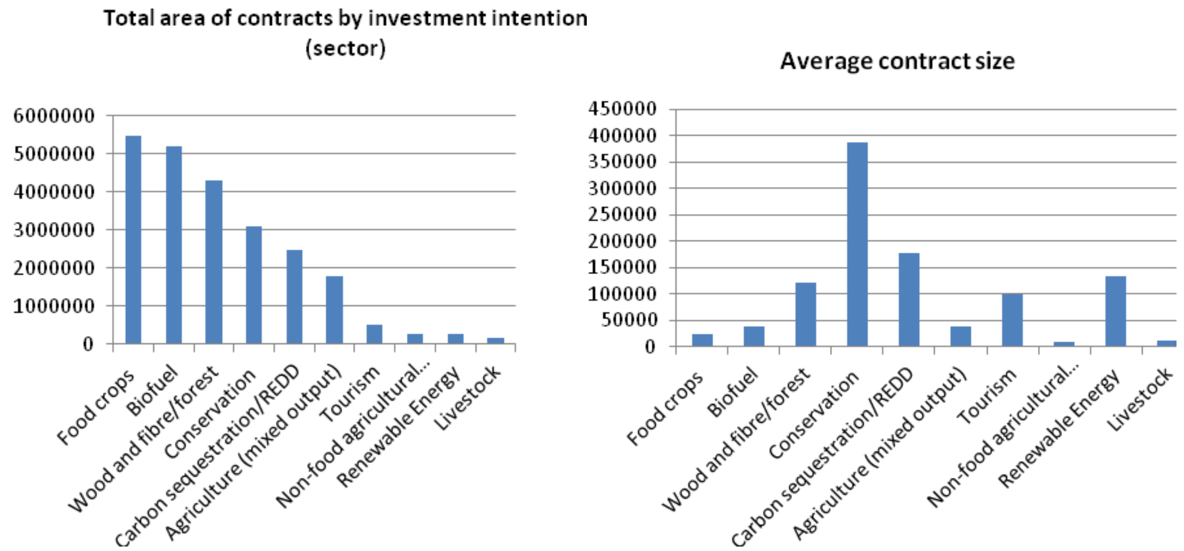


a) b)

Source: Land Matrix accessed October 2015. Data refer to contracts concluded (national and foreign investors) and include only countries with area of contracts larger than 0.6 of total area acquired in Africa

It is very important to underline that according to our data (figure 5) this pattern of large acquisitions does not depend on the concentration of investments in sectors that usually operate on large scale.

Figure 5. Investments by sector and average size of deals



Source: Land Matrix. Accessed October 2015

Contracts in conservation, carbon sequestration (i.e. land privately acquired for carbon finance), renewable energy, forestry and tourism (eco-tourism) are, as expected, particularly extensive on average[16], but Figure 5 shows that also the average size of investments in food crops and biofuels (more than 20,000 ha), which together account for about 50% of total land acquired in Africa, is very large (Karsenty, 2007 and 2011; Schoneveld, 2014).

Finally, the case study literature indicates that the vast majority of documented recent projects of FDI in land is run as large plantations –since large areas of land are commonly offered on very favourable terms by host governments that perceive commitments to investment and employment, rather than financial transfers per se, as their main benefit - creating a strong incentive for establishing company-managed plantations, rather contract farming approaches (Cotula *et al.*, 2009; GTZ, 2009).

4. Conclusions

A large literature on inequality and growth has firmly established: the negative impact of asset (land) inequality on long term growth, a strong role of land inequality as a determinant of income inequality and the fact that high levels of inequality in asset ownership, once established, are very difficult to reverse.

[16] For example in the case of land allocated to industrial logging on the one hand concessionaires typically only have "limited" use rights withdrawal), on the other hand many individual companies cover several millions of hectares .

In our meta-analytical assessment of this literature we find that cross-section studies typically report a negative relationship between land inequality and growth, whereas panel studies present more diverse results, suggesting that the negative impact of land inequality on growth operates in the long run, possibly through credit constraints and institutional mechanisms. Furthermore country and regional specificities play a crucial role in explaining the heterogeneity found in the reported effects and the estimates of the land inequality–growth relationship are significantly affected by the development level of the countries included in the sample of the primary studies.

Land inequality negatively affects growth essentially in the long run and in the developing areas.

The relationship between land inequality and growth has been much investigated during the 80s and 90s but it has attracted less attention since. Focusing on Africa, we contend that research should instead be intensified since increasing commercial pressure on agriculture and increasing flows of foreign direct investments are reshaping the pattern of agrarian structures from traditional property rights towards more "modern" forms with possible increasing land concentration.

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Appendix 1. List of case studies and variables included in meta sample

Study	Effect Size	T-statistics	Standard Error
Alesina Alberto and Rodrik Dani (1994)	-0.0814	-5.4900	0.0148
Alesina Alberto and Rodrik Dani (1994)	-0.0641	-3.7900	0.0169
Alesina Alberto and Rodrik Dani (1994)	-0.0639	-3.6900	0.0173
Alesina Alberto and Rodrik Dani (1994)	-0.0646	-3.7100	0.0174
Alesina Alberto and Rodrik Dani (1994)	-0.0550	-5.2400	0.0105
Alesina Alberto and Rodrik Dani (1994)	-0.0523	-4.3800	0.0119
Alesina Alberto and Rodrik Dani (1994)	-0.0524	-4.3200	0.0121
Alesina Alberto and Rodrik Dani (1994)	-0.0521	-4.1900	0.0124
Balisacan M. Arsenio and Fuwa Nobuhiko (2003)	0.0010	3.0500	0.0003
Balisacan M. Arsenio and Fuwa Nobuhiko (2003)	0.0010	3.4100	0.0003
Caselli Mauro (2005)	0.0075	0.2449	0.0307
Caselli Mauro (2005)	0.0045	0.1457	0.0309
Caselli Mauro (2005)	-0.0785	-2.5650	0.0306
Caselli Mauro (2005)	-0.0771	-2.5791	0.0299
Caselli Mauro (2005)	-0.0645	-2.5828	0.0250
Caselli Mauro (2005)	-0.0755	-2.5998	0.0290
Caselli Mauro (2005)	0.0016	0.0606	0.0257
Caselli Mauro (2005)	0.0008	0.0302	0.0252
Caselli Mauro (2005)	-0.0682	-3.5994	0.0190
Caselli Mauro (2005)	-0.0816	-3.7743	0.0216
Caselli Mauro (2005)	-0.0333	-1.8964	0.0176
Caselli Mauro (2005)	-0.0360	-2.0547	0.0175
Deiniger Klaus and Olinto Pedro (2000)	-0.0111	-3.8276	0.0029
Deiniger Klaus and Olinto Pedro (2000)	-0.0032	-2.2857	0.0014
Deiniger Klaus and Olinto Pedro (2000)	-0.0065	-3.6111	0.0018
Deiniger Klaus and Olinto Pedro (2000)	-0.0060	-10.0000	0.0006
Deiniger Klaus and Olinto Pedro (2000)	0.0020	1.0000	0.0020
Deiniger Klaus and Olinto Pedro (2000)	-0.0036	-2.5714	0.0014
Deiniger Klaus and Olinto Pedro (2000)	-0.0049	-4.9000	0.0010
Deiniger Klaus and Olinto Pedro (2000)	-0.0040	-10.0000	0.0004
Deiniger Klaus and Olinto Pedro (2000)	-0.0041	-5.8571	0.0007
Deiniger Klaus and Olinto Pedro (2000)	-0.0053	-17.6667	0.0003
Deiniger Klaus and Olinto Pedro (2000)	-0.0001	-0.0286	0.0035
Deiniger Klaus and Olinto Pedro (2000)	0.0095	6.7857	0.0014
Deininger Klaus and Squire Lyn (1998)	-0.0340	-4.0700	0.0084
Deininger Klaus and Squire Lyn (1998)	-0.0220	-1.9500	0.0113
Deininger Klaus and Squire Lyn (1998)	-0.0370	-3.8500	0.0096
Deininger Klaus and Squire Lyn (1998)	-0.0270	-2.0900	0.0129
Deininger Klaus and Squire Lyn (1998)	-0.0390	-2.4300	0.0160
Deininger Klaus and Squire Lyn (1998)	-0.0530	-2.1000	0.0252
Deininger Klaus and Squire Lyn (1998)	-0.0160	-1.3800	0.0116
Deininger Klaus and Squire Lyn (1998)	-0.0120	-1.0500	0.0114
Deininger Klaus and Squire Lyn (1998)	-0.0410	-2.6600	0.0154
Deininger Klaus and Squire Lyn (1998)	-0.0500	-2.0800	0.0240
Deininger Klaus and Squire Lyn (1998)	-0.0360	-3.0700	0.0117
Deininger Klaus and Squire Lyn (1998)	-0.0280	-1.9200	0.0146
Deininger Klaus and Squire Lyn (1998)	-0.0530	-1.9900	0.0266
Deininger Klaus and Squire Lyn (1998)	-0.0620	-1.9200	0.0323
Deininger Klaus and Squire Lyn (1998)	-0.0470	-2.3600	0.0199
Deininger Klaus and Squire Lyn (1998)	-0.0520	-2.1600	0.0241
Deininger Klaus and Squire Lyn (1998)	-0.0350	-1.8800	0.0186

Deininger Klaus and Squire Lyn (1998)	-0.0430	-1.9100	0.0225
Deininger Klaus and Squire Lyn (1998)	-0.0270	-1.5900	0.0170
Deininger Klaus and Squire Lyn (1998)	0.0110	0.5500	0.0200
Fort Ricardo and Ruben Rued (2006)	-0.1210	-4.4815	0.0270
Fort Ricardo and Ruben Rued (2006)	-0.1040	-3.8519	0.0270
Fort Ricardo and Ruben Rued (2006)	0.1030	1.6094	0.0640
Fort Ricardo and Ruben Rued (2006)	-0.0700	-2.6923	0.0260
Fort Ricardo and Ruben Rued (2006)	-0.0770	-3.6667	0.0210
Fort Ricardo and Ruben Rued (2006)	-0.0710	-2.9583	0.0240
Fort Ricardo and Ruben Rued (2006)	-0.0569	-1.8474	0.0308
Keefer Philip and Knack Stephen (2002)	-0.0390	-3.2500	0.0120
Keefer Philip and Knack Stephen (2002)	-0.0260	-2.1667	0.0120
Li Honyi and Zou Heng-fu (1998)	-0.0300	-2.7690	0.0108
Li Honyi and Zou Heng-fu (1998)	-0.0300	-3.0590	0.0098
Li Honyi and Zou Heng-fu (1998)	-0.0340	-3.5930	0.0095
Li Honyi and Zou Heng-fu (1998)	-0.0310	-0.4520	0.0686
Li Hongyi, Squire Lyn and Zou Heng-fu (1998)	-0.0300	-3.5800	0.0084
Li Hongyi, Squire Lyn and Zou Heng-fu (1998)	-0.0300	-4.0500	0.0074
Li Hongyi, Squire Lyn and Zou Heng-fu (1998)	-0.0300	-3.5000	0.0086
Li Hongyi, Squire Lyn and Zou Heng-fu (1998)	0.0020	0.4000	0.0050
Li Hongyi, Squire Lyn and Zou Heng-fu (1998)	-0.0800	-1.4400	0.0556
Li Hongyi, Squire Lyn and Zou Heng-fu (1998)	0.0020	0.3600	0.0056
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	-0.0340	-2.1250	0.0160
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	-0.0190	-1.1176	0.0170
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	0.0100	0.4348	0.0230
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	0.0000	0.0000	0.0200
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	-0.0180	-1.0588	0.0170
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	-0.0090	-0.5000	0.0180
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	-0.0130	-0.7647	0.0170
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	-0.0080	-0.4211	0.0190
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	0.0110	0.5500	0.0200
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	0.0170	0.7391	0.0230
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	-0.0200	-1.1111	0.0180
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	0.0010	0.0526	0.0190
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	0.0150	0.6000	0.0250
Li Hongyi, Xu Lixin Colin, Zou Heng-fu (2000)	0.0320	1.0000	0.0320
Mo Pak Hung (2003)	-0.0474	-2.6200	0.0181
Mo Pak Hung (2003)	-0.0544	-2.6800	0.0203
Mo Pak Hung (2003)	-0.0417	-2.3300	0.0179
Mo Pak Hung (2003)	-0.0444	-2.4300	0.0183
Mo Pak Hung (2003)	-0.0020	-2.2700	0.0009
Mo Pak Hung (2003)	-0.0481	-2.3000	0.0209
Mo Pak Hung (2003)	-0.0365	-2.1700	0.0168
Mo Pak Hung (2003)	-0.0386	-2.0200	0.0191
Mo Pak Hung (2003)	-0.0158	-1.3500	0.0117
Mo Pak Hung (2003)	-0.0139	-1.2200	0.0114
Nunn Nathan (2007)	-0.4600	-0.9020	0.5100
Nunn Nathan (2007)	0.4500	0.8182	0.5500
Nunn Nathan (2007)	-0.1100	-1.0000	0.1100
Nunn Nathan (2007)	0.0700	0.6364	0.1100
Weede Erich (1997)	-0.0420	-2.8300	0.0148
Weede Erich (1997)	-0.0390	-2.6000	0.0150
Weede Erich (1997)	-0.0450	-3.3200	0.0136
Weede Erich (1997)	-0.0390	-1.8900	0.0206
Weede Erich (1997)	-0.0280	-1.0800	0.0259
Weede Erich (1997)	-0.0290	-1.0600	0.0274
Weede Erich (1997)	-0.0460	-1.8700	0.0246
Weede Erich (1997)	-0.0410	-1.6300	0.0252
Weede Erich (1997)	-0.0410	-1.6100	0.0255
Weede Erich (1997)	-0.0340	-1.6500	0.0206

Appendix 2. List of case studies included in meta sample

Alesina A. and Rodrik D. (1994), Distributive Politics and Economic Growth, *Quarterly Journal of Economics*, 109, 2, 465-90.

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